STOCK MARKET VOLATILITY DURING TIMES OF CRISIS: A COMPARATIVE ANALYSIS OF THE CONDITIONAL VOLATILITIES OF JSE STOCK INDICES DURING THE 2007/08 GLOBAL FINANCIAL CRISIS AND COVID-19.

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By

ZIXIAO WANG

G16W1466

ORCID:
https://orcid.org/0000-0002-4295-0181

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Supervisor: Professor Gavin Keeton

Co-supervisor: Professor Michael Rogan

ABSTRACT

This research analyses the comparative behaviour of stock market volatility during two crises. The goal of this research is to determine whether assumed cyclical and defensive sectors have either retained or revealed their expected properties during both the Global Financial Crisis (GFC) and COVID-19 by analysing sectoral volatility amid these two crises.

Understanding how volatility changes amid crises helps to determine whether the volatility assumptions of diversified investment portfolios for both defensive and cyclical sectors still held given the different causes of each crisis. In turn, this knowledge can assist with risk management and portfolio allocation in stock market investments. The study can also contribute towards the enhancement of financial markets' resistance against systemic risks through portfolio diversification, and aid government decision-making targeted at tackling the weaknesses of different economic sectors especially in times of overall economic weakness.

This research makes use of the GARCH model to analyse a group of daily time series that consists of eleven sectoral indices and one benchmark index, all based on the South African stock markets. These observed series are categorised into two full sample periods, one designated to the Global Financial Crisis (January 2006 to May 2009) and the other for COVID-19 (January 2018 to May 2021). These are further divided into two sets of sub-sample periods, each made up of a pre-crisis and during-crisis. Furthermore, the dummy variables representing the occurrence of structural breaks are inserted into the full sample periods' conditional variance equations. This is aimed at capturing the asymmetrical impact of the crises themselves on all observed series.

Based on the movement of volatility persistency from pre-crisis to during-crisis for both crises, the results show that, firstly, Health Care and Consumer Goods are considered defensive Sectors. Secondly, Banks, Basic Materials, Chemicals, Telecommunications, and Financials are considered cyclical Sectors. Thirdly, Automobiles & Parts, Consumer Services, and Technology are considered indeterminable Sectors due to the inconsistent behaviour of these sectors' volatility persistency throughout the sub-sample periods of both crises. Overall, according to the average volatility persistency, the observed series for COVID-19's full sample period are generally less volatile than those of the GFC. However, the sub-sample periods

suggest that the observed series for both pre-crisis and during-crisis periods of COVID-19 are more volatile than those same sub-samples of the Global Financial Crisis .

Being able to analyse the characteristics of stock market sectors is crucial for risk management and optimal portfolio allocation of stock market investments. This can be achieved through portfolio diversification by investing in a variety of stocks, both cyclical and defensive, and adjusted over time based the needs of stock market investors. Diversified portfolios do not only serve the interests of individual investors, but can also enhance the financial markets' overall resistance against systemic risks.

PLAGIARISM DECLARATION

I, Zixiao Wang, declares that except for references specifically indicated in the text and such help provided to me by my supervisors and my data sponsor (the Johannesburg Stock Exchange Limited), this thesis is wholly my own work and has not been submitted at any other University or Technikon for any degree purposes.

Signed by Zixiao Wang on this 3rd day of December 2021

Signature: ___________________________

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LIST OF ABBREVIATIONS

AFC	Asian Financial Crisis
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ADF	Augmented Dickey Fuller Test
ALSI	All-Share Index
Adj R^2	Adjusted R-Squared
BCT	Business Cycle Theory
BSE	Bombay Stock Exchange
CAPM	Capital Market Pricing Theory
CASE	Cairo Stock Exchange
CPI	Consumer Price Index
CVP	Conditional Volatility Persistency Model
COVID-19	Coronavirus Disease 2019
CAC40	Cotation Assistée en Continu Index
DJIA	Dow Jones Industrial Average
DOL	Degrees of Operating Leverage
DDC-FIGARCH	Dynamic Conditional Correlation Fractionally Integrated GARCH Model
DMS-GARCH	Double Markov Switching GARCH
EDC	European Debt Crisis
EMH	Efficient Market Hypothesis
EU	European Union
E-GARCH	Exponential GARCH
FTSE	Financial Times Stock Exchange
FTSE MIB	FTSE Milano Indice di Borsa Index
FTSE-100	FTSE-100 Index composing 100 companies listed on the London Stock Exchange of England, United Kingdom
GARCH	General Autoregressive Heteroskedasticity
GDAXI	Deutscher Aktien Index of the Frankfurt Exchange, Germany
GARCH-M	GARCH-in-Mean

GARCH-X	GARCH model with covariates denoted to ‘X’
GBR	Government Bill Rate
GDP	Gross Domestic Product
GDE	General Error Distribution
GFC	Global Financial Crisis
G-7	Group of Seven
HAR	Heterogenous Autoregressive Model
HMH	Heterogenous Market Hypothesis
HSI	Hang Seng Index
IPI	Industrial Production Index
IT	Information Technology
JB	Jacque-Berra
JPY	Japanese Yen
JKSE	Jakarta Composite Index
JSE	Johannesburg Stock Exchange
J135	Index Code assigned to ‘Chemicals’ listed on JSE
J203	Index Code assigned to ‘ALSI’ listed on JSE
J335	Index Code assigned to ‘Automobiles & Parts’ listed on JSE
J510	Index Code assigned to ‘Basic Materials’ listed on JSE
J520	Index Code assigned to ‘Industrials’ listed on JSE
J530	Index Code assigned to ‘Consumer Goods’ listed on JSE
J540	Index Code assigned to ‘Health Care’ listed on JSE
J550	Index Code assigned to ‘Consumer Services’ listed on JSE
J560	Index Code assigned to ‘Telecommunication’ listed on JSE
J580	Index Code assigned to ‘FTSE/JSE SA Financials’ listed on JSE
J590	Index Code assigned to ‘Technology’ listed on JSE
J835	Index Code assigned to ‘Banks’ listed on JSE
KLSE	Kuala Lumpur Stock Exchange
KOSPI	Seoul Composite Index
LM	Lagrange Multiplier
Log LHD	Log Likelihood
MPT	Modern Portfolio Theory
MRSR	Markov-switching Model Regression

MSM	Makarov Switching Model
M-ICSS	Modified Iterated Cumulative Sum of Squares
NSE	Nigerian Stock Exchange
NSE Nifty	National Fifty of the National Stock Exchange of India
NYSE	New York Stock Exchange
N225	Nikkei 225 Index
SENSEX	Stock Exchange Sensitivity Index (of the BSE)
SIC	Schwarz Information Criterion (SIC)
SMV	Stock Market Volatility
SSE	Shanghai Composite Index
TPM	Transition Probability Matrix
TSEI	Toronto Stock Exchange Index
TSPR	Time Series Predictive Regression
T-GARCH	Threshold GARCH
t-statistics	Tau Statistics
USD	United States Dollar
U.K	United Kingdom
U.S	United States (of America)
VAR	Vector autoregressive
ZA	Zivot-Andrew
ARCH	Autoregressive Conditional Heteroskedasticity
ADF	Augmented Dickey Fuller Test
BCT	Business Cycle Theory
CAPM	Capital Market Pricing Theory
CVP	Conditional Volatility Persistency Model
EMH	Efficient Market Hypothesis
GARCH	General Autoregressive Heteroskedasticity
GFC	Global Financial Crisis
HAR	Heterogenous Autoregressive Model
LM	Lagrange Multiplier
MSM	Makarov Switching Model
SMV	Stock Market Volatility
ZA	Zivot-Andrew

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CHAPTER1: INTRODUCTION

1.1 Research context

Stock market volatility (SMV) is defined as the rate at which stock prices rise, or fall given a particular set of returns (Fama and French, 2004). Generally, volatility and risk are positively correlated (Wang and Wu, 2015). A stock price that fluctuates quickly in the short term is considered highly volatile (Gerlanch *et al*., 2006). Historical volatility is a statistical measure of how the stock returns were scattered over a given timeframe (Aljaid and Zakaria, 2020). Modern Portfolio Theory suggests that SMV is a determinant factor for portfolio diversification aimed at maximising returns at a given level of risks (Fabozzi *et al*., 2002). A diversified portfolio consists of stocks from both defensive and/or cyclical sectors (Jelilov *et al*., 2020).

According to Cochrane (2006), Panait and Slavescu (2012), Branger ·*et al*. (2013) and Asinas (2018), defensive sectors consist of stocks that during any stages of the economic cycle exhibit stable levels of returns compared to stocks of cyclical sectors. Defensive sectors therefore consist of stocks that demonstrate low and stable levels of beta coefficients, return-correlation coefficients, premiums, standard deviation and volatilities when compared to cyclical sectors. The converse can be said about stocks of cyclical sectors when compared to defensive sectors. Investors may benefit/sacrifice upside performance during economic upturns by investing in cyclical/defensive sectors that provide more stable returns during downturns. This is because defensive stocks are typically located in sectors where demand is relatively inelastic to changes in economic activity. These sectors include utilities (water and electricity) and consumer non-durables such as soap and water (Frazzini *et al*., 2012). Cyclical stocks are in sectors that are significantly impacted by changes in the business cycle, such as automobiles, banks and construction services (Ole-Meiludie *et al*., 2014).

The theories outlining the potential approaches to which a comparative analysis of SMV can be conducted are the business cycle theory (BCT) (Mitchell, 1946 and Khomo and Aziakpono, 2007), and the efficient market hypothesis (EMH) (Malkiel, 1989, Sewell, 2011). The methodological modelling techniques incorporated from a theoretical perspective are: Markov-switching model (MSM) (Dueker, 1997 and Kim *et al*., 2002), Conditional Volatility

Persistence model (CVP) (Wang and Yang, 2018) and Heterogeneous Autoregressive model (HAR) (Su and Wang, 2019).

In brief, the BCT suggested that stock markets and the business cycle are interdependent. Both macro- and micro-economic variables affect the performance and price volatilities of stocks; whereas stocks are a forecasting indicator of how profitable and sustainable firms would be in the future phases of the business cycle, which in turn affects investors' speculation regarding the economy. However, empirical results show that cyclical sectors are more sensitive towards exogenous variables compared to defensive sectors, especially during transitional phases of the business cycle (Hamilton and Lin, 1996 and Eusepi and Preston, 2011).

The EMH states that securities prices reflect all currently available information. It is therefore difficult for financial market participants to outperform the market, as all available information is already reflected in share prices. However, Afordofe (2012) argues that individual stock market sectors may have unique relationships with macroeconomic variables. Mapanda (2019) notes that such differences are important as they offer opportunities for outperformance or hedging of risk not available in the overall index alone. Gottwald (2014) suggested that cyclical sectors exhibit higher market efficiency, where an investor's decision is based heavily on a multi-factor estimation of the intrinsic values of sectors. As a result, the differences between intrinsic values and market prices (expressed as the safety margin of a stock investment) were low for cyclical sectors compared to defensive sectors.

The Markov Switching Model, Conditional Volatility Persistency (a synonymity with the GARCH) model and Heterogenous Autoregressive model provide the methodological basis for the econometric modelling aimed at analysing the conditional volatility of stock indices. In Dueker (1997), MSM was incorporated with the GARCH model to forecast implied SMV. The combination captured SMV with improved accuracy during both periods of weak and strong shocks. In Wang and Yang (2018), the authors have applied 'information' as a source of variables in both CVP and HAR models. The results showed that SMV persistence increased with current stock returns of all types of stocks and corresponding stock indices. Babikir *et al.* (2010) have implemented structural breaks and GARCH models to analyse South African stock return volatility from 1995 to 2010. The authors showed that local stock market sectors have different combinations of risks and returns. Muzinda (2016) explored the impact of both good and bad news on South Africa's sectoral stock return volatility by using an asymmetric

GARCH analysis. The models suggested that both good and bad news have the same effect on sectors such as health care and consumer staples, possibly due to their defensive nature. In contrast, the highest levels of sectoral volatility were found in Telecommunications and Technology.

Therefore, the volatility pattern of sectors can change overtime, especially in response to a shock or crisis. Engle *et al*. (2013) suggested that macroeconomic factors of inflation and industrial output growth contributed significantly towards the aggregate daily SMV worldwide from 1890 to 2004. Hancock (2010) and Junkin (2012) indicated that macroeconomic factors such as economic growth and interest rates can all affect index prices in South Africa. The different reaction for different types of indices in response to shocks and during times of economic crisis in part reflects the way in which such shocks/crises impact on economic activity and firms' earnings. Thus, an inflation shock is likely to result in much higher interest rates, impacting more negatively on sectors impacted directly by interest rates than those which are not (Saleem *et al*., 2013, Muriuki, 2014).

An exchange rate crisis may benefit exporters and negatively impact sectors reliant on imports (Sikhosana and Aye, 2018, Fahlevi, 2019). Likewise, the 2008 Global Financial Crisis (GFC) is likely to have impacted on sectors differently from the 2020 COVID-19 crisis. This is because the former started as a financial crisis that exposed the poor state of the financial sector and then spilled over into other sectors of the economy. The second is a health crisis that because of resultant lockdowns and the disruption of global trade had a serious negative impact on global production and demand in sectors such as energy, tourism and transportation and, initially, the stock market as a whole, but a positive impact on health care (He *et al*., 2020, Shen *et al*. 2020, Sun *et al*., 2021).

Overall, SMV was especially significant during both the GFC and the current COVID-19 crisis. Mapanda (2019) noted that the impact of interest rates on stock prices changed after the GFC for both the telecommunication and technology indices of the JSE. Valls Martínez and Martín Cervantes (2020) suggested that the renewable and green energy sectors of the major global economies were more adaptable and resilient towards SMV amid the recent COVID-19 crisis. Comparing the returns of the published sectoral indices of the Johannesburg Stock Exchange (JSE) during both crises will help determine whether the volatility assumptions of diversified investment portfolios for both defensive and cyclical sectors still held given the different causes of each crisis. The answers to this question are important because, firstly, they will assist in risk management and portfolio allocation, where investors can use the findings to construct portfolios aimed at maximizing returns at a given level of risk (Rasmussen, 2002). Secondly, the analysis can contribute towards overall financial market stability by aiding the construction of well-diversified investment portfolios that enhance the financial market's resistance against systemic risks (Frey and Hledik, 2018, Ji *et al*., 2020). Thirdly, the analysis can aid government policy making by revealing the relative strength or weakness of different economic sectors in times of overall economic weakness.

1.2 Goals of the Research

The main goal of this research is to comparatively determine whether assumed cyclical and defensive sectors under observation have retained their sectoral properties during both the GFC and COVID-19. The assumption is that these assumed sectors will remain either cyclical or defensive throughout both crises. However, the characteristic of two sectoral indices used in this research cannot be assumed (or is 'un-predeterminable'). Therefore, the sub-goal of this research is to identify whether 'un-predeterminable' sectors can be classified as cyclical or defensive sectors during both the GFC and COVID-19. Together, both the main- and sub-goal of this research can be achieved with reference to the statistical results discussed in Chapter 4.

The classification of sectoral indices is based upon empirical findings of Chapter 2 including the context of South Africa. However, such classification varied between authors due to changes in research contexts and goals. Therefore, both assumed and 'un-predeterminable' sectors categorised in this particular research may differ to those of other authors.

1.3 Methods, Procedure, and Techniques

Data used is daily time series supplied to the author by the JSE. Additional data were acquired from Yahoo Finance from February to May 2021. Two separate sample sizes are used for each crisis, reflecting pre-crisis and the crisis periods. The first full sample period from January 2006 to May 2009 is used for analysing the GFC. The second full sample period from January 2018 to May 2021 is used for analysing the period of COVID-19. The sample sizes are organised to include at least 12 months prior to the crisis and then the length of the crisis itself for the GFC and the latest time period at time of writing for COVID-19. Arguably, the crisis of COVID-19 is still affecting the world and the international stock markets.

Following Muzinda (2016), Adekoya and Nti (2020) and Mazur *et al*. (2021), eleven JSE sectoral indices are used for the comparative analysis of both sample periods. These sectoral indices are discussed in detail in Chapter 3. The methodological analysis is targeted at measuring the conditional volatility during both periods. The first part of the analysis consists of a group of *priori* tests used to identify possible patterns, relationships, responses, trends, and spuriousness of the data. Afterwards, following the work of Adesina (2017), the second part of the analysis consists of the GARCH diagnostics and GARCH (1, 1) regressions used to obtain the level of volatility persistency of all series under observation.

As a final step of this research, all observed series[1] throughout all sample periods are run through a GARCH-in-Mean (or GARCH-M) models using three different specifications. The purpose of the GARCH-M model analysis is to comment on the direction, size, and significance of the daily returns in relation to the conditional variances. Subsequently, this helps to understand whether or not a higher level of risk is associated with a higher level of return. Based on the findings and results in Chapter 4, the research is able to provide suggestions regarding potential investment/hedging options restricted to the observed series. However, the concluding section (Chapter 5) of this research will not focus on commenting about the results of the GARCH-M model, because the model itself specialises on the analysis of risk premiums, rather than the focal point of this research, which is volatility.

1.4 Layout of thesis

From this point onward, the research moves onto Chapter 2 (literature review) which is divided into theories, followed by theoretical methodologies, and empirical findings. After establishing the theoretical and empirical foundations, Chapter 3 discusses the data and methodologies adopted and their relevance towards achieving both the main goal and sub-goal of this research. Subsequently, Chapter 4 presents the findings and results. Lastly, Chapter 5 makes concluding remarks on the extent to which the research goal and sub-goal have been achieved. In addition, Chapter 5 outlines the areas for future research.

[1] All observed series includes all eleven sectoral indices and the benchmark index under observation.

CHAPTER 2: LITERATURE REVIEW

2.1 Organisation of literature review

This chapter is divided into two parts. Part one (subsections 2.2 to 2.9) consists of the theoretical backgrounds on which the research is based, which starts with theories and ends with theoretical methodologies. Part two (subsections 2.10 to 2.13) is a review of the empirical findings on how stock market volatilities have behaved during both the GFC and COVID-19.

2.2 Modern Portfolio Theory (MPT)

MPT was based on the introduction of portfolio selection by Markowitz in 1952. It can be regarded as a mathematical framework that assembles a portfolio of assets in order to maximise expected returns at a given level of risk. MPT indicates that investment diversification is the core to portfolio construction, where assets of different risk and return combinations are included. Howells and Bain (2008) proposed that risk is the difference between actual return and expected return. Risk can be categorised into upside and downside risks. The former occurs when the actual return exceeds the expected return, and the opposite is true for the latter. This suggests that individual expectations regarding risk is symmetrical. However, MPT assumes that risk expectation is asymmetrical between investor types. For instance, risk averse investors prefer an asset that has the least amount of quantifiable risk at a given level of return. Therefore, such an investor will only accept a riskier asset for a higher return.

Markowitz (1959) also acknowledges that risk can be reduced through portfolio diversification without having to give up on potential returns. This can be achieved by selecting a group of less return-correlated assets. Nevertheless, risks cannot be fully eliminated through diversification. This is because that risk can be systematic and unsystematic according to Thompson (1976) and Montgomery and Singh (1984). On one hand, systematic risks are inherent to the market as a whole under the influence of economic, financial and geo-political factors. They are unpredictable and difficult to avoid. On the other hand, Hotvedt and Tedder (1978) and Rosenberg (1991) suggested that unsystematic risk is diversifiable because it is uniquely observed from a specific firm or industry. Factors of unsystematic risk can be attributed to firm financial status, corporate vision, entrance and exit requirements, new competition and regulation *et cetera*.

Swisher and Kasten (2005) indicated that the efficient frontier proposed by Markowitz (1959) should also be accounted for when engaged in portfolio diversification. The efficient frontier curve is upward sloping and flattens out gradually at high levels of expected returns, which reflects a diminishing marginal rate of return. The determinant factors of an efficient frontier are its correlation coefficient, returns and standard deviation. An efficient portfolio should either offer the highest return for a given level of risk. Compared to cyclical sectors, defensive sectors contain stocks that exhibit low and stable levels of beta coefficients, return-correlation coefficients and standard deviation.

2.3 Business Cycle Theory (BCT)

The concept of the business cycle traces back to the work of Burns and Mitchell (1946). In general, the business cycle is repetitive because an economy must experience an expansionary phase, followed by a contractionary phase, and then a revival phase until the economy reaches its developmental peak once again. Similarly, Khomo and Aziakpono (2007) proposed that there are four business cycle phases namely: upturn (expansion), upper turning point (peak), downturn (contraction) and lower turning point (trough).

Over the years, studies have disputed what factors underly the continuity of the business cycle. To begin with, Zarnowitz (1991) and Chatterjee (2001) suggest that the economy is trapped in a self-sustaining cycle where each phase would ultimately lead to the next phase. In contrast, Monetarists believe that the business cycle is caused by changes in monetary aggregates due to adjustments in monetary policies (Sims, 1980). Upswings in economic activities are attributive towards a loosened monetary policy, whereas downswings in economic activities are a result of a tightened monetary policy. Therefore, one can argue that changes in money supply directly cause fluctuations in economic activities, which in turn leads the economy towards different phases of the business cycle.

However, Hansen and Wright (1992) suggested that, according to the real business cycle theorists, changes in productivity/output are the main cause of the cyclical movements in the economy. Enhanced output is due to improved technologies and skills of labour, which in turn positively affect the supply side of the economy. Thus, different from a monetary perspective, fluctuations in output are not directly affected by changes in monetary and fiscal policies.

Goodspeed (2009) and Næs *et al*. (2011) suggested that the stock market is a crucial indicator of business cycle turning points. A strengthening in stock market liquidity and returns are usually followed by a boost in economic activities and *vice versa*. In addition, Goodspeed (2009) stressed that, while the stock market and the business cycle do not imply causality, the performance of a stock market (bullish or bearish) is often associated with the start of an economic expansion or recession. This is because stock markets often react to forecasted macroeconomic indicators such as exchange rates, inflation and interest rates especially during transitioning phases of a business cycle.

Therefore, the stock markets tend to lead the business cycle dictated by three potential explanatory factors. Firstly, changes in share prices appear to be responsible for the subsequent speculation and performance of share prices and business confidence, and in turn lead to changes in economic activities (Hamilton and Lin, 1996). Secondly, as mentioned in the previous paragraph, investors invest based on forecasted macroeconomic variables rather than current/observed economic variables (Eusepi and Preston, 2011). Lastly, investors tend to make investment decisions based on leading microeconomic and finance indicators such as company profit, debt-to-equity ratio, debt-to-asset ratio and takeover bids *et cetera* (Hol, 2007).

According to Bodie *et al*. (2005) and Sumarsono (2016), market sectors can perform differently during various phases of the business cycle, where cyclical sectors are more sensitive to changing exogenous variables than defensive sectors. An additional explanation can be found within the industry (microeconomic and finance) analysis which focuses on the extent to which industries are sensitive towards the business cycle.

2.3.1 Industry analysis

Bodie *et al*. (2005) and Deleersnyder *et al*. (2009) explained that there are two aspects that determine an industry's sensitivity to the business cycle. Firstly, industries can be categorised into different degrees of operating leverage (DOL). DOL measures a firm's income sensitivity to changes in revenue. A firm with a higher level of DOL tends to have a higher level of operating efficiency, but at the cost of sacrificing a significant amount of income when revenue decreases. Therefore, high DOL firms should be affected to a greater extent by changes in revenue during each phase of the business cycle compared to low DOL firms. This relationship is also consistent with the findings of Bhattacharjee *et al.* (2015).

Secondly, industries can also be classified by the level of debt financing or leverage ratio, which assesses the ability of a firm to meet its financial obligations. An increase in leverage ratio is due to an increase in debt accumulation. Unless a firm can generate a higher return rate than the interest rate on its loans, a high leverage ratio should be a warning to investors, because the accumulated amount of debt may eventually become uncontrollable. In general, an increase in leverage ratio is associated with a higher interest rate and the more sensitive a firm will become to the business cycle. Consequently, the returns and share price of the firm will become more volatile, and *vice versa*. This relationship is consistent with the findings of Thurner *et al.* (2012) and Halling *et al.* (2016).

While a high operating leverage ratio and financial leverage may deem a firm to be too high of an investment risk, Bodie *et al.* (2005) advised that these factors should not always have the same weightings in making investment decisions during different phases of the business cycle. During an economic upturn, firms with high investment risks could potentially perform better than those with low investment risks, while firms with low investment risks tend to perform better during economic downturns. For instance, at the beginning of a recession, interest rates are high, while aggregate demand and consumption expenditures are low. Investments in defensive sectors such as consumer staples, insurance and pharmaceuticals would be more attractive due to inelastic demand for their products. This is consistent with the findings of Frazzini *et al.* (2012) and Panait and Slavescu (2012).

Towards the end of a recession, the earnings of financial firms that are sensitive to changes in macroeconomic variables tend to do better due to an increase in loan demand coupled with low levels of inflation and interest rates. At the beginning of an upturn, cyclical sectors such as capital goods, consumer durables, equipment, transportation and construction tend to perform well due to a boost in economic activities. These are consistent with the findings of Branger *et al.* (2013) and Ole-Meiludie *et al.* (2014). At the peak of an economic expansion, both inflation and interest rates will rise due to excess demands for consumer goods and services (Bodie *et al.*, 2005). This means that primary and secondary sectors involved in extracting and manufacturing of natural resources become more attractive investments choices. This is because that these sectors have high levels of liquidity and operation stability that would offset the effects of rising inflation.

2.4 Efficient Market Hypothesis (EMH)

The EMH states that, at any given time in a highly liquid market, stock prices are efficiently valued to reflect all the available information related to the stock market (Fama, 1991). This belief originates from the assumption that market participants view stock prices rationally based on all current and future intrinsic and external factors.

The weak version of the EMH suggests that the current stock price of a firm fully consists of information captured in the historical prices (Malkiel, 1989, Borges, 2010, Sewell, 2011). The semi-strong version of the EMH asserts that the current stock price fully incorporates all corporate factors (from the financial statements) and macroeconomic factors (such as inflation and interest rates) in the form of publicly available information (Jensen, 1978 and Wang, 1985). Prices will adjust immediately to reflect changes in publicly available information. The strong version of the EMH indicates that the current stock price fully consists of all existing public and private/insider information (Yalçin, 2010 and Degutis and Novickytė, 2014). Therefore, the EMH illustrates that exogenous factors can have an impact on stock prices, which in the case of this research, is specifically referring to the impact of the GFC and Covid-19 on stock market volatility.

Contrary to the EMH theory, Ferguson (1989) and Shiller (2000) suggested that behavioural factors play a more important role in explaining stock market volatility through their influence on stock prices. Cognitive psychologists such as Kahneman and Tversky adhered to the notion that individuals tend to overreact and react differently to losses than gains. Therefore, informed individuals may not necessarily act rationally. The authors had put forth evidence to suggest that individuals tend to over-extrapolate from small samples, which might explain investors' overconfidence that slow-growth companies will be able to keep growing in terms of earnings. Furthermore, Scott *et al*. (1999) declared that some individuals tend to be overconfident in both their unique abilities and quality of information for making investment decisions, which may have exemplified the problem of representativeness bias.

The studying of market patterns such as Calendar Anomalies are used to capture stock market volatility from a trend analysis viewpoint, where the reappearance of certain market anomalies cannot be fully explained by both EMH and behavioural psychology. To illustrate, firstly, the January Effect is a popular seasonality/cyclicality rule in the equity markets worldwide based on the research of Rozeff and Kinney (1976) who researched on the monthly return rates of the New York Stock Exchange from 1904-1974. The study showed that the differences between a stock's mean return over the period of a year is mainly due to its own abnormal and large mean returns in January (Wong *et al*., 2006, Mylonakis and Tserkezos, 2008 and Norvaisiene *et al*., 2015). Secondly, the Weekdays Effect was documented in the U.S stock market by Osborne (1962), where Mondays were typically dominated by low mean returns. Jain and Joh (1988) indicated that the exchange volume of the NYSE (New York Stock Exchange) on Mondays was approximately 90% of its usual volume from Tuesday to Friday. Jaffe *et al*. (1989) suggested that average stock returns on Mondays are both significantly negative and lower compared to those on Tuesdays to Fridays. However, Kiymaz and Berument (2003) indicated that stock markets were most volatile on Mondays in Germany and Japan, while the same was only true on Fridays for Canada and the United States. These findings emphasised the impact also of geographical locations on market anomalies.

In sum, both behavioural psychologies and calendar anomalies suggest that the EMH is an inaccurate assumption made about the overall financial markets. However, Samuelson (1965) and Dybvig and Ross (1989) believed that the unrealistic equilibrium of the EMH is nonetheless useful for the studying of market inefficiencies that exist in reality. Hence, the real financial markets consist of participants such as arbitrageurs, general investors, and hedgers who are all seeking to make abnormal profits. Financial markets are therefore only comparatively more efficient if they are highly competitive and developed, such as in the case for the NYSE and the Tokyo Stock Exchange, *et cetera*. In other words, the EMH only governs the financial markets over certain phases and can also be replicated to a certain extent by econometric models designed to capture stock markets volatilities.

2.5 Conditional Volatility Persistence (CVP) models

Stock market volatility is a crucial factor for making investment decisions, because volatility reflects the risk or uncertainties associated with investment returns (Christianti, 2018). A share or index characterised by volatility persistence signals that its present return (today) has a huge influence on predicting the volatility of its own returns in the future (tomorrow). An increase in volatility persistency thus shows that a share or index is becoming an investment with more risks over time. Nonetheless, there is not a threshold level of volatility persistency that distinguishes a share or index as cyclical (perceived as an investment with more risks) or defensive (perceived as a safer investment category). Consequently, one can make a better-informed investment decision when comparing the volatility persistency of two or more shares or indices, because the concept of risk then becomes a relative term.

CVP models were designed to account for the volatility persistency within time series in a stock market context and are often synonymous to the univariate GARCH (General Autoregressive Conditional Heteroskedasticity) family models. According to Wang and Yang (2017) and Chen and Wang (2021), both CVP and GARCH refer to the non-linear regression designed by Engle (1989) to investigate stock market volatility (through the analysis of volatility persistence) conditional upon exogenous variables modelled to capture their influences on the endogenous variable.

The discussion of the CVP model construction procedure is based on Christianti (2018) who demonstrated how stock market volatility of sectoral returns can be investigated with a foundational GARCH model. The work of Karmakar (2005) is used as complementary to that of Christianti (2018). To start, the first step towards building a GARCH model involves the transformation of the raw time series data (closing prices) into logarithmic daily returns. The method was also adopted by Karmakar (2005) and Wang and Yang (2017). The second step features in the undergoing of Ljung-Box's *Q*-statistics test for serial correlation and Autoregressive Conditional Heteroskedasticity Lagrange-Multiplier (or ARCH-LM) test for heteroskedasticity. If serial correlation and heteroskedasticity have been detected within the time series, the pre-requisitions for undergoing a GARCH model regression would have been satisfied.

The third step focuses on specifying and regressing both the conditional mean and variance equations that together formulates the GARCH model. The results obtained from the regression would indicate the volatility persistency level of the time series and is demonstrated by the sum of the ARCH and GARCH coefficients within the GARCH model. In like manner, Jondeau and Rockinger (2003), Karmakar (2005) and Bentes and Mendes da Cruz (2011) have also formulated their GARCH models using the same specifications and regressions. From the empirical findings discussed in subsection 2.12 to 2.13, it can be said that cyclical sectors exhibit a higher level of volatility persistency (and therefore an investment with more risks) throughout the sample periods and especially during a period of crisis or recession. In contrast, defensive sectors display a lower level of volatility persistency (and are therefore safer as an investment category) throughout the sample periods and especially during a period of crisis or recession.

The last step is to conduct a market volatility forecast and subsequently evaluate the forecasting accuracy of the one-day ahead market volatility denoted to h_{t+1}. These two steps are aimed at diagnosing the accuracy in which the GARCH model had forecasted market volatility, and in turn reflects how precisely was the realised volatility replicated by the model. For the purpose of this research, forecasting the conditional volatility is targeted at producing a visual representation of conditional volatility, which is aimed at graphically capturing changes in the level of volatility (thus riskiness) in both defensive and cyclical indices over the period of the GFC and COVID-19.

Nonetheless, there are a few limitations regarding the GARCH model. Firstly, Black (1976) found that stock returns are negatively correlated to changes in volatility. In particular, volatility tends to rise in response to bad news, where excess returns are typically lower than expected returns. In contrast, volatility tends to fall in response to good news, where excess returns are typically higher than expected returns. However, the GARCH model assume that only the magnitude of excess returns can determine the conditional volatility/variance of the series, rather than the positivity or negativity of excess returns. This is accounted for by the exponential GARCH or E-GARCH model.

Secondly, the GARCH model has been designed to maintain the non-negativity of the conditional variance. The ARCH coefficients are intentionally adjusted into positive values for all periods throughout the observed time series. Therefore, the sum of the ARCH and GARCH coefficients, which measures the level of volatility persistency, can occasionally be inaccurate. Lastly, the GARCH model does not make clear the duration for which volatility shocks persist. The shock may either be persistent (carried forth into the future stock returns), or it may be transitory (occurred during certain periods of the series). The exact interpretation depends on stylised modelling of GARCH specifications, which had been accounted for by the asymmetrical effect coefficient of the Threshold GARCH or T-GARCH model.

2.6 Markov Switching Model (MSM)

The GARCH model was discussed in the previous section. Therefore, the fundamentals of a Markov-switching process should be established in this section before moving onto the next section that explains how both GARCH and MSM can be combined to estimate and forecast stock market volatility. Rogan (2020) has provided a specific two-regime MSM framework for understanding regime switching. Firstly, let the regime dependent variable, in other words, the observed series (y_t) be able to switch in between two regimes expressed as:

$$y_t = \alpha_{10} + \alpha_1 y_{t-1} + \varepsilon_{1t}, if\ y_t\ is\ in\ regime\ 1 \ldots [2.1]$$

$$y_t = \alpha_{20} + \alpha_2 y_{t-1} + \varepsilon_{2t}, if\ y_t\ is\ in\ regime\ 2 \ldots [2.2]$$

In the two equations above, α_{10} and α_{20} are the regime switching constants for regime 1 and 2 respectively, where $\alpha_1 y_{t-1}$ and $\alpha_2 y_{t-2}$ are the lagged values of the two regime and e_{1t} and e_{2t} are the regime switching error terms. Accordingly, time series transit through a set of finite regimes, where regimes are unobserved. The transition time between regimes and the duration of each regime are both random.

Then, let P denoted to a transition probability matrix (TPM) for two regimes. Regime 1 ($S_t=1$) is a period of economic recession while Regime 2 ($S_t=2$) is a period of economic expansion. Afterwards, let P_{11} denote to the probability of an economy remaining in Regime 1 in period ($t+1$) given that it is currently in Regime 1 in period (t). Also, let P_{22} denote to the probability of an economy remaining in Regime 2 in period ($t+1$) given that it is currently in Regime 2 in period (t). Given P_{11} and P_{22}, the TPM can be expressed in Table 1 as:

Table 1: the transition probability matrix (TPM)

	Regime 1 (t+1)	*Regime 2 (t+2)*
Regime 1 (t)	P_{11}	P_{12}
Regime 2 (t)	P_{21}	P_{22}

Therefore, according to Table 1, ($1-P_{11} = P_{12}$) is the process of Regime 1 in period t switching to Regime 2 in period $t+1$. Likewise, ($1-P_{22} = P_{21}$) is the process of Regime 2 in period t switching to Regime 1 in period $t+1$. In summary, there are a finite number of unobserved regimes of a time series in an MSM. If there are two regimes (1 and 2) in a Markov switching process, then S_t, following a first-order Markov process, denotes to a random variable such that $S_t = 1$ or $S_t = 2$. The current value of S_t depends only on the immediate past value of itself (S_{t-1}). The regime in which the process is situated is unknown, but the probability can be estimated.

2.6.1 MSM-GARCH: a combination of GARCH and MSM

MSM-GARCH is a model that combines both the MSM and GARCH models. It is utilised for examining the asymmetrical effects in the conditional mean and conditional variance of financial time series. The purpose is to capture the state or regime switching process in stock prices, which in turn can be used to estimate and forecast the transitioning process of stock market volatility. The work of Chen *et al.* (2009) will be discussed in brief to show the fundamental procedure undertaken to incorporate the conditional mean and variance equations of the GARCH model into the regime switching processes.

To start, Chen *et al.* (2009) used a Markov chain to determine the two-regime-switching processes in both the conditional mean and variance equations of the MSM-GARCH model listed expressed as:

$$y_t = \begin{cases} \Phi_0^{(1)} + \sum_{i=1}^{p} \Phi_i^{(1)} y_{t-i} + \sum_{j=1}^{q} \psi_i^{(1)} x_{t-j} + \alpha_t \; if \; s_t = 1, \\ \Phi_0^{(2)} + \sum_{i=1}^{p} \Phi_i^{(2)} y_{t-i} + \sum_{j=1}^{q} \psi_i^{(2)} x_{t-j} + \alpha_t \; if \; s_t = 2, \end{cases} \quad \ldots [2.3]$$

$$h_t = \begin{cases} \alpha_0^{(1)} + \sum_{i=1}^{g} \alpha_i^{(1)} \alpha_{t-i}^2 + \sum_{i=1}^{k} \beta_i^{(1)} h_{t-i} + \alpha_t \; if \; s_t = 1, \\ \alpha_0^{(2)} + \sum_{i=1}^{g} \alpha_i^{(2)} \alpha_{t-i}^2 + \sum_{i=1}^{k} \beta_i^{(2)} h_{t-i} + \alpha_t \; if \; s_t = 2, \end{cases} \quad \ldots [2.4]$$

In the two equations of [2.3] and [2.4], the conditional mean equation of [2.3] has the following components: y_t is the rate of return, Φ is an autoregressive mean parameter, and ψ represents the likelihood of the return to remain in a particular regime. The conditional variance equation of [2.4] has the components of α and β which represent the ARCH and GARCH effects respectively in estimating volatility persistence.

The same components shown in both equation [2.3] and [2.4] are as follows: S_t is a discrete stationary sequence that represents the discrete regime space {1, 2} in which y_t is situated. Both *t-i* and *t-j* are the unobserved regime associates that either takes a value of 1 or 2 and α_t is a continuous time Markov chain of X_{t-j} that can be written as $\alpha(X_{t-j}) = \varepsilon_t \sim i.i.d\, N(0, \sigma^2)$. Cárdenas-Gallo *et al*. (2012) and Mazivona (2012) have also expressed their conditional mean and variance equations in a similar manner.

Once the MSM-GARCH model is defined, the next step is to generate the Bayesian inference likelihood function. This is aimed at accounting for the leptokurtosis[2] in financial time series and used for deriving the conditional posterior distributions for both variance parameters and regime distributions.[3] Moolman (2004), Cárdenas-Gallo *et al.* (2012), and Abounoori *et al.* (2016) have also accounted for the likelihood functions in formulating their versions of the MSM-GARCH model. Finally, after taking the likelihood functions into consideration, the conditional mean in [2.3] and variance in [2.4] equations can be evolved into equation [2.5] and [2.6] respectively and expressed as the following:

$$\mu_t = \Phi_0^{(j)} + \sum_{i=1}^{p} \Phi_i^{(j)} y_{t-i} + \sum_{j=1}^{q} \psi_i^{(j)} x_{t-j} \ldots [2.5]$$

$$h_t = \alpha_0^{(j)} + \sum_{i=1}^{g} \alpha_i^{(j)} \alpha_{t-i}^2 + \sum_{i=1}^{k} \beta_i^{(j)} h_{t-i} \ldots [2.6]$$

[2] Leptokurtosis is a scenario where a probability density curve has got fatter tails and a higher peak exhibited in the mean value than the normal distribution.

[3] Conditional posterior probability refers to a random event or uncertain proposition that is assigned to a variable (the variance parameters and regime distributions in this case) after relevant evidence, generated from an experiment or survey, has been accounted for.

2.7 Heterogenous Autoregressive models (HAR)

Initially proposed by Corsi (2004), the HAR was formulated based on the heterogenous market hypothesis (HMH). The HMH states that the same market information can be interpreted differently according to the unique types of financial market participants. These participants (such as market makers, dealers, brokers, intermediary individuals, arbitrageurs, hedgers and institutional and individual investors) have specified trading horizons and subsequently generate different volatility frequencies. This has been incorporated by the HAR model as daily, weekly, and monthly volatilities that would impact the overall financial market in the short-term, medium-term and long-term respectively. The work of Qu and Ji (2014) is discussed briefly as it provides a foundational understanding of how HAR can be modelled and tested.

To start, the first step in constructing an HAR model is to identify price jumps in the time series. Specifically, in a financial market context, a price jump is regarded as a volatile movement in security prices that occurred suddenly over a short period of time, due to the severe impact of changes in exogenous variables outside the financial markets. Volatility in financial markets can either be classified as a regular noise (JV_t) or a price jump (Z_t). Thus, the nature of volatility should be investigated by different methods. After identifying the nature (regular noise or price jump) of volatility, the next step is to estimate the realised volatility using the HAR models. The basic HAR model was proposed by Müller *et al.* (1997) and Corsi (2004) expressed as:

$$lnRV_t = \alpha_0 + \alpha_d lnRV_{t-1} + \alpha_w lnRV_{t-5:\,t-1} + \alpha_m lnRV_{t-22:\,t-1} + \varepsilon_{1,t} \ldots [2.7]$$

In equation [2.7], $lnRV_{t-1} = \sum_{j=1}^{1} RV_{t-j}$ is the logarithmic past daily realised volatility, $lnRV_{t-5:\,t-1} = \sum_{j=1}^{5} RV_{t-j}$ is the logarithmic past weekly realised volatility, and $lnRV_{t-22:\,t-1} = \sum_{j=1}^{22} RV_{t-j}$ is the logarithmic past monthly realised volatility. Furthermore, α_d, α_w and α_m evaluates the investors' input to the general market volatility in the short-term, medium-term and long-term respectively.

In addition to the basic HAR model in equation [2.7], the A(adaptive)HAR-RV-CJ model shown in equation [2.8] below proposed that realised volatility should be estimated with the inclusion of continuous regular noise ratio-statistics (CV_t) associated with volatility coefficients of alpha (α), regular noise ratio-statistics (JV_t) associated with volatility coefficients of beta (β) and time structures (D_t). The modification is aimed at enhancing the forecast accuracy of a pure HAR model and can be expressed as:

$$lnRV_t = \alpha_0 + \alpha_1(lnCV)_{t-D_1:\,t-1} + \alpha_2(lnCV)_{t-D_2:\,t-1} + \alpha_3(lnCV)_{t-D_3:\,t-1} + \beta_1(lnJV)_{t-D_1:\,t-1} + \beta_2(lnJV)_{t-D_2:\,t-1} + \beta_3(lnJV)_{t-D_3:\,t-1}\ \varepsilon_{3,t} \ldots [2.8].$$

2.8 Summary of theories

Part one of Chapter 2 has outlined the three theories (MPT, BCT, and EMH) covering stock market prices and their volatility as well as the four theoretical methodologies (CVP, MSM, MSM-GARCH, and HAR) used for modelling and capturing stock market volatility. To put these into a stock market perspective, the MPT illustrated that, through portfolio diversification, an investor can benefit from maximised returns and minimised risks through investing in a portfolio of diversified assets. While unsystematic risks can be mitigated, systematic risks are generally difficult to avoid. However, the perception of risk is asymmetrical amongst different types of investors. Therefore, the ideal balance between risk and return can be accounted for by the efficient frontier curve which reflects the stock beta coefficients, stock correlation coefficients, stock returns and standard deviations of stocks.

The aforementioned indicators are primary guidelines (or *priori* tests) for constructing a suitable portfolio that caters for individual needs. From the empirical results discussed in subsection 2.12 to 2.13 below, defensive sectors normally have a lower sectoral correlation coefficient with the other indices. Also, defensive sectors usually demonstrate a lower standard deviation and a higher return compared to cyclical sectors during times of crises and/or recessions. In contrast, it is possible for the stock returns of cyclical sectors to overperform defensive sectors during economic upturns and peaks.

Subsequently, the BCT suggested that the performances of stocks tend to be interdependent with the business cycle. In particular, macro- and micro-economic variables would be adjusted especially amid the transitioning phases of the business cycle and these adjustments impact on firms in terms of share performances and price volatilities. However, empirical results from subsection 2.12 to 2.13 show that these exogenous variables have a weaker impact on defensive sectors compared to cyclical sectors. An additional explanation is offered by the industrial analysis, where not all firms are affected equally by the business cycle, because firms are characterised by different levels of financial soundness. A firm that is financially healthier will be affected to a lesser extent by the business cycle as a whole. As a result, its share returns will be less volatile during transitionary phases of and throughout business cycle.

The impact of changes in exogenous (both macro- and micro-economic) variables can be reflected as 'information' absorbed by the stock markets. Therefore, the EMH illustrated that investment decisions should also account for the possibility of making abnormal profits based on information availability. Theoretically, abnormal profits can be made if stock prices are not efficiently valued due to insufficient amount of information absorbed by the stock markets. Cyclical sectors usually exhibit higher levels of market efficiency compared to defensive sectors. This is because cyclical sectors as a whole are more sensitive towards movements in information/exogenous variables compared to defensive sectors.

Furthermore, behavioural psychologies can also affect the efficiency with which information can be received by the stock markets. This is because investors may react to losses and gains differently, tending to overreact to losses compared to gains. Therefore, informed investors may not necessarily act rationally. On top of that, individual investors may over-extrapolate from small samples and become overconfident about their capacity to make investment decisions to the best interest of themselves. Equally important, calendar anomalies based on trend analysis can also capture the seasonality of equity market behaviour that cannot be fully explained by psychology. For example, stocks may generate a higher or lower return during certain days, weeks or months of a year.

2.9 Practicality of theories under the research context:

In terms of the research, the theories and theoretical methodologies have provided the guideline with regards to the data and methodological arrangements. Specifically, guided by the BCT, the data is arranged into two full sample periods designated for each crisis. However, in order to particularly capture how stock market volatility has reacted to a period of crisis, each full sample period was further divided into two sub-sample periods. The two sub-sample periods for each crisis are denoted as 'pre-crisis' and 'during-crisis. The sub-samples are created under the EMH, which suggests that 'information' has an asymmetrical impact on stock market volatility during different periods of time. More importantly, according to the empirical findings from subsection 2.12 to 2.13, cyclical sectors tend to react more to the asymmetrical effect of information during times of crises when compared to defensive sectors.

Taking the phenomenon of asymmetrical effect into account, a dummy variable (structural break) has been inserted into the GARCH model regression for each full sample period. Subsequently, the structural break has informed the precise date in which the asymmetrical effect of information has occurred for all series under observation during the two full sample periods. See subsection 3.4 in Chapter 3 for detailed explanation regarding the rationale for including a dummy variable in the full sample periods (and not the sub-sample periods).

Furthermore, the data arrangement can also assist with the testing of the research sub-goal, which is to verify whether 'un-predeterminable' sectors have demonstrated properties of either defensive or cyclical sectors during both the GFC and COVID-19 crises when compared to the full sample and pre-crisis periods.

In addition, according to the CVP model, if the ARCH and GARCH coefficients of Consumer Goods, compared to other 'un-predeterminable' sectors, had summed up to a lower value during all sample periods, then this would be considered as another sign of a defensive sector. In contrast, if Consumer Goods exhibited higher values of the aforementioned outputs during all sample periods, then it has demonstrated features of a cyclical sector.

2.10 Stock market volatility during crises

The subsections below will discuss the empirical findings presented by different authors about stock market volatility during both the GFC and COVID-19 from the perspectives of the developed countries, developing countries and South Africa. Therefore, there will be one introduction followed by three subsections dedicated to the literature review of each crisis. Each subsection consists of one or two benchmark studies discussed in detail.

2.11 The impact of the GFC

The GFC was rooted in an oversupply of credit and underassessment of risk that gradually eroded the global financial system (Pretorius and De Beer, 2014). As a result, financial institutions worldwide became unwilling to conduct interbank lending which caused liquidity in the interbank funding markets to dry up. Governments had to intervene by providing extraordinary support to financial institutions by buying their debts and bailing out distressed companies. The intermediate phases of the GFC led to the final bankruptcy of Lehman Brothers in September 2008. This incident injected panic and uncertainty into the global financial system. The aftermath contributed towards the short-term collapse of the global stock markets, and the destruction of household wealth.

Although the GFC caused a significant shock in South Africa, the crisis did not exert as severe an influence on the country's stock market compared to countries such as the U.S. and the U.K. (Madubeko, 2010). This is because, firstly, the characteristics of the South African financial markets were not the same as those plagued by the crisis (Pretorius and De Beer, 2014). For instance, the country had no serious exposure to asset-backed securities, derivative instruments, foreign assets, and sub-prime mortgages. Secondly, in terms of public debt, the country's debt-to-GDP ratio stood at only 27% at the end of 2008. Lastly, the country adopted a policy to gradually liberalise exchange controls, which significantly enhanced market liquidity and broadened the base of investors.

Nevertheless, Mapanda (2019) noted that the local telecommunication and technology sectors showed different levels of reaction to changes in interest rates after the GFC. The same was true for the JSE ALL Share Index and Industrial Index in their reactions to changes in inflation after the GFC. Thus, it can be said that the GFC did (to some extent) restructure the sensitivities of some local sectoral indices to changes in macroeconomic variables.

2.11.1 GFC: a developed country experience

From a macroeconomic variable perspective, Abbas *et al*. (2019) showed that both the economies and financial markets of developed nations have been severely affected by various crises including the GFC and illustrated how such severe impacts can be captured by exogenous variables using the VAR-GARCH model. The author examined the relationship between stock return, volatility, and macroeconomic fundamentals for the G-7 countries during periods of crisis, including the GFC. The VAR-GARCH model captures the direction and magnitude of the spillovers effect between index returns and macroeconomic variables.

The sample series ranged from July 1985 to June 2015. Stock exchange indices incorporated into the study were: CAC40 (France), DJIA (U.S), FTSE-100 (UK), FTSE MIB (Italy), GDAXI (Germany), Nikkei 225 (Japan) and TSEI (Canada). The macroeconomic variables were the consumer price index (CPI), crude oil price in local currency (OIL), exchange rates against the U.S dollar (ER), government bill rate (GBR), industrial production index (IPI) and M2 money supply~~.~~

The statistical outputs of Abbas *et al*. (2019) suggested that an average decline in the short-term GBR increased the leverage effect of the G-7 return volatility during the GFC. In contrast, an expansionary monetary policy of M2 supply increased the deleveraging effect of the G-7 return volatility amid the GFC. Inflation increased the leverage effect of the return volatilities of some G-7 countries, due to a rise in average inflation rate during the GFC. . The exchange rates increased the leverage effects of return volatilities, based on the impact of an appreciation in the U.S Dollar against other G-7 currencies. The oil price increased the return volatilities' leverage effect in France due to the hike in local oil prices amid the crisis, while it had the least impact for the return volatility of other G-7 countries.

The VAR-GARCH model showed that, during the GFC, all macroeconomic variables had contributed approximately 10% of spillovers effect towards the return volatility of Canada and Italy, followed by 8% towards that of Germany, the U.S, and the U.K, and 7% towards France and Japan. Therefore, macroeconomic variables had different impacts on both the leverage effect and spillovers effect on the G-7 return volatility during the GFC. The results were in agreement with a similar study conducted by Masuduzzaman (2012).

A similar study was conducted by Wei-Chong *et al*. (2011) on the forecasting ability of three macroeconomic variables (gold price, crude oil price and the JPY/USD exchange rate) on the Japanese stock market (Nikkei 225). The models implemented were GARCH, E-GARCH and T-GARCH. The sample series ranged from May 1997 to July 2009. Results illustrated that the T-GARCH model outperformed the remaining two models. However, results from all three models demonstrate that none of the three macroeconomic variables had an impact on the Japanese stock market over the period studied. These findings were also in agreement with Abbas *et al*. (2019) findings for Japan within the G-7 context.

2.11.2 GFC: a developing country experience

From an African stock market perspective, Tella *et al*. (2011) studied the contagion of return volatility of the Egyptian, Nigerian and South African stock markets during the GFC using the E-GARCH model, which aimed at analysing the impact of a crisis on stock market volatilities, which serves as a referencing guide to implementing the univariate GARCH model for this research. The study also adopted the method of reporting descriptive statistics before discussing the E-GARCH model, which served as a set of priories to observe the behaviour of stock market volatilities and is relevant to the methodological style of this research. The sample series started from June 30th 2007 to June 31st 2009 and included the All-Share indices of the Cairo Stock Exchange (CASE), Nigerian Stock Exchange (NSE) and Johannesburg Stock Exchange (JSE).

To begin with, the summary statistics suggested that the mean returns for all three indices were comparatively higher during 2007-08 than in 2009. Nonetheless, the mean returns in 2007-08 were significantly reduced compared to in 2006. The authors indicated that this phenomenon could be due to fragile economies and financial markets recovering at a slower pace after the crisis than the global economy as a whole. The standard deviation of all three indices, on the other hand, moved according to the mean returns, which indicated a positive relationship between risk and return during the pre-, during- and post-crisis periods. However, the kurtosis and skewness values suggested that, throughout the sample period, the CASE index return was the least affected by the crisis out of all the three All-Share indices, while in comparison, the JSE index return was the most affected. This could be explained by the fact that the JSE, compared to the CASE, is more integrated into the international stock markets. Therefore, the magnitude of return volatility contagion amongst the three indices was asymmetrical.

Lastly, Tella *et al*. (2011) estimated the E-GARCH model parameter for all three indices. The coefficient of expected risk suggested that stock return and volatility were directly related to each other for the JSE All-Share, but there was no clear evidence of such a relationship for the CASE and NSE All-Share indices. The coefficient of the GFC was positive and significant only for the JSE, meaning that the crisis only had a significant impact on the South African stock market, while evidence suggested that the crisis had an insignificant impact on the CASE and NSE. The results of the GARCH regression confirmed that the crisis had worsened volatility clustering indiscriminately for all three exchanges during the period studied, though the CASE was affected by the GFC to a greater extent than the NSE and the JSE. Overall, both the asymmetrical and leverage effects were present on the CASE and rejected on the NSE and JSE during the crisis. These findings agreed with those of Olowe (2009), which had found forth that the GFC had only had a sudden and short-lived impact on the NSE and JSE.

A comparable study was conducted by Joshi (2012), who researched the impact of the GFC on the behaviour of Asian stock market volatilities using a GARCH model. Data were collected in the form of stock index prices from India, mainland China, Hong Kong (China), Malaysia, Japan, Indonesia and South Korea. The corresponding indices were respectively represented by the Bombay Stock Exchange (BSE), Shanghai Composite (SSE), Hang Seng (HSI), Kuala Lumpur Stock Exchange (KLSE), Nikkei 225 (N225), Jakarta Composite (JKSE) and Seoul Composite (KOSPI). The data started from January 1st 2001 to February 3rd 2010.

Firstly, from the descriptive statistics, the standard deviation indicated that all indices were more volatile during the GFC. Secondly, the mean return suggested that all indices were less profitable on average during the GFC. Likewise, the large values of Jarque-Bera statistics revealed that all indices were not normally distributed during the GFC. Thirdly, the Kurtosis values were large for all indices during the GFC which reflected the leptokurtic or thick tail in all indices. In other words, again, all stock markets became more volatile during the GFC. Lastly, the ARCH-LM test confirmed the presence of ARCH effect in all indices. This meant that all indices were heteroskedastic (highly volatile).

In terms of the GARCH parameters, aside from Malaysia's KLSE, all other indices had shown high levels of volatility persistency. This confirmed that, in general, all Asian indices were highly volatile during the GFC. The volatility persistency for mainland China, Hong Kong (China), Japan, and South Korea was especially close to unity throughout the entire sample period. This could be explained by the fact that these stock markets were highly developed and integrated with the international financial system, with mainland China as an exception. Moreover, the results showed that during the GFC, all indices exhibited higher levels of volatility persistency compared to the pre-crisis and full sample periods. In addition, the dummy variable of the GARCH regression was positive and significant for all the indices except for South Korea's KOSPI for the full sample period. This suggested that the introduction of structural break in GARCH has captured a spike in volatility during the GFC.

2.11.3 GFC: The South African experience

From a sectoral perspective, Ole-Meiludie *et al.* (2014) conducted a comparative study on the effect of financial crises on the performance of defensive stocks in South Africa. The main goal of the study was to investigate whether defensive sectors listed on the JSE retained their non-cyclical nature during both the Asian Financial Crisis (AFC: December 1st 1996 to August 31st 1999) and the GFC (December 1st 2007 to August 31st 2009). The authors' goals are akin to that of this research of classifying stock market sectors as cyclical or defensive. The method was aimed at analysing the risk level of stocks by comparing the individual stock beta coefficients with the overall market including the four different benchmark indices (ALSI, Large-Caps, Medium-Caps, and Small-Caps). This approach was aimed at ensuring the robustness of the results under investigation and is useful in guiding the construction of priories for this particular research.

To begin with, a series of linear regressions, including beta coefficient estimators of individual stocks, were performed on the individual companies[4] selected from the JSE Top-40 and weighted with the four benchmark index returns listed on the JSE. From the linear regressions, results showed that the beta coefficient of defensive stocks decreased during both AFC and GFC. This meant that the non-cyclical features of defensive stocks enhanced in times of crises. In contrast, the average cyclical sectors presented an increase in return volatility in times of crises. These two contrasting results were exhibited in all sizes of market capitalisation.

Afterwards, a variance test was conducted during both crises to support the findings of the beta observations. Evidence revealed that there was a correlation between a decrease in a defensive stock's beta and a decrease in its variance during a period of recession. Likewise, a correlation was also confirmed between an increase in a cyclical stock's beta and an increase in its variance during a period of recession. The author also suggested that both stock market return and risk are positively correlated, where certain sectors experienced a higher return than the overall South African stock market within the full sample period. These sectors included Consumer Goods, Consumer Services, Healthcare, Telecommunication, and Gas and Oil sectors. Nevertheless, in an identical study conducted by Arguile (2012), the author illustrated that the Telecommunication and Oil and Gas sectors failed to sustain a higher-than-average mean

[4] Some of these companies operate within the sectors of consumer goods, consumer services, healthcare and pharmaceutical. These sectors are considered defensive due to the inelastic demand for relevant goods and services.

return and exhibited a higher level of beta coefficient and standard deviation during the GFC. The only sectors that remained defensive throughout the sample period under observation, in terms of average returns, were Consumer Goods, Consumer Services, and Healthcare.

2.12 The impact of the COVID-19 pandemic

Different from the GFC, the outbreak of COVID-19 was at first a public health issue, but soon spread throughout the world and caused concerns regarding economic and financial related matters. Stock markets in Italy, Iran and South Korea responded one month after the Wuhan lock down in February 2020 (Gormsen and Koijen, 2020). Overall, from March 11th 2020 when COVID-19 was classified as a global pandemic (and for the remaining periods of March 2020), major stock exchanges in China, France, Germany, South Korea, and many other countries experienced a 2-3% decrease in daily return. Amongst different industries, the gold price demonstrated relative stability, whereas crude oil exhibited a period of the highest level of price volatility at an industry level during the second half of March 2020.

According to Ali *et al.* (2020), by March 2020, the equity markets in the U.S. and EU had accumulated an approximate drop in value of 30%. In June 2020, the expected dividend growth for that year had dropped by 2.0% and 3.1% respectively for the U.S. and EU markets. Within four months of the initial outbreak, the initial disruptions to global supply chains and financial stabilities had corrected and the S&P500 and the Euro Stoxx 50 had experienced a V-shaped recovery by April 2020 and restored to stability around May 2020.

In South Africa, uncertainties due to COVID-19 spread across the stock market in early 2020. JSE stock returns were particularly volatile during March 2020, with the Exchange experiencing its largest single-day drop since 2008 in stock market value on March 12th 2020 (JSE, 2020). On the other hand, the Exchange witnessed its best trading day since 1997 when the market gained more than 7% on March 24th 2020 (Bloomberg, 2020). The downgrade of the country’s investment grade to ‘−BB’ in April, the disruption of global supply chains in May and June, and the rise in debt-to-GDP ratio to 70% towards the end of 2020, all contributed towards the spillovers of COVID-19 between the local economy and local financial markets.

2.12.1 *COVID-19: a developed country experience*

Gunay *et al*. (2021) studied the impact of the first wave of COVID-19 on the Australian stock market using both the DDC-FIGARCH[5] and Markov regime switching models from an event study perspective. The former model was used to investigate the contagion effect between the Chinese equity market and Australian sectoral indices. The latter model was used to examine the impact of COVID-19 on the volatility of Australian sectoral indices. The authors gathered the data from eleven Australian stock market sectors. The entire sample series ranged from January 1st, 2015 to June 5th, 2020.

References taken from the authors can assist with identifying structural breaks in between crises based on the occurrence of events, which in turn shows the extent to which stock markets reacted during periods of crises. The DDC-FIGARCH sets a methodological framework for the priori observation of stock market volatility based on their severity of correlation and can also potentially transform a priori of stock market correlation into a coefficient of the GARCH model in future studies.

The DDC-FIGARCH analysis, throughout the sample series, showed that the highest level of correlation between Australian and Chinese markets occurred for consumer discretionary, financial, and industrial indices. Specifically, during the first wave of COVID-19, consumer staples, energy and materials became more correlated with the Chinese equity market. In contrast, the Australian sectors of financial, healthcare, IT and utilities exhibited a lower level of correlation with the Chinese equities. Later on, these findings were, once again confirmed by the findings of a similar study conducted by Brueckner *et al*. (2020)

Instead of analysing the impact of COVID-19 on stock market indices from a purely time series approach, Narayan *et al*. (2021) studied how COVID-19 related government policies contributed towards the volatility of stock returns within the G-7 stock markets amid the pandemic. The method implemented was a time series predictive regression (TSPR) model with the incorporation of relevant policy coefficients that may have possibly influenced G-7 stock returns. The study has put forth an example of analysing stock market volatility by accounting for the effect of policies in response to COVID-19 in a typical time series

[5] DDC-FIGARCH stands for the dynamic conditional correlation fractionally integrated GARCH model. This type of GARCH model is designed to study the contagion effect often between two or more financial markets or sectors within a financial market.

econometric regression focusing on the Covid-19 pandemic. Although the full sample size is short, it does illustrate the possibilities of conducting the research using sub-sample periods to examine the impact of Covid-19 over different phases of a crises. In particular, the policy coefficients accounted for the impact of three government policies, namely: lockdowns, stimulus packages (hereafter referred to as 'package') and travel bans. The entire sample period covered from July 1st, 2019 to April 16th, 2020. Ultimately, the sum of all exogenous variables illustrated the level of volatility persistency for each G-7 stock indices over the sample period.

None of the 'package coefficients' satisfied the conditions of being positive and statistically significant. This meant that all G-7 packages designed to support the corresponding economies failed to positively contribute towards local stock returns. In terms of the 'travel ban coefficients', the resulting values were mixed, but most were statistically significant, except for Germany's Dax Performance and Italy's FTSE MIB Index. Therefore, travel bans did increase the volatility of the G-7 stock returns. However, the influence of these travel bans contributed both positively (an increase in stock return) and negatively (a decrease in stock return) throughout the sample period. To conclude, the sum of all three policy coefficients and other exogenous variables contributed largely and significantly towards an increase in volatility persistency of G-7 stock returns during the pandemic.

2.12.2 COVID-19: a developing country experience

Bora and Basistha (2020) investigated the asymmetrical effect of COVID-19 on the Indian stock market volatility using the T-GARCH model. The data used for this study were the daily closing prices of the NSE Nifty and BSE Sensex indices from September 3rd 2019 to July 10th 2020, which allowed for a comparative univariate GARCH model analysis of the impact of Covid-19 on two different indices. Furthermore, the study's sample period was divided into pre- and during-crisis periods, which directly observes the magnitude of stock market volatility during different phases of a crisis using the asymmetrical coefficient (λ). In particular, the days before January 30th, 2020 were considered the pre-COVID-19 period and the days after were considered the actual COVID-19 period. The data were arranged as such because the first positive case of India was confirmed on January 30th, 2020.

In terms of the T-GARCH (1, 1) regression, the positive and significant asymmetry term (λ) within BSE Sensex ($\lambda = 0.041$, $p = 0.05$) and NSE Nifty ($\lambda = 0.358$, $p = 0.00$) was captured, which confirmed that bad news had a larger impact than good news on both series. Moreover, it could also be said that negative shocks tended to increase the volatility of both indices more than positive shocks. In addition, the dummy variable coefficient of the T-GARCH model has captured the asymmetrical effect of COVID-19 on BSE Sensex, while the opposite was true for NSE Nifty, which is consistent with the findings of Sahoo (2020).

In like manner, Apergis and Apergis[6] (2020) investigated the role of COVID-19 on the Chinese stock returns from an event study perspective. The method implemented was the GARCH-X model, which allowed for COVID-19 related information (confirmed cases of infection and death) to be accounted for by a univariate GARCH framework when examining the impact of a crisis on stock market volatility. The sample period was from January 22nd 2020 (when the first COVID-19 case was recorded) to April 30th 2020 using daily data.

The dependent variables were the stock prices collected from companies listed on the 'A Shares' of both the Shanghai Stock Exchange and the Shenzhen Stock Exchange.[7] The proxies or independent variables incorporated into the conditional mean equation of the GARCH-X model were: *COVID19-1* (total confirmed cases), *COVID19-2* (total deaths), *T-bills* (one-month interbank loan rate) and *oil price* (daily oil prices). In contrast, the conditional variance equation only incorporated *COVID19-1*, *COVID19-2* and a lagged variable of the daily stock returns.

Results showed that, firstly, in terms of the conditional variance equation, the sum of ARCH and GARCH coefficients were less than one, which satisfied the condition of mean reversion. In addition, the sum of the coefficients was close to unity, which showed that volatility within the Chinese daily stock returns was characterised by long memory and volatility persistence. Secondly, in terms of the conditional variance equation, the coefficients of *COVID19-1* and *COVID19-2* were both negative and statistically significant within the variance equation. Total deaths were comparatively more influential on stock returns than those of total confirmed cases. This illustrated that, in general, COVID-19 had a negative impact on the mean stock returns in

[6] Nicholas Apergis and Emmanuel Apergis
[7] A-Shares listed on the two largest emerging Chinese stock exchanges were included in the conditional mean equation of the GARCH-X model. This was since Chinese A-Shares, settled in on-shore RMB, are generally more appeal to both citizens and foreigners.

China, which is consistent with the conclusion of Corbet *et al*. (2021). Similarly, both oil prices and T-bills had a negative and significant impact on Chinese mean stock returns.

2.12.3 COVID-19: The South African experience

Morena and Bonga-Bonga (2020) studied the impact of gold and oil price fluctuations on the South African equity market from a volatility spillovers approach. The method implemented was the VAR-ADDC-GARCH model.[8] For short, the model will be referred to as VAC-GARCH. The study is significant due to this kind of study being rare at the time of publication, where only a single study had captured the impact of commodity futures on both the magnitude of and spillovers of volatility of the South African equity market throughout a number of crises. The study went beyond the univariate GARCH model regressions by analysing how past volatilities had been carried forward into future volatilities, thus showing the extent to which volatility persists. The data used was the daily closing prices of the FTSE/JSE series: All Share Index, Financial, Industrial, Resources, oil futures (OIL) and gold futures (GOLD). The sample period was from January 3rd 2006 to April 23rd 2020. The purpose for choosing this period of time was aimed at capturing the effect of the GFC, the 2010/11 European Debt Crisis (EDC) and other later crises, including the COVID-19 global pandemic in early 2020.

In order to capture the spillovers effect, the VAR model to be incorporate into the GARCH model. The VAC-GARCH model regression revealed that, firstly, a 1% volatility shock to OIL in the current period increased the conditional volatility of All Share Index by 0.009% in the following period. Secondly, OIL shock increased the volatility of all other sectoral indices. On the other hand, GOLD did not have a significant impact on the conditional volatility of sectoral returns. The findings indicated that the spillovers effect of sectoral indices reflected an interdependent relationship between commodity prices and sectoral profitability. Thus, with the disruption of global supply chains, logistic restrictions and travel bans, the increase in volatility of Brent crude oil and gold would logically increase the volatility of the various sectors of the economy amid COVID-19.

The next step of the study was about testing volatility spillovers for all sectoral indices during the short-term and long-term respectively by utilising the coefficients of α_{ij} and β_{ij}. The purpose

[8] VAR-ADDC-GARCH stands for 'vector autoregressive asymmetric dynamic conditional correlation GARCH'

was to capture how past volatilities from *j* (the short term) had transmitted into the future volatilities of *i* (in the long term), which observes how previous volatilities have been carried forward into the volatilities today. Results demonstrated that volatilities were persistent and characterised by long memory, where volatilities in the past have transmitted into the volatility today, because the two additional coefficients were close to unity and statistically significant for all the sectoral indices.

In conclusion, it could be said that COVID-19 had brought about a period of stock market turbulence and caused the sectoral indices to be more volatile during the initial stages of the pandemic (or the first four months of 2020 from January to April).

2.13 Summary of literature review

Part two of Chapter 2 reviewed the impact of crises on stock market volatility during both the GFC and COVID-19 where a variety of findings and results were presented. Typically, the GARCH model indicated that high levels of volatility persistency and long memory were characteristics of more developed financial markets rather than of those that were still developing during both crises. The majority of studies that focused on E-GARCH models revealed that stock market volatility was more sensitive towards bad news than good news amid crises. Most of the research regarding T-GARCH models illustrated that stock market volatility was influenced by the asymmetrical or leverage effect during times of crises. This shows that different GARCH-family models could capture how stock market volatilities reacted variably before and during crises by incorporating various type of variables.

From a macroeconomic perspective, Wei-Chong *et al*. (2011) and Abbas *et al*. (2019) touched on the extent to which macroeconomic variables affected stock market volatility during times of crises. The variables accounted for were exchange rates, gold prices, inflation, short-term interest rates, M3 money supply and oil prices. It was discovered that stock markets worldwide (i.e., international, regional, developing or developed) were significantly affected by inflation, short-term interest rates, M3 money supply and oil prices during crises.

Apergis and Apergis (2020) and Gunay *et al*. (2021) incorporated the flow of information (i.e., trade volumes, confirmed COVID-19 cases, confirmed COVID-19 death cases, pandemic wavelets) into their analysis of the impact of COVID-19 on stock market volatility. Results suggest that stock markets were generally more volatile during the first wave of COVID-19 and that confirmed COVID-19 deaths had a more significant impact on stock market volatility than confirmed cases amid the pandemic. In addition, a unique study by Narayan *et al*. (2021) found that COVID-19 related measures (lockdown, travel ban, stimulus packages) contributed towards increased stock market volatility amid COVID-19. Although both studies were focused on developed countries, the same variables could also be applied to developing countries in future international and regional studies.

From a sectoral perspective, Arguile (2012), Ole-Meiludie *et al*. (2014), and Gunay *et al*. (2021) provided primary evidence that distinguishes between the impact of crises on cyclical sectors and defensive sectors. On one hand, sectors considered to be defensive, such as Consumer Goods, Consumer Services, Finance, Healthcare, Pharmaceuticals and Utilities, exhibited stable levels of return and risk combination throughout full sample periods and displayed above-average mean return during times of crises. On the other hand, cyclical sectors often include Distribution, Gas, Industrial, Oil, Technology and Telecommunication. These sectors displayed high levels of return during economic upturns but associated risk variables such as sectoral beta coefficients and standard deviations were significantly larger amid crises.

To conclude, firstly, stock market volatilities usually increase during times of crises either unconditionally or conditional upon the inclusion of a number of external factors such as financial health indicators, government policies, information, and exogenous variables. Secondly, compared to cyclical sectors, the volatilities of defensive sectors usually remained stable before and during times of crises, though short-term deviations have occurred due to the impact of various external factors. In contrast, cyclical sectors usually displayed volatile movements during times of crises. This meant that the performance of defensive sectors did temporarily diverge from investor expectations of low volatility during certain periods of time (by becoming more volatile during times of crises), due to the interactions between external factors. Nonetheless, as expected, most findings supported the result that cyclical sectors were more volatile during times of crises compared to defensive sector.

CHAPTER 3: DATA AND METHODOLOGY

3.1 Data arrangement

Data used will be daily time series with two separate sub-sample sizes reflecting pre-crisis and during-crisis of each full sample period. The first full sample period from January 2006 to May 2009 is used for analysing the GFC. The second full sample period from January 2018 to May 2021 is used for analysing the period of COVID-19. Following Muzinda (2016), Adekoya and Nti (2020) and Mazur *et al*. (2021), eleven JSE sectoral indices and one JSE benchmark index (FTSE/JSE ALSI) were chosen for the econometric analyses. The analytical applications utilised for the analyses are EViews, Excel, and Stata.

The observed sectoral indices are: J135 (Chemicals), J335 (Automobiles & Parts), J510 (Basic Materials), J520 (Industrial), J530 (Consumer Goods), J540 (Health Care), J550 (Consumer Services), J560 (Telecommunication), J580 (Financials), J590 (Technology) and J835 (Banks). The observed benchmark index is J203 (All Share). All observed indices are presented as daily returns denoted by $R_t = \left[\frac{(X_t - X_{t-1})}{(X_{t-1})}\right]$, where X_t represents current values, X_{t-1} represents lagged values. These data were provided for academic research by permission of the Johannesburg Stock Exchange (JSE) Limited. Additional data were acquired from Yahoo Finance from February to May 2021.

In terms of sectoral classification, on one hand, the assumed cyclical sectors are Banks, Basic Materials, Consumer Goods, Consumer Services, Financials, Technology, and Telecommunication. On the other hand, the assumed defensive sectors are Chemicals, Health Care, and Industrial. The 'un-predeterminable' sector is Automobile & Parts. Both assumed and 'un-predeterminable' sectors are classified according to the empirical findings of Chapter 2 which also includes the context of South Africa. However, such classifications varied between authors due to changes in research context and goals. Therefore, the categorisation of defensive and cyclical sectors is not unified among the authors, given the purpose of their individual studies. For instance, the study of Chinzara (2010) on how macroeconomic variables such as M3 money supply, oil prices and industrial production have impacted sectoral indices of the South African stock markets from a conditional volatility perspective using GARCH, E-GARCH, and T-GARCH models. The author found that both Consumer Goods and Consumer

Services are classified as defensive given that the conditional variance equations of all three models have suggested mild level of volatility persistency throughout the GFC. Arguile (2012) and Ole-Meiludie *et al*. (2014) indicated that, in terms of the South African equity market, Health Care was a defensive sector due to its defensive characteristics such as a low beta coefficient and correlation coefficient with the remaining sectoral indices concerned in their studies focusing on the GFC. In contrast, cyclical sectors included Telecommunication and Oil and Gas, due to their declined average mean return, and increased beta coefficients during the GFC

Morena and Bonga-Bonga (2020) studied the impact of gold and oil prices on South African equity market from a volatility spillovers perspective, using the VAC-GARCH model. The author indicated that, given the limited sample size available at the time, Finance, Pharmaceutical and Utilities displayed a combination of stabilised return and risk throughout the full sample period of the COVID-19 global pandemic. In contrast, cyclical sectors included Distribution, Industrial, and Technology.

With regards to the sample periods, they have been organised to include at least 12 months prior to the crisis and then the length of the crisis itself (Cheteni, 2016). The two full sample periods contain approximately 850 observations each. An equal number of observations can minimise the effect of sample bias when performing econometric testing. For each crisis, there are two sub-sample periods (denoted as pre-crisis and during-crisis) separated from the full sample periods. For the GFC, pre-crisis ranges from January 2006 to June 2007 and during-crisis period is ranged from July 2007 to May 2009. In terms of COVID-19, pre-crisis ranges from January 2018 to November 2019 and during-crisis ranged from December 2019 to May 2021 (the date on which data were obtained).

Together, all assumed and 'un-predeterminable' sectors, for both the whole and sub-sample periods, are used for verifying the research assumption, which states that cyclical and defensive sectors have retained their sectoral properties throughout both crises. Furthermore, Automobiles & Parts is utilised to achieve the research sub-goal, which is to identify whether 'un-predeterminable' sectors have shown properties of either cyclical or defensive sectors throughout both the GFC and COVID-19 crises.

3.2 Order of econometric analysis

The methodology is designed such that a series of *priori* tests are conducted first in order to identify possible patterns, relationships, responses, trends, and spuriousness of the data. These include:[9] 1.) a correlation matrix; 2.) sectoral beta coefficients weighted with the benchmark index 3.) ARCH effect test; 4.) descriptive statistics; 5.) unit root tests (Augmented Dickey-Fuller test, Phillip-Perron test, and Zivot-Andrew test); 6.) the construction of a dummy variable to capture the structural break and 7.) GARCH diagnostics to identify the appropriate error distribution utilised when performing the GARCH regression. Afterwards, following the work of Adesina (2017), the GARCH (1, 1) regressions are conducted to obtain the statistical outputs on volatility persistency in the various JSE sectoral indices before and during each crisis and for the full sample periods. Following Elyasiani and Mansur (1998), Bonga (2019), and Nugroho *et al*. (2019), the GARCH-M(1,1) model regressions are conducted to examine whether or not there is a positive relationship between expected risk and expected return, that is, a higher level of risk is compensated by a higher level of return.

3.3 Correlation Matrix

Statistically, correlation describes the statistical relatedness between two or more variables, measured by the correlation coefficients of each variable. The variables become more correlated with each other (or that volatility spillsover from one index to another) as the correlation coefficient increases, especially when it gets closer to the value of one. As Morena and Bonga-Bonga (2020) have indicated, cyclical sectors are usually more correlated with the remaining financial markets during times of crises, whilst defensive sectors remain at approximately the same level of correlation. The difference in reaction between cyclical and defensive sectors to crises can be potentially used to distinguish the sectors chosen for observation in this thesis. In general, sectoral indices are more correlated with each other during times of crises due to an overall increase in stock market volatility.

[9] The *priori* tests are a series of econometric and mathematical tests that generate certain expectations about the volatility of all observed series. These expectations can either support or contradict the GARCH model regression which determines the volatility of the observed series.

3.3.1 Sectoral Beta coefficient

The correlation matrix can be extended into the beta coefficients by constructing the variance-covariance matrix, which in turn assists with the construction of the beta coefficients of sectoral indices. Beta coefficients are *priori* indicators of sectoral risk in relation to the whole stock market. As a *prior* test, the sectoral beta coefficient measures the risk level of a stock when weighted with a benchmark index, and is often adopted in the Capital Asset Pricing Model (CAPM). However, for the purpose of this thesis, the goal is to obtain the sectoral betas coefficients of all observed series in relation to the benchmark index, because they generate *priori* expectations on how sectoral indices would behave in different time periods. For example, defensive sectors usually exhibit a lower beta coefficient / risk level compared to cyclical sectors throughout the business cycle, which implies a lower sectoral volatility. Cyclical sectors usually display a higher risk level throughout the business cycle and especially during times of crises compared to defensive sectors.

The benchmark index has a beta of 1.0 and other sectoral betas are presented according to the extent in which they deviate from the beta of the benchmark index. The sectoral beta can be written as $\beta = \frac{Covariance}{Variance}$, which states that the sectoral beta equates to the covariance of the sectoral return with the benchmark return divided by the variance of the benchmark return over the sample period. The sectoral betas are calculated upon obtaining the covariance matrix discussed in the previous section.

3.4 Unit Root tests and the dummy variables

The Augmented Dickey Fuller (ADF) test tests the null hypothesis that a unit root exists in a time series sample. The alternative hypothesis depends on the data format. Hence, the sample series may have to be first-differenced in order to reject the null. In addition, the Phillip-Perron test for unit root is also conducted to ensure the robustness of each series' stationarity. In terms of the Zivot-Andrew (ZA) unit root test, Zivot and Andrews (1992) incorporated an endogenous breakpoint (or structural break), based on the Perron (1989) test for unit root, by utilising a series of full sample period of the time series and different dummy variables for each possible breakpoint. Different to Perron (1989), the ZA unit root test treats the structural breaks as an outcome of the unit root estimation process, rather than a predetermined exogenous variable. Therefore, the ZA unit root test helps to locate a structural break that had occurred within a time series. Methodologically, the ZA breakpoint is determined by the Tau (*t)* statistic obtained from the minimum (or most negative) ADF test. Based on the ZA breakpoints, the dummy variables have taken the value of zero before the occurrence of the structural breaks, and the value of one afterwards. Subsequently, the dummy variables have account for the asymmetrical impact of both the GFC and COVID-19 on the sectoral indices throughout the full sample periods.[10]

To clarify, the ZA breakpoint was only incorporated into the full sample periods. This is because, as a *priori*, the ZA breakpoints obtained from the full sample periods have provided an insight regarding how sensitively did the sectoral indices react to both the GFC and COVID-19, since not all sectoral indices have experienced a structural break on the same calendar date amid periods of crises. Subsequently, the dummy variables are based on the ZA breakpoints for each and every observed series. According to the empirical findings of Chapter 2, cyclical sectors were comparatively more sensitive to a crisis than defensive sectors. This is to say that cyclical sectors usually experienced a structural break during a crisis and the opposite can be said about defensive sectors. Thus, the extent to which the ZA breakpoint dates coincide with the classification of sectoral indices can be used as a *priori* analysis about whether the Sectors have remained cyclical or defensive throughout the crises.

However, the sub-sample periods are not designed to capture the structural break in sectoral indices. Rather, the sub-sample periods (already categorised into periods of pre- and during-crisis) are designed to examine the changes in volatility and volatility persistency of sectoral indices between the two different phases of each crisis. In other words, the sub-sample periods are not considered as a period of crisis themselves. Consequently, the sub-sample periods did not have to incorporate the dummy variable in the corresponding conditional variance equations and were demonstrated in equation [3.2] and [3.3]. Authors who have excluded the dummy variable from their sub-sample periods but included them in their full sample periods are: Babikir *et al*. (2010), Sed'a (2012), Chaudhary (2020) and Gunay *et al*. (2021).

[10] Structural breaks indicate when a significant change in time series has occurred (Stata, 2021). Subsequently, the dummy variables are based on the structural breaks (which may or may not occur amid a crisis) rather than the crises themselves. This is because that some observed series may not necessarily become volatile amid a crisis, but at other times too. Therefore, basing the dummy variables on the structural breaks is arguably better than a specific event that may be considered as the starting-point of a crisis (Bai and Perron, 1998, Miron and Tudor 2010, Jung and Maderitsch, 2014, and Abdennadher and Hallara, 2018).

3.5 Presence of ARCH effect

The presence of ARCH effect is observed from the residuals of the time series. Also, the ARCH effect is a generalised autoregressive (AR) representation of the squared residuals of the time series. The Lagrange-Multiplier test is used for detecting the ARCH effect within time series. If ARCH effect exists, then the series is heteroskedastic, which is a prerequisite for conducting the actual GARCH model regression.

3.6 Histogram of Normal Distribution and corresponding Descriptive statistics

The histogram of normal distribution is obtained from Stata. The descriptive statistics in EViews (2020) report: the mean, maximum and minimum values, standard deviation, Skewness, Kurtosis, and Jacque-Berra Statistics. For the purpose of this research, both the maximum and minimum values are not discussed, because the mean return is more meaningful in picturing the volatility patterns of the observed series. In like manner, the standard deviations are not discussed because this research focuses on examining stock market volatility based on the conditional variance of the GARCH model. However, the values not discussed are still provided in Appendix A.

3.7 GARCH Diagnostic

GARCH diagnostics are performed to judge which type of error distribution is appropriate for each and every series under observation. This in turn affects the values of the GARCH model coefficients that are utilised to analyse volatility persistency. The diagnostic procedure consists of three options provided by EViews namely: normal (Gaussian), student's *t*, and Generalised Error Distribution.

3.8 GARCH (1, 1) regression

Sectoral returns (R_t) will be regressed as a dependent variable in both the conditional mean and variance equations in the GARCH (1 ,1) regression. Firstly, the conditional mean equation for the full sample periods of both the GFC and COVID-19 is expressed as follows:

$R_t = \mu + \rho R_{t-1} + \varepsilon_t \ldots [3.1]$

In equation [3.1], (μ) is the conditional mean used to observe an index's average return, (ρ) is a coefficient that estimates the significance of the lagged average return (R_{t-1}) in predicting the current average return (R_t), and (ε_t) is an error term. The conditional variance equation for the full sample periods of both crises is expressed as follows:

$$h_t = \omega + D_i + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \ldots [3.2]$$

In equation [3.2], ω is the constant, D_i is the dummy variable which denotes to the occurrence of the structural break, α is the ARCH coefficient and β is the GARCH coefficient. Volatility persistency is indicated by ($\alpha + \beta$). Accordingly, if $(\alpha + \beta) > 1$, then the series is characterised by long-term memory, which means that volatility is highly persistent within that particular series. However, if $(\alpha + \beta) < 1$, then the series is characterised by short- to medium-term memory, where volatility only persists into the future for a limited period of time. Usually, defensive sectors exhibit a lower volatility persistence compared to cyclical sectors before and during crises. Volatility persistence of cyclical sectors tend to rise during crises.

Apergis and Apergis (2020) noted that if $(\alpha + \beta) > 1$, then the series is considered as non-mean reverting, which means that volatility today persists infinitely into the future. This would be problematic as it is impossible for current exogenous variables (presented in the form of market information) to indefinitely impact the series into the future. Nevertheless, authors such as Chinzara (2010), and Chaudhary *et al.* (2020) did illustrate that market indices in both developed and developing countries can be characterised by a volatility persistency above the value of 1 during times of crises.

Furthermore, the dummy variable coefficient (D_i) in equation [3.2] is a representation of the asymmetrical effect (changes in volatility patterns) of the crises themselves on each sectoral index and the benchmark index. The coefficient is incorporated to capture a sectoral index's reaction to news (or information) represented by a significant intra-day shock to the index value. D_i takes the value of zero (0) before the structural break, and thereafter the value of one (1) after the structural break. The ZA test for structural break determines when the structural break occurred. D_i is only inserted within the conditional variance equation. The p-value of D_i should be insignificant for defensive indices because, according to the theories of CVP and EMH and the empirical findings, ‘information’ (or the incorporation of asymmetrical effect in terms of the research) has a limited impact on restoring the volatility of defensive indices.

Therefore, D_i would expectedly be insignificant for defensive sectors because the incorporation of a structural break (that indicates the transitioning from pre-crises into crises) would not affect the sectoral returns of defensive sectors. In contrast, cyclical sectors should exhibit a positive and significant dummy variable coefficient, because information is absorbed more efficiently and effectively by these sectors when compared to defensive sectors. In addition, the variance equation for the four sub-sample periods is such that:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \ldots [3.3]$$

In equation [3.3], except for D_i, all other variables have been included. This is because that, as explained in subsection 3.4, sub-sample periods do not have to incorporate structural breaks.

3.9 GARCH-M (1, 1) regression

The GARCH-M model is often utilised to examine whether the expected return on an asset is related to its expected risk. For the purpose of this research, the GARCH-M regression analysis is split into three groups of specifications.

$$R_t = \rho R_{t-1} + \beta_R + u_t \ldots [4.1]$$

$$h_t = \omega + D_v + \Sigma_{k=1}^{p}\theta_k h_{t-k} + \Sigma_{i=1}^{q} b_i u_{t-i}^2 \ldots [4.2]$$

Equation [4.1] and [4.2] represent the first specification. In equation [4.1], R_t is the conditional mean of an observed series. The equation is such that R_t depends on the conditional variance, or the GARCH term (β_R). If the GARCH term is positive and significant, then a risk premium is confirmed to exist within an observed series. Similar to Equation [3.2] under the GARCH (1, 1) regression, (h_t) in equation [4.2] represents the conditional variance. For the first specification, ‘D_v’ is added to equation [4.2] as the dummy variable to test out whether or not the capturing of volatility can be improved by accounting for the structural breaks of the full sample periods of the observed series for both crises.

$R_t = \rho R_{t-1} + D_R + \beta_R + u_t \ldots$ [4.3]

Equation [4.3] and [4.2] represents the second specification. In equation [4.3], D_R is the dummy variable inserted into the conditional mean equation, which measures the extent to which structural breaks have a positive and significant impact on the size, direction, and relationship between risk and return.

$h_t = \omega + \Sigma_{k=1}^{p} \theta_k h_{t-k} + \Sigma_{i=1}^{q} b_i u_{t-i}^2 \ldots$ [4.4]

Equation [4.4] and [4.3] represents the third specification. For equation [4.4], the dummy variable has been deleted to test whether there is a risk premium irrespective of whether volatility is correlated with the structural break. Finally, equation [4.1] and [4.4] are used to examine the existence of a risk premium for all observed series for the sub-sample periods of both crises.

To clarify, all dummy variables used in the GARCH-M model specifications discussed above are based on the same structural break points obtained via the ZA test.

CHAPTER 4: FINDINGS AND RESULTS

4.1 Findings from correlation matrix

In Appendix A, Tables A1 to A1.2 indicate a moderate-to-high level of sectoral correlation between all the observed series for the full- and both sub-sample periods of the GFC. Series that remained highly correlated with the other sectoral indices throughout all sample periods of the GFC are: Financials, Banks, Consumer Services, and Industrial. Only Automobiles & Parts (J335) experienced a low level of sectoral correlation with all the other sectors throughout all sample periods. Basic Materials, Telecommunication, and Healthcare, became more correlated with the other indices during-crisis compared to pre-crisis. Lastly, Chemicals, Technology, and Consumer Goods became less correlated with the other indices during-crisis compared to pre-crisis.

Also in Appendix A, Tables A2 to A2.2 suggest a moderate level of sectoral correlation between all the observed indices for both the full- and sub-sample periods of COVID-19. Automobiles & Parts and Technology maintained the lowest level of sectoral correlation throughout all sample periods. The indices that maintained the highest level of sectoral correlation throughout all sample periods of COVID-19 are: Industrial, Consumer Goods, Banks, Health Care, and Telecommunications. Furthermore, when compared to pre-crisis, the observed series that became more correlated with the other indices during-crisis are Chemicals, Consumer Services, and Basic Materials. In contrast, Financials became less correlated during-crisis with the other indices.

In sum, based on Table A1 to A2.2, the *priori* of sectoral correlation indicates that Automobiles & Parts exhibited the characteristics of a defensive sector for both the GFC and COVID-19 by its low level of sectoral correlation throughout all sample periods. In contrast, Basic Materials presented the characteristics of a cyclical sector because, compared to pre-crisis, it became more correlated with the other sectors during-crisis for both crises. However, the inconsistent results obtained for the remaining observed sectoral indices do not show clear characteristics of either defensive or cyclical sectors based on the correlation matrix.

4.2 Findings from the sectoral beta coefficient

In terms of the GFC (Table A3), almost all sectoral beta coefficients have decreased in value during-crisis compared to pre-crisis. The exception was Basic Materials whose beta coefficient increased. This is an indication of an overall reduction in investment risk of the South African stock markets during the GFC. The result contradicts the expectation that investment risk would increase during a crisis.

With regards to COVID-19 (Table A4), the sectoral beta coefficients increased during-crisis compared to pre-crisis for Automobiles & Parts, Basic Materials, Chemicals, Consumer Goods, Financials, and Technology. This is in line with the *priori* expectation that investment risk for these sectors will rise during the COVID-19 global pandemic. In contrast, sectoral beta coefficients during-crisis when compared to pre-crisis decreased for Banks, Consumer Services, Health Care, Industrial, and Telecommunication. This indicates that investment risk for these sectors has decreased amid COVID-19.

Overall, Automobiles & Parts mostly had the lowest sectoral beta coefficient throughout all sample periods of both crises. The opposite is true for Basic Materials. These results to a large extent support the findings of subsection 4.1, which indicated that Automobiles & Parts has the lowest sectoral correlation with the overall market throughout all sample periods of both crises, whereas the opposite was again true for Basic Materials.

4.3 Findings from the stationarity tests and the ZA test for structural breaks

Table A5 indicates that, according to the Augmented Dickey Fuller (ADF) test, all observed series are stationary at the 1% level of significance for the full sample periods of both the GFC and COVID-19. The Phillip-Perron (PP) test for unit roots in Table A5.2 likewise suggests that all observed series throughout all sample periods (for both the GFC and COVID-19) are stationary at the 1% level of significance. The Tau statistics (or *t*-statistics) for both the ADF and PP tests are above their corresponding test critical values. Therefore, all observed series are stationary when transformed from closing prices into sectoral returns.

The Zivot-Andrew (ZA) test indicates that Chemicals, Telecommunication, Financials, Technology and Banks are stationary at the 5% level of significance for the full sample period of the GFC. The ZA test also indicates that Consumer Goods, Health Care, and Consumer Services are stationary at the 5% level of significance for the full sample period of COVID-19. These findings from the ZA test do not reject the null hypothesis of non-stationarity. The other sectors were all stationary at the 1% level of significance for the full sample period of both the GFC and COVID-19.

In addition, the ZA test suggests that the structural breaks for the various sectors during the GFC's full sample period mostly appeared in June, September, and October of 2008. The two exceptions are Consumer Services (which experienced a structural break in July 2006 ie. before the GFC) and Banks (in November 2007 as the early-warning signs of the crisis became evident). In general, most observed series experienced a structural break during-crisis, but only 12 to 16 months after the start (July 2007) of the GFC. This could be explained by the fact that the South African stock markets were affected to a lesser extent by the crisis compared to countries such as the U.K. and the U.S. (Madubeko, 2010).

The ZA test demonstrated that the structural breaks for COVID-19's full sample period mostly appeared in March 2020, which coincided with the earliest discovery of novel Coronavirus in South Africa and the subsequent introduction of lockdown restrictions. Three exceptions are Health Care (which experienced a structural break in October 2018), Consumer Services (January 2020), and Consumer Goods (November 2020). This is a *priori* sign that COVID-19 will have a greater positive impact on stock market volatility than the GFC.

Overall, all observed series experienced a structural break closer to the start of the COVID-19 pandemic than the commencement of the GFC. Furthermore, Table A5.1 shows that according to the Augmented Dickey Fuller (ADF) test all observed series are stationary at the 1% level of significance throughout all sub-sample periods for both crises. In general, all observed series are stationary with and without structural breaks included in the tests.

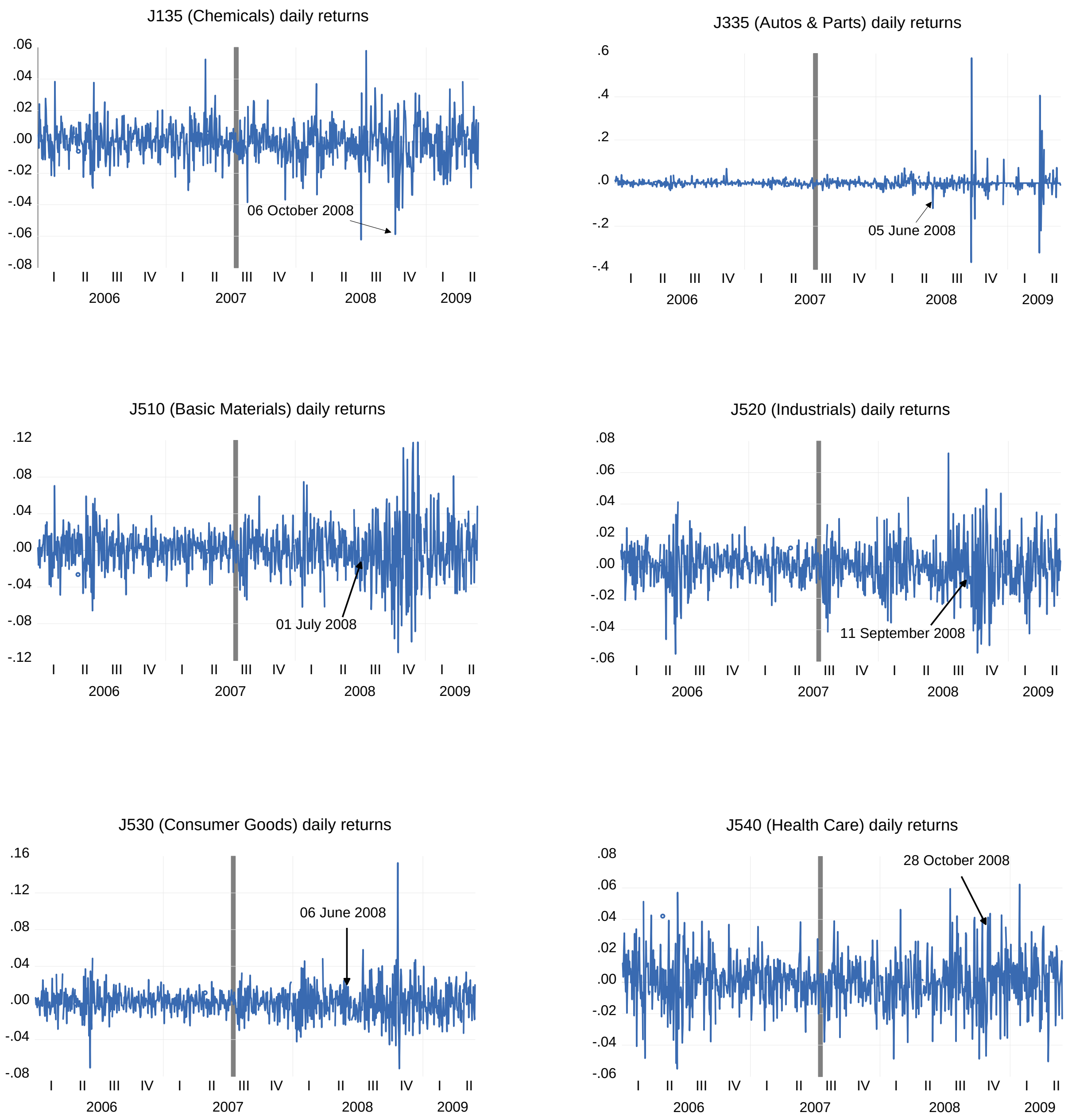
4.4 Graphing of daily returns

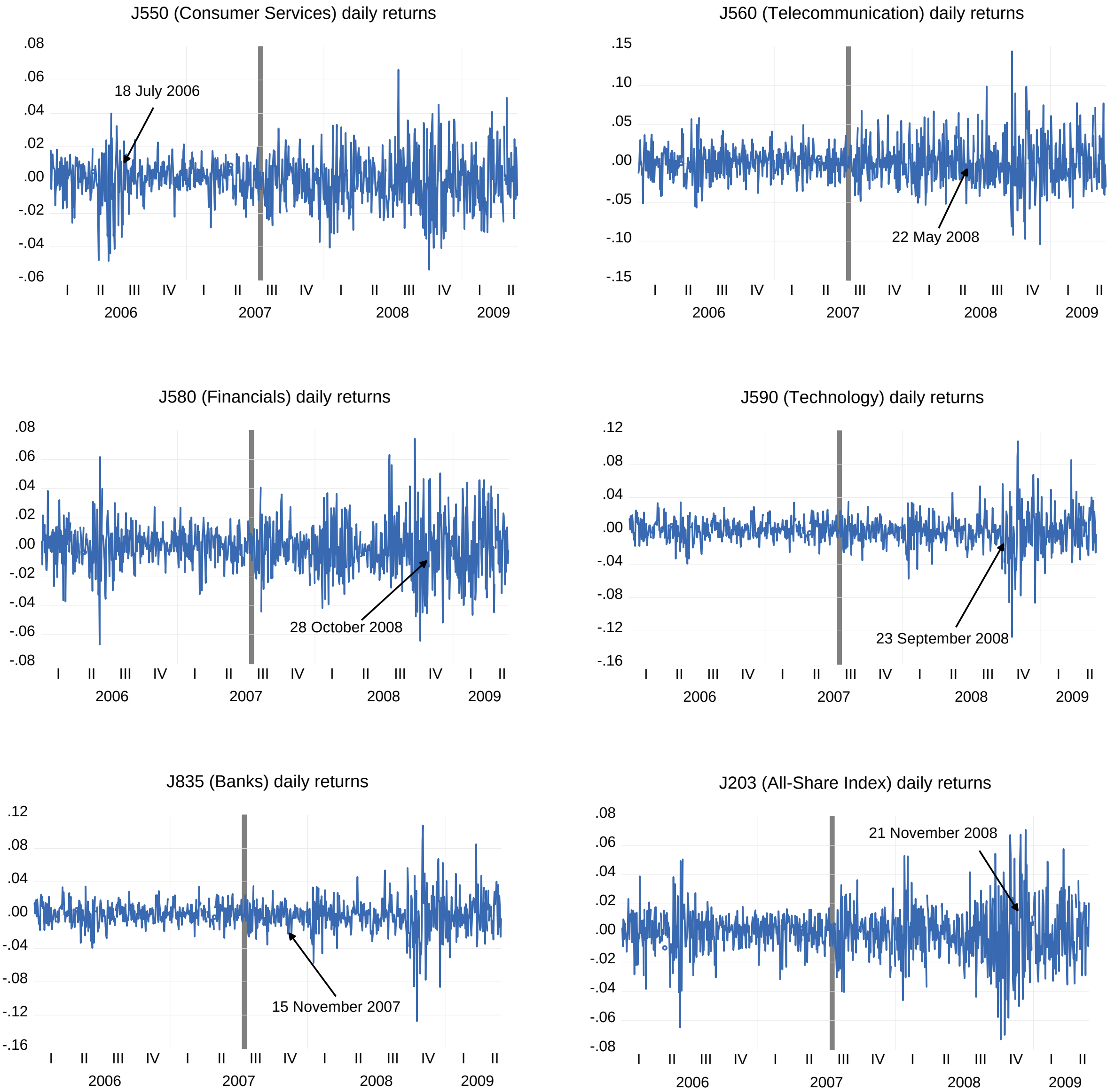
The graphing of daily returns is a visual representation of the observed series' volatility patterns. This serves as a *priori* of how observed series have fluctuated pre- and during-crisis. In all tables, the arrows and their corresponding dates (e.g.: 06^{th} October 2008) are pointing at the structural break. As a reminder, the dummy variable takes the value of zero (0) before the structural break and it takes the value of one (1) from the structural break onwards.

4.4.1 Daily returns of observed series for the full sample period of the GFC.

Figure 1 below shows the volatility patterns of all observed series for the GFC. Each figure has been inserted with a vertical line shaded in bold which represents the approximate starting of the GFC (July 10-20, 2007, or mid-July of 2007).

Figure 1: daily returns of all observed series for the GFC's full sample period





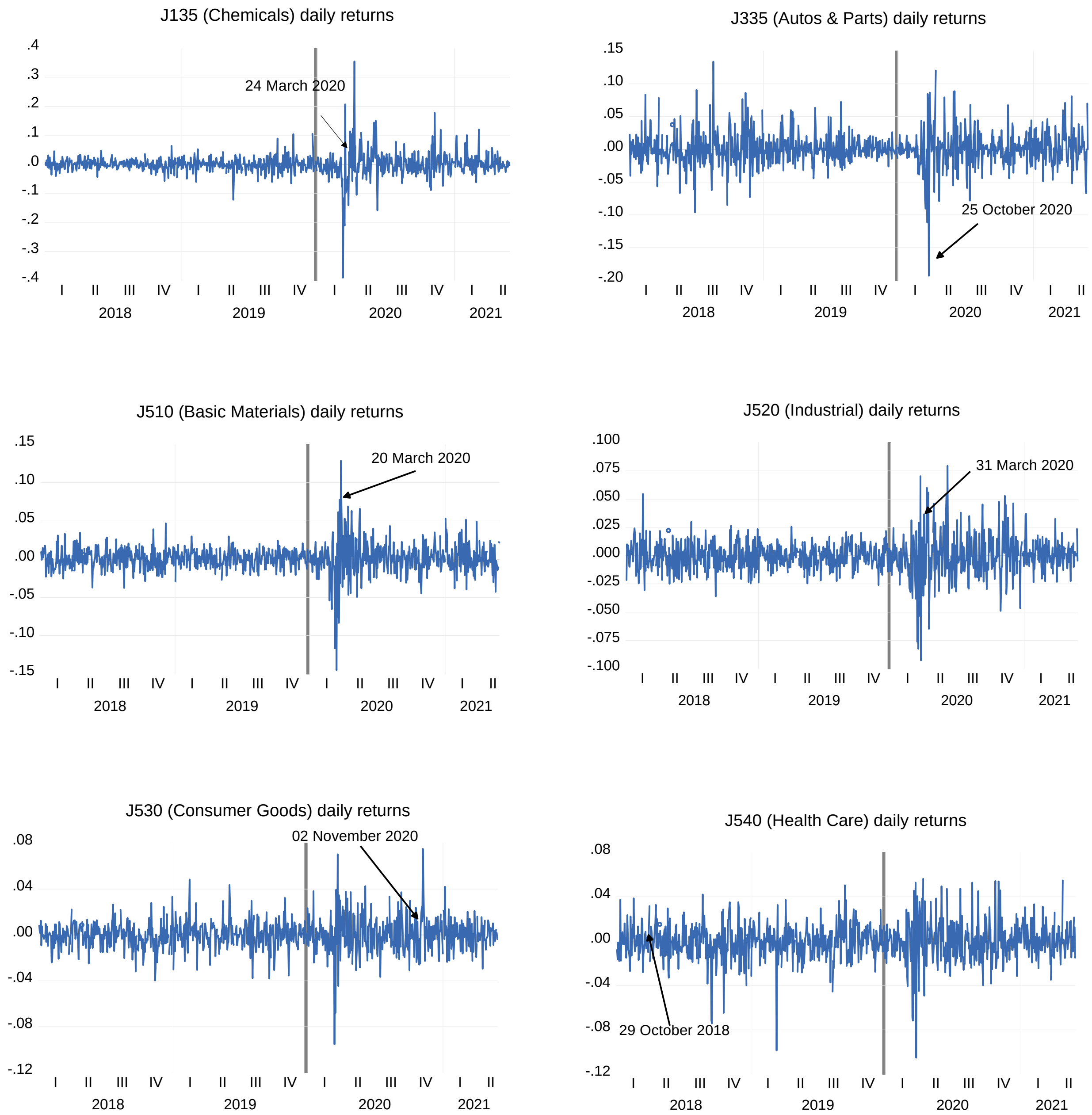
Source: Author's investigation.

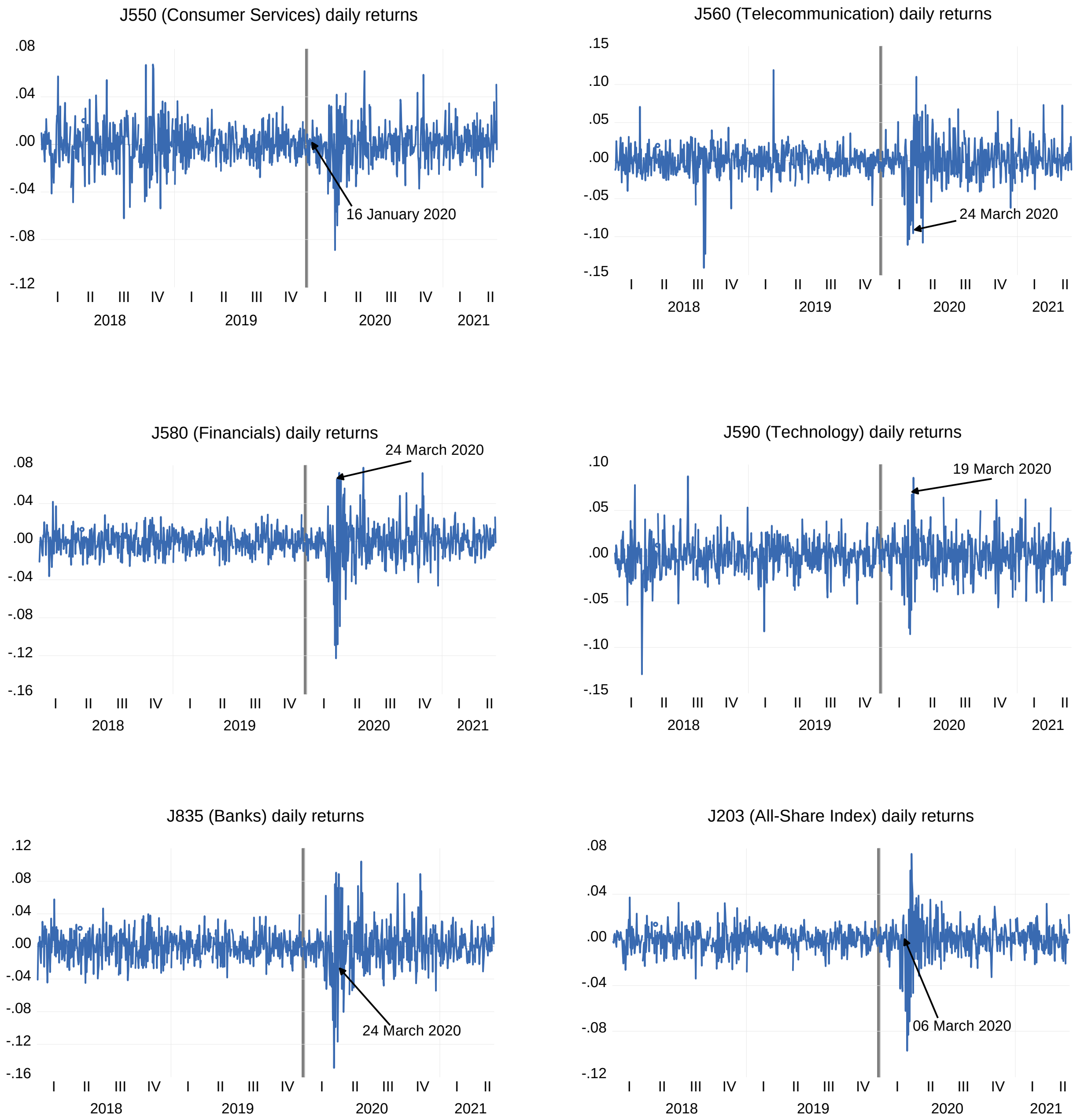
Figure 1 indicates that most observed series are more volatile extensively beyond the start (10-20 July 2007) of the GFC. The exception appears to be Health Care which appears to be highly volatile from a visual perspective throughout the full sample period of the GFC. Overall, most sectoral indices experienced their structural breaks around Q3-Q4 of 2008, possibly due to the significant deteriorating conditions of South Africa's employment, exports, net direct and portfolio investment, and overall GDP growth in July-December 2008. These economic consequences of the GFC were reflected in the JSE, where major stock returns in both USD and ZAR dropped by approximately 30% and 15% respectively in Q3-Q4, the largest declines of South African stock returns during the Global Financial Crisis (Pretorius and De Beer, 2014).

4.4.2 Daily returns of observed series for the full sample period of COVID-19

Figure 2 below shows the volatility patterns of all observed series for COVID-19. Each figure has been inserted with a vertical line shaded in bold which represents the approximate starting of COVID-19 (December 20-31, 2019).

Figure 2: daily returns of all observed series for COVID-19's full sample period





Source: Author's investigation.

It can be observed from Figure 2 that most observed series are more volatile closely after the start (20-31 December 2019) of the COVID-19 global pandemic. The only exception appears to be Health Care where it appears to be highly volatile from a visual perspective throughout the full sample period of COVID-19. Notice that Health Care was less responsive towards the commencement of a crisis for the full sample periods of COVID-19. Therefore, this serves as a *priori* speculation that Health Care will keep showing characteristics of defensive sectors for the during-crisis sample period of COVID-19. Overall, most sectoral indices experienced a structural break, particularly on 20 March 2020, this could be due to the worldwide disruption of various supply chains and financial market panics caused by the COVID-19 pandemic (Gormsen and Koijen, 2020).

4.5 Findings regarding the presence of ARCH effect

Table A6 shows the F-statistics from the ARCH-LM tests for the full sample periods of both the GFC and COVID-19. All observed series have confirmed the presence of ARCH effect (or heteroskedasticity) at the 1% level of significance, except for Chemicals and Basic Materials which for the full sample period of the GFC are significant only at 5% and 10% respectively.

Table A6.1 shows the F-statistics from the ARCH-LM tests for the sub-sample periods of both crises. Automobiles & Parts is statistically insignificant (or homoscedastic) for the GFC pre-crisis period, and most observed series are heteroskedastic for COVID-19's pre-crisis. For the during-crisis periods of both the GFC and COVID-19, all observed series were statistically significant at either the 1% or 5% level, except for Consumer Goods which is significant only at the 10% level.

Overall, the results of the ARCH-LM tests are consistent with the conditional variance graphs in both Figure 5 and 6 from Appendix C. Accordingly, Figure 5 which demonstrated a lack of volatility in daily returns specifically for Automobiles & Parts for the GFC's pre-crisis period, while Figure 6 illustrated a lack of volatility in daily returns for most observed series for the pre-crisis period of COVID-19.

4.6 Testing of normality

Testing of normality is based on the histograms of normal distribution, skewness values, kurtosis values, and the Jacque-Berra statistics.

4.6.1 Findings from the histograms of normal distribution

Figures 3 (from Appendix B) demonstrate the presence of 'fat tails' within all observed series during the full sample of the GFC. All observed series appear to be leptokurtic (peak distribution), except for Automobiles & Parts (which appears to be a flat distribution/ platykurtic). Leptokurtic distribution is a common phenomenon in financial time series. With regards to the full sample of COVID-19, Figures 4 (from Appendix B) clearly show that most observed series are leptokurtic and confirmed the presence of 'fat tails', except for Health Care which displayed a lack of 'fat tails' (platykurtic).

4.6.2 Findings from the Skewness values and Kurtosis values

From Tables A7 to A8.2, it can be observed that all Skewness values deviated from zero (0) throughout all sample periods of both crises. This again demonstrates that all observed series are 'fat-tailed' either towards the right (for positive values) or towards the left (for negative values). Furthermore, from Table A7 to A8.2, all Kurtosis values are above three (3) throughout all sample periods of both crises. This means that all observed series are leptokurtic.

4.6.3 Findings from the Jacque-Berra statistics

Tables A7 to A 7.2 in Appendix A contain the descriptive statistics for both the full- and sub-sample periods of the GFC. In terms of both the full sample and during-crisis, the JB-statistics for all observed series are statistically significant at the 1% level. This suggests that all observed series are abnormally distributed for those two periods. However for the pre-crisis period, the JB-statistics of Telecommunication and Technology are statistically significant at only the 10% level and thus have failed to reject the null hypothesis for both series.[11]

Tables A8 to A 8.2 in Appendix A show the descriptive statistics for both the full- and sub-sample periods of COVID-19. For both the full sample and during-crisis periods, the JB-statistics for all observed series are significant at the 1% level. However, with regards to pre-crisis, the JB-statistics of Basic Materials, Financials, and Banks are all statistically insignificant above the 10% level and so also fail to reject the null hypothesis.

Failing to reject the null hypothesis does not imply the acceptance of the alternative hypothesis (Kozak and Piepho, 2018 and EViews, 2020). This is because the sub-sample periods for this particular research (with less than 500 observations each) are considered small. Based on the

[11] In order to reject the null hypothesis of a normal distribution, the level of significance of the JB-statistics must be below the 5% level.

approximated *p*-values of the chi-squared distribution table, obtained using the Monte Carlo Simulation, the acceptance of the alternative hypothesis should only be confirmed for a large sample size of at least 2000 observations (Kozak and Piepho, 2018).

4.6.4 Findings from the mean returns

The mean returns (calculated from the daily returns) of all observed series for both the full- and sub-sample periods of the GFC can be found in Tables A7 to A7.2 in Appendix A. Except for Automobiles & Parts, Chemicals, and Financials, the remaining observed series have maintained a positive mean return for the full sample period. For pre-crisis, all observed series have obtained a positive mean return. For during-crisis, most observed series (except for Telecommunication) displayed a negative mean return. The findings are consistent with the author's expectations that the mean returns of stock markets should generally perform better pre-crisis and gradually decline towards the commencement and during a crisis.

The mean returns of all observed series for both the full- and sub-sample periods of COVID-19 can be found in Tables A8 to A8.2. Except for Financials, Health Care, Industrial, and Telecommunication, the remaining observed series have maintained a positive mean return for the full sample period. For pre-crisis, most observed series obtained a negative mean return, except for Basic Materials and Automobiles & Parts. For during-crisis, most observed series displayed a positive mean return, except for Financials. Therefore, solely from the mean returns for COVID-19, it can be observed that the South African stock markets weakened pre-crisis and strengthened during-crisis.

Table 2: mean returns for the full sample period of both crises

Sectors	Full GFC	Full COVID-19	Difference between the two crises
Chemicals	-0.00014	0.000617	0.08%
Automobiles & Parts	-0.000321	0.00041	0.07%
Basic Materials	0.00069	0.000902	0.02%
Industrial	0.00028	-0.000335	-0.06%
Consumer Goods	0.000556	0.000119	-0.04%
Health Care	0.000541	-0.000406	-0.09%
Consumer Service	0.000315	0.000097	-0.02%
Telecommunication	0.000868	-0.0000456	-0.09%
Financials	-0.0000106	-0.000226	-0.02%
Technology	0.00035	0.000248	-0.01%
Banks	0.000212	0.0000348	-0.02%
All-Share Index	0.000569	0.000237	-0.03%
Average	**0.00028**	**0.00012**	**-0.016%**

Source: Author's investigation.

Note: the average mean returns do not consist of the All-Share Index's mean returns.

Overall, according to Table 2, the average mean return during COVID-19's full sample period is 0.016% lower than during the GFC. However, this does not suggest that, on average, all observed series have performed worse during the COVID-19 global pandemic, as the full sample periods are composed of both pre- and during crises sample periods. Therefore, it is important to observe how mean returns have changed overtime from pre-crisis to during-crisis.

Table 2.1: mean returns for the sub-sample periods of both crises

Sectors	Pre-crisis GFC	During-crisis GFC	Diff.	Pre-crisis COV	During-crisis COV	Diff.
Chemicals	0.002743	-0.001226	-0.40%*	-0.000735	0.001121	0.19%*
Automobiles & Parts	0.000765	-0.001115	-0.19%	0.000434	0.000347	-0.01%
Basic Materials	0.001778	-0.000111	-0.19%	0.000568	0.001319	0.08%
Industrial	0.001503	-0.000583	-0.21%*	-0.000586	0.0000264	0.06%
Consumer Goods	0.001215	-0.0000892	-0.13%	-0.00025	0.000612	0.09%
Health Care	0.001517	-0.000156	-0.17%	-0.00086	0.000252	0.11%
Consumer Service	0.001274	-0.000378	-0.17%	-0.00022	0.000535	0.08%
Telecommunication	0.0013	0.000554	-0.07%	-0.000492	0.000712	0.12%
Financials	0.001043	-0.000766	-0.18%	-0.000317	-0.0000771	0.02%
Technology	0.001344	-0.000335	-0.17%	-0.000539	0.001329	0.19%*
Banks	0.000949	-0.00032	-0.13%	-0.000544	0.000179	0.07%
All-Share Index	0.0001353	-0.000284	-0.16%	-0.000113	0.000715	0.08%
Average	**0.00129**	**-0.00038**	**-0.166%**	**-0.00030**	**0.00053**	**0.082%**

Source: Author's investigation.

Note: the average mean returns do not consist of the All-Share Index's mean returns.

With reference to Table 2.1, it appears that all observed series' mean returns declined within the during-crisis sample period of the GFC, when compared to its own pre-crisis sample period. The opposite is true for the COVID-19 global pandemic, where almost all observed series, except for Automobiles & Parts, experienced an increase in mean returns within the during-crisis sample period.

Consequently, it is still unclear at this stage as to which sectoral indices can be categorised as defensive or cyclical, because almost all observed series have shown similar reactions in each crisis. This contradicts to the empirical findings of many authors mentioned in Chapter 1, who have demonstrated in their research that cyclical sectors should display low returns during periods of crises, and much higher returns outside periods of crises. However, according to the findings of this study, all observed series would have been considered cyclical during the GFC due to a uniform weakening in mean returns, and that most observed series would have been considered defensive during the COVID-19 global pandemic, as their mean returns strengthened.

In the GFC's during-crisis sample period, the average mean return declined by 0.166% compared to its own pre-crisis. In contrast, COVID-19's during-crisis, the average mean return increased by 0.082% compared to its own pre-crisis. However, the average mean return of COVID-19's pre-crisis period is 0.158% lower than the GFC's pre-crisis period. Whereas, the average mean return of COVID-19's during-crisis period is 0.091% higher than the GFC's during-crisis period.

Therefore, solely from the changes and different impacts of both the mean returns and average mean returns, it appears that most observed series weakened after the start of the GFC, which is expected given the crisis' impact on global and local financial markets, despite the latter entities have been affected to a lesser extent. Nonetheless, it has been illustrated that most observed series have strengthened since the starting of the COVID-19 global pandemic, which is unexpected given that the health crisis itself has caused severe disruptions in world supply chains and overall economic productivity

4.7 Results from the GARCH Diagnostics

Tables A11 to A12.5 present the GARCH diagnostics indicators from the GARCH model regression (for all observed series) run on three different types of error distributions each.

These indicators include: ARCH and GARCH coefficients; log likelihood; adjusted R-squared; Schwarz Information Criterion value; and the F-statistic's probability Chi-square obtained from the ARCH-LM test. The final results are reported in Table A13.

4.8 Findings from the GARCH regression coefficients

Subsection 4.8.1 to 4.8.3 reports the results regarding the impact of distant news and recent news on all observed series during both the GFC and COVID-19.

4.8.1 The impact of distant news and recent news: the GFC

Tables A9 and A9.1 in Appendix A contain the outputs of the ARCH (α) and GARCH (β) coefficients for both the full- and sub-sample periods of the GFC respectively. In terms of the GFC's full sample period, on average, recent news (denoted to β) has a larger impact on all observed series than distant news from the past (denoted to α) by 70.81%. It can also be observed that, for the GFC's pre-crisis period, β has a larger impact on all observed series than α by 62.02% on average. For the GFC's during-crisis period, β has a larger impact on all observed series than α by 62.19% on average.

4.8.2 The impact of distant news and recent news: COVID-19

Tables A10 and A10.1 A contain the outputs of the ARCH (α) and GARCH (β) coefficients for both the full- and sub-sample periods of the COVID-19 respectively. In terms of COVID-19's full sample period, on average, β has a larger impact on all observed series than α respectively by 65.24 %. It can also be observed that, for COVID-19's pre-crisis period, β has a larger impact on all observed series than α by 69.28% on average. For COVID-19's during-crisis period, β has a larger impact on all observed series than α by 56.26% on average.

4.8.3 The impact of distant news and recent news: the GFC vs. COVID-19

On average, β has a larger impact than α on all observed series by 7.27% for COVD-19's pre-crisis period when compared to the GFC's pre-crisis period. In contrast, β has a smaller impact than α on all observed series by 5.93% for COVD-19's during-crisis period when compared to the GFC's during-crisis period. In general, the α and β coefficients are all positive and statistically significant (either at a 1% or 5% level), which means that both recent and distant news have contributed positively towards the volatility of all observed series. This is consistent with the results from the empirical findings in Chapter 2.

4.9 Volatility persistency.

All observed series' volatility persistency denotes to '$\alpha+\beta$' for both the GFC and COVID-19 can be found in Table A9 to A10.1 in Appendix A. The subsections below from 4.9.1 to 4.9.3 discuss the results of both the volatility persistency for and differential impact on the full- and sub-sample periods for both crises.

4.9.1 Volatility persistency: findings from the GARCH regressions for the GFC

Table 3: GARCH regression for the GFC's full sample period

Sectors	ω	α	β	D_i	(α+β)
Chemicals	0.00000919 *	0.0869*	0.8519*	-0.0023****	0.9388
Auto & Parts	0.000000273*	0.2018*	0.8748*	0.0373****	1.0766
Basic Materials	0.00000956 **	0.0928*	0.8932*	-0.0166****	0.9860
Industrial	0.00000419**	0.1321*	0.8519*	-0.0017****	0.9840
Consumer Goods	0.00000527*	0.1208*	0.8645*	-0.0018****	0.9853
Health Care	0.00000760**	0.0529*	0.9179*	0.0023****	0.9708
Consumer Services	0.00000374*	0.1046*	0.8799*	0.0005****	0.9845
Telecommunication	0.00000529**	0.0543*	0.9395*	-0.0011****	0.9938
Financials	0.00000538**	0.1226*	0.8628*	-0.0074****	0.9854
Technology	0.00000598*	0.1024*	0.8809*	-0.0004****	0.9833
Banks	0.000133**	0.1131*	0.8636*	0.0044**	0.9767
All-Share Index	0.0000140**	0.1207*	0.8656*	0.000362****	0.9863

Source: Author's investigation.

Note: level of significance is indicated by the p-values at 1% (*), at 5% (**), at 10% (***), and insignificant (****)

According to Table 3 above, although the volatility persistency (hereafter referred to as $\alpha+\beta$) of Healthcare is featured in long-memory (where $\alpha+\beta$ = 0.9708) for the GFC's full sample period, it proven to be resilient during the GFC, where $\alpha+\beta$ = 0.8187 during-crisis.

Furthermore, the dummy variables for most observed series are negative, which indicates that, for the full sample period of the GFC, the actual $\alpha+\beta$s are lower than they would have been after accounting for the structural breaks. However, all negative dummy variables are statistically insignificant, which means that the reduction of the actual $\alpha+\beta$ for their corresponding series are also insignificant as a result. Nonetheless, Banks was positively and significantly affected (at the 5% level of significance) by D_i (0.0044). This means that accounting for the structural break did improve the accuracy of Banks' $\alpha+\beta$, because the actual $\alpha+\beta$ of Banks is effectively higher than it would have been without accounting for the structural breaks.

Table 3.1: GARCH regression for the GFC's sub-sample periods

Sectors	Pre-crisis				during-crisis			
	ω	α	β	(α+β)	ω	α	β	(α+β)
Chemicals	0.0000271**	0.2180*	0.6135*	0.8315	0.00000974*	0.0698*	0.8741*	0.9439
Auto & Parts	0.0000192**	0.0780**	0.7613*	0.8393	0.000237*	0.5484**	0.2999*	0.8483
Basic Materials	0.0000187**	0.1083**	0.8365*	0.9448	0.0000128**	0.0778*	0.9083*	0.9861
Industrial	0.00000809**	0.1376*	0.7933*	0.9309	0.00000531**	0.1293*	0.8576*	0.9869
Consumer Goods	0.00000836**	0.0998*	0.8405*	0.9403	0.00000668**	0.0800**	0.9014*	0.9814
Health Care	0.0000122**	0.0902*	0.8599*	0.9501	0.0000495**	0.1284**	0.6903*	0.8187
Consumer Services	0.00000762*	0.1494*	0.7834*	0.9328	0.00000530**	0.0577**	0.9227*	0.9804
Telecommunication	0.0000652**	0.1065**	0.7162*	0.8227	0.0000154**	0.0425*	0.9420*	0.9845
Financials	0.00000797**	0.1070*	0.8443*	0.9513	0.00000731**	0.1260*	0.8609*	0.9869
Technology	0.0000116**	0.0576**	0.8165*	0.8741	0.0000127*	0.1401*	0.8389*	0.9790
Banks	0.0000241**	0.0995*	0.8285*	0.9280	0.0000140***	0.1078*	0.8749*	0.9827
All-Share Index	0.00000824**	0.1254**	0.8236*	0.9490	0.00000590**	0.1160*	0.8729*	0.9889

Source: Author's investigation.

Both Table 3 and Table 3.1 indicate that, despite showing a huge increase in $\alpha+\beta$ during-crisis, Chemicals is the only sectoral index that displayed a very low and stable level of volatility persistency throughout all sample periods of the GFC, especially when compared to the remaining observed series.

Table 3.2: Differential impact of volatility persistency for the GFC's sub-sample periods

Sectors	Pre-crisis GFC	During-crisis GFC	Difference
Chemicals	0.8315	0.9439	11.24%
Automobiles & Parts	0.8393	0.8483	0.90%
Basic Materials	0.9448	0.9861	4.13%
Industrial	0.9309	0.9869	5.60%
Consumer Goods	0.9403	0.9814	4.11%
Health Care	0.9501	0.8187	-13.14%
Consumer Services	0.9328	0.9804	4.76%
Telecommunication	0.8227	0.9845	16.18%
Financials	0.9513	0.9869	3.56%
Technology	0.8741	0.979	10.49%
Banks	0.9280	0.9827	5.47%
All-Share Index	0.9490	0.9889	3.99%
Average	**0.8288**	**0.8732**	**4.44%**

Source: Author's investigation.
Note: the numerical values are the sum of α and β, which is the volatility persistency (α+β); the average volatility persistency does not consist of the All-Share Index's volatility persistency.

According to Table 3.2, compared to pre-crisis, most observed series experienced an increase in $\alpha+\beta$ during-crisis. Thus, most observed series became more volatile for the duration of the GFC. The one exception is Health Care which demonstrated a decrease in $\alpha+\beta$ by 13.14% during-crisis. The most significant increases in $\alpha+\beta$ during-crisis were observed in Telecommunications (16.18%), Chemicals (11.24%), and Technology (10.49%).

Moderate-level increase in $\alpha+\beta$ during-crisis were Industrial (5.60%), Banks (5.47%), Consumer Services (4.76%), Basic Materials (4.13%), Consumer Goods (4.11%), and Financials (3.56%). The $\alpha+\beta$ of the All-Share Index increased by 3.99% (to 0.9889) during-crisis when compared to pre-crisis (where $\alpha+\beta$ = 0.9490). Thus, it can be said that the South African stock markets were, as expected, more volatile for the GFC's during-crisis period.

4.9.2 Volatility persistency: findings from the GARCH regressions for COVID-19

Table 4: GARCH regression for COVID-19's full sample period

Sectors	ω	α	β	D_i	(α+β)
Chemicals	0.0000400*	0.2207*	0.7804*	0.0025****	1.0011
Auto & Parts	0.0000373**	0.2532*	0.7345*	0.0014****	0.9877
Basic Materials	0.00000632**	0.0775*	0.8998*	0.0014***	0.9774
Industrial	0.00000463**	0.0899*	0.8887*	0.0010****	0.9786
Consumer Goods	0.0000107*	0.0865*	0.8565*	0.0009****	0.9430
Health Care	0.0000145**	0.0605*	0.8909*	0.0012****	0.9514
Consumer Services	0.0000109**	0.0868*	0.8758*	0.0008***	0.9626
Telecommunication	0.0000178*	0.0634*	0.8991*	0.0032****	0.9625
Financials	0.00000880*	0.1318*	0.8324*	0.0017****	0.9642
Technology	0.000115*	0.1264*	0.6011*	0.0012****	0.7275
Banks	0.0000122*	0.1036*	0.8700*	0.0022***	0.9736
All-Share Index	0.00000645*	0.1027*	0.8497*	0.0017****	0.9524

Source: Author's investigation.

In terms of Table 4, Chemicals show a long memory above unity for both the full sample period ($\alpha+\beta$ = 1.0011) and during-crisis ($\alpha+\beta$ = 1.0537) of COVID-19. Thus, by becoming significantly more volatile during-crisis, the Chemicals index was not able to maintain a low and stable level of $\alpha+\beta$ for both the GFC and COVID-19.

In addition, within COVID-19's full sample period, D_i for most observed series is positive and statistically insignificant above the 10% level, which suggest that the inclusion of structural breaks generally predicted an increase in the actual $\alpha+\beta$ of all observed series for the full sample period of COVID-19, but insignificant. However, Basic Materials (0.0014), Consumer Services (0.0008), and Banks (0.0022) were positively and significantly affected (all at 10%) by D_i. This means that accounting for the structural break did improve the accuracy of Banks' $\alpha+\beta$, because the actual $\alpha+\beta s$ of these three series are effectively higher than it would have been without accounting for the structural breaks.

Table 4.1: GARCH regression for COVID-19's sub-sample periods

Sectors	Pre-crisis				during-crisis			
	ω	α	β	(α+β)	ω	α	β	(α+β)
Chemicals	0.0000180**	0.0397**	0.9209*	0.9606	0.000209*	0.5147*	0.5390*	1.0537
Auto & Parts	0.0000550*	0.2049*	0.7720*	0.9769	0.0000143*	0.1859*	0.8214*	1.0073
Basic Materials	0.0000479**	0.0574**	0.8299*	0.8873	0.0000171**	0.1027*	0.8640*	0.9667
Industrial	0.0000111**	0.0753*	0.8383*	0.9136	0.0000957**	0.1282*	0.8593*	0.9875
Consumer Goods	0.00000111*	0.0201*	0.9132*	0.9333	0.0000148**	0.1692*	0.7917*	0.9609
Health Care	0.0000139**	0.3231**	0.6074*	0.9305	0.0000162**	0.0965*	0.8580*	0.9545
Consumer Services	0.00000693*	0.0733*	0.9028*	0.9762	0.0000144**	0.1301*	0.8344*	0.9645
Telecommunication	0.0000168**	0.0548*	0.8992*	0.9540	0.0000196**	0.0615*	0.9074*	0.9689
Financials	0.0000173**	0.0581**	0.8268*	0.8849	0.0000129**	0.1900*	0.8213*	1.0113
Technology	0.0000224	0.0275**	0.9137*	0.9412	0.0000961*	0.2235*	0.5691*	0.7926
Banks	0.0000307**	0.0318**	0.8556*	0.8874	0.0000159**	0.1493*	0.8371*	0.9864
All-Share Index	0.000000552**	0.0537**	0.8885*	0.9422	0.0000112**	0.1553*	0.7907*	0.9460

Source: Author's investigation.

According to Table 4.1, on the one hand, Automobiles & Parts remained fairly stable throughout all sample periods of COVID-19, although it was characterised in long memory above unity during-crisis ($\alpha+\beta$ = 1.0073). On the other hand, Banks displayed a low level of $\alpha+\beta$ (0.8849) pre-crisis, but also demonstrated a sharp increase in $\alpha+\beta$ (1.0113) during-crisis.

Table 4.2: Differential impact of volatility persistency for COVID-19's sub-sample periods

Sectors	Pre-COVID	During-COVID	Difference
Chemicals	0.9606	1.0537	9.31%*
Automobiles & Parts	0.9769	1.0073	3.04%
Basic Materials	0.8873	0.9667	7.94%*
Industrial	0.9136	0.9875	7.39%*
Consumer Goods	0.9333	0.9609	2.76%
Health Care	0.9305	0.9545	2.40%
Consumer Services	0.9762	0.9645	-1.17%
Telecommunication	0.954	0.9689	1.49%
Financials	0.8849	1.0113	12.64%*
Technology	0.9412	0.7926	-14.86%*
Banks	0.8874	0.9864	9.90%*
All-Share Index	0.9422	0.9460	0.38%
Average	**0.8538**	**0.8879**	**3.40%**

Source: Author's investigation.

Note: the numerical values are the sum of α and β, which is the volatility persistency (α+β); the average volatility persistency does not consist of the All-Share Index's volatility persistency.

According to Table 4.2, compared to pre-crisis, once again, most observed series experienced an increase in $\alpha+\beta$ during-crisis, except for Consumer Service (-1.17%) and Technology (-14.86%). Some of the most significant increases in $\alpha+\beta$ during crisis were observed in Financials (12.64%), Banks (9.90%), Chemicals (9.31%), Basic Materials (7.94%), and Industrial (7.39%). This means that most observed series became more volatile during the spreading of the COVID-19 global pandemic.

Compared to COVID-19's pre-crisis, the observed series that demonstrated a low-to-moderate level increase in $\alpha+\beta$ for COVID-19's during-crisis are: Automobiles & Parts (3.04%), Consumer Goods (2.76%), HealthCare (2.40%), and Telecommunication (1.49%). The All-Share Index demonstrated an increase in $\alpha+\beta$ of 0.38% (to 0.9422) during-crisis compared to pre-crisis (where $\alpha+\beta$ = 0.9460). Thus, the South African stock markets were, as expected, generally more volatile during the COVID-19 global pandemic. But the increase in volatility was less than during the GFC.

4.9.3 Differential impact of volatility persistency: GFC versus COVID-19

Table 5: differential impact of volatility persistency between the GFC and COVID-19

Sectors	Full sample GFC	Full Sample COVID-19	Difference between the two crises
Chemicals	0.9388	1.0011	6.23%*
Automobiles & Parts	1.0766	0.9877	-8.89%*
Basic Materials	0.986	0.9774	-0.86%
Industrial	0.984	0.9786	-0.54%
Consumer Goods	0.9853	0.943	-4.23%
Health Care	0.9708	0.9514	-1.94%
Consumer Service	0.9845	0.9626	-2.19%
Telecommunication	0.9938	0.9625	-3.13%
Financials	0.9854	0.9642	-2.12%
Technology	0.9833	0.7275	-25.58%*
Banks	0.9767	0.9736	-0.31%
All-Share Index	0.9863	0.9524	-3.39%
Average	**0.9054**	**0.8691**	**-3.63%**

Source: Author's investigation

Note: the numerical values are the sum of α and β, which is the volatility persistency (α+β); the average volatility persistency does not consist of the All-Share Index's volatility persistency.

In terms of Table 5, the full sample period of COVID-19 suggests a 3.63% lower average $\alpha+\beta$ than that of the GFC. Overall, the during-crisis average $\alpha+\beta$ have increased by 4.44% (for the GFC) and 3.40% (for COVID-19) compared to their corresponding pre-crisis average $\alpha+\beta$.

The All-Share Index for COVID-19's full sample period shows a 3.39% lower average $\alpha+\beta$ than that of the GFC. This suggests that the overall South African stock markets are less volatile for the current period of the COVID-19 global pandemic than that of the GFC. However, when comparing the same set of sub-sample periods between the two crises, it can be observed that, firstly, the average $\alpha+\beta$ for COVID-19's pre-crisis is 2.50% higher than that of the GFC. Secondly, the average $\alpha+\beta$ for COVID-19's during-crisis is 1.46% higher than during-crisis of the GFC.

Authors such as Arguile (2012) and Hong *et al*. (2021) have indicated that sub-sample periods are more informative in terms of comparing changes in average $\alpha+\beta$, because they allow average $\alpha+\beta$ to be focused within and compared between specific economic situations of one or more crises. Therefore, based on the changes in average $\alpha+\beta$ of the sub-sample periods, it can be said that all observed series became more volatile in COVID-19's during-crisis, compared to the GFC's during-crisis.

4.10 Results from the GARCH-M (1, 1) regressions.

Table 6 and 7 present the results of the GARCH-M model regressions for the full sample periods of both crises but focusing on the second specification (out of all three). This is because that, when examining the first specification of the GFC's full sample period in Table D1, the results suggest that, although the dummy variables were statistically significant at either the 5% and 10% level for Chemicals, Automobiles & Parts, Basic Materials, Industrial, Consumer Goods, Telecommunication, Financial, Technology, and Banks, hardly any sectoral indices exhibited a risk premium. The only exception is Industrial, where a risk premium exists in the sectoral index (β_R = 0.0817; significant at the 5% level), given that conditional volatility is positively correlated with the structural break (D_V = 0.0000133; significant at the 10% level).

In terms of the first specification for COVID-19's full sample period in Table D2, although the dummy variables were statistically significant at either the 5% and 10% level for Chemicals, Automobiles & Parts, Basic Materials, Consumer Goods, and Telecommunication, only two sectoral indices exhibited a risk premium. The only exception was Consumer Goods (β_R = 0.0817; significant at the 5% level), where a risk premium exists in the sectoral index, given that conditional volatility is negatively corelated with the structural break (D_V= -0.00000366; significant at the 5% level). Therefore, incorporating the dummy variables into the conditional variance equations, but not so for the conditional mean equations, had very limited impact on the outcome of most sectoral indices' risk premiums. Hence, no risk premium was found in most sectoral indices, irrespective of the significance of the correlation between conditional volatility and structural breaks.

Secondly, regarding the third specification of the GFC's full sample period in Table D1, the result shows that there are no risk premiums found within any sectoral indices, irrespective of whether conditional volatility is corelated with structural break in the conditional variance equations. Nevertheless, the incorporation of the dummy variables in the conditional mean equation shows a positive and significant relationship between risk premiums for most sectoral indices, except for Industrial, Health Care, and Consumer Services.

With regards to the third specification of COVID-19's full sample period in Table D2, the result also shows that there are no risk premiums found within any sectoral indices, irrespective of whether conditional volatility is corelated with structural break in the conditional variance equations. The incorporation of the dummy variables in the conditional mean equation shows a positive but insignificant relationship between risk premiums for most sectoral indices, except for Basic Materials, Industrial, Telecommunications, and Financials.

Table 6: full-sample period GARCH-M (1, 1) results of all observed series for the GFC

	Sectors	Mean equation				Variance Equation		
		ω	R_t	β_R	D_R	ω	β_V	D_V
Second specification	Chemicals	0.00000582 ****	0.0844 **	3.5224 ****	-0.0023 ****	0.0000127 *	0.8131 *	0.00000903 ****
	Auto & Parts	-0.000502 ****	-0.0713 **	4.1117 ****	-0.0014 *	0.0000453 *	0.7603 *	0.000647 ***
	Basic Materials	-0.000782 ****	0.0123 ****	7.5662 ***	-0.009737 *	0.0000155 **	0.8775 *	0.0000400 ****
	Industrial	0.00143 **	0.0808 **	-1.9056 ****	-0.0013 ***	0.00000608 *	0.8131 *	0.0000129 ***
	Consumer Goods	0.000663 ****	-0.0367 ****	3.5452 ***	-0.003127 ***	0.00000743 *	0.8483 *	0.0000158 ****
	Health Care	-0.002034 ****	0.0991 *	9.2433 ***	0.0014 ***	0.0000557 *	0.6177 *	0.0000299 ****
	Consumer Services	0.001128 ****	0.1389 *	-4.2035 ****	0.000516 ***	0.00000524 *	0.8817 *	-0.00000195 ****
	Telecommunication	-0.000255 ****	-0.0164 ****	5.2252 ****	-0.005903 ***	0.0000663 *	0.7228 *	0.000129 ****
	Financials	-0.000149 ****	0.0546 ****	2.4149 ****	-0.0000184 ***	0.00000744 **	0.8468 *	0.0000126 ****
	Technology	0.001378 ****	0.0809 ****	-4.6598 ****	0.002440 ***	0.0000221 *	0.7327 *	0.0000867 ****
	Banks	-0.000345 ****	0.0299 ****	5.0598 ****	-0.00356 ***	0.0000138 **	0.8635 *	0.0000106 ****
	All-Share Index	0.000540 ****	0.0174 ****	2.1836 ****	-0.0000457 ****	0.00000575 **	0.8549 *	0.00000717 ***

Source: Author's investigation.
Note: the dummy variable inserted into the mean equations (D_R) of the GARCH-M model does not serve the same purpose as those (D_i) inserted into the variance equation of the GARCH model in Table 3 and Table 4. Here, D_R is indicative of the existence or absence of a risk premium, rather than contributing positively or negatively towards the volatility persistency of the observed series.

Table 6 shows that, based on the GARCH term in the mean equation (β_R), a positive and significant relationship (at 10%) between expected returns and expected risks is exhibited in the sectors of Basic Materials (β_R=7.5662, p=0.0826), Consumer Goods (β_R=3.5452, p=0.0844), and Health Care (β_R=9.2433, p=0.0512). This means that an increase in expected risk is compensated by an increase in expected returns (and thus the existence of a risk premium is confirmed) within these three sectors for the full-sample period of the GFC.

Furthermore, the dummy variable inserted into the mean equation (D_R) is mostly negative and significant at the 1% level and 10% level, which indicates that the incorporation of structural breaks into the conditional mean equations has effectively predicted the reduction of the actual risk premiums in most observed series for the full sample period of the GFC. Exceptions are Health Care, Consumer Services, and Technology, where D_R is positive and significant. This confirms that the risk premiums for Health Care and Consumer services are positively and significantly correlated to the dummy variables inserted into the corresponding conditional mean equations. In addition, the risk premium of Basic Materials, Consumer Goods, and Health Care is also due to the positive correlation between the conditional volatility and the structural breaks (D_V) in their conditional variance equation correspondingly.

Table 7: full-sample period GARCH-M (1, 1) results of all observed series for COVID-19

	Sectors	Mean equation				Variance Equation		
		ω	R_t	$β_R$	D_R	ω	$β_V$	D_V
Second specification	Chemicals	0.0000805 ****	0.0659 ***	0.1499 ****	0.002216 ***	0.0000478 *	0.7511 *	0.0000349 ****
	Auto & Parts	-0.000293 ****	-0.1316 **	2.2323 ****	0.000827 ****	0.0000207 *	0.7945 *	0.0000127 ****
	Basic Materials	0.0000720 ****	-0.006868 ****	3.3818 ****	0.000729 ***	0.00000772 **	0.8848 *	0.00000599 ****
	Industrial	-0.0000306 ****	-0.0142 ****	-4.3482 ****	0.0025 ***	0.00000639 **	0.8567 *	0.00000437 ****
	Consumer Goods	-0.001308 ****	0.0519 ****	7.7513 ***	0.001253 ****	0.00000424 *	0.9358 *	-0.00000302 ***
	Health Care	0.002243 ****	-0.0106 ***	-13.8903 ****	0.001895 ***	0.0000407 *	0.7634 *	0.00000475 ****
	Consumer Services	-0.000671 ****	0.0075 ****	2.5863 ****	0.000729 ***	0.00000948 *	0.8689 *	0.00000244 ***
	Telecommunication	0.000484 ****	-0.0167 ****	-2.9039 ****	0.0036 **	0.0000191 *	0.8891 *	0.00000517 ****
	Financials	-0.000508 ****	0.0045 ****	0.2071 ****	0.001591 ***	0.00000962 *	0.8208 *	0.00000461 ****
	Technology	0.001472 ****	0.0312 ****	-4.2799 ****	0.001297 ****	0.000120 *	0.5861 *	-0.00000179 ****
	Banks	-0.0000299 ****	-0.0259 ****	-0.8203 ****	0.002321 ****	0.0000128 **	0.8658 *	0.00000231 ****
	All-Share Index	-0.000240 ****	0.0214 ****	3.9921 ****	0.000934 ****	0.00000645 *	0.8464 *	0.00000113 ***

Source: Author's investigation

Table 7 shows that, based on the GARCH term in the mean equation ($β_R$), a positive and significant relationship (at 10%) between expected returns and expected risks is exhibited only in Consumer Goods ($β_R$=7.7513, *p*=0.0813). This means that an increase in expected risk is compensated by an increase in expected returns (and thus the existence of a risk premium is confirmed) within this particular sector for the full-sample period of COVID-19.

The dummy variable inserted into the mean equation (D_R) is mostly positive and significant at the 10% level for most observed series, which indicates that the incorporation of structural breaks has effectively predicted the increase in their risk premiums. Undoubtfully, many D_R are insignificant (****), where the level of significance is above the 10% threshold. Overall, regardless of the direction and significance of the dummy variables, Table 7 suggests that a risk premium was confirmed to exist only in Consumer Goods based on the GARCH term.

Finally, Table D3 and Table D4 (in Appendix D) shows that, based on the GARCH terms, all observed series for the sub-sample periods of both crises do not have a risk premium. This is an expected finding given the GARCH-M model specifications for the sub-sample periods are on a basic level.

4.11 Classification of sectoral indices

Based on the analysis of subsections 4.1 to 4.10, the sectoral indices could be generally grouped as cyclical and defensive Sectors shown by Table 8. Health Care index maintained a low and stable level of $\alpha+\beta$ throughout all sample periods of both the GFC and COVID-19 crises. Therefore, Health Care performed as a defensive sector throughout both crises in South Africa. The Chemicals and Industrial indices cannot be concluded to be defensive Sectors as had been expected. This is due to their moderate-to-high level increases in $\alpha+\beta$ during-crisis for both the GFC and COVID-19 crises. As a result, both the Chemicals and Industrial indices are concluded to in fact be cyclical sectors. Basic Materials, Telecommunication, Financials, and Banks maintained a moderate-to-high level increase in $\alpha+\beta$ throughout all sample periods of both the GFC and COVID-19. Thus, these sectors are concluded also to be cyclical. Consumer Goods cannot be concluded to be cyclical as had been assumed in the research goal due to its low level increase in $\alpha+\beta$ for the sub-sample periods of both the GFC and COVID-19. Consequently, Consumer Goods is in fact a defensive sector in South Africa.

Although Automobiles & Parts was a defensive sector during the GFC, it appears to be cyclical during the COVID-19 crisis. Thus, Automobiles & Parts cannot be considered either defensive or cyclical. The Consumer Services and Technology indices were also indeterminable. This is because when compared to their pre-crisis periods' $\alpha+\beta$ for both crises, these two sectors became more volatile for the GFC during-crisis, but less volatile during the COVID-19 crisis.

Table 8: Classification of the observed series within all sample periods for both the GFC and COVID-19

Sectors	GFC		COVID-19		Overall classification based on both crises
	full sample (α+β)	Classification	full sample (α+β)	Classification	
Banks	0.9767	Cyc	0.9736	Cyc	Cyclical
Basic Materials	0.9860	Cyc	0.9774	Cyc	Cyclical
Chemicals	0.9388	Cyc	1.0011	Cyc	Cyclical
Industrial	0.9840	Cyc	0.9786	Cyc	Cyclical
Telecommunication	0.9938	Cyc	0.9625	Cyc	Cyclical
Financials	0.9854	Cyc	0.9642	Cyc	Cyclical
Consumer Goods	0.9853	Def	0.9430	Def	Defensive
Health Care	0.9708	Def	0.9514	Def	Defensive
Auto & Parts	1.0766	Def	0.9877	Cyc	Indeterminable
Consumer Services	0.9845	n/a	0.9626	n/a	Indeterminable
Technology	0.9833	n/a	0.7275	n/a	Indeterminable

Source: Author's investigation
Note: Cyc = Cyclical; Def = Defensive. Table 8 is constructed based on the results and findings in Chapter 4, and specifically regarding the subsections of volatility persistency (α+β), which ranged from subsection 4.9.1 to 4.9.3, and focusing on Table 3.2 and Table 4.2.

CHAPTER 5: CONCLUSION

5.1 Summary of the research

This research conducted a comparative analysis of stock market volatility in South Africa amid the GFC and COVID-19. The goal was to identify sectoral indices that retained the characteristics of being either defensive or cyclical throughout both crises. To do so, daily time series of eleven sectoral indices and the JSE-Alsi benchmark index were analysed using GARCH (1, 1) regressions in order to obtain their conditional variances in both full sample and sub-sample periods for each crisis.

To commence the analysis, the Business Cycle Theory and Efficient Market Hypothesis were discussed to understand how stock markets are expected to react to different economic situations and new information. This provided the theoretical basis for distinguishing between defensive and cyclical sectors and how each type of sector is expected to behave in different circumstances. To capture how time series reacted to times of crisis econometrically, the Markov-switching model, Conditional Volatility Persistency model, and Heterogeneous Autoregressive model were identified as possible methodological techniques for achieve the research objectives. The Conditional Volatility Persistency model was deemed most suitable for achieving the goals of this research.

In conducting the actual econometric testing, a series of *priori* tests were carried out. These included: 1) correlation matrix; 2) sectoral beta coefficient constructed by weighting with the benchmark index; 3) ARCH effect; 4) descriptive statistics; 5) unit root tests; 6) construction of dummy variables to capture structural breaks; and 7) GARCH diagnostics to identify the appropriate GARCH model error distributions. GARCH (1, 1) regressions were then performed with the insertion of dummy variables in the conditional variance equations of the full sample periods of both crises. GARCH (1, 1) regressions were performed on the sub-sample periods for both crises (before-, during- and after-crisis) without dummy variables.

The GARCH (1, 1) regressions suggested that recent news has contributed positively, and to a larger extent than distant news to the volatility of all observed series during all sample periods for both crises, which is common amongst GARCH model regressions. Furthermore, almost all sectoral indices have become more volatile for the during-crisis sample periods of both crises, when compared to each and every observed series' pre-crisis sample periods. Thus, the discussion surrounding the changes in $\alpha+\beta$ for both crises alone cannot bring about decisive categorisations of sectoral indices, i.e.: defensive, cyclical, or indeterminable. Therefore, the analysis of the differential impacts of $\alpha+\beta$ in percentage terms by accounting for Table 3.2 and Table 4.2 in Chapter 4 can more effectively assist with this goal. Furthermore, Although the full sample period of COVID-19 has a lower average $\alpha+\beta$ than that of the GFC (see Table 5), the sub-sample periods show otherwise. The average $\alpha+\beta$ for COVID-19 pre-crisis and during-crisis are higher than the same periods of the GFC. Therefore, all observed series are generally more volatile during the COVID-19 pandemic than during the GFC.

Finally, based on Table 8 in Chapter 4, it was determined that the cyclical sector consists of Banks, Basic Materials, Chemicals, Industrial, Telecommunication, and Financial. The defensive sector consists of Consumer goods and Health Care. The indeterminable sector consist of Automobiles & Parts, Consumer Services, and Technology.

5.2 Investment implications

It was noted in the Introduction that an understanding of how stock market volatility of sectoral indices changed during both crises helps to determine whether the volatility assumptions for both defensive and cyclical sectors of diversified investment portfolios held during both crises, despite the different causes of each crisis. This knowledge can assist with future risk management and portfolio allocation of stock market investments (Rasmussen, 2002), which is achievable through portfolio diversification. In turn, a diversified portfolio composing both defensive and cyclical stocks and adjusted overtime can serve the interests of stock market investors, for the purpose of cushioning investors during a period of financial market uncertainties, or for generating profits.

More importantly, from a societal aspect, portfolio diversification of both individual and organisational investors can contribute towards the enhancement of the financial markets' overall resistance against systemic risks (Frey and Hledik, 2018, Ji *et al*., 2020). Specifically, with reference to the GARCH (1, 1) and GARCH-M (1, 1) regressions for all sample periods of both crises, both Health Care and Consumer Services show characteristics of a defensive sector and can be used to cater for an investor's need to balance out the performance of an investment portfolio during turbulent times. This is based on the fact that these two sectors have displayed a stable level of volatility throughout all sample periods, and a positive risk premium for the full sample periods of both crises, after the GARCH-M model specification had accounted for structural breaks in both the conditional mean and variance equations.

5.3 Areas for further research

This research has shortfalls, but can nevertheless be used as a guideline for further research. Firstly, this research focused on comparing stock market volatility between phases of two crises. Further research can include the periods in-between the crises (from May 2009 to December 2017) in order to analyse how stock market volatility has changed overtime. This will allow such a study to include other significant periods of market turmoil, such as the 2009-2012 European Debt Crisis, that may have had a major impact on global stock markets including South Africa. It will also examine whether sectoral volatility had changed over the period, and the impact this might have had during the COVID-19 crisis.

Secondly, this research used the univariate GARCH model to analyse the conditional volatility of observed series. Further research could use the E-GARCH and T-GARCH models to obtain results on whether sectoral indices and the benchmark index have comparatively reacted to both good and bad news, and the asymmetrical impact of information at times of crisis (such as the commencement of a crisis) or over time.

Thirdly, this research designed its dummy variables based on the occurrence of structural breaks that marked a significant change in daily time series (or daily returns). Further research can investigate the possibility of choosing a specific date that signified the start of a crisis if the focus is on comparing stock market volatility amid times of crisis. However, if future research focuses on continuous data series without dividing these into periods of crises, then more than one dummy variable might be needed to capture the start of more than one crisis, or events that would have marked the start of those crises.

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APPENDICES

APPENDIX A

Table A1: Full sample periods correlation matrix for the GFC using daily returns

	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
J135	1.0000	**0.6482**	**0.8263**	0.9300	0.8991	0.8921	0.9240	**0.8100**	0.9001	0.8866	0.8412	0.9058
J335	0.6482	1.0000	0.5343	0.6316	0.6071	0.6309	0.6487	0.5360	0.6189	0.6124	0.5898	0.6040
J510	0.8263	**0.5343**	1.0000	0.8775	0.8643	0.8201	0.8572	**0.7897**	0.8595	0.8347	0.8147	0.9662
J520	0.9300	**0.6316**	**0.8775**	1.0000	0.9363	0.9284	0.9651	**0.8801**	0.9573	0.9044	0.9154	0.9598
J530	0.8991	**0.6071**	**0.8643**	0.9363	1.0000	0.8924	0.9213	**0.8346**	0.9217	0.8807	0.8656	0.9413
J540	0.8921	**0.6309**	**0.8201**	0.9284	0.8924	1.0000	0.9235	**0.8339**	0.9212	0.8734	0.8853	0.9078
J550	0.9240	**0.6487**	**0.8572**	0.9651	0.9213	0.9235	1.0000	**0.8728**	0.9520	0.9062	0.9122	0.9464
J560	0.8100	**0.5360**	**0.7897**	0.8801	0.8346	0.8339	0.8728	1.0000	0.8846	0.8111	0.8579	0.8822
J580	0.9001	**0.6189**	**0.8595**	0.9573	0.9217	0.9212	0.9520	**0.8846**	1.0000	0.8866	0.9768	0.9537
J590	0.8866	**0.6124**	**0.8347**	0.9044	0.8807	0.8734	0.9062	**0.8111**	0.8866	1.0000	0.8370	0.9013
J835	0.8412	**0.5898**	**0.8147**	0.9154	0.8656	0.8853	0.9122	**0.8579**	0.9768	0.8370	1.0000	0.9114
J203	0.9058	**0.6040**	**0.9662**	0.9598	0.9413	0.9078	0.9464	**0.8822**	0.9537	0.9013	0.9114	1.0000

Source: Author's investigation.
Note: a higher correlation coefficient indicates the existence of a correlation between two sectoral indices. This suggests that those two indices responded to an exogenous shock in similar ways.

Table A1.1: pre-crisis correlation matrix for the GFC using daily returns

	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
J135	1.0000	0.9676	**0.9521**	0.9754	0.9696	0.9513	0.9725	**0.9446**	0.9673	0.9704	**0.9433**	0.9718
J335	**0.9676**	1.0000	**0.9369**	0.9673	0.9645	0.9504	0.9689	**0.9356**	0.9621	0.9650	**0.9369**	0.9620
J510	0.9521	**0.9369**	1.0000	0.9638	0.9674	0.9486	0.9595	**0.9397**	0.9680	0.9545	**0.9479**	0.9900
J520	0.9754	**0.9673**	**0.9638**	1.0000	0.9821	0.9742	0.9908	**0.9668**	0.9886	0.9783	0.9726	0.9882
J530	0.9696	**0.9645**	**0.9674**	0.9821	1.0000	0.9662	0.9794	**0.9566**	0.9845	0.9735	**0.9605**	0.9884
J540	**0.9513**	**0.9504**	**0.9486**	0.9742	0.9662	1.0000	0.9737	**0.9540**	0.9754	0.9612	**0.9652**	0.9729
J550	0.9725	**0.9689**	**0.9595**	0.9908	0.9794	0.9737	1.0000	**0.9660**	0.9872	0.9778	0.9710	0.9856
J560	**0.9446**	**0.9356**	**0.9397**	0.9668	0.9566	0.9540	0.9660	1.0000	0.9687	0.9530	**0.9557**	0.9672
J580	0.9673	**0.9621**	**0.9680**	0.9886	0.9845	0.9754	0.9872	**0.9687**	1.0000	0.9758	0.9900	0.9920
J590	0.9704	**0.9650**	**0.9545**	0.9783	0.9735	0.9612	0.9778	**0.9530**	0.9758	1.0000	**0.9541**	0.9768
J835	**0.9433**	**0.9369**	**0.9479**	0.9726	0.9605	0.9652	0.9710	**0.9557**	0.9900	0.9541	1.0000	0.9745
J203	0.9718	**0.9620**	0.9900	0.9882	0.9884	0.9729	0.9856	**0.9672**	0.9920	0.9768	0.9745	1.0000

Source: Author's investigation.

Table A1.2: during-crisis correlation matrix for the GFC using daily returns

	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
J135	1.0000	**0.0275**	0.3565	0.4874	0.3263	0.3209	0.4526	0.2830	0.3932	0.3535	0.3111	0.4381
J335	0.0275	1.0000	-0.0329	0.0017	-0.0420	0.0493	0.0700	0.0277	0.0203	0.0284	0.0543	-0.0213
J510	**0.3565**	**0.0329**	1.0000	0.6170	0.5295	0.3599	0.5204	0.4138	0.5072	0.4596	0.4276	0.9348
J520	0.4874	**0.0017**	0.6170	1.0000	0.6149	0.5539	0.7520	0.6145	0.7548	0.4829	0.6757	0.7902
J530	**0.3263**	**0.0420**	0.5295	0.6149	1.0000	0.3754	0.5129	0.4205	0.5460	0.3936	0.4480	0.6706
J540	**0.3209**	0.0493	0.3599	0.5539	0.3754	1.0000	0.5144	0.4104	0.5644	0.3709	0.5221	0.4960
J550	0.4526	0.0700	0.5204	0.7520	0.5129	0.5144	1.0000	0.5764	0.7242	0.5001	0.6640	0.7051
J560	**0.2830**	**0.0277**	0.4138	0.6145	0.4205	0.4104	0.5764	1.0000	0.6244	0.3575	0.5746	0.6195
J580	**0.3932**	**0.0203**	0.5072	0.7548	0.5460	0.5644	0.7242	0.6244	1.0000	0.4342	0.9410	0.7414
J590	**0.3535**	**0.0284**	0.4596	0.4829	0.3936	0.3709	0.5001	0.3575	0.4342	1.0000	0.3712	0.5298
J835	**0.3111**	0.0543	0.4276	0.6757	0.4480	0.5221	0.6640	0.5746	0.9410	0.3712	1.0000	0.6523
J203	0.4381	**0.0213**	0.9348	0.7902	0.6706	0.4960	0.7051	0.6195	0.7414	0.5298	0.6523	1.0000

Source: Author's investigation.

Table A2: full sample period correlation matrix for COVID-19 using daily returns

	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
J135	1.0000	**0.5858**	0.7684	0.7433	0.7152	0.6826	0.7134	0.7133	**0.5614**	0.6343	0.7244	0.7601
J335	**0.5858**	1.0000	0.7458	0.7863	0.7690	0.7813	0.7837	0.7340	**0.5773**	0.7153	0.7263	0.7978
J510	**0.7684**	**0.7458**	1.0000	0.8869	0.9096	0.8581	0.8755	0.8273	**0.6444**	0.8367	0.8307	0.9614
J520	**0.7433**	**0.7863**	0.8869	1.0000	0.9030	0.9111	0.9341	0.8773	**0.7208**	0.8239	0.9371	0.9511
J530	**0.7152**	**0.7690**	0.9096	0.9030	1.0000	0.8794	0.8935	0.8295	**0.6636**	0.8435	0.8266	0.9473
J540	**0.6826**	**0.7813**	0.8581	0.9111	0.8794	1.0000	0.8937	0.8498	**0.6839**	0.8094	0.8633	0.9188
J550	**0.7134**	**0.7837**	0.8755	0.9341	0.8935	0.8937	1.0000	0.8714	**0.7001**	0.8302	0.9058	0.9545
J560	**0.7133**	**0.7340**	0.8273	0.8773	0.8295	0.8498	0.8714	1.0000	**0.6695**	0.7693	0.8556	0.8905
J580	**0.5614**	**0.5773**	0.6444	0.7208	0.6636	0.6839	0.7001	0.6695	1.0000	0.6104	0.7293	0.7074
J590	**0.6343**	**0.7153**	0.8367	0.8239	0.8435	0.8094	0.8302	0.7693	**0.6104**	1.0000	0.7693	0.8988
J835	**0.7244**	**0.7263**	0.8307	0.9371	0.8266	0.8633	0.9058	0.8556	**0.7293**	0.7693	1.0000	0.9115
J203	**0.7601**	**0.7978**	0.9614	0.9511	0.9473	0.9188	0.9545	0.8905	**0.7074**	0.8988	0.9115	1.0000

Source: Author's investigation.

Table A2.1: pre-crisis correlation matrix for COVID-19 using daily returns

	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
J135	1.0000	**0.0103**	0.5800	0.3232	0.3120	0.2505	0.2707	0.1882	0.3371	**0.2338**	0.2630	0.5068
J335	0.0103	1.0000	**0.0460**	0.1301	**0.0294**	0.1664	0.1553	0.1309	0.0964	**0.0372**	0.0811	0.1356
J510	0.5800	**0.0460**	1.0000	0.2795	0.4464	0.2403	0.3244	0.1486	0.2461	**0.2236**	0.1767	0.6498
J520	0.3232	**0.1301**	**0.2795**	1.0000	**0.1813**	0.5029	0.6054	0.4833	0.8373	0.3215	0.8135	0.7371
J530	0.3120	**0.0294**	0.4464	0.1813	1.0000	0.2349	0.2006	0.0936	0.1483	**0.2053**	0.0626	0.4789
J540	0.2505	**0.1664**	**0.2403**	0.5029	**0.2349**	1.0000	0.3567	0.3293	0.4818	**0.1704**	0.4271	0.4994
J550	0.2707	**0.1553**	0.3244	0.6054	**0.2006**	0.3567	1.0000	0.4025	0.6291	**0.2448**	0.6118	0.8153
J560	0.1882	**0.1309**	**0.1486**	0.4833	**0.0936**	0.3293	0.4025	1.0000	0.5147	**0.1498**	0.4892	0.4907
J580	0.3371	**0.0964**	**0.2461**	0.8373	**0.1483**	0.4818	0.6291	0.5147	1.0000	0.3021	0.9517	0.7701
J590	0.2338	**0.0372**	**0.2236**	0.3215	**0.2053**	0.1704	0.2448	0.1498	0.3021	1.0000	0.2504	0.4192
J835	0.2630	**0.0811**	**0.1767**	0.8135	**0.0626**	0.4271	0.6118	0.4892	0.9517	**0.2504**	1.0000	0.7054
J203	0.5068	**0.1356**	0.6498	0.7371	0.4789	0.4994	0.8153	0.4907	0.7701	0.4192	0.7054	1.0000

Source: Author's investigation.

Table A2.2: during-crisis correlation matrix for COVID-19 using daily returns

	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
J135	1.0000	**0.1876**	0.4885	0.4666	0.3540	0.2699	0.4168	0.4553	**0.1994**	**0.1351**	0.4500	0.5116
J335	0.1876	1.0000	0.2459	0.3678	0.2535	0.3814	0.4004	0.2858	**0.1429**	**0.2075**	0.2811	0.3701
J510	0.4885	**0.2459**	1.0000	0.4965	0.5577	0.4026	0.4767	0.4390	**0.1646**	0.4167	0.4373	0.8856
J520	0.4666	**0.3678**	0.4965	1.0000	0.4922	0.5693	0.7095	0.5242	**0.3344**	**0.1582**	0.7604	0.6698
J530	0.3540	**0.2535**	0.5577	0.4922	1.0000	0.3563	0.4982	0.3479	**0.1933**	**0.2892**	0.3516	0.6657
J540	0.2699	**0.3814**	0.4026	0.5693	0.3563	1.0000	0.5720	0.4734	**0.2770**	**0.2154**	0.5194	0.5577
J550	0.4168	0.4004	0.4767	0.7095	0.4982	0.5720	1.0000	0.5819	**0.3211**	**0.2852**	0.7083	0.7070
J560	0.4553	**0.2858**	0.4390	0.5242	0.3479	0.4734	0.5819	1.0000	**0.2684**	**0.2044**	0.5386	0.5854
J580	0.1994	**0.1429**	0.1646	0.3344	0.1933	0.2770	0.3211	0.2684	1.0000	**0.0871**	0.3778	0.2841
J590	0.1351	**0.2075**	0.4167	0.1582	0.2892	0.2154	0.2852	0.2044	**0.0871**	1.0000	0.1602	0.6285
J835	0.4500	**0.2811**	0.4373	0.7604	0.3516	0.5194	0.7083	0.5386	**0.3778**	**0.1602**	1.0000	0.6577
J203	0.5116	**0.3701**	0.8856	0.6698	0.6657	0.5577	0.7070	0.5854	**0.2841**	0.6285	0.6577	1.0000

Source: Author's investigation.

Table A3: all sample period sectoral beta coefficients for the GFC

Periods / Sectors	Pre-crisis	During-crisis	Full sample
Chemicals	0.9628	0.2856	0.8564
Automobiles & Parts	0.9546	0.0512	0.7970
Basic Materials	1.0168	1.4066	1.0779
Industrial	0.9820	0.6309	0.9268
Consumer Goods	0.9849	0.6200	0.9278
Health Care	0.9861	0.4115	0.8960
Consumer Services	0.9800	0.5652	0.9150
Telecommunication	0.9939	0.9291	0.9839
Financials	0.9931	0.7177	0.9498
Technology	0.9721	0.5711	0.9091
Banks	1.0046	0.8282	0.9770

Source: Author's investigation.
Note: a sectoral beta coefficient above 1.0000 indicates that the sectoral index is more volatile than the overall market denoted to the benchmark index of the FTSE/JSE All-share.

Table A4: all sample period sectoral beta coefficients for COVID-19

Periods / Sectors	Pre-crisis	During-crisis	Full sample
Chemicals	1.0823	1.6379	1.0585
Automobiles & Parts	0.3401	0.6742	0.9462
Basic Materials	0.8121	1.3089	1.0199
Industrial	0.8644	0.8321	0.9798
Consumer Goods	0.5596	0.6636	0.9537
Health Care	0.8236	0.6519	0.9627
Consumer Services	1.3882	0.7300	0.9914
Telecommunication	0.9420	0.9391	0.9928
Financials	0.9165	0.9875	0.9938
Technology	0.8455	0.8555	0.9818
Banks	1.2093	1.1503	1.0209

Source: Author's investigation.

Table A5: full sample period stationarity tests for both crises using daily returns

Sectors	Augmented Dickey Fuller Test		Zivot-Andrew Test			
			GFC		COVID-19	
	GFC *t*-stats	COVID *t*-stats	*t*-stats	breakpoints	*t*-stats	Breakpoints
Chemicals	-27.0110*	-16.9737*	-18.5766**	10/06/2008	-11.9861*	03/24/2020
Auto & Parts	-26.0534*	-29.6660*	-14.3695*	06/05/2008	-18.7598*	03/25/2020
Basic Materials	-27.5157*	-14.4717*	-15.2652*	07/01/2008	-14.3159*	03/20/2020
Industrial	-27.2926*	-29.9664*	-21.1826*	09/11/2008	-18.3141*	03/31/2020
Consumer Goods	-30.4759*	-18.6173*	-30.5590*	06/06/2008	-18.8570**	11/02/2020
Health Care	-26.7379*	-29.0261*	-18.3401*	10/28/2008	-16.2803**	10/29/2018
Consumer Services	-25.9519*	-29.0309*	-26.0836*	07/18//2006	-29.2389**	01/16/2020
Telecommunication	-22.8875*	-30.4756*	-16.9476**	05/22/2008	-16.1600*	03/24/2020
Financials	-27.8925*	-28.4885*	-16.5389**	10/28/2008	-28.84781*	03/24/2020
Technology	-27.3664*	-27.6072*	-27.7610**	09/23/2008	-27.8613*	03/19/2020
Banks	-19.1829*	-29.6164*	-17.4145**	11/15/2007	-29.8757*	03/24/2020
All-Share Index	-27.4805*	-14.4783*	-18.0813*	11/21/2008	-15.0320*	03/06/2020

Source: Author's investigation.
Note: level of significance is indicated by the p-values at 1% (*), at 5% (**), and at 10% (***). The 'breakpoints' from the Zivot-Andrew Test indicates the date in which a structural break had occurred within the observed sample period and are used to construct the dummy variable.

Table A5.1: sub-sample period ADF Test for both crises using daily returns

Sectors	GFC		COVID-19	
	Pre-crisis *t*-stats	During-crisis *t*-stats	Pre-crisis *t*-stats	During-crisis *t*-stats
Chemicals	-18.9941*	-20.6545*	-22.5760*	-15.5105*
Automobiles & Parts	-18.3437*	-20.8094*	-15.0402*	-18.6676*
Basic Materials	-19.8001*	-20.4639*	-22.1848*	-19.8591*
Industrial	-16.6201*	-21.3950*	-23.3883*	-19.4522*
Consumer Goods	-20.4949*	-23.0089*	-18.9062*	-15.0729*
Health Care	-18.8394*	-19.2968*	-20.9404*	-19.8269*
Consumer Services	-15.3618*	-20.4824*	-21.9292*	-18.9513*
Telecommunication	-18.5242*	-18.0191*	-22.2338*	-20.4765*
Financials	-19.3290*	-20.8556*	-22.9045*	-18.3460*
Technology	-18.8197*	-21.1997*	-20.0789*	-18.8489*
Banks	-18.9374*	-17.4941*	-24.0294*	-18.8555*
All-Share Index	-19.5838*	-21.1181*	-22.1346*	-20.1245*

Source: Author's investigation.

Table A5.2: All period PP Test for both crises using daily returns

Sectors	GFC Full Sample t-stats	GFC Pre-crisis t-stats	GFC During-crisis t-stats	COVID-19 Full Sample t-stats	COVID-19 Pre-crisis t-stats	COVID-19 During-crisis t-stats
Chemicals	-27.1717*	-17.9774*	-20.6545*	-25.0423*	-22.7470*	-16.0241*
Automobiles & Parts	-48.0941*	-18.3425*	-35.2307*	-29.6660*	-23.6330*	-18.6686*
Basic Materials	-27.6831*	-19.7998*	-20.5360*	-30.0334*	-22.1911*	-19.8865*
Industrial	-27.2377*	-16.6150*	-21.3950*	-29.9659*	-23.3756*	-19.4510*
Consumer Goods	-30.7276*	-21.6391*	-23.1829*	-29.1452*	-18.8675*	-20.9671*
Health Care	-26.6565*	-19.5268*	-19.0989*	-29.0272*	-21.1104*	-19.9376*
Consumer Services	-25.7937*	-15.0829*	-20.4241*	-29.1377*	-21.9569*	-19.9713*
Telecommunication	-31.1510*	-19.0718*	-23.3615*	-31.1510*	-22.2327*	-20.4378*
Financials	-28.1176*	-20.5601*	-20.9210*	-28.5040*	-22.9062*	-18.3843*
Technology	-27.3676*	-16.6641*	-20.9210*	-27.5674*	-20.0836*	-18.8465*
Banks	-28.6997*	-20.4569*	-21.1517*	-29.6305*	-24.1193*	-18.8555*
All-Share Index	-28.4299*	-19.5921*	-21.2360*	-30.1664*	-22.1345*	-20.1649*

Source: Author's investigation.

Table A6: full sample period ARCH-LM test for both crises using daily returns

Sectors	GFC ARCH-LM	COVID-19 ARCH-LM
Chemicals	65.67942**	226.4356*
Automobiles & Parts	245.2132*	134.8171*
Basic Materials	49.0558***	311.6605*
Industrial	156.1447*	243.8300*
Consumer Goods	93.68897*	104.5226*
Health Care	90.51990*	80.13998*
Consumer Services	137.8754*	118.8933*
Telecommunication	160.7573*	140.8589*
Financials	152.7709*	391.3290*
Technology	277.4264*	70.64254*
Banks	125.1292*	291.1477*
All-Share Index	349.7352*	124.4977*

Source: Author's investigation.

Note: The ARCH-LM test reports the numerical values of the observed R-Squared.

Table A6.1: subsample period ARCH-LM test for both crises using daily returns

	GFC		COVID-19	
Sectors	pre-crisis ARCH-LM	during-crisis ARCH-LM	pre-crisis ARCH-LM	during-crisis ARCH-LM
Chemicals	63.1688**	60.7149*	39.9379****	91.0794*
Auto & Parts	35.6934****	163.9628*	73.9608*	79.5814*
Basic Materials	65.6149**	162.5413*	37.5060****	124.8764*
Industrial	99.6528*	74.0629*	36.8000****	93.5145*
Consumer Goods	62.0576**	51.9311**	38.9945****	48.0713***
Health Care	77.7436*	57.1604**	37.0056****	80.2365*
Consumer Services	107.9459*	59.0448*	81.7775*	80.9503*
Telecommunication	61.6802**	81.9714*	63.0990**	106.6417*
Financials	76.3494*	77.8809*	36.7625****	157.6115*
Technology	47.0961***	125.2660 *	30.2028****	81.9273*
Banks	75.0722*	72.7548*	34.6689****	120.5767*
All-Share Index	89.9478*	138.7052*	33.7846****	154.4994*

Source: Author's investigation.

*Note: a p-value of **** indicates an insignificant level of ARCH effect above 10% (***). In other words, there is a lack of heteroskedasticity within the series. This is commonly observed within the pre-crisis sample periods.*

Table A7: full sample period descriptive statistics for the GFC using daily returns

Sectors	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Stats
Chemicals	-0.000140	0.000142	0.057973	-0.062339	0.012031	-0.173145	6.01452	325.6492*
Auto & Parts	-0.000321	0.000000	0.579582	-0.367733	0.037391	4.157110	107.7077	390286.6*
Basic Materials	0.000690	0.000924	0.118087	-0.111405	0.025728	0.124993	5.787244	277.0296*
Industrial	0.000280	0.000996	0.072344	-0.055459	0.014182	-0.106324	4.971653	139.1170*
Consumer Goods	0.000556	0.000153	0.152717	-0.071688	0.016064	0.914496	13.17851	3783.261*
Health Care	0.000541	0.000713	0.062229	-0.055138	0.016194	0.063412	4.049446	39.52876*
Consumer Services	0.000315	0.000794	0.066168	-0.053829	0.014300	-0.083760	4.272082	58.23632*
Telecommunication	0.000868	0.000334	0.144135	-0.104043	0.025682	0.414055	5.395032	227.1763*
Financials	-0.0000106	-0.0000892	0.074116	-0.066909	0.017015	0.140978	4.524237	84.99897*
Technology	0.000350	0.000431	0.107464	-0.127354	0.081073	-0.200407	10.20711	1843.144*
Banks	0.000212	-0.000956	0.090059	-0.090952	0.22835	0.177321	4.141352	50.53159*
All-Share Index	0.000569	0.001123	0.070729	-0.073005	0.015576	-0.058400	5.575494	345.9112*

Source: Author's investigation.

Table A7.1: pre-crisis descriptive statistics for the GFC using daily returns

Sectors	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Stats
Chemicals	0.001395	0.001363	0.052501	-0.030840	0.010457	0.299034	5.227078	77.54782*
Auto & Parts	0.000765	0.000000	0.066860	-0.034162	0.011044	0.890633	7.354877	322.8439*
Basic Materials	0.001778	0.003055	0.070473	-0.065745	0.018143	-0.189840	4.279961	25.99415*
Industrial	0.001503	0.002197	0.041174	-0.055459	0.011250	-0.757808	6.086514	172.4283*
Consumer Goods	0.001215	0.001182	0.048594	-0.070818	0.012031	-0.362653	7.100623	252.8922*
Health Care	0.001517	0.002288	0.057038	-0.055138	0.015729	-0.093542	4.384184	28.45159*
Consumer Services	0.001274	0.002049	0.039905	-0.048578	0.011490	-1.033017	6.204218	211.9762*
Telecommunication	0.001300	0.002408	0.058647	-0.056696	0.018304	-0.112506	3.582050	5.678933***
Financials	0.001043	0.001620	0.061721	-0.066909	0.013163	-0.310434	6.254716	160.1054*
Technology	0.001344	0.001127	0.034301	-0.039387	0.011687	-0.103887	3.548797	5.021754***
Banks	0.000949	0.001192	0.090059	-0.065430	0.018892	0.079003	4.689371	41.98454*
All-Share Index	0.001353	0.002856	0.050402	-0.064807	0.012845	-0.530234	6.353306	180.3849*

Source: Author's investigation.

Table A7.2: during-crisis descriptive statistics for the GFC using daily returns

Sectors	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Stats
Chemicals	-0.001226	-0.001112	0.057973	-0.062339	0.012936	-0.260780	5.897804	179.8878*
Auto & Parts	-0.001115	0.000000	0.579582	-0.367733	0.047936	3.407069	68,29486	89429.41*
Basic Materials	-0.000111	-0.001386	0.118087	-0.111405	0.029936	0.216850	5.007673	87.54111*
Industrial	-0.000583	-0.000875	0.072344	-0.054791	0.015890	0.141210	4.372631	40.75043*
Consumer Goods	-0.0000892	-0.000607	0.152717	-0.071688	0.018388	1.156031	12.31667	1912.029*
Health Care	-0.000156	-0.000219	0.016508	-0.050521	0.016508	0.172485	3.887326	18.80679*
Consumer Services	-0.000378	-0.001190	0.066168	-0.053829	0.015964	0.231934	3.613927	12.28567*
Telecommunication	0.000554	-0.002165	0.144135	-0.104043	0.029845	0.489136	4.724521	81.56801*
Financials	-0.000766	-0.001844	0.074116	-0.064364	0.019257	0.299349	3.797907	20.64821*
Technology	-0.000335	-0.000212	0.107464	-0.127354	0.021451	-0.125881	8.540699	638.3266*
Banks	-0.000320	-0.001939	0.082379	-0.090952	0.025266	0.229037	3.702557	14.59591*
All-Share Index	-0.000284	-0.000555	0.070729	-0.073005	0.019894	0.120676	4.223569	32.27395*

Source: Author's investigation.

Table A8: full sample period descriptive statistics for COVID-19 using daily returns

Sectors	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Stats
Chemicals	0.000617	-0.000818	0.354643	-0.390638	0.037848	-0.117564	29.32876	24581.81*
Auto & Parts	0.000410	-0.000427	0.133809	-0.193030	0.026736	-0.018303	8.696033	1150.486*
Basic Materials	0.000902	0.000939	0.128522	-0.144996	0.018319	-0.349662	13.85364	4194.383*
Industrial	-0.000335	-0.000601	0.079425	-0.092651	0.015873	-0.059325	7.654843	768.7949*
Consumer Goods	0.000119	-0.000125	0.075041	-0.095537	0.013685	-0.036309	8.479918	1064.983*
Health Care	-0.000406	-0.000581	0.056083	-0.105176	0.017364	-0.489903	7.171528	651.0739*
Consumer Services	0.0000970	-0.0000486	0.067109	-0.088891	0.016591	-0.044833	5.766577	271.6814*
Telecommunication	-0.0000456	-0.000219	0.119019	-0.140849	0.022273	-0.508185	9.953406	1751.034*
Financials	-0.000226	-0.0000625	0.077764	-0.122743	0.017454	-0.639272	11.64122	2702.482*
Technology	0.000248	0.000665	0.087387	-0.129437	0.020707	-0.286696	6.312117	400.6399*
Banks	0.0000348	-0.0000219	0.104194	-0.148980	0.022613	-0.204277	8.286304	996.8020*
All-Share Index	0.000237	0.000718	0.075316	-0.097213	0.012994	-0.772568	12.28280	3140.114*

Source: Author's investigation.

Table A8.1: pre-crisis descriptive statistics for COVID-19 using daily returns

Sectors	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Stats
Chemicals	-0.000735	-0.000321	0.103775	-0122077	0.020520	-0.161033	7.638656	431.5163*
Auto & Parts	0.000434	-0.001273	0.138809	-0.096313	0.024119	0.685227	6.790006	324.1691*
Basic Materials	0.000568	0.001012	0.046805	-0.037630	0.012001	0.084057	3.426515	4.194792****
Industrial	-0.000586	-0.001145	0.054634	-0.036130	0.011306	0.210004	3.713538	13.68231*
Consumer Goods	-0.000250	-0.002221	0.048349	-0.039749	0.011239	-0.014134	4.919673	73.56531*
Health Care	-0.000860	-0.005817	0.050303	-0.098624	0.015841	-0.806659	7.696571	492.1840*
Consumer Services	-0.000220	-0.005066	0.067109	-0.062229	0.016373	0.211459	5.205477	100.6496*
Telecommunication	-0.000492	-0.003523	0.119019	-0.140849	0.018458	-0.905402	16.71778	3821.154*
Financials	-0.000317	-0.001394	0.042005	-0.036405	0.011479	0.087871	3.149300	1.061294****
Technology	-0.000539	-0.004043	0.019385	-0.129437	0.019385	-0.489164	8.439317	609.5932*
Banks	-0.000544	-0.002197	0.057772	-0.044961	0.016586	0.030766	2.948608	0.128281****
All-Share Index	-0.000113	0.0000963	0.037170	-0.031712	0.009613	-0.031712	4.014142	20.60710*

Source: Author's investigation.

Table A8.2: during-crisis descriptive statistics for COVID-19 using daily returns

Sectors	Mean	Median	Max	Min	Std	Skewness	Kurtosis	JB Stats
Chemicals	0.001121	-0.002315	0.354643	-0.390638	0.052389	-0.141073	18.15803	3553.026*
Auto & Parts	0.000347	0.000000	0.120317	-0.193030	0.029836	-0.493978	9.146528	599.1010*
Basic Materials	0.001319	0.000829	0.128522	-0.144996	0.024176	-0.401708	10.26471	825.8063*
Industrial	0.0000264	-0.000274	0.079425	-0.092651	0.020321	-0.149492	6.107581	150.6639*
Consumer Goods	0.0006120	-0.00000897	0.075041	-0.095537	0.016325	-0.092252	8.208551	419.8955*
Health Care	0.000252	-0.000533	0.056083	-0.105176	0.019125	-0.283081	6.491147	193.3628*
Consumer Services	0.000535	0.000850	0.061626	-0.088891	0.016894	-0.355219	6.453384	192.1561*
Telecommunication	0.000712	-0.0000409	0.110238	-0.110759	0.026255	-0.328596	6.516465	197.8269*
Financials	-0.0000771	0.000161	0.077764	-0.122743	0.023018	-0.671113	8.632526	516.8735*
Technology	0.001329	0.001668	0.085748	-0.085713	0.022272	-0.151492	4.535393	37.8610*
Banks	0.000179	0.000292	0.104194	-0.148980	0.028618	-0.250403	7.007358	252.1211*
All-Share Index	0.000715	0.001619	0.075316	-0.097213	0.016366	-0.939263	10.71529	974.7184*

Source: Author's investigation.

Table A9: full sample period GARCH (1, 1) regression for the GFC

Sectors	ω	α	β	D_i	(α+β)
Chemicals	0.00000919 *	0.0869*	0.8519*	-0.0023****	0.9388
Auto & Parts	0.000000273*	0.2018*	0.8748*	0.0373****	1.0766
Basic Materials	0.00000956 **	0.0928*	0.8932*	-0.0166****	0.9860
Industrial	0.00000419**	0.1321*	0.8519*	-0.0017****	0.9840
Consumer Goods	0.00000527*	0.1208*	0.8645*	-0.0018****	0.9853
Health Care	0.00000760**	0.0529*	0.9179*	0.0023****	0.9708
Consumer Services	0.00000374*	0.1046*	0.8799*	0.0005****	0.9845
Telecommunication	0.00000529**	0.0543*	0.9395*	-0.0011****	0.9938
Financials	0.00000538**	0.1226*	0.8628*	-0.0074****	0.9854
Technology	0.00000598*	0.1024*	0.8809*	-0.0004****	0.9833
Banks	0.000133**	0.1131*	0.8636*	0.0044**	0.9767
All-Share Index	0.0000140**	0.1207*	0.8656*	0.000362****	0.9863

Source: Author's investigation.

Note: α (ARCH coefficient) and β (GARCH coefficient) respectively denotes to the impact of old news and recent news on the series. Volatility persistency is indicated by (α+β), where a value above 1.0000 indicates that a series is characterised by long-memory (or that volatility fades away only in the long-term). The dummy variable (D_i) shows extent to which the incorporation of structural breaks had affected the volatility of the series. A positive (negative) value means that such an incorporation had captured an increased (decreased) in the volatility of a series. However, the p-values show that D_i mostly had an insignificant (****) impact on the volatility of most series except Banks.

Table A9.1: sub-sample period GARCH (1, 1) regression for the GFC

Sectors	Pre-crisis				during-crisis			
	ω	α	β	(α+β)	ω	α	β	(α+β)
Chemicals	0.0000271**	0.2180*	0.6135*	0.8315	0.00000974*	0.0698*	0.8741*	0.9439
Auto & Parts	0.0000192**	0.0780**	0.7613*	0.8393	0.000237*	0.5484**	0.2999*	0.8483
Basic Materials	0.0000187**	0.1083**	0.8365*	0.9448	0.0000128**	0.0778*	0.9083*	0.9861
Industrial	0.00000809**	0.1376*	0.7933*	0.9309	0.00000531**	0.1293*	0.8576*	0.9869
Consumer Goods	0.00000836**	0.0998*	0.8405*	0.9403	0.00000668**	0.0800**	0.9014*	0.9814
Health Care	0.0000122**	0.0902*	0.8599*	0.9501	0.0000495**	0.1284**	0.6903*	0.8187
Consumer Services	0.00000762*	0.1494*	0.7834*	0.9328	0.00000530**	0.0577**	0.9227*	0.9804
Telecommunication	0.0000652**	0.1065**	0.7162*	0.8227	0.0000154**	0.0425*	0.9420*	0.9845
Financials	0.00000797**	0.1070*	0.8443*	0.9513	0.00000731**	0.1260*	0.8609*	0.9869
Technology	0.0000116**	0.0576**	0.8165*	0.8741	0.0000127*	0.1401*	0.8389*	0.9790
Banks	0.0000241**	0.0995*	0.8285*	0.9280	0.0000140***	0.1078*	0.8749*	0.9827
All-Share Index	0.00000824**	0.1254**	0.8236*	0.9490	0.00000590**	0.1160*	0.8729*	0.9889

Source: Author's investigation.

Table A10: full sample period GARCH (1, 1) regression for COVID-19

Sectors	ω	α	β	D_i	(α+β)
Chemicals	0.0000400*	0.2207*	0.7804*	0.0025****	1.0011
Auto & Parts	0.0000373**	0.2532*	0.7345*	0.0014****	0.9877
Basic Materials	0.00000632**	0.0775*	0.8998*	0.0014***	0.9774
Industrial	0.00000463**	0.0899*	0.8887*	0.0010****	0.9786
Consumer Goods	0.0000107*	0.0865*	0.8565*	0.0009****	0.9430
Health Care	0.0000145**	0.0605*	0.8909*	0.0012****	0.9514
Consumer Services	0.0000109**	0.0868*	0.8758*	0.0008***	0.9626
Telecommunication	0.0000178*	0.0634*	0.8991*	0.0032****	0.9625
Financials	0.00000880*	0.1318*	0.8324*	0.0017****	0.9642
Technology	0.000115*	0.1264*	0.6011*	0.0012****	0.7275
Banks	0.0000122*	0.1036*	0.8700*	0.0022***	0.9736
All-Share Index	0.00000645*	0.1027*	0.8497*	0.0017****	0.9524

Source: Author's investigation.

Table A10.1: sub-sample period GARCH (1, 1) regression for COVID-19

Sectors	Pre-crisis				during-crisis			
	ω	α	β	(α+β)	ω	α	β	(α+β)
Chemicals	0.0000180**	0.0397**	0.9209*	0.9606	0.000209*	0.5147*	0.5390*	1.0537
Auto & Parts	0.0000550*	0.2049*	0.7720*	0.9769	0.0000143*	0.1859*	0.8214*	1.0073
Basic Materials	0.0000479**	0.0574**	0.8299*	0.8873	0.0000171**	0.1027*	0.8640*	0.9667
Industrial	0.0000111**	0.0753*	0.8383*	0.9136	0.0000957**	0.1282*	0.8593*	0.9875
Consumer Goods	0.00000111*	0.0201*	0.9132*	0.9333	0.0000148**	0.1692*	0.7917*	0.9609
Health Care	0.0000139**	0.3231**	0.6074*	0.9305	0.0000162**	0.0965*	0.8580*	0.9545
Consumer Services	0.00000693*	0.0733*	0.9028*	0.9762	0.0000144**	0.1301*	0.8344*	0.9645
Telecommunication	0.0000168**	0.0548*	0.8992*	0.9540	0.0000196**	0.0615*	0.9074*	0.9689
Financials	0.0000173**	0.0581**	0.8268*	0.8849	0.0000129**	0.1900*	0.8213*	1.0113
Technology	0.0000224	0.0275**	0.9137*	0.9412	0.0000961*	0.2235*	0.5691*	0.7926
Banks	0.0000307**	0.0318**	0.8556*	0.8874	0.0000159**	0.1493*	0.8371*	0.9864
All-Share Index	0.000000552**	0.0537**	0.8885*	0.9422	0.0000112**	0.1553*	0.7907*	0.9460

Source: Author's investigation.

Table A11: full sample period GARCH diagnostic (Gaussian) for both crises

Full sample period GARCH diagnostic (Gaussian) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0869*	0.2018*	0.0928*	0.1509*	0.1209*	0.0529*	0.1046*	0.0543*	0.1235*	0.1024*	0.1131*	0.1207*
β	0.8519*	0.8747*	0.8932*	0.8331*	0.8645*	0.9179*	0.8799*	0.9395*	0.8583*	0.8809*	0.8635*	0.8656*
Log LHD	2579.73	2008.51	2026.50	2507.49	2407.07	2321.45	2483.55	1971.28	2351.07	2344.19	2077.32	2626.39
Adj R^2	-0.0043	-0.1411	-0.0127	0.0018	0.0006	0.0087	0.0079	-0.0023	-0.0025	0.0008	0.0095	-0.0011
SIC	-6.0374	-4.6917	-4.7397	-5.8662	-5.6293	-5.4274	-5.8097	-4.6015	-5.4908	-5.4810	-4.8459	-5.7772
Prob. Chi-square	0.6304	1.0000	0.9890	0.6852	0.8447	0.9923	0.5656	0.8949	0.9773	0.9869	0.9687	0.9567
Full sample period GARCH diagnostic (Gaussian) for COVID-19												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.2207*	0.1771*	0.0778*	0.0900*	0.0865*	0.0643*	0.0975*	0.0634*	0.1318*	0.1264*	0.1036*	0.1027*
β	0.7804*	0.8159*	0.8997*	0.8919*	0.8565*	0.8354*	0.8680*	0.8991*	0.8324*	0.6011*	0.8700*	0.8497*
Log LHD	1819.78	1983.05	2354.74	2446.49	2493.039	2273.98	2337.93	2103.52	2421.09	2118.00	2148.48	2639.87
Adj R^2	0.0215	-0.01206	0.0033	0.0012	-0.0027	-0.0009	-0.0021	0.0067	0.0035	0.0023	0.0019	0.0023
SIC	-4.2342	-4.6184	-5.4929	-5.7021	-5.8184	-5.3029	-5.4925	-4.9018	-5.6557	-4.9359	-5.0076	-6.1638
Prob. Chi-square	1.0000	0.1833	0.2100	0.5678	0.9953	0.9989	0.4143	0.9994	0.0781	0.7457	0.9719	0.3994

Source: Author's investigation.

Note: GARCH Diagnostics is performed to decide which error distribution (between the Gaussian, Student's t and General Error Distribution) is appropriate to use when preforming a GARCH regression. An appropriate error distribution is indicated by significant (α) and (β) coefficients; an insignificant 'Prob.Chi-square' of the ARCH-LM F-statistics; the largest Log Likelihood (Log LHD) and Adjusted R-Squared (Adj R^2) values; and the smallest Schwarz Information Criterion (SIC) value.

Table A11.1: sub-sample period GARCH diagnostic (Gaussian) for the GFC

Pre-crisis GARCH diagnostic (Gaussian) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.2351*	0.0780**	0.1073**	0.1376*	0.0998*	0.0902*	0.1494*	0.1065**	0.1070*	0.0575**	0.0995*	0.1254*
β	0.5925*	0.7613*	0.8365*	0.7933*	0.8405*	0.8599*	0.7834*	0.7062*	0.8443*	0.8165*	0.8285*	0.8236*
Log LHD	1047.15	1083.89	922.78	1108.53	1075.25	971.12	1115.22	908.99	1043.92	1064.92	906.56	1059.60
Adj R^2	0.3007	-0.0028	0.0004	0.0092	0.0056	-0.0036	0.0312	-0.0028	-0.0024	0.0093	-0.0028	-0.0005
SIC	-5.9340	-6.1275	-5.2043	-6.2687	-6.0780	-5.4813	-6.3070	-5.1253	-5.8984	-6.0188	-5.1113	-5.9883
Prob. Chi-square	0.2380	0.9113	0.9244	0.8144	0.8551	0.1993	0.7714	0.2814	0.8277	0.8549	0.4985	0.7801
During-crisis GARCH diagnostic (Gaussian) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0698*	0.1646*	0.0778**	0.1486*	0.1170*	0.1183**	0.0605**	0.0425*	0.1260*	0.1401*	0.1078*	0.1141*
β	0.8741*	0.4754*	0.9082*	0.8419*	0.8747*	0.6675*	0.9191*	0.9420*	0.8609*	0.8389*	0.8749*	0.8737*
Log LHD	1474.18	990.1020	1104.45	1396.44	1327.32	1346.95	1373.12	1064.19	1301.95	1280.36	1158.94	1303.02
Adj R^2	0.0032	0.1372	0.0042	-0.0033	-0.0020	0.0172	0.0046	-0.0039	0.0019	0.0001	0.0023	0.0002
SIC	-5.8698	-3.9218	-4.3819	-5.5570	-5.2788	-5.3578	-5.4527	-4.2199	-5.1767	-5.0898	-4.6013	-5.1811
Pron. Chi-square	0.7040	1.0000	0.8661	0.8110	0.8717	0.1166	0.6762	0.8262	0.9442	0.9976	0.9291	0.9459

Source: Author's investigation.

Table A11.2: sub-sample period GARCH diagnostic (Gaussian) for COVID-19

Pre-crisis period GARCH diagnostic (Gaussian) for COVID-19												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0239 ***	0.2049 *	0.0574 **	0.0753 **	0.0201 *	03231 **	0.0733 *	0.0548 *	0.0581 **	0.0275 **	0.0318 **	0.0537 **
β	0.9209*	0.7220*	0.8299*	0.8387*	0.9132*	0.6074*	0.9028*	0.8992*	0.8268*	0.9137*	0.8556*	0.8885*
Log LHD	1204.04	1130.04	1437.911	1472.56	1488.341	1308.84	1316.20	1243.46	1461.16	1213.69	1287.57	1549.86
Adj R^2	-0.0016	-0.0016	-0.0021	0.0022	0.0181	-0.0017	-0.0021	-0.0020	-0.0001	0.0046	0.0061	-0.0027
SIC	-4.9770	-4.6636	-5.9518	-6.0968	-6.1628	-5.4118	-5.4425	-5.1382	-6.0491	-5.0136	-5.3227	-6.4202
Prob. Chi-square	0.9458	0.1201	0.3652	0.8993	0.2845	0.9994	0.8666	0.9998	0.8714	0.9506	0.9589	0.9639
During-crisis period GARCH diagnostic (Gaussian) for COVID-19												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.5147*	0.1859*	0.1027*	0.1282*	0.1692*	0.0965*	0.1301*	0.0615*	0.1900*	0.2342*	0.1493*	0.1553*
β	0.5390*	0.8214*	0.8640*	0.8593*	0.7917*	0.8580*	0.8344*	0.9074*	0.8213*	0.5681*	0.8371*	0.7907
Log LHD	655.63	850.56	924.81	969.62	1029.61	973.36	1016.18	865.41	961.21	908.95	861.88	1087.48
Adj R^2	0.0327	-0.0249	-0.0038	-0.0063	0.0039	-0.0034	-0.0026	-0.0003	-0.0017	-0.0024	-0.0046	-0.0073
SIC	-3.4640	-4.5177	-4.9190	-5.1612	-5.4855	-5.1815	-5.4129	-4.5980	-5.1297	-4.8333	-4.5789	-5.7983
Prob. Chi-square	0.9999	0.5062	0.1126	0.7929	0.9992	0.8025	0.4735	0.6824	0.2996	0.8994	0.2385	0.3557

Source: Author's investigation.

Table A12: full sample period GARCH diagnostic (Student's t and GED) for the GFC

Full sample period GARCH diagnostic (Student' s t) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0768*	16.410***	0.0912*	0.1321*	0.0937*	0.0619*	0.09745*	0.0511*	0.1226*	0.1147*	0.1180*	0.1177*
β	0.8902*	0.2480*	0.8956*	0.8519*	0.8872*	0.9107*	0.8916*	0.9425*	0.8628*	0.8577*	0.8640*	0.8696*
Log LHD	2619.74	2396.56	2028.41	2512.29	2415.99	2334.13	2486.87	1981.44	2354.23	2363.60	2081.95	2628.48
Adj R^2	-0.0042	-0.0011	-0.00284	0.0025	-0.00054	0.0089	0.0078	-0.0026	-0.0016	0.0012	0.0086	-0.0019
SIC	-6.1237	-5.5979	-4.7363	-5.8696	-5.6424	-5.4494	-5.0896	-4.6020	-5.4903	-5.519	-4.8488	-5.7772
Prob. Chi-square	0.7957	1.0000	0.9894	0.7232	0.8556	0.3f067	0.5846	0.9361	0.9737	0.9914	0.9668	0.9612
Full sample period GARCH Diagnostic (GED) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0779*	0.2789*	0.0919*	0.1412*	0.1084*	0.0582*	0.1023*	0.0516*	0.1234*	0.1086*	0.1173*	0.1193*
β	0.8795*	0.4873*	0.8946*	0.8427*	0.8751*	0.9129*	0.8842*	0.9428*	0.8604*	0.8676*	0.8629*	0.8673*
Log LHD	2616.25	2391.31	2027.85	2511.66	2414.03	2335.49	2486.25	1980.32	2353.60	2361.07	2082.97	2627.84
Adj R^2	-0.0044	-0.0012	-0.00420	0.0022	-0.00052	0.0087	0.0078	-0.0023	-0.0017	0.0014	0.0088	-0.0018
SIC	-6.1155	-5.5856	-4.7349	-5.8681	-5.6377	-5.4526	-5.0808	-4.6150	-5.4889	-5.5136	-4.8513	-5.7739
Prob. Chi-square	0.7557	1.0000	0.9894	0.7023	0.8624	0.4964	0.5650	0.9315	0.9753	0.9895	0.9674	0.9606

Source: Author's investigation.

Table A12.1: full sample period GARCH diagnostic (Student's t and GED) for COVID-19

	Full sample period GARCH diagnostic (Student' s t) for tCOVID-19											
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0777*	0.3173*	0.0594*	0.0891*	0.03642*	0.0605*	0.0868*	0.0455*	0.1184*	0.1656*	0.0918*	0.0857*
β	0.9068*	0.7221*	0.9131*	0.8873*	0.9476*	0.8909*	0.8758*	0.9309*	0.8381*	0.6243*	0.8768*	0.8710*
Log LHD	1913.25	2029.68	2370.90	2450.83	2532.92	2316.04	2357.93	2169.13	2424.85	2153.09	2151.32	2655.00
Adj R^2	0.0092	-0.0064	0.0019	0.0022	0.0005	-0.0008	-0.0021	0.0062	0.0034	0.0005	0.0018	0.0035
SIC	-4.4703	-4.7202	-5.5230	-5.7044	-5.9043	-5.3939	-5.4925	-5.0483	-5.6566	-4.9359	-5.0076	-6.1915
Prob. Chi-square	1.0000	0.3499	0.2132	0.5158	0.9346	0.9999	0.3755	0.9980	0.5338	0.8524	0.3321	0.5151
	Full sample period GARCH Diagnostic (GED) for tCOVID-19											
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.08932*	0.2532*	0.0693*	0.0899*	0.0433*	0.0595*	0.0932*	0.0525*	0.1245*	0.1435*	0.0973*	0.0935*
β	0.8916*	0.7345*	0.9045*	0.8887*	0.9346*	0.8763*	0.8684*	0.9150*	0.8357*	0.6228*	0.8742*	0.8613*
Log LHD	1905.29	2040.57	2366.36	2449.86	2526.38	2311.79	2355.97	2156.93	2424.89	2145.38	2151.12	2654.01
Adj R^2	0.0004	-0.0027	0.0012	0.0025	0.0011	-0.0006	-0.0023	0.0063	0.0034	0.0007	0.0017	0.0045
SIC	-4.4516	-4.7699	-5.5124	-5.7021	-5.8889	-5.3839	-5.4879	-5.0196	-5.6568	-4.9924	-5.0059	-6.1892
Prob-Chi-square	1.0000	0.3560	0.2101	0.5552	0.9700	0.9997	0.4114	0.9991	0.5362	0.8234	0.2037	0.4115

Source: Author's investigation.

Table A12.2: pre-crisis period GARCH diagnostic (Student's t and GED) for the GFC

Pre-crisis period GARCH diagnostic (Student' s t) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.2166*	0.2217****	0.1023**	0.1072**	0.0791**	0.0888**	0.1319*	0.1300***	0.0942**	0.0594***	0.0889**	0.1334**
β	0.6185*	0.4436***	0.8408*	0.8437*	0.8552*	0.8777*	0.8179*	0.6739*	0.8662*	0.8564***	0.8516*	0.8252*
Log	104735	1110.13	924.42	1111.93	1078.56	976.25	1120.29	910.65	1048.85	1066.27	908.24	1065.44
Adj R^2	0.30086	-0.0084	0.0001	0.0078	0.0051	-0.0042	0.0254	-0.0030	-0.0028	0.0093	-0.0026	-0.0044
SIC	-5.9184	-6.2611	-5.1969	-6.2714	-6.0802	-5.4938	-6.3193	-5.1182	-5.9099	-6.0097	-5.1041	-6.0050
Prob. Chi-square	0.2102	0.9468	0.9122	0.7903	0.8215	0.2490	0.7455	0.2743	0.7914	1.0000	0.4928	0.7654
Pre-crisis period GARCH Diagnostic (GED) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.2180*	0.1373****	0.1045**	0.1194*	0.0896**	0.0855**	0.1414*	0.1148****	0.0982**	0.0587***	0.0931**	0.1996**
β	0.6135*	0.5452***	0.8397*	0.8225*	0.8482*	0.8752*	0.8001*	0.6969*	0.8589*	0.8555*	0.8430*	0.8263*
Log	1047.69	1116.33	924.23	1111.68	1079.25	976.12	1119.40	910.92	1048.80	1065.98	908.45	1063.80
Adj R^2	0.30096	-0.0073	-0.0001	0.0076	0.0053	-0.0057	0.0259	-0.0036	-0.0023	0.0091	-0.0027	-0.0047
SIC	-5.9203	-6.2966	-5.1958	-6.2700	-6.0841	-5.4931	-6.3541	-5.1195	-5.9096	-6.0081	-5.1053	-5.9956
Prob. Chi-square	0.2114	0.9390	0.9101	0.8001	0.8454	0.2054	0.7306	0.2778	0.7925	0.8674	0.4791	0.7707

Source: Author's investigation.

Table A12.3: during-crisis period GARCH diagnostic (Student's t and GED) for the GFC

During-crisis period GARCH diagnostic (Student' s t) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0610 *	2111.29 ****	0.0781 *	0.1293 *	0.0800 **	0.1268 **	0.0577 **	0.0318 **	0.1313 *	0.1566 *	0.1275 *	0.1151 *
β	0.9228*	0.1755*	0.9083*	0.8576*	0.9014*	0.7207*	0.9227*	0.9552*	0.8589*	0.8178*	0.8659*	0.8737*
Log LHD	1502.22	1285.58	1104.76	1398.90	1327.32	1353.13	1373.12	1069.45	1303.62	1297.14	1162.07	1303.02
Adj R^2	0.0027	0.0214	0.0043	-0.0018	-0.0008	0.0171	0.0046	-0.0026	0.0015	-0.0003	0.0010	0.0002
SIC	-5.9702	-5.0984	-4.3707	-5.5544	-5.3175	-5.3702	-5.4631	-4.2286	-5.1710	-5.1449	-4.6014	-5.1685*
Prob. Chi-square	0.8950	1.0000	0.8697	0.8792	0.9185	0.1117	0.6853	0.9118	0.9374	0.9983	0.9223	0.9459
During-crisis period GARCH Diagnostic (GED) for the GFC												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0661 **	0.5484 **	0.0778 *	0.1387 *	0.1027 *	0.1294 **	0.0595 **	0.0338 **	0.1294 *	0.1452 *	0.1222 *	0.1160 *
β	0.9011*	0.2999*	0.9083*	0.8499*	0.8848*	0.6903*	0.9201*	0.9534*	0.8593*	0.8308*	0.8679*	0.8729*
Log LHD	1497.86	1407.34	1104.59	1398.29	1329.49	1354.60	1373.34	1069.11	1302.78	1296.91	1162.53	1303.16
Adj R^2	0.0029	-0.0026	0.0043	-0.0020	-0.0013	0.0172	0.0046	-0.0029	0.0017	-0.0003	0.0007	0.0002
SIC	-5.9527	-5.5884	-4..3701	-5.5519	-5.3059	-5.4070	-5.4515	-4.2273	-5.1676	-5.1440	-4.6032	-5.1691
Prob. Chi-square	0.8559	1.0000	0.8682	0.8530	0.8943	0.1116	0.6776	0.9281	0.9390	0.9980	0.9250	0.9456

Source: Author's investigation.

Table A12.4: pre-crisis period GARCH diagnostic (Student's t and GED) for COVID-19

Pre-crisis period GARCH diagnostic (Student' s t) for COVID-19												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	-0.0113 *	0.2418 **	0.0510 ***	0.0717 ***	-0.0199 *	0.3403 ***	0.0671 **	0.0133 ***	0.0540 ***	0.0518 ***	0.0315 **	0.0514 **
β	1.0159*	0.7110*	0.7489*	0.8332*	0.9133*	0.6264*	0.9072*	0.9244*	0.8265*	0.8372*	0.8548*	0.8925*
Log LHD	1221.29	1163.81	1439.19	1473.12	1495.59	1335.49	1325.83	1289.54	1461.13	1242.35	1287.53	1555.11
Adj R^2	-0.0021	-0.0016	-0.0019	0.0022	0.0177	-0.0032	-0.0024	-0.0020	-0.0001	0.0031	0.0061	-0.0028
SIC	-5.0326	-4.7920	-5.9443	-6.0862	-6.1803	-5.5104	-5.4699	-5.3181	-6.0360	-5.1206	-5.3097	-6.4293
Prob. Chi-square	1.0000	0.1114	0.3479	0.8890	0.2898	0.9999	0.8604	0.8350	0.8734	0.9815	0.9588	0.9638
Pre-crisis period GARCH diagnostic (GED) for COVID-19												
Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.0269 ****	0.2044 **	0.0510 ***	0.0749 ***	-0.0156 *	0.3113 ***	0.0713 **	0.0279 **	0.0540 ***	0.033 ****	0.0324 **	0.0534 ***
β	-0.6134 ****	0.6956 *	0.7378 *	0.8383 *	0.9074 *	0.6227 *	0.9025 *	0.9022 *	0.8261 *	0.8938 *	0.8563 *	0.8882*
Log LHD	1217.851	1168.98	1438.36	1472.58	1493.72	1331.66	1324.48	1274.90	1461.20	1235.27	1287.60	1555.16
Adj R^2	-0.0022	-0.0021	-0.0019	0.0022	0.0176	-0.0025	-0.0025	-0.0026	-0.0000	0.0034	0.0061	-0.0028
SIC	-5.0182	-4.8137	-5.9408	-6.0840	-6.1724	-5.4943	-5.4643	-5.2568	-6.0364	-5.0910	-5.3100	-6.4295
Prob. Chi-square	0.8178	0.1100	0.3586	0.8974	0.3374	0.9998	0.8734	0.9962	0.8721	0.9654	0.9590	0.9627

Source: Author's investigation.

Table A12.5: during-crisis period GARCH diagnostic (Student's t and GED) for COVID-19

During-crisis period GARCH diagnostic (Student' s t) for COVID-19

Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.1435**	0.4018**	0.0849*	0.1200*	0.1055**	0.1031**	0.1106**	0.06517**	0.1626*	0.2370**	0.1235*	0.1165*
β	0.8180*	0.7103*	0.8888*	0.8582*	0.8531*	0.8509*	0.8340*	0.9270*	0.8110*	0.5722*	0.8580*	0.8409*
Log LHD	697.44	865.42	937.52	973.99	1047.60	981.78	1026.53	884.97	965.45	911.32	865.99	1095.68
Adj R^2	0.0355	-0.0133	-0.0020	-0.0041	0.0049	-0.0018	-0.0026	0.0002	-0.0024	-0.0030	-0.0048	-0.0030
SIC	-3.6740	-4.5820	-4.9717	-5.1689	-5.5668	-5.2110	-5.4529	-4.6877	-5.1367	-4.8301	-4.5851	-5.8267
Prob. Chi-square	1.0000	0.1268	0.0746	0.8119	0.9998	0.8054	0.4979	0.5741	0.2525	0.8940	0.1851	0.3071

During-crisis period GARCH diagnostic (GED) for COVID-19

Sectors	J135	J335	J510	J520	J530	J540	J550	J560	J580	J590	J835	J203
α	0.2201*	0.3035*	0.0929*	0.1194*	0.1252**	0.0981**	0.1146**	0.0608**	0.1726*	0.2350**	0.1335*	0.1278**
β	0.7173*	0.7354*	0.8760*	0.8578*	0.8413*	0.8557*	0.8321*	0.9220*	0.8036*	0.5720*	0.8511*	0.8293*
Log LHD	691.80	871.77	935.01	975.29	1044.38	981.60	1025.82	885.83	965.33	911.88	866.40	1095.47
Adj R^2	0.0326	-0.0029	-0.0019	-0.0035	0.0048	-0.0018	-0.0028	0.0008	-0.0019	-0.0026	-0.0047	-0.0038
SIC	-3.6435	-4.6164	-4.9582	-5.1759	-5.5494	-5.2101	-5.4491	-4.6923	-5.1360	-4.8332	-4.5873	-5.8255
Prob. Chi-square	1.0000	0.1981	0.0520	0.8219	0.9997	0.8011	0.4948	0.6194	0.2679	0.8880	0.1963	0.3099

Source: Author's investigation.

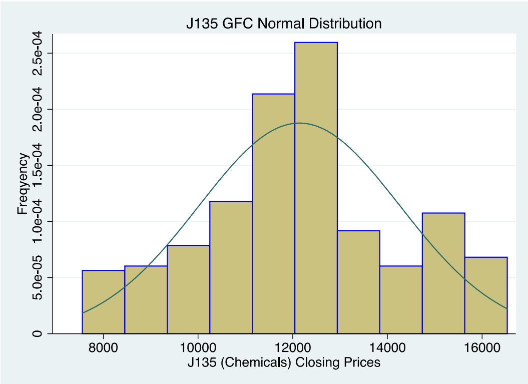
Table A13: choice of error distribution based on the GARCH diagnostic results

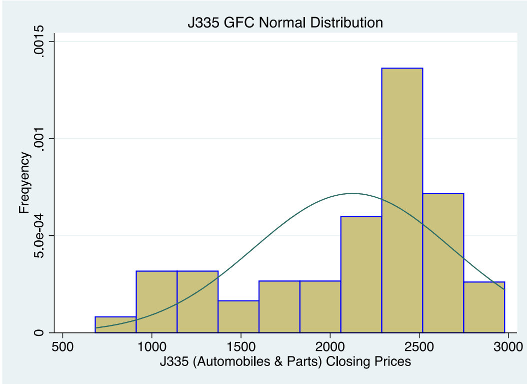
Sectors	GFC Full sample period	 Pre-crisis	 During-crisis	COVID-19 Full sample period	 Pre-crisis	 During-crisis
Chemicals	Student’s t	GED	Norm.Dist	GED	Norm.Dist	Norm.Dist
Auto & Parts	Norm.Dist	Norm.Dist	GED	Norm.Dist	Norm.Dist	Norm.Dist
Basic Materials	Norm.Dist	Norm.Dist	GED	Norm.Dist	Norm.Dist	Norm.Dist
Industrial	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist
Consumer Goods	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist
Health Care	Norm.Dist	Norm.Dist	GED	Student’s t	Norm.Dist	Student’s t
Consumer Services	Norm.Dist	Norm.Dist	Norm.Dist	Student’s t	Norm.Dist	Norm.Dist
Telecommunication	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist
Financials	Student’s t	Norm.Dist	Norm.Dist	GED	Norm.Dist	Norm.Dist
Technology	Norm.Dist	Student’s t	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist
Banks	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist
All-Share Index	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	Norm.Dist	GED

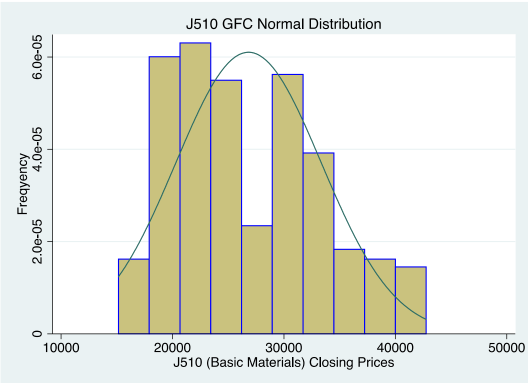
Source: Author’s investigation.
Note: ‘Norm.Dist’ stands for ‘Normal Distribution’

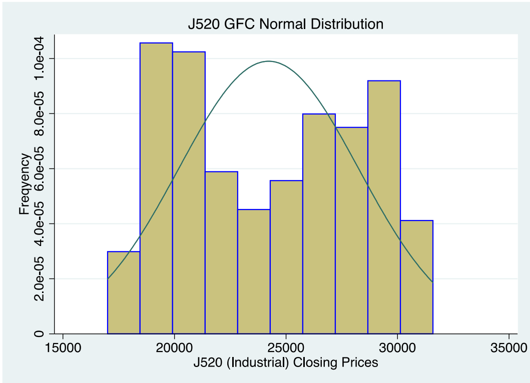
APPENDIX B

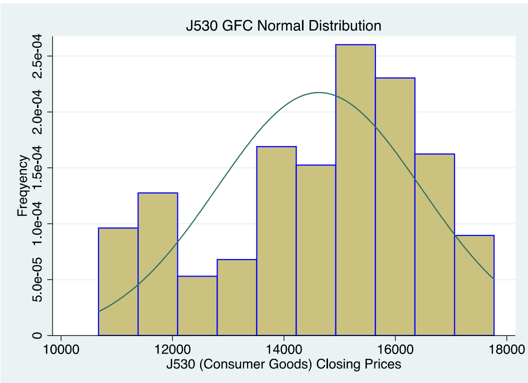
Figure 3: histogram of all observed series for the GFC's full sample period

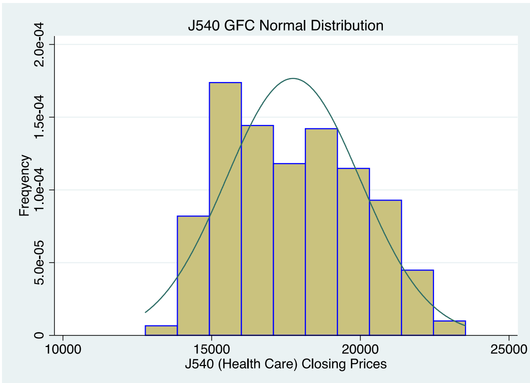


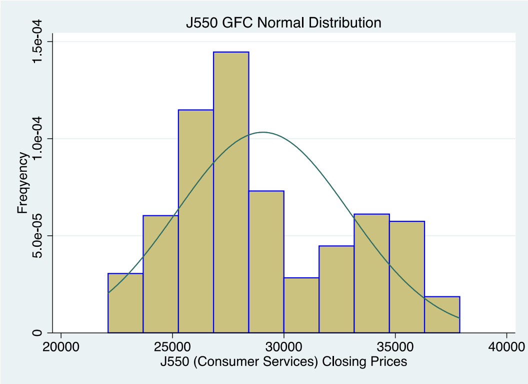


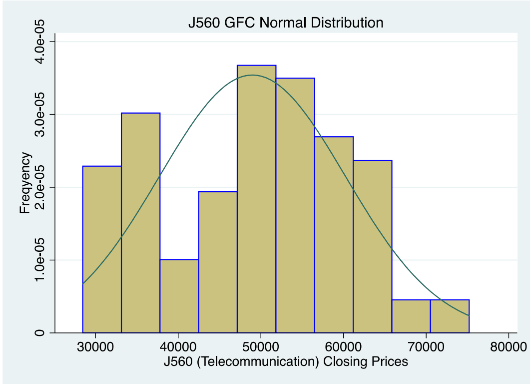


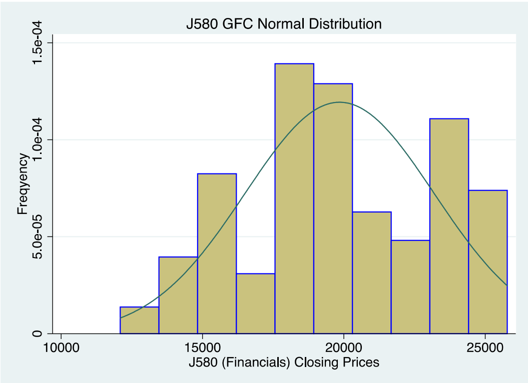


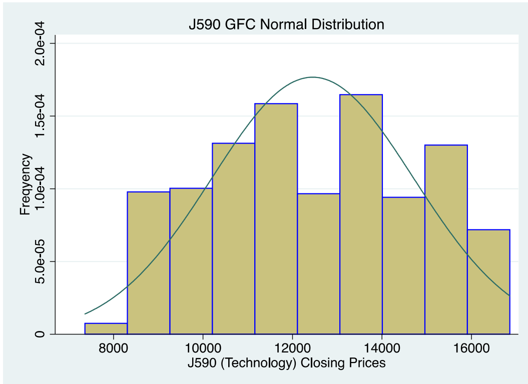


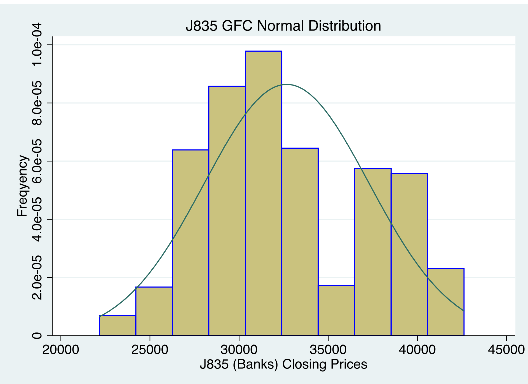


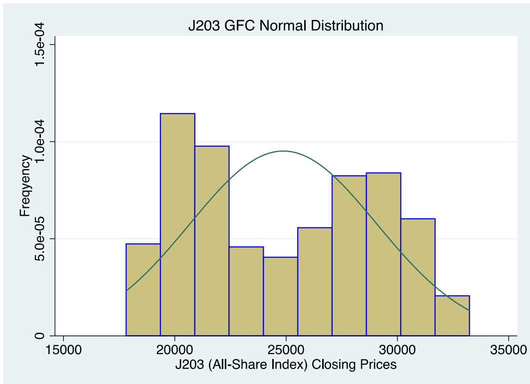






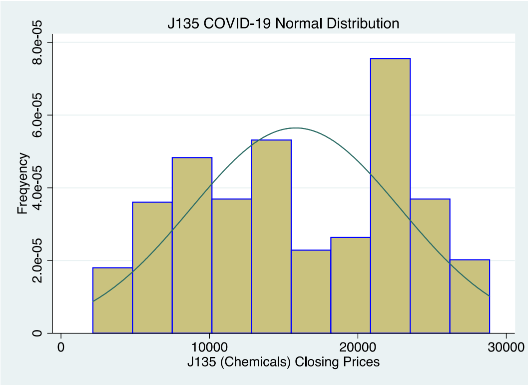


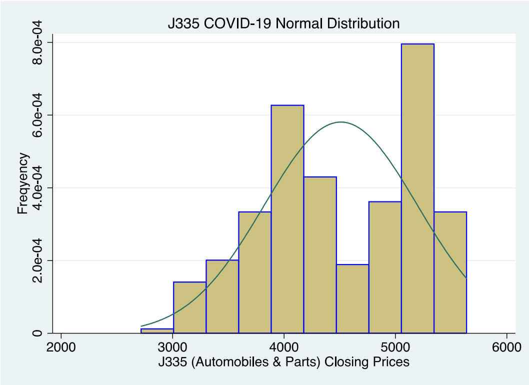


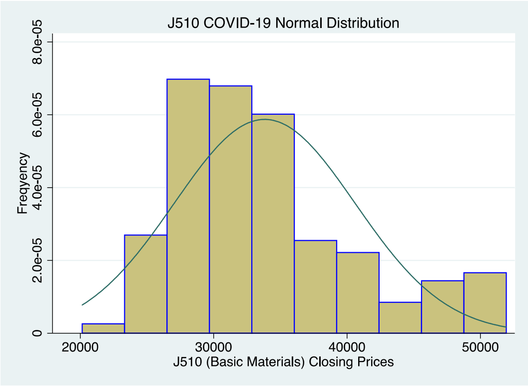


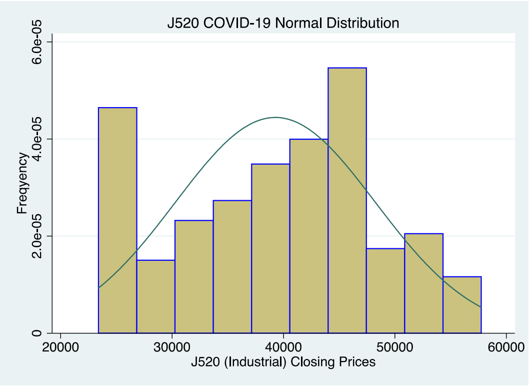
Source: Author's investigation.

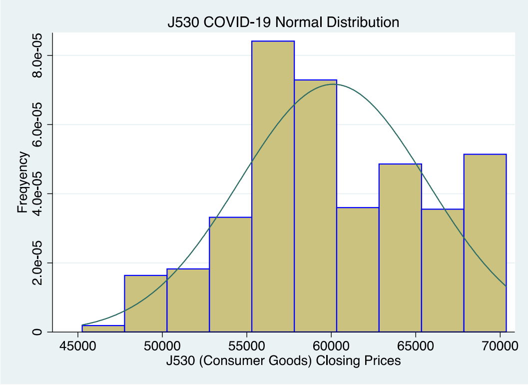
Figure 4: histogram of all observed series for COVID-19's full sample period

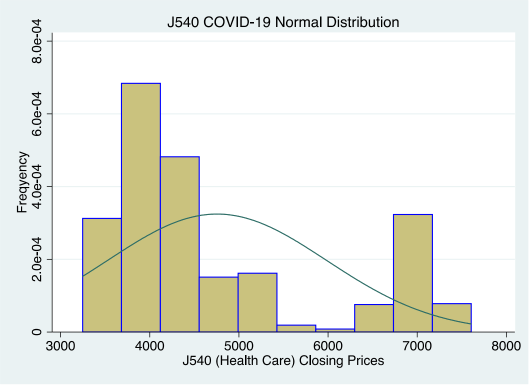


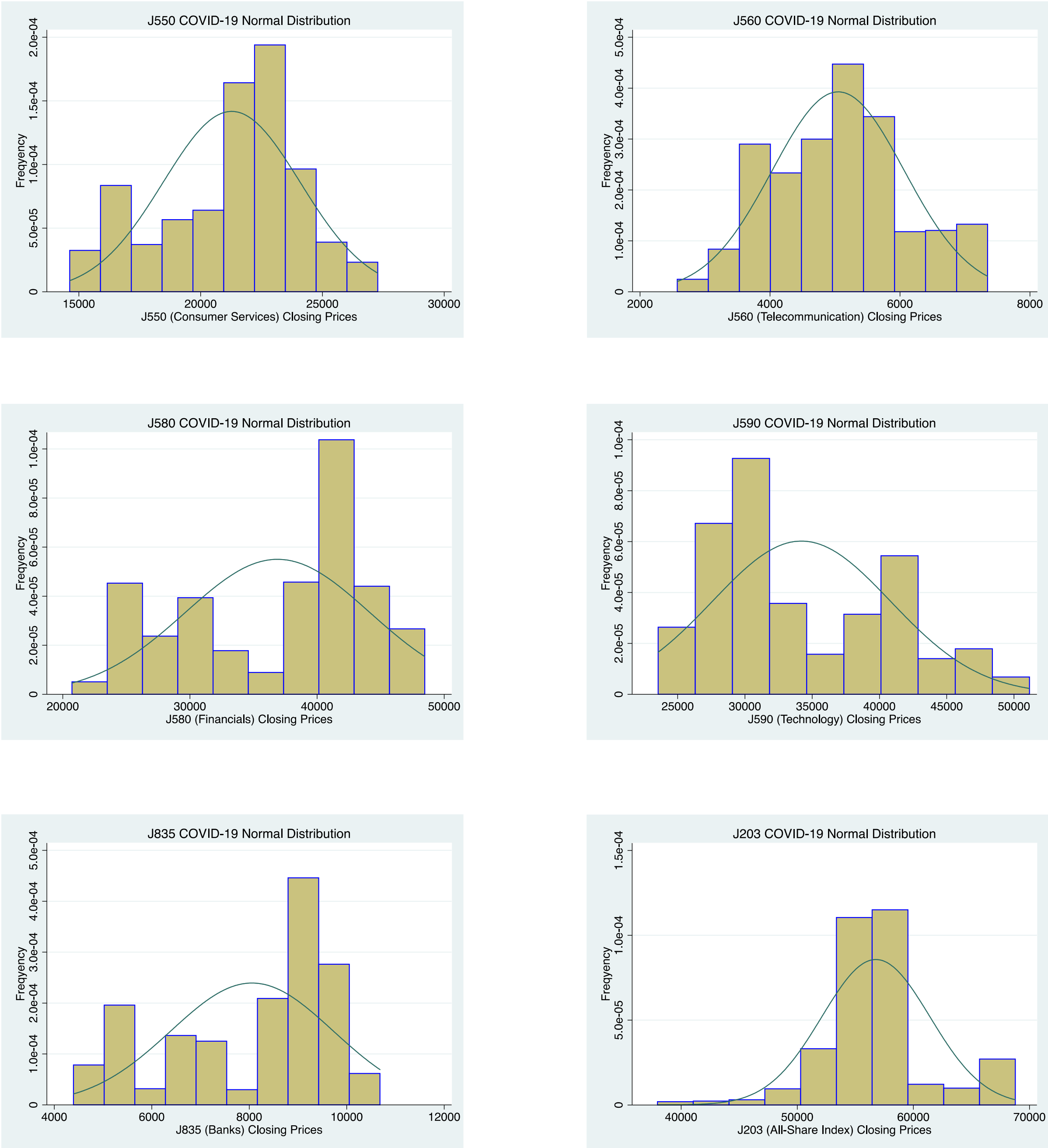








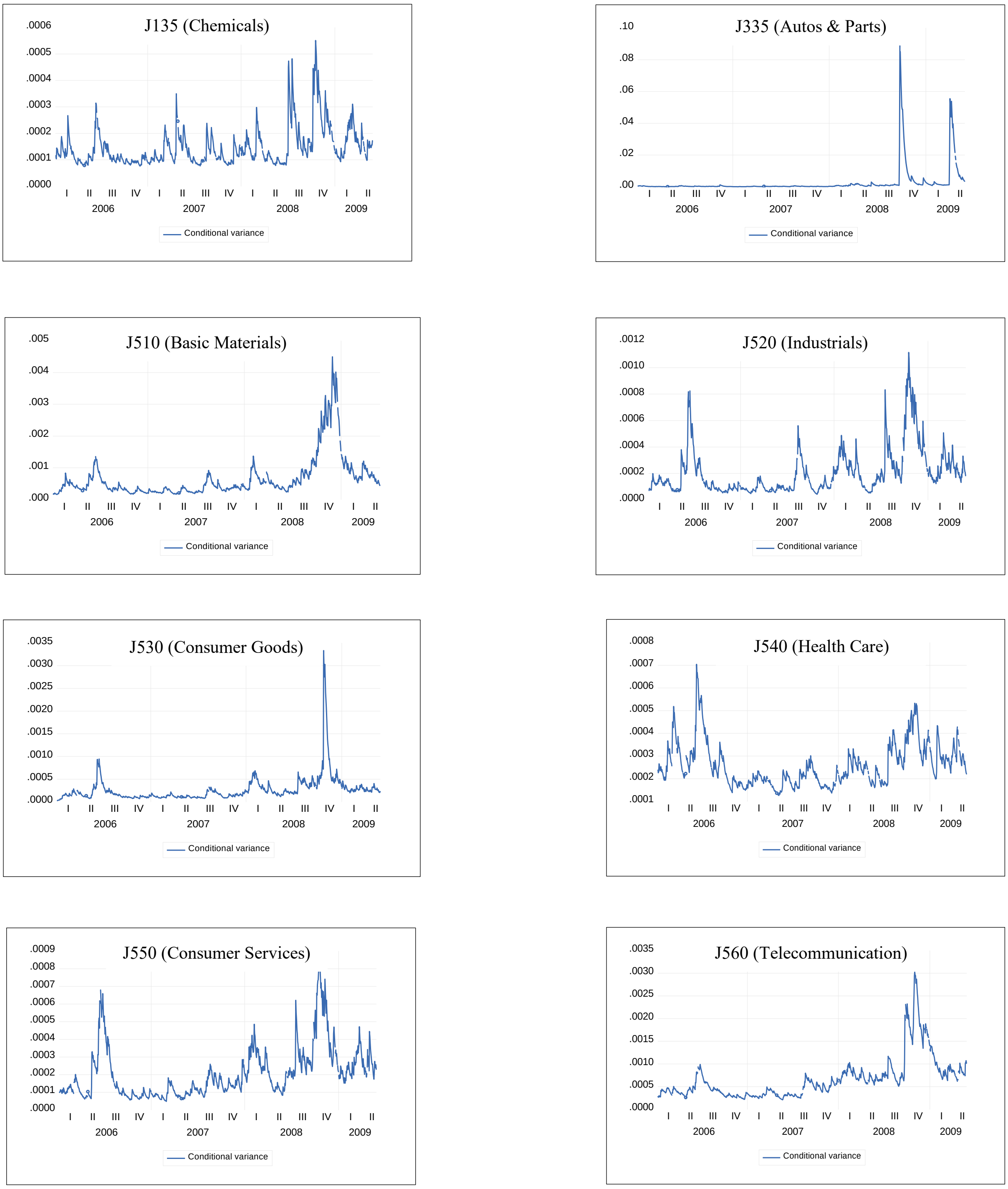


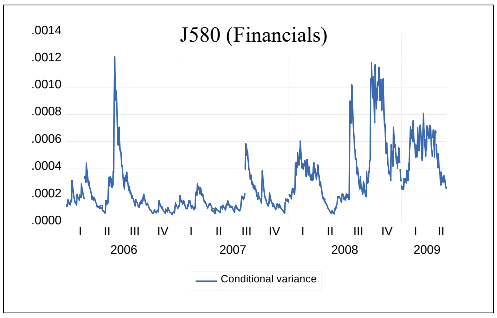


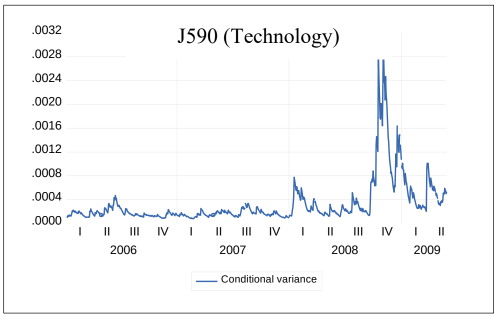
Source: Author's investigation.

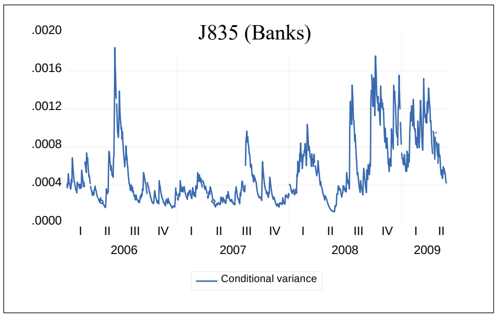
APPENDIX C

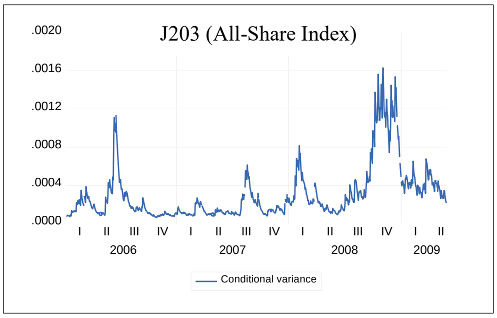
Figure 5: conditional variance for the GFC's full sample period





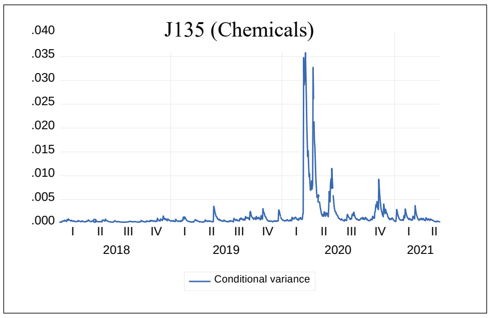


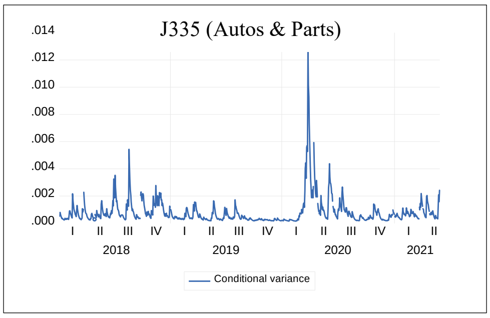


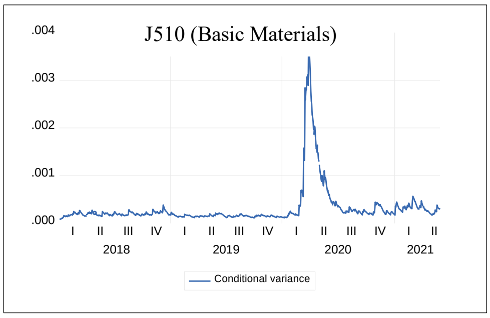


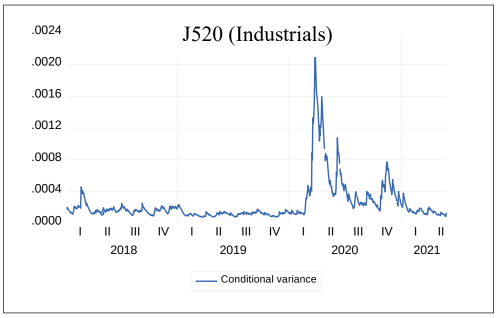
Source: Author's investigation.

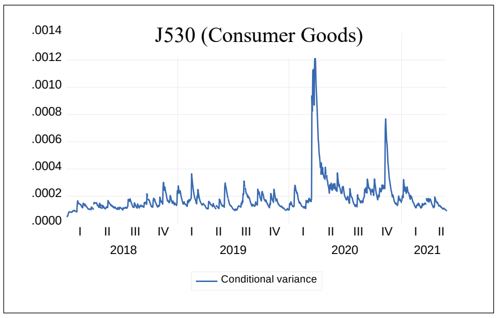
Figure 6: conditional variance for COVID-19's full sample period

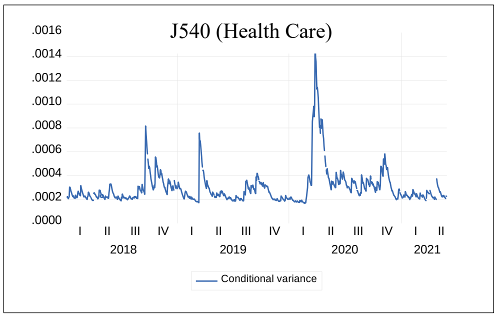


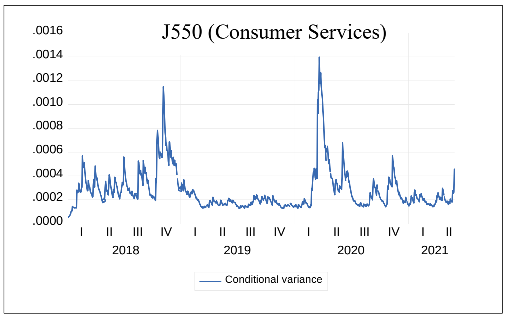


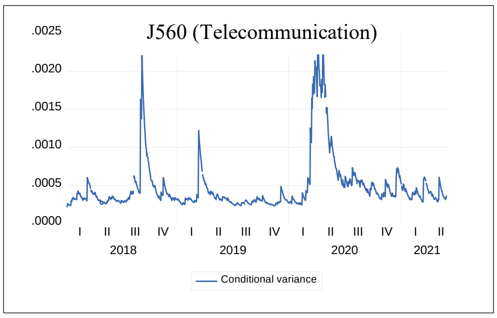


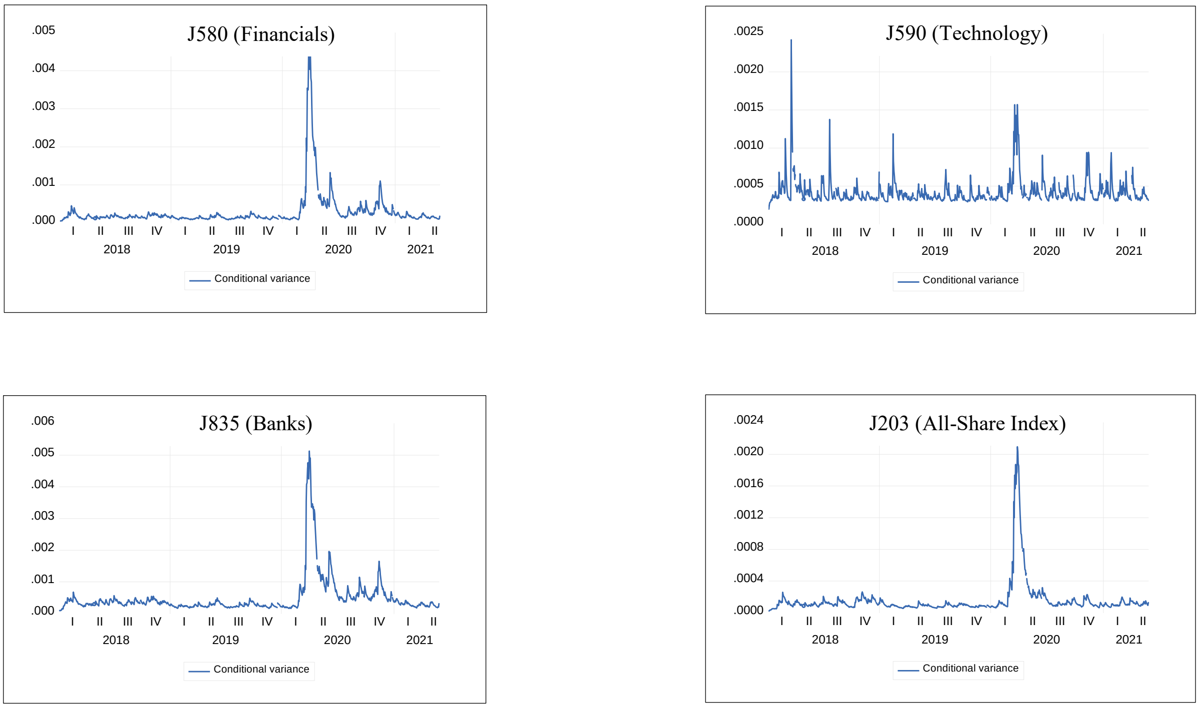












Source: Author's investigation.

APPENDIX D

Table D1: full sample period GARCH-M regression for the GFC

	Sector	Mean equation				Variance Equation		
		C_R	R_t	β_R	D_R	C_V	β_V	D_V
First specification	Chemicals	0.000852 ****	0.0863 **	-5.1433 ****	-	0.0000130 *	0.8089 *	0.00000487 ***
	Auto & Parts	-0.0000973 ****	-0.0436 ****	0.2129 ****	-	0.0000408 *	0.5924 *	0.000646 **
	Basic Materials	0.001044 ****	0.0198 ****	0.6343 ****	-	0.0000163 **	0.8699 *	0.0000387 ***
	Industrial	0.0016 *	-4.0578 ****	0.0817 **	-	0.00000616 *	0.8119 *	0.0000133 ***
	Consumer Goods	0.001061 ****	-0.0332 ****	-1.0466 ****	-	0.00000727 *	0.8520 *	0.0000155 **
	Health Care	-0.002327 ****	0.1007 **	11.3087 ****	-	0.0000553 *	0.6196 *	0.0000227 ****
	Consumer Services	0.001577 **	0.1388 **	-4.2923 ****	-	0.00000535 *	0.8815 *	-0.00000205 ****
	Telecommunication	0.001588 ****	-0.0085 ****	-0.3450 ****	-	0.0000607 *	0.7418 *	0.000119 ***
	Financials	-0.000124 ****	0.0545 ****	2.2189 ****	-	0.00000743 **	0.8469 *	0.0000125 ***
	Technology	0.000981 ****	0.0796 ****	-1.8913 ****	-	0.0000224 *	0.7299 *	0.0000888 **
	Banks	-0.000245 ****	0.0393 ****	1.7141 ****	-	0.0000144 **	0.8627 *	0.0000103 ***
	All-Share Index	0.000543 ****	2.1489 ****	0.0173 ****	-	0.00000574 **	0.8549 *	0.00000716 ****
		C_R	R_t	β_R	D_R	C_V	β_V	D_V
Second specification	Chemicals	0.00000582 ****	0.0844 **	3.5224 ****	-0.0023 ****	0.0000127 *	0.8131 *	0.00000903 ***
	Auto & Parts	-0.000502 ****	-0.0713 **	4.1117 ****	-0.0014 *	0.0000453 *	0.5603 *	0.000647 ***
	Basic Materials	-0.000782 ****	0.0123 ****	7.5662 ***	-0.009737 *	0.0000155 **	0.8775 *	0.0000400 ***
	Industrial	0.00143 **	0.0808 **	-1.9056 ****	-0.0013 ***	0.00000608 *	0.8131 *	0.0000129 ***
	Consumer Goods	0.000663 ****	-0.0367 ****	3.5452 ***	-0.003127 ***	0.00000743 *	0.8483 *	0.0000158 **
	Health Care	-0.002034 ****	0.0991 *	9.2433 ***	0.0014 ***	0.0000557 *	0.6177 *	0.0000299 ***
	Consumer Services	0.001128 ****	0.1389 *	-4.2035 ****	0.000516 ***	0.00000524 *	0.8817 *	-0.00000195 ***

	Telecommunication	-0.000255****	-0.0164****	5.2252****	-0.005903***	0.0000663*	0.7228*	0.000129***
	Financials	-0.000149****	0.0546****	2.4149****	-0.0000184***	0.00000744**	0.8468*	0.0000126***
	Technology	0.001378****	0.0809****	-4.6598****	0.002440***	0.0000221*	0.7327*	0.0000867***
	Banks	-0.000345****	0.0299****	5.0598****	-0.00356***	0.0000138**	0.8635*	0.0000106***
	All-Share Index	0.000540****	0.0174****	2.1836****	-0.0000457****	0.00000575**	0.8549*	0.00000717****
		C_R	R_t	β_R	D_R	C_V	β_V	D_V
Third specification	Chemicals	0.000123****	0.07988**	2.4953****	-0.0019***	0.00000913*	0.8527*	-
	Auto & Parts	-0.000330****	-0.0944**	1.8557****	-0.0349*	0.0000116*	0.7481*	-
	Basic Materials	-0.000300****	0.0116****	5.5922****	-0.006838*	0.00000891**	0.8975*	-
	Industrial	0.001425***	0.0784**	-1.7883****	-0.001256****	0.00000475*	0.8322*	-
	Consumer Goods	0.000771****	-0.0316****	2.4885****	-0.002316***	0.00000526*	0.8648*	-
	Health Care	-0.002171****	0.0987*	9.5074****	0.001811****	0.0000595*	0.6125*	-
	Consumer Services	0.001040****	0.1395*	-4.2326****	0.000611****	0.00000377*	0.8784*	-
	Telecommunication	0.001225****	-0.0202****	1.4887****	-0.001912***	0.00000531***	0.9394*	-
	Financials	-0.000134****	0.0536****	2.2818****	0.0000494***	0.00000606*	0.8588*	-
	Technology	0.001886**	0.0809****	-6.2437****	0.003881***	0.00000498*	0.8947*	-
	Banks	-0.000295***	0.0309****	4.5629****	-0.0031**	0.0000139*	0.8651*	-
	All-Share Index	0.000522****	0.0161****	2.2011****	0.000106****	0.00000508**	0.8620*	-

Source: Author's investigation.

Table D2: full sample period GARCH-M regression for COVID-19

	Sector	Mean equation				Variance Equation		
		C_R	R_t	β_R	D_R	C_V	β_V	D_V
First specification	Chemicals	0.000310 ****	0.0654 ***	0.4492 ****	-	0.0000475 *	0.2322 *	0.0000368 ***
	Auto & Parts	-0.000178 ****	-0.1312 **	2.4447 ****	-	0.0000204 *	0.7957 *	0.0000132 ***
	Basic Materials	0.0000112 ****	-0.0066 ****	4.4085 ****	-	0.00000764 **	0.8857 *	0.00000606 ***
	Industrial	-0.0000920 ****	-0.0098 ****	-0.4924 ****	-	0.00000646 *	0.8552 *	0.00000467 ****
	Consumer Goods	-0.000681 ****	0.0510 ****	5.3388 ***	-	0.00000854 *	0.8833 *	-0.00000366 **
	Health Care	0.003109 ***	-0.0081 ****	-11.8627 ***	-	0.0000389 *	0.7810 *	0.00000188 ****
	Consumer Services	-0.000531 ****	0.0079 ****	3.1473 ****	-	0.00000947 *	0.8685 *	0.00000265 ****
	Telecommunication	0.0000784 ****	-0.1243 ****	0.6301 ****	-	0.0000191 *	0.8899 *	0.00000606 ***
	Financials	-0.000447 ****	0.0067 ****	1.9643 ****	-	0.00000979 *	0.8192 *	0.00000526 ****
	Technology	0.001801 ****	0.0323 ****	-3.9616 ****	-	0.000118 *	0.5919 *	-0.00000354 ****
	Banks	0.0000375 ****	-0.0234 ****	0.6895 ****	-	0.0000129 *	0.8653 *	0.00000292 *****
	All-Share Index	-0.000150 ****	0.0223 ****	5.5911 ****	-	0.00000635 *	0.8481 *	0.00000139 ****
		C_R	R_t	β_R	D_R	C_V	β_V	D_V
Second specification	Chemicals	0.0000805 ****	0.0659 ***	0.1499 ****	0.002216 ***	0.0000478 *	0.7511 *	0.0000349 ***
	Auto & Parts	-0.000293 ****	-0.1316 **	2.2323 ****	0.000827 ****	0.0000207 *	0.7945 *	0.0000127 ***
	Basic Materials	0.0000720 ****	-0.006868 ****	3.3818 ****	0.000729 ***	0.00000772 **	0.8848 *	0.00000599 ***
	Industrial	-0.0000306 ****	-0.0142 ****	-4.3482 ****	0.0025 ***	0.00000639 **	0.8567 *	0.00000437 ****
	Consumer Goods	-0.001308 ****	0.0519 ****	7.7513 ***	0.001253 ****	0.00000424 *	0.9358 *	-0.00000302 **
	Health Care	0.002243 ****	-0.0106 ***	-13.8903 ****	0.001895 ***	0.0000407 *	0.7634 *	0.00000475 ****
	Consumer Services	-0.000671 ****	0.0075 ****	2.5863 ***	0.000729 ***	0.00000948 *	0.8689 *	0.00000244 ****
	Telecommunication	0.000484 ****	-0.0167 ****	-2.9039 ****	0.0036 **	0.0000191 *	0.8891 *	0.00000517 ****

	Financials	-0.000508 ****	0.0045 ****	0.2071 ****	0.001591 ***	0.00000962 *	0.8208 *	0.00000461 ****
	Technology	0.001472 ****	0.0312 ****	-4.2799 ****	0.001297 ****	0.000120 *	0.5861 *	-0.00000179 ****
	Banks	-0.0000299 ****	-0.0259 ****	-0.8203 ****	0.002321 ****	0.0000128 **	0.8658 *	0.00000231 ****
	All-Share Index	-0.000240 ****	0.0214 ****	3.9921 ****	0.000934 ****	0.00000645 *	0.8464 *	0.00000113 *
		C_R	R_t	β_R	D_R	C_V	β_V	D_V
Third specification	Chemicals	0.000192 ****	0.0649 ***	0.1015 ****	0.0025 ****	0.0000399 *	0.7809 *	-
	Auto & Parts	-0.000331 ****	-0.1337 **	2.1563 ****	0.0011 ****	0.0000198 *	0.8111 *	-
	Basic Materials	0.0000590 ****	-0.0066 ****	3.3054 ****	0.000805 ***	0.00000608 **	0.9019 *	-
	Industrial	-0.0000636 ****	-0.0141 ****	-3.9879 ****	0.0025 **	0.00000488 *	0.8821 *	-
	Consumer Goods	-0.000908 ****	0.0514 ****	5.7049 ****	0.000858 ****	0.0000101 *	0.8629 *	-
	Health Care	0.002277 ****	-0.0099 ****	-13.2540 ****	0.0016 ****	0.0000417 *	0.7744 *	-
	Consumer Services	-0.000680 ****	0.0068 ****	2.4939 ****	0.000805 ****	0.0000106 *	0.8670 *	-
	Telecommunication	0.000449 ****	-0.0171 ****	-2.7642 ****	0.003626 *	0.0000183 *	0.8965 *	-
	Financials	-0.000514 ****	0.0058 ****	0.2449 ****	0.001628 ***	0.00000879 *	0.8326 *	-
	Technology	0.001465 ****	0.0313 ****	-4.2786 ****	0.001318 ****	0.000119 *	0.5864 *	-
	Banks	-0.0000325 ****	-0.0249 ****	-0.7930 ****	0.002320 ****	0.0000123 *	0.8698 *	-
	All-Share Index	-0.000240 ****	0.0216 ****	3.9089 ****	0.000978 ****	0.00000641 *	0.8502 *	-

Source: Author's investigation.

Table D3: sub-sample period GARCH-M regression results for the GFC

	Sector	Mean equation			Variance Equation	
		C_R	R_t	β_R	C_V	β_V
Pre-crisis	Chemicals	-0.0000208 ****	0.0599 ****	14.2108 ****	0.0000317 **	0.5212 *
	Auto & Parts	-0.001920 ****	-0.0082 ****	12.4937 ****	0.0000193 **	0.7639 *
	Basic Materials	0.000364 ****	-0.0799 ****	6.0248 ****	0.0000175 ****	0.8454 *
	Industrial	0.001075 ****	-0.0596 ****	-13.0193 ****	0.0000112 ****	0.8412 *
	Consumer Goods	0.000563 ****	-0.0723 ****	7.0487 ****	0.00000839 **	0.8401 *
	Health Care	0.002501 ****	0.0152 ****	-1.8479 ****	0.0000121 ***	0.8604 ****
	Consumer Services	0.002664 *	0.1548 **	-11.5910 ****	0.00000778 *	0.7788 *
	Telecommunication	0.001804 ****	0.0017 ****	-1.3341 ****	0.0000646 *	0.6990 *
	Financials	0.000532 ****	-0.0089 ****	5.2370 ****	0.00000812 ***	0.8424 *
	Technology	0.007218 ****	0.1228 **	-15.7610 ****	0.00000561 ****	0.9266 *
	Banks	-0.0000923 ****	-0.0088 ****	7.0629 ****	0.0000269 ****	0.8151 *
	All-Share Index	0.000939 ****	-0.0505 ****	5.5476 ****	0.00000804 **	0.8265 *
		C_R	R_t	β_R	C_V	β_V
During-crisis	Chemicals	-0.001538 ****	0.0777 ****	3.4908 ****	0.00000924 *	0.8799 *
	Auto & Parts	-0.012858 ****	-0.4599 ****	9.4728 ****	0.00000675 *	0.7723 *
	Basic Materials	-0.000803 ****	0.0748 ****	2.0407 ****	0.0000129 ***	0.9081 *
	Industrial	0.000722 ****	0.0486 ****	-2.4284 ****	0.00000535 ***	0.8383 *
	Consumer Goods	0.016224 ****	-0.0229 ****	-17.9139 ****	0.000219 **	0.7900 *
	Health Care	-0.005361 ***	0.1434 *	20.0023 ****	0.0000807 *	0.6473 *
	Consumer Services	-0.002204 ****	0.0959 **	8.8449 ****	0.00000530 ****	0.9213 ****
	Telecommunication	0.001538 ****	-0.0238 ****	0.0169 ****	0.0000154 ***	0.9421 ****
	Financials	-0.001885 ***	0.0752 ****	4.6566 ****	0.00000722 **	0.8586 *
	Technology	0.00000717 ****	0.0342 ****	-0.6324 ****	0.0000127 *	0.8383 *
	Banks	-0.001833 ****	0.0643 ****	3.1663 ****	0.0000141 **	0.8734 *
	All-Share Index	-0.000829 ****	0.0461 ****	3.7543 ****	0.00000575 ****	0.8747 *

Source: Author's investigation.

Table D4: sub-sample period GARCH-M regression results for COVID-19

	Sector	Mean equation			Variance Equation	
		C_R	R_t	β_R	C_V	β_V
Pre-crisis	Chemicals	-0.000829 ****	0.0465 ****	3.7543 ****	0.00000575 ****	0.8747 ****
	Auto & Parts	-0.003750 **	-0.1766 ****	9.8612 ****	0.0000720 *	0.7746 *
	Basic Materials	-0.004034 ****	-0.0425 **	19.9044 ****	0.000104 *	0.8512 *
	Industrial	0.001075 ****	-0.05958 ****	-13.0193 ****	0.0000112 ****	0.8412 *
	Consumer Goods	-0.002103 ****	0.1400 **	12.5162 ****	0.00000108 *	1.0131 *
	Health Care	0.005214 ****	0.0024 ****	-15.3077 ****	0.000206 **	0.8236 *
	Consumer Services	-0.001583 ****	0.0093 ****	6.7763 ****	0.00000707 **	0.9012 *
	Telecommunication	0.000267 ****	-0.0149 ****	-1.4263 ****	0.0000172 **	0.8979 *
	Financials	-0.010662 ****	-0.0482 ****	19.5870 ****	0.0000847 **	0.8952 *
	Technology	0.008153 ****	0.0618 ****	-11.9552 ****	0.000240 *	0.8110 *
	Banks	-0.002082 ****	-0.0943 ****	-17.4064 ****	0.000175 *	0.7844 *
	All-Share Index	-0.001259 ****	-0.0146 ****	13.0621 ****	0.0000598 *	0.9037 *
		C_R	R_t	β_R	C_V	β_V
During-crisis	Chemicals	0.001386 ****	0.1162 **	0.2368 ****	0.000213 *	0.6338 *
	Auto & Parts	0.000692 ****	-0.1226 **	0.3956 ****	0.0000141 *	0.8222 *
	Basic Materials	0.000982 ****	0.0074 ****	2.4072 ****	0.0000168 **	0.8656 *
	Industrial	0.001193 ****	0.0411 ****	-2.3353 ****	0.00000971 ***	0.8579 *
	Consumer Goods	0.000918 ****	0.0147 ****	-1.3816 ****	0.0000144 ***	0.8349 *
	Health Care	0.002302 ****	-0.0366 ****	-4.4267 ****	0.0000173 **	0.8508 *
	Consumer Services	0.000918 ****	0.01477 ****	-1.3816 ****	0.0000144 **	0.8349 *
	Telecommunication	0.001456 ****	-0.0314 ****	0.0174 ****	0.0000196 ****	0.9075 *
	Financials	0.0000662 **	0.0600 ****	-0.4893 ****	0.0000130 **	0.7908 *
	Technology	0.002822 ****	0.0102 ****	-3.7031 ****	0.0000977 *	0.8016 *
	Banks	0.001338 ****	0.0541 ****	-0.6669 ****	0.0000160 **	0.8367 *
	All-Share Index	0.000917 ****	0.0025 ****	2.7704 ****	0.0000110 **	0.8950 *

Source: Author's investigation.