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Covid-19 Impact on Johannesburg Stock Exchange for the duration of the pandemic period

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Declaration

I, **Siyabonga Remgius Dube**, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorise the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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Abstract

For a considerable time and for different reasons, the financial system shocks endured during rare events continue to pique investors' and policymakers' keen interest. Consequently, this study explores COVID-19's impact on the JSE. The pandemic caused significant shocks to financial systems and economies. Uncertainties emanating from investor fear in response to the pandemic outbreak affected portfolio investment decisions. Additionally, policymakers implemented 'social distancing' and stringent measures to restrict the contagion of the health crisis, which had a disruptive impact on global value chains. To limit these adverse effects, policymakers — subject to budgetary constraints — implemented fiscal, monetary, and other stimulus packages to lessen the adverse impact on the real economy.

Extensive studies have examined the reaction and recovery of financial and economic markets following pandemic-induced shocks. These studies draw on theories from behavioural finance, financial risk contagion, and the efficient market hypothesis to analyse market responses and stability. This dissertation builds on the existing literature by examining the health crisis' transmission to the financial markets in an emerging economy. The study employed new deaths and stringency measures implemented during the pandemic period as proxies for COVID-19 and assessed their impact on ALSI returns, the variable of interest, using a quantile regression estimation technique.

The results indicate a level of collinearity and multicollinearity between ALSI returns and global financial market performance indicators. The correlation between ALSI returns, the S&P 500 and Implied Volatility is statistically significant at 0.716 and –0.600 respectively. This outcome indicates the deepened integration of South African financial markets with the globe. The flight to safe havens was not observed. Contrasting ALSI returns with macroeconomic factors represented by crude oil and the rand–dollar exchange rate, the relationships are statistically insignificant. The real economy disturbances do not appear to have been transmitted to the financial markets in the long term. Progress in vaccine development and coordinated global policy interventions may have limited the sustained adverse impact on the real economy.

This study offers key recommendations for portfolio design, policymaker intervention timing, and the balance between economic stimulation and containment efforts during pandemics.

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Abbreviations

ADF	Adjusted Dirk-Fuller
ALSI	All Share Index
APT	Arbitrage Pricing Theory
ARCH	Autoregressive Conditional Heteroskedasticity
BCO	Brent Crude Oil
CAC40	Cotation Assistée en Continu
CAPM	Capital Asset Pricing Model
CAT	Catastrophe Bond
CAViaR	conditional autoregressive value at risk
CDF	Cumulative Distribution Function
Covid-19	Corona Virus Disease
DCC-GARCH	Dynamic Conditional Correlation Generalized AutoRegressive Conditional Heteroskedasticity
EGARCH	Exponential General Autoregressive Conditional Heteroskedastic
EMF	Emerging Frontier Markets
EMH	Efficient Market Hypothesis
EXC	Rand Dollar Exchange Rate
FTSE/JSE	Financial Times Stock Exchange
JSE	Johannesburg Stock Exchange
GDP	Gross Domestic Product
GFC	Global Financial Crisis
IID	independent and identically distributed
EMV-ID	Infectious Disease Equity Market Volatility Tracker
LMICs	Low Middle-Income Countries
M_RATE	Mortality Rate
MSME	Micro Small Medium Enterprises
OLS	Ordinary Least Squares
PEFF	Pandemic Emergency Financing Facility
S&P 500	Standard and Poor 500
SDG	Sustainable Development Goals
SARS	Severe acute respiratory syndrome
SPV	Special Purpose Vehicle
SPX	Standard & Poor 500 Index
STRI	Stringency Index
VAR	Value at Risk
VIX	Implied Volatility
WHO	World Health Organisation

Chapter 1
Introduction

1.1Background of the study

COVID-19 became a global pandemic in March 2020. By November 2020, the WHO reported 50 million new infections and 1.2 million deaths. By 23 May 2023, at the end of the pandemic period, WHO data reflected 766 million new infections and 6.9 million confirmed deaths. These statistics, published in the WHO's *Weekly Epidemiological COVID-19 Update* (25 May 2023), form the backdrop for this study, which investigates how the COVID-19 impacted the JSE.

Understanding the collapse and subsequent recovery of equity market prices following the outbreak is critical for investors' portfolio management decisions and policymakers' strategic planning. Such insights can equip stakeholders with mechanisms for responding to future pandemics. Yarovaya et al. (2022) categorise COVID-19, in line with previous pandemics, as an extreme, rare 'black swan' event. However, other scholars, including Chen et al. (2020) and Rozell (2019) provide empirical evidence indicating increasing frequency and severity in epidemic and pandemic outbreaks.

Table 1.1: New Covid-19 confirmed cases deaths - 21 May 2023

WHO Region	New cases in last 28 days (%)	Change in new cases in last 28 days *	Cumulative cases (%)	New deaths in last 28 days (%)	Change in new deaths in last 28 days *	Cumulative deaths (%)
Western Pacific	1 052 248 (46%)	38%	**203 645 258 (27%)**	1 465 (10%)	9%	**411 885 (6%)**
Europe	572 906 (25%)	-45%	**276 366 950 (36%)**	5 373 (36%)	-44%	**2 237 150 (32%)**
Americas	484 889 (21%)	-41%	**192 775 054 (25%)**	6 655 (44%)	21%	**2 954 027 (43%)**
South-East Asia	146 614 (6%)	-31%	**61 152 597 (8%)**	1 143 (8%)	61%	**805 869 (12%)**
Eastern Mediterranean	26 859 (1%)	-48%	**23 374 087 (3%)**	330 (2%)	-63%	**351 231 (5%)**
Africa	6 835 (<1%)	11%	**9 530 267 (1%)**	19 (<1%)	6%	**175 365 (3%)**
Global	**2 290 351 (100%)**	**-21%**	**766 844 977 (100%)**	**14 985 (100%)**	**-17%**	**6 935 540 (100%)**

Source: WHO Weekly Epidemiological COVID 19 publication to depict the tabulation of pandemic statistics across global regions.

Table 1.1 presents WHO's COVID-19 new infections and mortality data (as at 21 May 2023), summarising the global trajectory of the pandemic. Historically, the world has endured numerous pandemic outbreaks—SARS, the Spanish Flu, Hong Kong Flu, Avian Flu, Ebola, and COVID-19. The COVID-19 crisis magnitude devastated livelihoods and economies across both advanced and emerging markets. Global institutions continue to emphasise the need for pandemic preparedness, indicating that more outbreaks are likely.

Policy makers and investors across the world, are concerned, with: (1) pre-emptive preparation, including prevention measures; (2) treatment regimes, and mitigation strategies to curb the spread of future pandemics, (3) appropriate fiscal and monetary policies along with stimulus packages to counteract the adverse effect on economies and households, and for investors, portfolio allocation decisions and strategies in anticipation of pandemic outbreak events in the future.

In South Africa, COVID-19 first infection was announced on 5 March 2020. Authorities declared a national state of disaster and implemented stringent stringency measures to curb transmission. These measures affected all enterprises through (1) government-imposed restrictions on economic activity, (2) reduced labour capacity due to hospitalisation, and (3) voluntary distancing behaviour rooted in infection anxiety. Restrictions were tightened or eased in response to wave projections or declining case numbers.

On a global scale, financial markets (equities, bonds, cryptocurrencies) experienced significant volatility and sharp downturns driven by fear, herding behaviour, and contagion from interconnected markets (So et al., 2021). Heffernan (1990) defines a financial market as an exchange mechanism involving 'security, expected return, and liquidity'. These instruments are traded by firms in the financial sector.

The three financial markets participants relevant in the present study are (1) issuers of security instruments to raise capital, (2) rational investor who participates in the market to maximise the expected return with necessary liquidity, and (3) regulators (policy makers) who monitors the market efficiency. Subsequent to the initial capital raising instrument issuance, the financial market enables continuous secondary securities trading amongst investors.

Beyond capital-raising events, financial markets facilitate the secondary trading of securities. In South Africa, exchange control laws govern capital flows, typically via structured market platforms. This study focuses on the JSE**,** a key pillar of the financial system.

The JSE comprises 10 industries and 41 sectors, each assigned a code. The distribution of listed firms and their relative market capitalisation is shown in *Table 1.2*.

Table 1.2: Sectoral composition of the JSE

Sector	Firms	% of Firms	Market Cap	% of Market Cap
J500 – Oil & Gas	4	1.1%	0.0	0.0%
J510 – Basic Materials	56	15.8%	35,521.34	15.2%
J520 – Industrials	62	17.5%	39,513.57	16.9%
J530 – Consumer Goods	22	6.2%	58,020.22	24.9%
J540 – Health Care	10	2.8%	4,475.92	1.9%
J550 – Consumer Services	47	13.3%	21,869.38	9.3%
J560 – Telecommunications	6	1.2%	4,603.88	2.0%
J570 – Utilities	0	0.0%	0.0	0.0%
J580 – Financials	126	35.6%	30,179.59	12.9%
J590 – Technology	21	5.9%	39,353.62	16.9%

Source: Author generated table with the sectoral data dated 31 December 2019 extracted from the JSE.

The COVID-19 financial literature intersects with four major financial development hypotheses of (1) Schumpeter's (1912) *supply-led* hypothesis, (2) Robinson's (1952) and King & Levine's (1993) *demand-led* view, (3) Ho, Pham & Nguyen's (2021) *feedback* loop hypothesis, and Perera & Paudel's (2009) *neutrality* view.

While these paradigms differ in causality, all acknowledge the deep interlinkage between finance and economic development. Notably, Machado et al. (2021) find that, across 36 Sub-Saharan countries, adding financial layers does not always enhance economic growth. This complexity bolsters academic interest in how pandemic-induced financial shocks permeate wider economic systems.

Some scholars, including Miescu & Rossie (2021), contend that pandemic shocks cause simultaneous contraction in financial and macroeconomic systems. Others, such as Goldstein et al. (2021), suggest a decoupling occurred during COVID-19 in the United States: real economy shocks did not result in total financial market collapse. Instead, disruptions were transmitted primarily through corporate bond and money markets.

Applying contagion theory, Yaranova et al. (2021) find that media announcements influenced investor sentiment, and pandemic uncertainty disrupted macroeconomic fundamentals via financial markets

From the JSE perspective, Vengesai (2022) attributes COVID-19's transmission primarily to investor psychology—specifically fear, panic, and anxiety. While many studies focus on early-pandemic responses, this study is distinct in examining JSE dynamics over the entire pandemic period**,** as defined by WHO.

The research on JSE dynamic during the pandemic period remains limited. This study endeavoured to expand knowledge on COVID-19's influence on JSE during the full pandemic period as determined by WHO. The literature cited above is reviewed earnestly in Chapter 2.

1.2 Research Problem Statement and Scope

The interface of pandemics, financial markets and the macro economy, presents challenges for policy makers and investors alike. The appropriate asset allocation, stringency measures, monetary and fiscal policy interventions depends on deep knowledge of the extent, severity and recovery of financial market reactions to pandemics.

The study aims to address following problems:

- Understanding financial market reaction to the pandemic induced uncertainty shocks.
- Policy intervention implications for future pandemic outbreaks.

1.2.1 A case for South Africa

Like many other jurisdictions, South African financial markets were devasted by COVID-19 event outbreak. National Treasury economic outlook publication revised economic prospects due to COVID-19. The stark contraction of the economy induced by global pandemic shock and unprecedented government-imposed restrictions to contain new infections was evident. The publication highlighted severe disruptions in financial markets globally, evidenced by extreme volatilities and unprecedented flight to safety capital outflows from developing countries. In the same publication, evidently (1) the South African Rand depreciated by 18.2 % in contrast with other emerging markets at 4.6%, (2) by June 2020 the investor premium on return on assets increased to 5.2% compared to 3.2% in December 2019. Clearly, COVID-19 increased the risk outlook on South African assets.

The lockdown measures resulted in severe contraction across all economic sectors. The important context in this regard, is that South Africa, was already in a period of successive economic decline since the GFC, and this culminated in a paltry 0.2% economic growth in 2019. During the peak of COVID-19, the economy was forecasted to shrink by a further 7.2% with the Business Confidence Index reaching historical lows. With the South African economy peculiar position at the time, there is justification for in depth studies on how COVID-19 affected various aspects of the economy. Faced with the constrained fiscus position, the financial markets' is one of the channels through which the country can attract foreign direct investments. The reaction and recovery of the JSE in response to an external shock of a global scale concerns both investors and policy makers alike. The performance of the ALSI returns against selected independent variables will improve understanding of the financial market and COVID-19.

1.2.2 Literature gaps in the previous studies

COVID-19 brought about significant volatility in the stock markets globally. A significant body of empirical knowledge exists on the adverse impact crises (including pandemics) exert on financial markets. In their review of literature on the same matter, Gormsen and Koijen (2023) explained that stock market prices collapse upon the occurrence of a pandemic due to the risk aversion and investor behaviour theories that indicate reactions to elevated 'risk aversion' and bearish 'investors' sentiment'. However, explaining the classical v-curve swift recovery is particularly challenging especially considering that, globally, the first vaccine approval was in December 2020. Several researchers explored the COVID-19 induced uncertainty shocks impact on financial markets from different perspectives. The body of work is elaborated further in the literature review section.

There, however, still exist a gap in the literature which firstly relates to the causal relationship not being analysed for the duration of the pandemic. Secondly, to the author's best knowledge, no other study has examined COVID-19 impact on the JSE using a quantile regression model. The present study closes that gap by capturing the data for the entire pandemic period. This will assist to identify whether there is a disconnect between the pandemic progression and the financial markets' reaction and recovery. Lastly, to the author's best knowledge, the empirical examination of COVID-19 impact on the JSE on an aggregated basis is limited.

Most studies sought to examine COVID—19 induced shocks from a financial markets' sectoral heterogeneity lens. The motive is to enable investors to alter their strategies towards sectors that are resilient to the pandemic and for policy makers to discriminate the interventions and relief efforts based on the sectors hardest hit. The present study hypothesises an alternative lens that examines the financial market impact on an aggregated basis. In the emerging economy, all the sectors are impacted, the difference relate only to the magnitude. This approach further gives investors the benefits of diversification, especially where there is sectoral composition consist of few companies in total and where there is dominance of few large companies.

1.3 Limitations of the Study

This study, inherently, has limitations. It does not seek to examine the channels through which pandemics shocks transmit to the financial markets. It does not seek to understand the COVID-19 induced shock volatility transmission to the financial markets. Neither does it seeks to examine how government actions to restrict the pandemic contagion spillover to the financial markets. These aspects are studied elsewhere. Instead, this study narrowly focuses on how the pandemic outbreak affected JSE returns and through quantile regression methodology. This question aims to assist policy makers in determining the appropriate measures at their disposal to curtail the pandemic spread, implement fiscal and monetary policies and introduce other stimulus interventions to cushion the economy and the citizens from the adverse impact to the economic. Additionally, it seeks to assist investors make appropriate investment decisions that can be applied for the duration of the pandemic period.

1.4 Study Questions and Scope

Through the quantile regression methodology, the study answers the question:

- How did the COVID-19 induced uncertainty shock impact financial markets return in South Africa?

1.5 Research objectives and hypotheses

The study objective is to:

- Examine the COVID-19 induced uncertainty risk shock impact to the JSE returns over the duration of the pandemic period.

1.5.1 Research Assumptions or Hypotheses

Ho: The COVID-19 induced uncertainty risk shock had an adverse effect on the JSE returns.

This will be tested against the alternative hypothesis:

H1: The COVID-19 induced uncertainty risk shock did not affect JSE returns adversely.

The study thus, aims, to explore how pandemic outbreaks impacted the equities market on the JSE during the pandemic period. The effect dynamic will assist long term investors with relevant diversification strategies and portfolio allocation decisions. The policy makers, in understanding the extent, duration and timing of the stringency measures and appropriate fiscal, monetary and stimulus measures. The value of future studies may create additional viable alternative risk management strategies that can minimise the financial loss impact from business interruptions resulting from pandemic outbreaks.

The author postulates that the financial market losses suffered at the occurrence of the pandemic event are short-lived as found by Gagnon et al. (2023). The financial recovery commences when there is certainty on measures implemented to contain pandemic contagion and the monetary, fiscal and other stimulus interventions.

The next chapter reviews scholarly literature relevant to this study. The first part defines key terms and concepts. Thereafter, literature on historical pandemics outbreaks is reviewed in relation to the likelihood of future pandemic events. Finally, as the literature suggests that there are future outbreaks in the horizon, the impact on financial markets and appropriate methodologies for studying historical pandemics are reviewed.

1.6 Scope and Justification of the Study

The pandemic event generates shocks in financial systems, leading to losses in shareholder value and disruptions to demand and supply value chains. Authorities implement social distancing measures to curtail the pandemic contagion. At the same time, uncertainty among investors creates volatility in financial markets.

The study is limited to exploring COVID-19 transmission to the JSE returns in the long term. The knowledge gained from the study will aid investors in applying suitable asset allocation and hedging strategies during pandemic events. It will also help policy makers to determine suitable stringency measures that do not prolong or induce harm to the real economy during pandemic outbreaks. This study will also open new avenues for future work to assist enterprises in maintaining their sustainability during future outbreaks until supply value chains and demand side disturbances are contained.

1.7Organization of the study

This study consists of five chapters. Chapter 1 introduces the study with the background to build the case for the research question and objectives. Chapter 2 defines key concepts and reviews relevant theoretical frameworks and empirical literature on the pandemic, its transmission to the JSE, the relationship between the fear factor emanating from COVID-19 new deaths, and stringency measures to contain the pandemic.

The history of pandemics literature and financial markets impact is reviewed to strengthen policy considerations. The authorities will have tools for possible interventions in preparation for future pandemics. Chapter 3 discusses the research approach, research philosophy and research methods applied. It also clarifies the variable of interest, exploratory variables, their measurement and data sources. Chapter 4 presents empirical results, while Chapter 5 summarises key conclusions, policy recommendations, and proposals for future explorations.

Chapter 2
Literature Review

2.1 Introduction

This chapter defines key concepts relevant to the study and explores literature on the history and future of pandemics, the effect of pandemics on financial markets, theoretical foundations, and empirical findings. The discussion culminates in an appraisal of the quantile regression methodology employed in the present research to assess market reactions to COVID-19 shocks.

2.2 Definition of terms

2.2.1 Pandemic

Morens et al. (2009), citing WHO, define a pandemic as a geographically widespread infectious disease outbreak resulting in ‘morbidity and mortality’ and causing substantial ‘economic, social, and political disruption’. The World Bank similarly frames pandemics in terms of the expected maximum impact on human lives and economic structures.

2.2.2 Financial markets

Heffernan (1990), adopting a characteristics-based definition, describes financial markets in terms of ‘security, expected return and liquidity’, and identifies them as mechanisms for exchanging financial products issued by firms in the financial sector. This study specifically examines the All Share Index (ALSI), an equities market platform on the JSE.

2.3 The History, Future, Frequency and Severity of Pandemics Outbreaks

Although this study does not forecast the timing of future pandemics, past patterns of frequency and severity provide a useful foundation for anticipating possible outbreaks. Major historical pandemics include the 1918 Spanish Flu, 2003 SARS, 2019 COVID-19, and the 2022 Mpox outbreak. Scholars such as Chen et al. (2020) and Rozell (2019) suggest modelling forecasts more such outbreaks in future.

Supporting this, Jones et al. (2008) and Morse (1995) identified a rising trend in pandemic frequency and severity. Morse et al. (2012) noted global ecological and social factors contributing to the proliferation of infectious diseases. The WHO, recognising this trend, launched its Blueprint for 'Disease X' in 2018, aimed at anticipating emerging pathogens and bolstering global preparedness.

Biological risks such as bioterrorism, laboratory accidents, and environmental degradation are among the additional triggers flagged by Dodds & Dodds (2019), citing examples such as the 1979 Sverdlovsk anthrax leak and deliberate outbreaks like the 1984 salmonella release in Oregon.

Numerous researchers, especially in science and medicine fields, have generated a significant body of knowledge on prediction and prevention of future pandemic outbreaks. Bartlett and Hayden (2005), Bickis and Bickis (2007), Wolfe (2009), and Morse et al. (2012) are all interested in pandemics work aspects. Similarly, the "pandemics modelling" studies of Rozell (2019) and Chen et al. (2020) agree with the world authorities that the "frequency" and "severity" of pandemic outbreaks is on the rise. Dodds & Dodds (2019) identifies the human behaviour that increases human-wildlife interaction as the driver of the "frequency and severity" of pandemic and epidemic outbreaks.

Additional determinants, according to Dodds & Dodds (2019), include "bioterrorism, biological warfare, and accidents". Dodds & Dodds (2019 cites (1) the University of Wisconsin and Erasmus MC laboratories' success in transmitting H5N1 to mammals, (2) the Sverdlovsk military laboratory accidental release of anthrax in 1979, (3) the intentional release of salmonella in Oregon by Bhagwan Shree Rajneesh in 1984, and (4) the Arum Shinrikyo cult followers intentionally spraying anthrax in Tokyo. Additionally, Morse (1995) and Jones et al. (2008) identified global interconnectedness, mobility, human-wild animals' interface and the degradation of natural environments as drivers that propel proliferation, frequency and severity of pandemics.

In our globally interconnected world, the 'spark risk' of a pandemic can escalate rapidly due to cross-border human mobility. Thus, while the timing of future outbreaks remains uncertain, policymakers and researchers are increasingly focused on crafting strategies that balance infection control with economic continuity.

2.4 Asset Pricing Theory and Capital Asset Pricing Theory Literature

This study investigates the pandemic events shocks exerts on financial markets. The investor perspective when responding to the pandemic shock draws attention to (1) stock market returns expectations, and (2) investor behaviour during the pandemic crises or shocks. From a pricing perspective, the APT attributes asset returns dynamic to macroeconomic factors and associated sensitivities (betas). On the other. CAPM attributes systemic risk as the primary determinant of asset performance and that non-systematic risks are not rewarded.

This study uses CAPM to calculate log-normal returns. From a behavioural lens, Enow (2022) used a Threshold GARCH model and found asymmetric investor reactions across JSE sectors, signalling inefficiencies. While this may deviate from Fama's (1965) Efficient Market Hypothesis (EMH), EMH still underpins the study's assumption that investor responses to pandemic information are reflected in stock prices.

Liu et al. (2020) and Burns et al. (2006) also observed delays in decision-making – referred as investor hesitancy. Previous pandemics like Ebola (Ichev & Marinč, 2018), SARS (Chen et al. 2009), and Avian Flu (Bloom et al. 2018) exhibited either minimal or short-lived impacts on market returns.

The CAPM's key assumption is that systemic risk is the sole determinant that affects the performance of the market. In this regard, an investor that holds a company specific or non-systematic risk is not rewarded for taking the specific risk position. The CAPM assumption, unlike the APT, does not offer the investor the opportunity to diversify the investment portfolio. Consequently, the log normal returns of the financial markets to be used in the study are determined based on the CAPM model.

With respect to investor behaviour during a pandemic, Enow (2022) used the Threshold GARCH model to study overreaction and underreaction in six main sectors of the JSE during the COVID-19 pandemic. Enow (2022) found an "asymmetric pattern" suggesting existence of market inefficiencies. Fama's (1965) efficient market hypothesis was juxtaposed against empirical observations of investor behaviour in decision making when information related to the pandemic outbreak, transmission, hospitalisation, mortality, and vaccination programmes became available. Notwithstanding Enow's (2022) findings, the classical EMH theory is the basis for understanding how pandemic information influences investor reaction to stock markets volatility. Additionally, Liu et al., (2020) suggest that when faced with uncertainties from a pandemic outbreak, investors delay investment decisions.

Similarly, Burns et al. (2006) observed that investor decision making is delayed until market recovery begins. The resultant supply and demand imbalances cause downward adjustments to stock returns. The COVID-19 pandemic was preceded by many other epidemiological outbreaks. Empirically, Vengesai (2022) cited Bloom et al. (2018), Del Giudice and Paltrinieri (2017) as well as Ichev and Marinč's (2018) Ebola impact on stock markets returns in various jurisdictions and found the impact, in the main, to be statistically insignificant. With SARS pandemic, Chen et al. (2009) found an inversely related returns in consumer sectors in Taiwan. The mortality rate is presumed to be the ultimate proxy for the fear generated by the occurrence of a pandemic.

2.5 Empirical Literature

2.5.1 Introduction to Empirical Literature

This subsection discusses perspectives of different authors on the impact of pandemic outbreak shocks as they are transmitted to financial markets. The first perspective is on the history, frequency and severity of pandemic events. This perspective is essential in understanding whether pandemic outbreaks are extremely rare "black swan" events that are mitigated by both investors and policy makers. The second perspective highlights how asset pricing theories become pertinent in understanding how systemic risks, pricing equilibrium disturbances and investor behaviour are affected by shocks emitted by the pandemic events.

The third perspective explores the literature on empirical evidence on financial markets and historical pandemics. Most literature focuses on the immediate aftermath of an outbreak, while literature covering the entire pandemic duration is limited. The fourth aspect reviews literature on COVID-19 impact on the JSE. Finally, from a methodological perspective, the literature on quantile regression is reviewed.

This study offers an alternative view on pandemic dynamic on the JSE, first by applying a different methodology (quantile regression) compared to previous studies that used ordinary least squares approaches. Secondly, it examines the impact over the entire pandemic period, including subsequent waves compared to limiting the analysis to the first few months, as explored by previous studies.

First, Gormsen and Koijen (2023) in their literature review post the pandemic observed that the pandemic exerted “transitionary shocks” to the financial markets. In seeking to explain the sudden recovery of financial markets, some researchers, including Nemec and Špaček (2020), Ashraf (2020) and Wei and Han (2021) explored the link between monetary policy, fiscal policy interventions and financial markets. However, such responses do not account for the lag within which the interventions transmit to the economy. Additionally, while the stimulus monetary policy measures were expected to preserve the economic activities, the stringency measures disturbed supply value chains and dampened consumer demand.

Traditional risk aversion and investor behaviour theories do not appear to adequately account for financial markets significant recovery after the initial collapse. The studies of He et al. (2020), Vengesai (2022), Liu et al. (2020), Zhang et al. (2020), Baker et al. (2020), Cepoi (2020), Ashraf (2020), Ullah (2023), Chomba (2021), Sansa (2020), Azimli (2020), Zeinedini et al. (2022), Assifuah-Nunoo et al. (2022) examined COVID-19 impact in the immediate aftermath. Secondly, the studies investigated asset classes that could offer a refuge haven to the investors. Because these studies addressed the immediate aftermath of the pandemic induced. the subsequent recoveries in various jurisdictions were omitted in the analyses.

Yarovaya et al. (2022) used a unit root test to analyse market reactions and subsequent recovery, but that study does not explore the motivating factors that re-ignited the recovery or whether the recovery is persistent. Furthermore, Yarovaya et al.’s (2022) analysis was only limited to China and did not capture the developments in other jurisdictions.

The present study, in South Africa, extends the pandemic period under examination, applied quantile regression methodology and aggregates the JSE. Future studies can explore the determinants of financial markets' sudden recovery reactions in relation to the traditional theories on investor behaviour and macro-economic policies lag.

The causal relationship between financial markets and pandemics outbreaks continue to interest many researchers since the Spanish flu pandemic. Baker et al. (2020) examined shocks on stock markets caused by COVID-19, reviewing historical data dating back to the early 1900. They found no evidence that attributed daily large market volatilities to the new pandemic related information. Baker et al. (2020) included the Spanish Flu that recorded deaths which far exceeded those of COVID-19 at the date of their study. The authors further cited Barro et al. (2020) who also noted that "the influenza pandemics of 1957-58 and 1968" recorded "excess mortality rates" that far exceeded COVID-19 in the USA.

Similarly, with 1985 data, Baker et al. (2020) evidence did not show the pandemic significantly impacting USA stock markets. Baker et al. (2020) contrasted fatalities count endured at each previous pandemic and epidemics with the stock markets daily returns volatilities and observed that daily returns in the COVID-19 pandemic era were extremely sensitives to the new information on the pandemic fatalities trajectory during the study period juxtaposed against previous pandemics. Baker et al. (2020) further found SARS in 2003 and Ebola in 2015 recorded insignificant "short-lived" volatilities, and the Avian Flu and Swine Flu epidemics did not show any effect of significance.

On analysis of empirical evidence on the same subject, Chomba (2021) observes that the empirical body of knowledge on the subject matter is dependent on the hypothesis and the "perspective" studied by the researcher. On the SARS 2003 outbreak, Chomba (2021) cited Chen et al., (2007), Nippani and Washer (2004), and Loh (2006) on the findings above. Nippani and Washer (2004) found SARS to have influenced adversely just China and Vietnam from a sample of eight countries under investigation. Finally, Loh (2006) found airline stocks in Singapore, Canada, Thailand, China, and Hong Kong experienced adverse effects, but the overall stock market was less volatile.

The COVID-19 induced shock transmission to economy raises significant concerns for policy makers and investors. The initial COVID-19 literature studied the effect on equity markets, with a peculiar focus on daily volatilities influenced by information transmission as the pandemic develops. This strand of research emphasised behavioural finance theory including, panic, fear and investor herding behaviour.

Early research tracked the new infections, transmissions to other countries, and fatality announcements through various platforms. In this regard, Zhang, Hua and Ji (2020) examined the systematic risks sparked by COVID-19 in twelve sovereign and observed that stock markets reaction was determined by the outbreak “severity” in each specific country.

Similarly, Bai et al. (2021) from a contagion perspective, expanded the investigation to study the volatilities of global stock markets fifteen- year period ending on April 2020. The authors found that recent pandemic outbreak impacts can be significant and positive, however, the different policy makers’ responses yielded different stock markets reactions. Bai et al. (2021) only studied COVID-19 from December 2019 to 30 April 2020. The present study differs from others since it covers all the COVID-19 waves as it seeks to understand the impact on the JSE from March 2020 to May 2023.

Cepoi (2020) further explored the role of news dissemination approach through a panel regression model, examining how news information influenced COVID-19 influence in Germany, USA France, United Kingdom, Italy and Spain. Cepoi (2020) assessed how investors responded to pandemic information and the study found inconsistent correlations. The author thus highlighted the importance of credible, official information dissemination channels to facilitate informed investor decision-making.

The subsequent literature progressed to assess how pandemics shocks affect financial markets in relation to fiscal policies, macroeconomic policies, and monetary policies.

Ashraf (2020) confirmed the existence of an adverse relationship between daily equity market movements and daily reported COVID-19 deaths in 64 countries. The study found a statistically insignificant influence COVID-19 deaths exerted on financial markets. The author concluded that while financial markets volatilities reacted instantaneously to the outbreak, as the pandemic progressed, the extent of impact was determined by the pandemic severity.

Wei and Han (2021) studied COVID-19 and monetary policies in thirty-seven countries' financial markets covering from January 2011 to 30 April 2020 for traditional and non-traditional (stimulus packages) monetary policies. The study found that the monetary policies implemented in the COVID-19 era had statistically weak effects on four indicators that were under consideration. The pandemic weakened the monetary policy interventions strength in financial markets.

From a different perspective, He et al. (2020) used "conventional t-tests and non-parametric Mann–Whitney tests" in Western, European, and Eastern economies. COVID-19 had an adverse effect in financial markets performance in the studied countries. He et al. (2020) cited the studies of Ciner (2021), Czech et al. (2020), Haroon and Rizvi (2020), Mirza et al. (2020), Sansa (2020) and Zhang et al. (2020.) emphasized the point that although relationship exist, however caution need to be exercised due to limited time series data observations. In addition, Just and Echaust (2020) and Tahat and Ahmed (2020) supported this observation and made recommendations that studies in future should increase the time series period for results that can provide accurate statistical indications. This study is responding to this gap by extending the observation to cover the full 179-week period.

Louaas and Picard (2020) observed that COVID-19 affects different sectors in a "heterogeneous" manner. The stocks listed on the CAC40 showed that while some economic sectors suffered significantly, others benefited considerably during the pandemic outbreak. Louaas and Picard (2020) thus built a model that exploits the "heterogeneity" in how various economic sectors react to the pandemic event.

Sansa (2020) study on Chinese and American markets found COVID-19 infections had a statistically significant influence. However, Sansa (2020) faced limitations with the risk of variable bias, as only two variables formed part of that study. Additionally, the study only covered twenty-five days, omitting observations for the remainder of the pandemic period. Zhao et al. (2023) study on the similar variables in emerged and emerging economies, found that the pandemic was transmitted to these markets differently. The main channels of COVID-19 transmission for emerged economies were the "economic criteria" and "social criteria" in developing economies.

For South African financial markets (equities), this study explores COVID-19 impact on JSE performance for the benefits of the policy makers and investors' decision-making processes. The ALSI consists of 99% firms listed on the JSE. The Index Rules provide that companies' eligibility is reviewed quarterly. Empirically, Chomba (2021) used examined COVID-19 effect on enterprises that constitute the FTSE/JSE Top 40 index and found evidence of volatility and abnormal adverse returns for most equities under examination. The author attributes the negative returns to government stringency measures and pessimistic investor sentiments.

Akinola et al. (2021) adapted D'Orazio and Dirks' (2020) fixed effect model through a panel data regression method to examine how reported daily infections affected the stock exchange market return of twenty JSE listed companies from November 2020 to January 2021. This study targeted the first wave post the initial outbreak in March 2020 in South Africa. The study found a positive directional movement for officially reported cases and stock market prices.

Similarly, Vengesai (2022) found a heterogeneous positive relationship between the selected economic sectors due to the search for "safe haven" and citizens stimulus relief support measures. Vengesai (2022) reviewed the literature of Hung et al. (2021), Baker et al. (2020), Al-Awadhi et al. (2020), Yilmazkuday (2021), Ngwakwe (2020), He et al., (2020), Takyi and Bentum-Ennin (2021), Hatmanu and Cautisanu (2021), Yan and Qian (2020), and reached an overall conclusion that, empirically, COVID-19 impacted stock markets in an inconsistent and unconvincing manner.

The major drawback of the studies cited above, in relation to the area of interest, is that the study period only covers a short-term period, (first few weeks or months) after the pandemic event. The current study seeks to understand the causal relationship over the duration of the pandemic period. Two exogenous factors, however, influenced the financial market during the pandemic period: (1) subsequent pandemic waves, and (2) the intervention of the policy makers through stringency measures and relief packages. Importantly, the stringency measures were tightened or relaxed based on the pandemic dynamic. The study does not seek to determine the "treatment effect" of the stringency measures. That concept is examined elsewhere; however, the present study included the stringency index as the control variable.

To address this drawback, a few authors increased the period of study to cover more months after the initial outbreak. Assifuah-Nunoo et al. (2022) increased the study period to May 2021, Ullah (2023) to December 2020, Zeinedini et al. (2022) to January 2021, Sharma (2022) to May 2021 and Ampofo et al. (2023) to February 2022. These studies still have a pandemic period gap since they still do not cover the entirety of the pandemic period, however, their appeal includes the fact that with the longer study period, the dataset was collected is time series and the methodology used is quantile regression. These two features align with the present study.

Ullah (2023) longer time series for daily market returns (1 January 2020 to 12 December 2020) examined COVID-19 effect on both emerged and emerging countries bearing the brunt of the pandemic. In the study, Ullah (2023), from a methodological view used the estimated generalised least square regression and quantile regression models. Both Ullah (2023) and this study address the "central limit theorem" biased methods that are applied by most researchers. These OLS methods disregard the view of Kuan et al. (2012) as cited by Ullah (2023), that the independent variables relate differently with market returns at different quantiles.

Assifuah-Nunoo et al.'s (2022) study through the quantile regression methodology, closely examined whether crude safe haven status amid the COVID-19 in selected African countries. On the other hand, Sharma (2022) focused on commodities' financialisation in COVID-19 and the GFC periods developed countries and developing countries. With the commodities and global stock markets, Sharma (2022) found asymmetrical structure.

In Iranian stock markets, Zeinedini et al. (2022) found that gold had an insignificant relationship with COVID-19, while crude oil had a significant negative relationship. Ampofo et al. (2023) found investor anxiety caused panic behaviour in the UK and USA markets. Wang et al. (2025) found severe adverse COVID-19 induced shock impact in Taiwanese stock market. This influence diminished subsequently and the nature of the structure and dependency characteristics changing over-time.

Evidently, from the studied reviewed, there is limited examination of the COVID-19 impact for the duration of pandemic period. Regarding crisis events and financial markets, only Naifar (2016) demonstrated that Global Islamic index dynamics (co-movement and dependency structure) against certain financial markets and real economy changed during global shocks, such as the GFC in 2008. In the same study of 58 equities, Naifar (2016), found a complete transformation from left-tailed to right-tailed structure “asymmetry dependence” in emerging economies evidencing strong decoupling from the global stock index.

Within the quantile regression methodology context, Yarovaya et al. (2022) applied quantile unit-root tests for “return persistence” to study how financial markets asset classes from 17 April 2018 to 20 June 2020 reacted to extreme shocks (including COVID-19) and subsequent recovery. The stock indices studied by the authors were in the Asian, American and European markets in contrast to this study which focuses on the FTSE/JSE ALSI and S&P 500. Yarovaya et al. (2022) aimed to examine whether the shocks have a “permanent effect” that accumulates and causes a “stochastic trend” suggesting that movements of the asset classes have a “nonstationary and non-mean-reverting” unit root. The alternative hypothesis tested by the authors was that the shocks have temporal effects (stationary and mean-reverting) and are offset by future opposite directional shocks. The study found “heterogeneity in reactions and recovery patterns” crosswise and within different asset categories. The equities markets displayed strong “mean reversion” characteristics, notwithstanding the magnitude of the shock.

Unlike this study, Yarovaya et al. (2022) excluded developing economies. This study applied the quantile unit root test approach focussing on Africa’s major stock market. Further, according to Salomons and Grootveld (2003), empirical evidence suggests that the investors’ behaviour towards emerging markets is different to that towards emerged markets, especially concerning the concept of “flight to safety” in times of crisis. According to Omane-Adjepong and Alagidede (2021), there was no evidence that precious metals offered a “safe-haven” for investors. Tahatet al. (2021), however, found that emerging economies’ stock markets faced ‘risk aversion’ consequences and the effects of emerged markets contagion phenomenon.

Table 2.1 shows the reviewed literature on quantile regression in a time-series dataset setting with crisis events’ impact on asset returns as an area of interest, and shocks (crisis) effects.

Table 2.1 Review of literature on COVID-19 and other crises impact on financial markets (quantile regression)

Study	Purpose and jurisdiction	Data type	Methodology	Key results
Assifuah-Nunoo et al. (2022)	Oil haven status during a pandemic shock	02 January 2020 to 06 May 2021	**Quantile regression**	Crude oil was not a refuge in oil-exporting
Zeinedini et al. (2022)	Global oil and gold prices	Daily global oil and gold prices data from 20 February 2020 to January 2021	**Quantile regression**	The study found a general insignificant impact on gold prices, however significant adverse effect on the oil prices was observed.
Sharma (2022)	Compared commodities between two recent crises (GFC and pandemic)	Daily data from 07 July 2008 to 6 May 2021	**Quantile regression**	asymmetric dependence structure
Azimli (2020)	Studied "dependence and structure" of risk and return relationship	01 January 2020 to 31 March 2020	**Quantile regression**	Risk return dependency and structure differed in different quantiles.
Ampofo et al. (2022)	Investor herding behaviour	5 December 2017 to 28 February 2022 for USA and 9 January 2018 to 28 February 2022 for UK	**Quantile regression**	Herding behaviours were found in certain quantiles
Naifar (2016)	Global Islamic index dynamics (co-movement and dependency structure) against 58 equity markets during times of financial crisis		**Quantile regression**	Left=tailed structure changed to a right-tailed "asymmetric dependence" during GFC.
Yarovaya et al. (2022)	Studied "return persistence" on different asset classes	17 April 2018 to 20 June 2020	**Quantile unit root test**	heterogenous dynamic across and within asset classes.
Chirila and Chirila (2015)	Explored financial markets stability after the onset of crises	Central and East European countries	Quantile regression	The study found that financial markets in the selected counties behaved differently under normal market conditions when compared to extreme conditions

Some studies used traditional regression methods COVID-19 impact on financial markets. Table 2.2 below summarises the literature on these studies. Future studies may explore the appropriateness of different methodologies in terms of effectiveness, robustness and power when analysing the impact of pandemic events and other shocks in financial market systems.

Table 2.2: Literature review on COVID-19 and other crises impact on financial markets (other methodologies)

Study	Purpose and jurisdiction	Data type	Methodology	Key results
He et al. (2020)	Analysed COVID-19 impact on daily stock returns	1 June 2019 to 22 March 2020	Conventional t-tests and non-parametric Mann–Whitney tests	COVID-19 exerted negative influence on financial market returns
Vengesai (2022)	COVID-19 impact on sector returns on the JSE	all the ten sectors of the JSE from March 2020 to February 2022.	Autoregressive Distributed Lag (ARDL) model estimated with a Pooled Mean Group estimator	In the short-run, COVID-19 impacted the different sectors on the JSE differently (heterogeneity effect).
Liu et al. (2020)	COVID-19 and stock markets in 20 countries	20 December 2019 and 18 March 2020	Event study	COVID-19 negatively impacted stock returns
Zhang et al. (2020)	Financial markets and COVID-19 in selected jurisdictions	27 January 2020 to 27 March 2020	Minimum Spanning Tree Analysis	The study found that global financial market risks increased substantially and. individual stock market reactions were country specific – dependent on COVID-19 severity.
Bai et al. (2021)	Effects of pandemics on volatility of USA, China, UK and Japan stock markets from	January 2005 to April 2020	Extended GARCH-MIDAS model and Infectious Disease Equity Market Volatility Tracker (EMV-ID)	Pandemic outbreaks can have “significant positive impact on present permanent volatility of international stock markets” however because of differentiation in policy makers responses to the pandemic due to heterogeneity effect of the event
Cepoi (2020)	determinant of the relationship COVID-19 against stock market returns in America and selected European countries		a panel regression model	Inconsistent correlation between news on COVID-19 and stock market returns
Ashraf (2020)	COVID-19 deaths and financial markets in 64 countries	22 January 2020 to the 17 April 2020	a panel pooled ordinary least squares regression	Statistical insignificant relationship between financial market returns and new COVID-19 deaths
Wei and Han (2021)	COVID-19 and the transmission of monetary policy	1 January 2011 to 30 April 2020	event study approach	monetary policy interventions implemented after the COVID-19 outbreak had statistical insignificant effects

	interventions to the financial markets			on all four financial market indicators under consideration
Ullah (2023)	COVID-19 impact on daily returns on emerged and emerging economies	1 January 2020 to 12 December 2020	panel estimated generalized least square and quantile regression approach	COVID-19 infections influenced market returns adversely. COVID-19 mortality had an insignificant positive impact on markets returns in developing economies
Chomba (2021)	COVID-19 on the FTSE/JSE Top 40 index		event study methodology	volatility and abnormal adverse returns for most equities
Sansa (2020)	COVID-19 impact on SSE and New York Dow Jones	1 March 2020 to 25 March 2020	Simple Regression in Double Log and Semi Log Linear models	COVID-19 infections against financial markets studied
Akinola et al. (2021)	COVID-19 daily infection on twenty JSE listed firms	November 2020 to January 2021	Fixed effect model through a panel data regression method	positive co-movement between COVID-19 infections and stock market values
Zhao et al. (2023)	COVID-19 on financial markets			COVID-19 transmit to developed economies through the “economic criterion” and, “social criterion” in developing economies

2.6 Chapter Summary

The literature review chapter defines some of the key concepts and conceptualises the key terms related to pandemic risk and financial markets. The section highlights the history of pandemics, examines COVID-19 induced shocks on financial markets literature, and specifically reviews literature on how COVID-19 influence the JSE equities market. Additionally, literature from a methodological perspective is reviewed.

Chapter 3
Methodology

3.1 Introduction

This chapter outlines the research approach, philosophical underpinnings, and methods employed to address the research questions and achieve the study's objectives. It details the variable of interest (ALSI returns), explanatory variables (including COVID-19-related data and global/macro-financial indicators), and the rationale for adopting quantile regression.

3.2Research Approach

The study adopts a positivist philosophical stance, utilising the hypothetico-deductive model to test pre-stated quantitative hypotheses. Quantitative methods support systematic inquiry, comparative measurement, and hypothesis validation — appropriate to the study's measurable variables and reliance on statistical analysis. Park et al. (2020) stress the value of internal rigour in positivist models, although Bergmann (2023) notes they may not explain generative mechanisms such as context and process. Recognising these limitations, the author employs a quantile regression framework to assess ALSI returns across multiple points in the distribution, offering a robust view of market response dynamics.

Whilst acknowledging the strength of the quantitative methodology "to distinguish correlation from causation," Bergmann (2023) acknowledges that it may not be "sufficient for understanding generative mechanisms" as they are dependent on "process, contexts, and underlying conditions". The author of this study acknowledges that the severity of the pandemic's progression can be affected by existing preparedness protocols, the capacity of health infrastructure and the ability of authorities to trace, monitor and correctly report all cases. Nevertheless, the study exclusively utilises the quantitative methodology, specifically utilising the quantile regression framework.

Bergmann (2023) further explains that within the positivism paradigm, the causality between the controlled variables is examined to produce new knowledge or to develop the scientific theory that confirms the world view (ontology) from a “facts” perspective. Thus, the episteme pandemic induced shocks on financial markets and the measurement of factual data of historical performance, as well as statistical analysis and inferential conclusions, emanate from the causal relationships between variables that are being studied.

In formulating the research strategy, in conformity with the traditional positivism paradigm, the study applied the quantile regression statistical analysis. Park et al. (2020) indicate that the key attribute that renders the positivism paradigm acceptable in scientific, business management and social studies is the objective approach to examining the assumed knowledge. This includes ontological and epistemological philosophy, methodology, data collection (source and sample size) and validation, all of which remain free from any external biases, including those of the researcher.

The author of this study sought to leverage this objectivity, as well as the internal validation and rigor of the positivist stance, to improve the acceptability of the outcomes. Park et al. (2020) highlight that the “degree of internal validation mechanism in the positivist paradigm is positively correlated to the extent of the rigor.” They further identify several threats to the rigor, including “maturation”, “history”, “participants attrition”, “statistical regression”, and “interaction between selection and maturation,” all of which are relevant to this study. It is in acknowledgement of the threats that the author adopted the quantile regression framework because it provides a comprehensive view of the data points across all quantiles.

3.3Research Design

The study uses a descriptive and correlational design to explore relationships among variables, supported by normality, collinearity, and model-fit tests. This design enables a data-driven examination of COVID-19’s influence on JSE returns. Various tests are performed including normality, collinearity, rank scores and goodness of fit. These tests enable the author to characterise the dataset and to draw conclusions relevant to the hypotheses introduced in Chapter 1.

3.3.1 Sample size and data source

The severity of the transmission in the long term, this study sought to assess whether JSE stock market returns demonstrate resilience against extreme shocks from pandemics. The does not seek to predict future pandemic events. The study seeks to empirically analyse the relationship between extreme pandemic uncertainty risk shocks on the JSE. While the pandemic was officially declared on 11 March 2020, WHO classified COVID-19 as a health crisis in January 2020. Accordingly, the data was collected at weekly intervals of 179 weeks ending on 04 Amy 2023.

Figure 3.1 graphically depicts the timeline of COVID-19 from the moment the WHO Health Crisis Committee announced a pandemic state from 11 March 2020. On 04 May 2023, WHO lifted the pandemic state. The South African authorities responded by implementing a 5-level risk adjusted strategy, with the first hard lock down (essentially level 5) enforced on 26 March 2020. On 04 April 2022, South Africa terminated officially the State of Disaster. The pandemic's notable spikes in COVID-19 transmission are shown as the First to Fourth waves.

The dataset covers the pandemic phase of COVID-19. Figure 3.1 indicates that the pandemic lasted about 165 weeks, according to WHO declarations. Even though, the pandemic was officially declared over on 04 May 2023, all lockdown restrictions in South Africa had already been lifted on 04 April 2022 when the state of disaster was terminated. Despite South African economic activities resuming fully without any restrictions for a 13-month period, this study examines the full 179-weeks of the pandemic state.

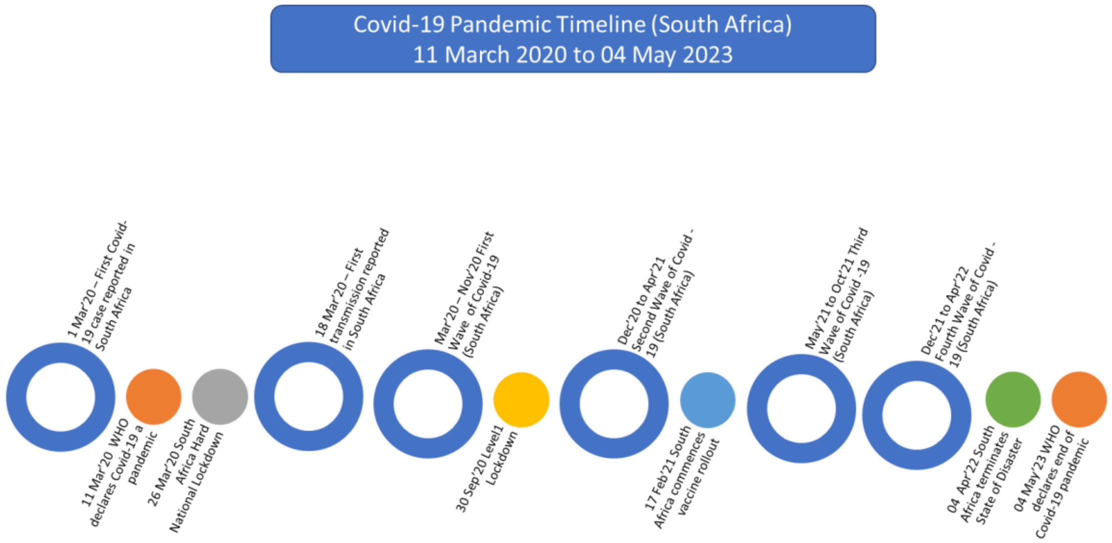

Figure 3.1: COVID-19 Pandemic progression

(Source: Author generated)

The depiction of the initial to fourth wave events in Figure 3.1, is aimed at capturing the entire pandemic period which commenced in March 2020 and ended in May 2023. The author suggests that it is in the best interest of policy makers and investors to understand COVID-19 impact on the JSE for the full pandemic state duration.

3.3.1.1 Dependent Variable ALSI data

Financial markets broadly refer to platforms where securities are traded. This study examines the relationship between the financial markets—represented by the ALSI—the outbreak of the pandemic, and the ensuing transmission trajectories. The performance of the ALSI during the pandemic is an area of particular interest and thus serves as the dependent variable.

Akinola et al. (2021) examined 20 companies listed on the JSE and found a weak interaction of COVID-19 new infections and stock returns. Their sample selection may have been influenced by the COVID-19 “heterogeneity” effect. Similarly, Vengesai (2022) discovered that COVID-19 uncertainty shock influenced JSE sectors in a heterogeneous manner, in the short term.

The closing price movements in the ALSI comprise monthly returns obtained from MarketWatch Historical Data for the period under consideration. In the quantile regression model, ALSI is denoted as *ALSI*.

3.3.1.2 Explanatory Covid New Infections and Deaths data (Mortality Rate)

The strength of a pandemic outbreak is influenced by its transmission speed both domestically and across borders, until herd immunity level is reached, or a vaccine is developed. In this study, new infections and new deaths are the independent variables. During the pandemic period, at two-weeks intervals, WHO collected and updated information on new infections and deaths per country, globally. The data provided to WHO was sourced from official health and information agencies in the respective countries—such as the NICD in South Africa. The mortality rate (new deaths) is an independent variable in this study, sourced from Our World Data, WHO (2024), which collects the official data supplied by WHO. COVID-19 variables (new infections and deaths) impact on financial markets was explored by Ashraf (2020), Ali et al. (2020), Ullah (2023), and Chomba (2021). All authors, except for Ashraf (2020) found COVID-19 variables related adversely to the returns because of changes in investor sentiments. Ashraf (2020), however, found deaths had statistically insignificant effect on stock market returns.

This study used the South African pandemic mortality rate variable, expressed as the ratio of smoothed weekly new deaths per million to smoothed weekly new infections per million. The accuracy and completeness of the new infections data depend on a country's testing and contact tracing capabilities. Similarly, the accuracy of classifying deaths in the presence of comorbidities poses challenges.

According to Checchi et al. (2005) "excess mortality" represents supernumerary deaths in a crisis period. Consequently, verified COVID-19 deaths plus "excess deaths" accounts for all deaths that occurred during the pandemic period. South Africa tracked "excess natural mortality" from May 2020. COVID-19 data is available when publicly announced by authorities whereas "excess natural mortality" is captured on actual date of death from the National Population Register. As a result, there is a timing difference between death dates and death announcement date.

Several studies indicate that COVID-19 officially reported deaths are substantially understated. Citing Adam (2022), Bradshaw et al. (2022) cites Adam (2022) to provide the substantial understating of COVID-19 global deaths. According to Bradshaw et al. (2022), Adam (2022) stated that the “five million” COVID-19 mortality reported globally is relatively low compared to excess deaths. The estimate of global excess deaths is between ten and twenty million. The similar trend was observed in South Africa. Bradshaw (2022) analysed the “excess natural deaths” recorded in the National Population Register in 2020 and estimated natural causes excess deaths of between 70 000–76 000 compared to 28 000 officially recorded COVID-19 deaths. Based on the intense “spatio-temporal correlation” with COVID-19 infection, authorities in attributes “85–95%...excess natural deaths” to the pandemic.

For this study, the incomplete reporting of Covid deaths does not invalidate study outcome. Empirically, the investor fear is induced by regular media reporting about the pandemic trajectory. Aggarwal et al. (2021) measured the “news chatter” with the Coronavirus Pandemic Index in twelve countries and found that the pandemic fear causes fear and panic where rational investors expect additional market risk premium. It follows thus that the unreported COVID-19 deaths will not have been known to investors to induce the panic or fear. The “excess natural deaths” phenomenon is thus not explored further in the present study. Additionally, this study does not explore whether under-reported new infections and excess deaths contributed to variations in ALSI performance during the period of the study. Future studies may explore this aspect.

3.3.1.3 Government Interventions (Stringency data)

The nexus between the macro-economic variables and financial markets performance is a well-studied phenomenon (see Tsaurai, 2016). Intuitively, authorities’ interventions to contain pandemic transmission negatively impact economic activities, on both supply and demand sides. Gagnon, et al. (2023) studied the pandemic variables impact on “real GDP …. for 90 countries over the period 2020 Q1 through 2021 Q4”. That study found pandemic deaths to have had a statistically insignificant effect on the domestic real economy. The study however found that the implementation and subsequent adjustments of stringency lockdown measures to restrict virus transmission significantly influenced real economy performance. Conversely, the relaxation of these lockdown measures in 2021 expedited the global economic recovery.

Moreover, Gagnon, et al. (2023) found that global trade was the significant channel that caused economic “contagion” across borders. The collapse of international trade proved to be significant even for the countries that had little or no exposure to the pandemic. Kejzar and Velic (2020) explore this issue further by examining whether the complexity of global value chain linkages as a transmitter of the trade collapse. The “severity” of lock downs created extensive demand and supply side shocks. The level of integration among countries in the “global value chain” increased the severity of the real economy collapse, especially in emerging countries.

Empirically, COVID-19 and the real economy relationship was influenced, predominatly, by government actions, with resultant spillovers on both the “demand and supply” sides, according to Gagnon, et al. (2023). Similarly, Saif-Alyousfi (2022) found that stringency measures had a significant adverse effect on financial markets in the USA, UK and the Middle East. Kheni and Kumar (2021) found Covid deaths and stringency measures significantly influenced the Indian financial markets, while Bakry et al. (2022) found inconsistent “investor interpretation” of risks associated with COVID-19 deaths, recovery rates, stringency measures, resulting in country-specific volatility response in financial markets.

The timing of transmission progression, subsequent waves and vaccinations in different economies is likely to affect sentiments, either negatively or positively, in the closely related economies. The Stringency Index data was sourced from Our World Data.

3.3.1.4 Global Financial markets Variables

The COVID-19 outbreak affected the globe, and the South African economy is open and integrated with the world’s economies. When considering variables for examination, like Vengesai (2022), global economy market factors are incorporated into the study. In this regard, Vengesai (2022) cites the study of Korajczyk and Viallet (1989), which internationalised the CAPM and hypothesised “foreign exchange risk and world market portfolio as the sources of global risk”. The dynamics of the transmission progression and the timing of vaccinations in different countries—and the impact this is likely to have on the results—brings forward the spectre of financial markets “contagion” due to globalisation.

The interconnectedness of the global economy results in events in one economy spilling over to others or triggering flight to safety behaviour, usually experienced by emerging economies. Bataineh (2022) further explains similar observations on the “return and volatility spillovers” between the FTSE *ALSI* (UK) and S&P 500 (USA) indices. The study found asymmetric contagion where the shocks in the USA market transfer to the UK market. Although, Baiteneh (2022) study was in the USA/UK geographic setting, the S&P 500 index will shed light on whether, the pandemic induced shocks spillover from USA to the South African market.

Additionally, Yilmazkuday (2023) found a COVID-19 case and S&P500 volatility to relate negatively on a significant scale. Finally, Azimli (2020) observed that COVID-19 altered the S&P 500 sectors returns dependence structure.

This study uses S&P 500 index as a variable to represent the world economy. The data is sourced from MarketWatch Historical Data, presented as opening and closing prices. The study used S&P 500 index log normal returns.

3.3.1.5 Investor fear (Implied Volatility Data)

The theories of economic behaviour, efficient markets, and rational investors suggest that information about the trajectory of new pandemic infections and deaths, influences investor choices in portfolio construction. Intuitively, the well-informed investor will seek safer investment havens. In this study, it is expected that the investor will hold a bearish sentiment about the performance of the asset class upon the occurrence of the pandemic event. The investor’s attitude or sentiment in our study was expressed through the independent variable of implied volatility, as calculated by The Chicago Board of Trading in the S&P 500 futures market.

The high implied volatility (VIX) value indicates investors uncertainty, and lower values indicate confidence in the financial markets. Authors who have sought to explain the relationship between investor behaviour and COVID-19, as reflected in implied volatility, include Grima et al. (2021), who found strong empirical evidence of co-integration between COVID-19, Implied volatility and the volatilities of other jurisdictions’ financial markets, and

Apergis et al. (2023) found implied volatility and high COVID-19 cases to relate positively. Low COVID-19 reported cases had no effect on implied volatility. The VIX information used in this study was sourced from MarketWatch historical data.

3.3.1.6 Macroeconomic Variables (Rand-Dollar Exchange rate and Crude Oil)

The internationalised CAPM includes the global macro-economic factors in the financial markets returns determination. According to Jumah (2013), domestic companies whose revenues and costs are exposed to global markets, will be impacted by changes in foreign currency denominated cashflows. Additionally, the South African economy considers both western and eastern economies as its largest trading partners. In this regard, for this study, the Rand-Dollar Exchange Rate and Crude Oil variables serves as proxies for international macroeconomic factors. Empirical evidence from Beckmann and Czudaj (2022) indicates that the presence of COVID-19 significantly increased foreign exchange currency volatilities, resulting in the accumulation of excess returns. From a crude oil viewpoint, Zhang and Hamori, (2021) found that, in the short term, COVID-19 uncertainties collapsed the crude oil prices, resulting in investors suffering significant losses. Assifuah-Nunoo et al. (2022) found crude oil not providing a “safe haven” in selected African countries’ stock markets.

The weekly Rand-Dollar Rate and Crude Oil data was obtained from MarketWatch historical prices. Table 3.1 shows the source of literature that specifically examined the relationship between each variable examined and the COVID-19 event. For the JSE, van der Westhuizen et al. (2020), in the examination of the spill-overs with currency markets, found evidence of exaggerated two-way contagion flow between the two markets which is driven by a large proportion of active foreign investors on the JSE. The inclusion of the Rand-Dollar Exchange Rate variable assist to understand the dynamic of the spillover from the foreign exchange market to the JSE.

The objective of the summation is to demonstrate that the selected variables, within the context of COVID-19 are of interest to various other researchers, although from different viewpoints.

Table 3.1 Variables description and sources table

		Source literature	Expected sign
		Dependent variable	
ALSI	JSE All share equity index	Akinola et al. (2021), Vengesai (2022).	Negative
		Independent variable	
M_RATE	Mortality rate for fatalities clinically proven to be caused by COVID-19	Ashraf, (2020). Ali et al. (2020), Ullah (2023), Chomba (2021)	Negative
STRI	Level of strictness index	Saif-Alyousfi (2022). Kheni, and Kumar, (2021). Bakry et al. (2022), Gagnon, et al. (2023), Kejzar and Velic (2020)	Negative
		Control variables	
SPX	Standard & Poor Index	Bataineh (2024). Yilmazkuday (2023). Azimli (2020)	Negative
VIX	Implied Volatility	Grima et al. (2021). Apergis et al. (2023).	Positive
EXC	South African Rand-US Dollar exchange rate	Beckmann, and Czudaj (2022).	Negative
BCO	Benchmark for internationally traded oil supplies	Zhang,and Hamori, (2021)	Negative

3.3.2 Quantile Regression Methodology

The present study employs quantile regression methodology because, according to Koenker and Bassett (1978), it preferred because: (1) robust to outliers, (2) it does not make any assumptions about parametric distribution of errors, (3) it is invariant to monotonic transformations, and (4) it enables the covariate analysis on the entire dependent variable (y) distribution. Table 2.1 in subsection 2.5.1 presents the literature of previous studies that used quantile regression in a time-series dataset setting in financial markets, an area of interest where such events generate shocks in financial systems.

This study explores the relationship of FTSE/ALSI index returns (dependent variable), with the independent variables (pandemic outbreak), government stringency measures, global macroeconomic factors, and global financial markets factors in the occurrence of extreme rare events such as pandemics—which empirically have been demonstrated to have a distribution with fat tails and outliers. In sub-section 3.3.1 the author explains the nature of the data that was used to analyse COVID-19 impact on the JSE. In summary, the data is time series in nature and was collected by respective primary data collectors at weekly intervals over the duration of the pandemic period (179) weeks.

This study essentially analyses the “causal and effect” of COVID-19 on the JSE returns. Various models are available to analyse the time series data when examining the “causal and effect” relationship amongst the variables. Moraffah et al.’s (2021) time series dataset can be analysed through various models, depending on the context and the objective of the analysis. The autoregressive and Bayensian Networks models are appropriate for classification, modelling and forecasting in time analysis. However, when conducting causal inference analysis, “causal treatment effect estimation and causal discovery” are appropriate. The present study did not seek to understand the intervention effect but rather sought to discover how the pandemic occurrence influenced JSE returns. The present study was thus set in the context of causal discovery. Regression analysis, in particular, ordinary least squares is widely used in time series data analysis; however, the present study used quantile regression.

It is beyond the scope of this study to contrast different least squares models; however, the quantile regression model is considered suitable in the present circumstances on account of extreme outliers and fat tails associated with pandemic occurrences. Consequently, the justification for using quantile regression in the present study is necessary because OLS based regression models are still very dominant.

The OLS regression model, examines how a dependent variable and independent variable/s vary from the mean of the sample dataset. The OLS assumes homoscedasticity, linearity, and normality of errors and is thus sensitive to outliers and extreme data points. The literature on the frameworks used by several authors to study the pandemic outbreak effects on stock markets performance is highlighted hereunder.

The Gauss-Markov Theorem provides that the “best linear unbiased estimators” in OLS setting holds true when the first six of seven assumptions are valid. These critical assumptions are linearity of coefficients and residuals, no endogeneity between residuals and independent variables, minimal multicollinearity, residuals have a zero population mean and residual is “independent and identically distributed” (IID), i.e., there is no autocorrelation and there is homoscedasticity.

Empirically, Naifar (2016) demonstrate vulnerability of stock market returns to extreme volatility when shocks occur (financial shocks, political events, pandemics). Allen, et al. (2011) observing the shift in the risk management "tail-based risk measures," draws investors' attention to the "lower tails" of abnormal returns distribution due to large losses. Allen, et al. (2011) also point out that the "Central Limit Theorem "and the "normality of covariates" assumption do not hold during extreme events. The OLS model's sensitivity to outliers and extreme data points limits its reliability when analysing data sets with such extreme values.

Even though the OLS regression model is widely used amongst statisticians, a significant body of literature exists offering the quantile regression approach to address some of the violated OLS assumptions. Haung et al. (2017) summarises how quantile regression complements other linear inferential methods where there is no homogeneity. The quantile regression uses quantiles to provide deeper insights of the entire outcome distribution as it "quantifies the heterogeneous effects of the covariates". Where the sampled data is characterised by asymmetries and fat tails, as is expected with the occurrence of pandemics that disturb normality in the financial markets, the median (the 50th percentile) is accepted as a superior centrality measure compared to the mean. Empirically, there is a growing number of researchers who have utilised quantile regression frameworks to investigate various relationships of interest.

Quantile Regression is insensitive to outliers and is more flexible, as observed by Naifar (2016), because the structure of variables the structure "can be symmetric, asymmetric with a right-tail dependence or a left-tail dependence" as it is not reliant on parametric assumptions. Engle and Manganelli (2004) cite several statisticians and researchers that analysed, applied and extended linear regression models, to accommodate various complexities. These include Koenker and Bassett's (1982) work on "heteroscedastic cases", Portnoy's (1991) study on "nonstationary dependent errors," and Bloomfield and Steiger's (1983) research on "time series models.", Additionally, Amemiya (1982) and Powell (1983) examined "simultaneous equations models," while Powell (1986), Buchinsky and Hahn (1998) focused on "censored regression models." "autoregressive quantiles" were proposed by Koenker and Zhao (1996) and Koul and Saleh (1995). Engle and Manganelli (2004) used autoregressive processes and introduced the CAViaR models. Similarly, Allen, et al. (2011) constructed an equity investment portfolio using quantile regression within the "Fama and French three-factor model" as an instrument to analyse investment and portfolio management.

In the Annual Review of Economics: Quantile Regression 40 Years On, Koenker (2017) reflects on the broaden developments in quantile regression that address many challenges of least squares models. These developments include "binary treatment effects, multiple treatments, concomitant covariates, and interactions", the method of quantiles, nonlinear (in parameters) quantile regression, "nonparametric quantile regression", application in "time-series models", application in "longitudinal data", application in "duration models", "causal models and instrumental variables, errors in variables, missing data, sample selection challenges" as well as in multivariate and functional data. This study applied quantile regression inferential method due to intuitive expectation of "outliers and fat tails" with occurrence of the pandemic shocks.

However, according to Xiao and Koenker (1999), GARCH models are designed for Gaussian conditions. Under the present study context, the pandemic induced uncertainty risk volatility is fraught with heavy tails and outliers.

In the study, ALSI relationship with selected variables is analysed across six quantiles $Q = \{0.05; 0.1; 0.5; 0.75; 0.9; 0.95\}$, inclusive of the median (50%). The quantile regression model is presented as follows:

$$Y = X'\beta + \varepsilon \ with \ Q_y\left(\frac{r}{X}\right) = X'\beta(\tau)$$

where Y represents the independent variable of interest, X a list of independent variables, and $Q_y\left(\frac{\tau}{X}\right)$ denotes the τth conditional quantile of Y, assumed to be linearly dependent on X'.

The distribution function $F(y) = (Y \leq y)$ differentiate a random variable y, while for any $o < r < 1$, $C(\tau) = \inf\{y : F(y) \geq \tau\}$is called the τth quantile of Y.

3.3.3 Measurement and description of variables

The financial markets' resilience in safeguarding investors' assets, notwithstanding the occurrence of extreme pandemic events is an area of interest in this study. Weekly log normal

$ALSI \ \ returns$ represent a dependent variable Y. The return of the ALSI is measured by the expression log $\frac{Month\ Closing\ Value\ -Month\ Opening\ Value}{Month\ Opening\ Value}$ or, $r_t = \log(1 + R_t) \approx R_t$ to approximate a continuous returns.

In accordance with the internationalised CAPM, the world economic factors are represented by the S&P 500 returns (denoted as SPX), Crude Oil (BCO) and Rand-Dollar exchange rate (EXH). The continuous SPX returns are determined in the same manner as ALSI returns as

$r_t = \log(1 + R_t) \approx R_t$.

The Implied Volatility (VIX) input is the "first order difference of the logarithm" determined by CBOE market volatility index and is denoted as VIX. For the Brent Crude Oil variable (BCO), the data is sourced from Nasdaq and oil prices expressed as "first difference of the logarithm" of weekly Brent crude oil prices. Similarly, the Rand/Dollar Exchange Rate (EXH) is expressed as the "first logarithm difference" of the weekly opening and closing exchange rate values.

3.3.4 Estimation techniques

According to Koenker and Basset (1978), a random sample $y_1, y_2, y_3, .. \ , .. y_n$ with the "empirical distribution function" $\hat{F}_y(\alpha) = \left(1/_n\right) \neq \{y_1 \leq \alpha\}$, the "empirical unconditional quantile function" is defined as:

$$\hat{Q}_y(\tau) = \hat{F}_y^{-1}(\tau) = inf\left\{\frac{\alpha}{\hat{F}_y(\alpha)} \geq \tau\right\}$$

Koenker and Bassett (1978) expressed the "quantile as the solution to a minimization problem":

$$\hat{Q}_y(\tau) = argmin_\alpha \left\{ \sum_{i:y_i \geq \alpha}^{n} \tau|y_i - \alpha| + \sum_{i:y_i < \alpha} (1 - \tau)\,|y_i - \alpha| \right\}$$

$$= argmin_\alpha \ \textstyle\sum_i \rho\tau\,(y_i - \alpha)$$

With the check function

$$\rho\tau(\mathcal{Z}) = \begin{cases} \tau\mathcal{Z}: & \mathcal{Z}\geq 0 \\ (\tau-1): & \mathcal{Z}<0 \end{cases}$$

Koenket and Basset (1978) further explain that in "linear dependence on a vector of exogenous variables" (X), the "linear conditional quantile function" can be written as follows:

$$Q_y\binom{n}{k} = inf\{\frac{\alpha}{F_y(\alpha/\chi) \geq \tau}\} = \sum_k (\beta_k(\tau)X_k = X'(\tau)$$

In this study, the pandemic outbreak variables, (mortality rate and stringency measure), global financial markets (S&P 500), key macroeconomic variables (rand-dollar exchange rate and crude oil prices), investor fear factor, represented by VIX. The ALSI returns relationship with independent variables is assessed across six quantiles $q = \{0.05, 0.10, 0.50, 0.75, 0.90, 0.95\}$, including the median (50%).

$ALSI = \alpha + \beta_1 spx + \beta_2 vix \vdash \beta_3 exh + \beta_4 bco + \beta_5 m\_rate + \beta_6 stri + \varepsilon$, at a given $Q(\tau)$.

Thus, the character of the relationship is evaluated on each specified quantile.

The causality of the "dependent" variable with "independent variables" includes covariance, goodness of fit and model significance tests for inference conclusions. Specifically, the Wald Process Test is conducted in line with Engle (1984) who presented the Wald test as $\xi_W = T(\hat{\theta}_1 - \theta_1^0)' j^{11-1}(\hat{\theta}_1 - \theta_1^0)$, and Koenker and Machado (1999) derived the variant of the Wald process as $w_n(\tau) = n\hat{\beta}_2(\tau)^f \Omega^{-1}\tilde{\beta}_2(\tau) \,/\, \omega^2(\tau) \Rightarrow Q^2_{q,n(\tau)}(\tau)$.

3.3.5 Quantile Augmented Dickey-Fuller Unit Root Tests

According to Ryan et al. (2024), 'stationarity', in time series analysis, denotes a "statistical characteristic of a stochastic process" of the data series. The statistical properties are stationary when they remain constant at data collection intervals. Ryan et al. (2024) further explain that statistical characteristics of the data or sample distribution being analysed enables the researcher to draw certain statistical inferences on the entire population. The stationary or weak stationarity of statistical properties (mean and/variance) over time improves reliability of model outputs, predictions and interpretability. Baumöhl and Lyócsa (2009) advance the view that where non-stationarity is present and not treated appropriately, the regression "spuriousness" is impacted. Zhao et al. (2023), found that for both emerged and emerging economies, the COVID-19 shock had a heterogeneous effect on financial markets.

Empirically, in South Africa, COVID-19 had three successive waves. The data covers the pandemic period of 179 weeks, representing a time series data set. Accordingly, unit root tests examine the presence of stationarity or non-stationarity due to trends, initial conditions, waves and autocorrelation. Additionally, Bahmani-Oskooee et al. (2020) suggest that classical time-series unit root tests do not exhaust all different shocks impacts at full range of the data set.

Koenker and Xiao (2004) as cited by Bahmani-Oskooee et al. (2020), note that the classical unit root tests perform poorly when data exhibits fat tails and extreme shocks. For this reason, Koenker and Xiao (2004) introduced the Quantile Kolmogorov–Smirnov (QKS) test to address the shortcomings of the classical unit tests, where normal distribution (Gaussian) is violated. Jiang and Chang (2016) argue that a quantile-based approach provides "a more complete inference of the unit root process," exploring the unit root characteristics on different quantiles. Bahmani-Oskooee et al. (2020) suggest that the Koenker and Xiao (2004) QKS is an extension of the standard ADF test. Consequently, this study adopts the standard ADF test, but at each quantile. The ADF test null hypothesis advocates for the presence of the unit root, that is $\alpha = 1$. To infer that the series is stationary, the p-value must be less than the applicable significance level, if the null hypothesis is to be rejected.

The present study examines the causal impact of COVID-19 for the duration of the pandemic period, testing for the presence unit root helps to understand whether the first wave of pandemic outbreak impact is persistent in the financial market prices, whether there is a return to normalcy in line with efficient market theory, and whether the initial impact of the initial shock is accumulated to subsequent pandemic waves. Yarovava et al. (2022) explicate this phenomenon of "shocks with permanent effect" which persist to create a 'stochastic trend' indicating that there is nonstationary unit root and 'non-mean reversion' of asset prices. Where shocks impacts are temporal, either the impact of the initial outbreak shock fades or is offset by future shocks, i.e., subsequent waves. Yarovava et al. (2022) argue that the 'quantile unit root test' is advantageous for examining the ALSI return series over different quantiles to obtain a full picture of the asset return stationarity, as opposed to a single unit root test of the average returns employed in the OLS regression analysis.

3.3.6 Goodness of Fit Statistic

Koenker and Machado (1999) define the goodness-of-fit criterion for quantile regression as $R^1(\tau) = 1 - \hat{V}(\tau)/\, \tilde{V}(\tau)$, an analog of R^2 from the least squares regression. Similar to R^2, Koenker and Machado (1999) in their goodness-of-fit proposal obtain $\beta(\tau)$ by constraining $\tilde{\beta}(\tau)$, resulting in $\hat{V}(\tau) \leq \tilde{V}(\tau)$, therefore $R^1(\tau)$ is between 0 and 1. They suggest that $R^1(\tau)$ is different from R^2 in the that R^2 "measures the relative success of two models for the mean function in terms of residual variance", whereas $R^1(\tau)$ "measures the relative success of the corresponding quantile regression models at a specific quantile in terms of an appropriately weighted sum of absolute residuals."

Chapter 4
Empirical Results

4.1 Introduction

This chapter shows quantile regression output analysis, examining the relationship between ALSI returns and the explanatory variables. First, a descriptive overview of the dataset is presented, then tests for stationarity, regression outputs across quantiles, diagnostic tests for model fit, and a summary of key findings.

4.2 Descriptive Statistics

The variable of interest is the weekly data (during the pandemic period, with a total duration of 179 weeks. The dependent variable of interest is the ALSI return, which represents 99% market capitalisation of stocks listed on the JSE. The control variables include the S&P 500 weekly return, denoted as SPX, and Implied Volatility, denoted as VIX, to represent global financial markets. The macroeconomic variables, Rand Dollar exchange rates (EXH) and crude oil price (BCO) movements, are a proxy of the real economy.

The independent pandemic variables include the mortality rate, representing weekly pandemic deaths (M_RATE), and pandemic transmission control measures, represented by the Stringency Index (STRI). The dependent variable (ALSI returns) measures the depth of the pandemic transmission in the economy, intuitively expected to inform investment decisions in the financial markets. Table 4.1 summarises the descriptive statistics.

Table 4.1: Descriptive statistics

Variable	**ALSI**	**M_RATE**	**STRI**	**SPX**	**VIX**	**EXC**	**BCO**
Mean	0,002	0,023	-0,032	0,002	0,015	0,002	0,003
Std. deviation	0,030	0,025	0,524	0,031	0,181	0,022	0,076
Minimum	-0,151	0,000	-6,917	-0,150	-0,391	-0,056	-0,293
Maximum	0,091	0,104	0,690	0,121	1,348	0,069	0,318
Shapiro-Wilk	< 0,0001	< 0,0001	< 0,0001	< 0,0001	< 0,0001	0,004	< 0,0001
Anderson-Darling	< 0,0001	< 0,001	< 0,001	< 0,0001	< 0,001	0,000	< 0,0001
Lilliefors	0,001	< 0,0001	< 0,0001	0,002	< 0,0001	0,002	0,003
Jacque-Bera	< 0,0001	< 0.0001	< 0.0001	< 0,0001	< 0.0001	0,027	< 0,0001
Observations	179	179	179	179	179	179	179

Note: ALSI is an equity index that represents 99% by market capitalisation of all equites listed on the main bourse of the JSE; (2) SPX = Standard & Poor Index represents an estimated 500 companies trading publicly in the USA stock exchange; (3) VIX = Implied Volatility, which is an indicator of market expectation of the future volatility as it measures market risk and investor sentiment; (4) EXC is used as a measure of South African Rand value against the US Dollar; (5) BCO is a benchmark to measure internationally traded oil supplies; (M_RATE) indicates fatalities clinically proven to be caused by COVID-19, and (7) STRI = index that indicates level of strictness of policy makers' social distancing measures.

Amongst the variables, the stringency measures had the highest median at 0.32. ALSI, SPX and Rand Dollar exchange rate recorded the lowest mean of 0.002. The independent variable of interest, absolute new weekly deaths, had the highest mean of 546 deaths.

4.3 Stationarity/Non-stationarity Quantile Unit Root Tests

Table 4.2 depicts ADF unit root test outputs at specified quantiles. The results in the Table 4.2, with a significance level 0,05, are interpreted as follows: At quantile 0.05 the ADF unit test output results for ALSI, SPX, EXC, BCO, M_Rate and STRI are greater compared to the critical value. Similarly, with higher the p-values against 0.05 significance level, the null hypothesis is accepted. The VIX variable unit value is lower than the critical value. The p-value is also less than the significance level. This indicate the heightened anxiety of the investors during the early onset of the pandemic.

The ADF unit test output at quantile 0.10 for ALSI, SPX, VIX, EXC, BCO and STRI with p-values greater than 0.05, indicate the unit root presence. The ADF unit test output at 0.50 quantile for EXC and M_RATE is greater that the critical values. Similarly, the p-values are higher compared to significance level. The unit root hypothesis presence is accepted. However, for ALSI, SPX, VX, BCO and STRI, the unit root output suggest that the series is stationary.

The ADF unit test outputs are lower compared to the critical value at quantiles 0.75, 0.90 and 0.95 for all variables. Similarly, the p-values are less than the level of significance. Consequently, we accept the alternative hypothesis that the series is stationary.

The present study explored COVID-19 impact on the JSE using a quantile regression methodology. Engle and Granger (1987) introduced the concept of cointegration. The fundamental assumption of least squares regression is that the series or variables under consideration are stationary. If this assumption is violated, inferences from the regression analysis can be spurious or misleading. Cointegration is a possible solution to non-stationarity. Cointegration tests become essential where the data series demonstrate nonstationary characteristics.

Table 4.2: Quantile Adjusted Dickey Fuller unit root test

	Q 0.05/(stationary)/k=2			Q 0.10/(stationary)/k=2			Q 0.50/(stationary)/k=5		
VARIABLE	**α(τ)**	**Critical Value**	**P-Value**	**α(τ)**	**Critical Value**	**P-Value**	**α(τ)**	**Critical Value**	**P-Value**
ALSI	-1,676	-14,216	0,469	-1,823	-3,652	0,560	-4,212	-3,416	0,005
SPX	-6,173	-14,216	0,117	-1,766	-3,652	0,617	-4,872	-3,416	0,000
VIX	-66,800	-14,216	**0,010**	-2,218	-3,652	0,399	-4,049	-3,416	0,009
EXC	-1,178	-14,216	0,603	-0,944	-3,652	0,881	-3,109	-3,416	0,098
BCO	-3,961	-14,216	0,186	-2,844	-3,652	0,175	-3,515	-3,416	0,040
M_RATE	-3,961	-14,216	0,186	4,538	-3,652	1,000	-2,517	-3,416	0,273
STRI	-3,961	-14,216	0,186	-3,41	-3,652	0,073	-4,373	-3,416	0,003
	Q 0.75/(stationary)/k=5			**Q 0.90/(stationary)/k=5**			**Q 0.95/(stationary)/k=5**		
VARIABLE	**α(τ)**	**Critical Value**	**P-Value**	**α(τ)**	**Critical Value**	**P-Value**	**α(τ)**	**Critical Value**	**P-Value**
ALSI	-4,956	-3,421	<0,0001	-5,503	-3,401	0,0001	-5,754	-3,417	<0,0001
SPX	-5,441	-3,421	<0,0001	-6,028	-3,401	<0,0001	-6,32	-3,417	<0,0001
VIX	-5,442	-3,421	<0,0001	-5,999	-3,401	<0,0001	-6,211	-3,417	<0,0001
EXC	-4,324	-3,421	0,003	-4,997	-3,401	0,001	-5,207	-3,417	0,0001
BCO	-3,758	-3,421	0,018	-4,436	-3,401	0,003	-4,491	-3,417	0,002
M_RATE	-3,749	-3,421	0,02	-3,824	-3,401	0,015	-3,815	-3,417	0,018
STRI	-4,936	-3,421	0,0001	-5,37	-3,401	<0,0001	-5,511	-3,417	<0,0001

Note: ALSI is an equity index that represents 99% by market capitalisation of all equites listed on the main bourse of the JSE; (2) SPX = Standard & Poor Index represents an estimated 500 companies trading publicly in the USA stock exchange; (3) VIX = Implied Volatility, which is an indicator of market expectation of the future volatility as it measures market risk and investor sentiment; (4) EXC is used as a measure of South African Rand value against the US Dollar; (5) BCO is a benchmark to measure internationally traded oil supplies; (M_RATE) indicates fatalities clinically proven to be caused by COVID-19, and (7) STRI = index that indicates level of strictness of policy makers' social distancing measures.

4.4 Standardised Beta Coefficient quantile regression (QR)

The beta coefficient as a measure of standard deviations, is standardised to eliminate the scaling effect. The interpretation of the variables' beta coefficient, statistically, helps in understanding the effect strength or weakness, as well as the direction (positive or negative). Table 4.3 represents the standardised beta coefficients across all quantiles.

Table 4.3 also tabulates the coefficients, standard errors and p-values. These were generated from XLStat software for each quantile. The t-values were manually derived by dividing the variable coefficients by the standard errors. The t statistic table was used to derive the p = values. The standardised beta coefficients measure the relationship size and direction of the variables.

The pandemic independent variables represented by the mortality rate (M_RATE) and stringency (STRI) show a statistically insignificant relationship with ALSI returns across all quantiles. The mortality rate, however, has a statistical insignificant positive relationship with ALSI returns at quantile 0.05, 0.50 and 0.90 where the standardised beta coefficient is 0.016, 0.011 and 0.116 respectively and quantiles 0.10, 0.75 and 0.95 indicate a negative relationship with standardised beta coefficients of 0.139, 0.015 and 0.065 respectively. The outputs revealing "heterogenous" relationships effect on variables at different quantiles explained by Haung et al., (2017) and proves the efficiency of quantile regression against OLS. Albeit insignificant, the results show a change in the dependency and structure of the ALSI returns in different quantiles on stringency and COVID-19 mortality rate. These findings are similar to that of Sharma (2022).

The S&P 500 is positively related to the dependent variable, ALSI. For 5% of the data (observations), a 1 unit increase in the ALSI returns is influenced by a 0.8 unit increase in the S&P 500. However, the explanatory variable influence reduces significantly as the pandemic move to higher quantiles. The influence decreases further to 0.332 for 95% of the data. At the median (quantile 0.5), 50% of the data indicates that the S&P 500 explains 0.449 of every 1 unit increase in ALSI returns. Compared with the mean results (ordinary least squares), the implied volatility influence is almost zero across all quantiles. The implied volatility relates negatively with ALSI returns; however, the correct interpretation is that the relationship direction is positive in nature. When the nominal value of the implied volatility is high, the implication is that the fear factor in the financial markets is high - see Grima et al. (2021) and Apergis et al. (2023). The reduction (negative) movement towards a lower value indicates that the financial markets are moving towards stability and the investor sentiment improves. Consequently, during the pandemic period, the investors, in the long term, remained confident in the global financial market.

Table 4.3: Beta Coefficient table depicting the standardised betas per each quantile

	(Q: 0,05):		**(Q: 0,10):**		**(Q: 0,50):**		**Q: 0,75**		**Q: 0,90):**		**Q: 0,95)**	
	Coefficients	**t**	**Coefficients**	**t**	**Coefficients**	**t**	**Coefficients**	**t**	**Coefficients**	**t**	**Coefficients**	**t**
Intercept	-0,032		-0,018		0,001		0,012		0,022		0,037	
M_RATE	0,016	0,046	-0,139	-0,835	0,011	0,130	-0,015	-0,172	0,116	0,847	-0,065	-0,236
STRI	-0,009	-0,517	-0,006	-0,741	-0,002	-0,569	0,000	-0,071	0,002	0,335	0,001	0,087
SPX	0,800**	2,105	0,549**	2,920	0,449***	4,590	0,549***	5,739	0,437**	2,846	0,332	1,069
VIX	0,026	0,404	-0,014	-0,430	-0,034**	-2,052	-0,031*	-1,893	-0,050**	-1,905	-0,063	-1,179
EXC	-0,187	-0,439	-0,085	-0,405	0,039	0,354	-0,050	-0,462	0,015	0,087	-0,163	-0,468
BCO	0,100	0,818	0,050	0,832	0,066**	2,101	0,039	1,271	0,031	0,639	0,060	0,599
R^2	0,490		0,473		0,307		0,289		0,309		0,328	
Adjusted R^2	0,478		0,460		0,291		0,273		0,293		0,312	
Observations	179		179		179		179		179		179	

Note: ALSI is an equity index that represents 99% by market capitalisation of all equites listed on the main bourse of the JSE; (2) SPX= Standard & Poor Index represents an estimated 500 companies trading publicly in the USA stock exchange; (3) VIX= Implied Volatility, which an indicator of market expectation of the future volatility as it measures market risk and investor sentiment (4) EXC is used as a measure South African Rand value against the US Dollar, (5) BCO is a benchmark to measures internationally traded oil supplies, (M_RATE) indicate fatalities clinically proven to be caused by Covid-19, and (7) STRI = index that indicates level of strictness of policy makers social distancing measures. Source: Author’s estimate from research data

The macroeconomic variables standardised coefficients are close to zero and statistically insignificant. In this study, the Brent crude oil has a statistically insignificant relationship with ALSI returns across all quantiles. The relationship is directionally positive. The increase in Brent crude oil prices, albeit statistically insignificant, explains the increase in the ALSI returns. At quantile 0.05, for every 1 unit of ALSI returns increase, Brent crude oil accounts for 0.1 points and at quantile 0.95, for every 1 unit increase in ALSI returns, Brent crude oil accounts for 0.06. This result is against Zeinedini et al. (2022) statistically significant negative relationship in Iranian stock markets and crude oil, and Assifuah-Nunoo et al. (2022) who found crude oil not to have safe- haven properties during the pandemic.

Citing Carlsson-Szlezak et al. (2020a,b), Brodeur et al. (2021) posit that COVID-19 induced uncertainties propagates to the economy through (1) constrained consumption because of dampening consumers' economic confidence and prospects due to extended social distancing measures, (2) COVID-19 induced uncertainty transmit to financial markets and to the real economy and (3) disturbance in the supply-side value chains due to labour demand and supply induced by health ailment and social distancing measures, curtailed manufacturing and unemployment increases. The initial response to these contracting GDP, was the collapse in the oil prices due to constrained demand.

Although, this study does not seek to measure the impact of both voluntary and government imposed social distancing measures, empirically Brent Crude Oil shocks and the South African Rand currency shocks transmit uncertainty to the financial markets similar to van der Westhuizen et al. (2022) observation. Consequently, an analysis of the monetary policy interventions is pertinent. First, Brodeur et al. (2021) clarifies the sequence of events. Social distancing may assist to curb the health contagion however they impede supply chains and labour activities resulting in collapsed consumer consumption. The erosion in both the investor and consumer sentiments collapsed labour and outputs markets resulting in diminishing gross domestic products.

South Africa's financing conditions were already precarious prior to the pre-COVID-19. The budget deficit gap was at 6.8% of GDP and worsened to 14.6% during 2020. The country's borrowing needs increased substantially hastened by the significant portfolio outflows in March 2020 due to a "flight to safety" phenomenon. The fiscal policy interventions included the introduction of income relief measures, supply stimulation through protective equipment procurement and extensive support of the health sector to manage the pandemic. From a monetary policy perspective, the SARB interventions were supported by a well-coordinated international quantitative easing measure.

According to Loewald (2021), South Africa’s monetary policy response included interest rates reduction (cumulative 275 basis points), liquidity injections in the money markets as and when needed, repurchasing of foreign-denominated bonds, macroprudential adjustments that entailed a capital relief through a guarantee facility for banks utilised for restructuring households debts. The atoned international investors returned to the South African markets as international cash flows returned and the rand strengthened against major currencies.

From a Crude Oil perspective, Gharib et al. (2021) observed the oil prices buble intersected with three exogenous factors (1) COVID-19. (2) Sadia Arabia-Russia oil price war, and (3) OPEC oil price cuts. According to Loenwald (2021), the Chinese economy recovery boosted spurred raw materials consumption and the subsequent uplift in the demand for oil.

From a South African Rand perspective, the Rand-Dollar exchange rate had, albeit minimal in size, a general negative relationship with ALSI returns during the pandemic period. The observation is similar to Ncube et al. (2024) regarding the rand deterioration caused increased stock volatilities in all economic sectors. Additionally, van der Westhuizen also confirmed the “interdependence” between the two markets. The authors found a “significant price spillovers from the exchange rate to the stock market and vice versa.”

For 5% (0,05 quantile) of the data, every 1 unit of ALSI returns is explained by a negative 0,187 unit of Rand-Dollar exchange rate movement. At quantile 0.95, the Rand-Dollar rate has a negative 0.163 relationship with ALSI returns. The median (quantile 0.5), however, indicates that the relationship is positive at 0.039. The dataset is sequentially structured from the pandemic commencement to the late stages of the pandemic demise. The negative relationship in the lower quantiles can be attributed to the pandemic induced uncertainty shocks in the two markets (financial markets and foreign exchange markets) initial reaction. The positive relationship at the quantile 0.50 may be caused by the effect of the stability emanating from the monetary policy interventions. The negative relationship in later quantiles is likely to have been caused by external factors outside the pandemic. This period coincided with the commencement of the war between Russia and Ukraine.

The observed relationship between the South African currency market and the JSE is consistent with van der Westhuizen et al. (2022) findings. The p-value statistical inference and interpretation follows Gibbon and Pratt (1975) approach where the p-value is compared to selected alpha. In this instance, the statistical inference from the quantile regression analysis shows that at quantile 0.05, the ALSI has a strong positive relationship with SPX based on the coefficient of 0.800. The p-value for this quantile, at 0.038 rejects the null hypothesis. From the statistically higher p-value compared to alpha 0.005, we can conclude the ALSI and S&P 500 relationship is not zero. At all other quantiles, the relationship is positive but statistically weak as evidence by both coefficients and p-value. For the VIX, EXC, BCO, M_Rate and STRI, the coefficients suggest that the relationship with ALSI is statistically insignificant. The values are higher than the alpha of 0,005 indicating that the relationship is not zero, albeit extremely weak.

In summary, the standardised beta coefficient of macroeconomic and pandemic variables suggests that there is a statistically insignificant relationship with ALSI returns during the pandemic period.

4.5 Goodness-of-fit Statistic for quantile regression

R^2 in the Table 4.4 is essentially $R^1(\tau)$, and represents the coefficient of determination at a specified quantile. At quantile 0.05, 49% of ALSI returns are explained by the independent variables. At all other quantiles (0.10, 0.50, 0.75, 0.90, 0.95), are weakly explained by returns on the S&P 500, implied volatility, the rand dollar exchange rate, crude oil, new COVID-19 deaths and tightening or relaxation of stringency measures during the pandemic period (47.3%, 30.7%, 28.9%, 30,9% and 32.8%, respectively). The remainder of the variability is attributable to other explanatory variables that are not part of the study or could not be measured.

The goodness-of-fit is considered weak to moderate when inferring the dependency of the variable of interest on the exploratory variables. The goodness-of-fit is even weaker at quantiles 0.10, 0.50, 0.75, 0.90 and 0.95. Therefore, the null hypothesis that the pandemic transmitted to financial markets in South Africa, from the viewpoint of a long-term investor cannot be accepted.

Table 4.1: Summary of the goodness of fit statistics

	Q: 0,05	Q: 0,1	Q:0,5	Q:0,75	Q:0,9	Q:0,95
Observations	179	179	179	179	179	179
R^2	0,490	0,473	0,307	0,289	0,309	0,328
Adjusted R^2	0,478	0,460	0,291	0,273	0,293	0,312
MAR	0,002	0,003	0,007	0,006	0,004	0,002
RMAR	0,046	0,059	0,086	0,078	0,061	0,047
MAPE	15,225	23,235	50,270	42,791	26,627	16,725
Cp	620,689	1289,188	3143,736	2564,054	1409,657	749,806
AIC	-1095,754	-1010,035	-870,492	-905,844	-997,258	-1086,056
SBC	-1076,629	-990,911	-851,368	-886,720	-978,133	-1066,932
PC	0,546	0,564	0,741	0,760	0,739	0,719

Source: Author's estimate from research data

The goodness of fit statistics suggest that the independent variables are statistically insignificant across all quantiles, excluding quantile 0.05 at an R-squared of 0.543.
When comparing the median (quantile 0.5) with the mean (ordinary least squares regression), the R-squared is 0.562.

4.6 Wald and Lagrange Multiplier tests

Wald, Likelihood Ratio and Lagrange Multiplier (Rank Score) tests assisted the study to ascertain how the model fit is affected by the six predictor variables at different quantiles. These tests assist the researcher to draw conclusions on the statistical significance or otherwise of any or all the variables. In this study, these tests assisted in inferring whether COVID-19 shock influenced the JSE. The tests fundamental question is does limiting the parameters to naught weaken the model fit? The different tests that assess the model fit from different lens are explained below.

4.2.5.1 Wald Test

The Wald process is suitable for use when the dataset has heteroskedastic characteristics. The test measures "the distance between the hypothesized β and an estimate under the maintained hypothesis as a process over τ" from Koenker & Machado (1999). Importantly, the drawing inferences using the Wald process is insensitive to the homoskedasticity assumption. When variables are statistically significant, the test accepts the null hypothesis, and their individual or collective removal will substantially harm the model fit.

The Wald test scores at each quantile in Table 4.5.

Table 4.2: Wald test output at significance level 0.05 indicates that inclusion of variables will not improve the model fit

Quantile	DF	Chi-square	Pr > Chi²
Q-0.05	6	2,525	0,866
Q-0.10	6	1,612	0,952
Q-0.50	6	1,472	0,961
Q-0.75	6	1,803	0,937
Q-0.90	6	1,640	0,950
Q-0.95	6	1,894	0,929

Source: Author's estimate from research data

For all the quantiles under consideration (0.05. 0.10, 0.50, 0.75, 0.90 and 0.95), the Wald test chi-square value is less compared to the critical value of 12.592. The null hypothesis cannot be rejected. For all the quantiles, we can conclude that the removal of the variables will not negatively impact the model.

4.2.5.2 Lagrange Multiplier test

Regarding the Lagrange Multiplier, according to Engle (1984), the test is "derived from a constrained maximisation principle." Lagrange Multipliers measure the constraint cost, the "slope of the likelihood function". The constraint is "rejected as consisted with the data" if the price is too high. Engle (1984) formulates the Lagrange Multiplier test under Lemma 1 as:

$\xi_{LM} = S_1\left(\tilde{\theta}, y\right)' j^{11} s_1\left(\tilde{\theta}, y\right) / T.$ According to Engle (1984), the Lagrange Multiplier measures the "smoothness" of the likelihood curve and resembles a constrained Chi-square distribution. In this study, the Lagrange Multiplier test under Lemma 1, has outputs shown in Table 4.6 for each quantile.

Table 2,6: Lagrange Multiplier score at significance level 0.05, independent variables do not improve the model fit:

Quantile	DF	Chi-square	Pr > Chi²
Q-0.05	6	3,495	0,745
Q-0.10	6	12,891	0,045
Q-0.50	6	14,098	0,029
Q-0.75	6	13,741	0,033
Q-0.90	6	5,002	0,544
Q-0.95	6	1,511	0,959

Source: Author's estimate from research data

For quantiles 0.10, 0.50 and 0.75, the Lagrange Multiplier test show a greater Chi-square compared to critical value of 12.592. Similarly, the p-value is significantly below 0.05 alpha at quantiles 0.10, 0.50 and 0.75. At these quantiles, the null hypothesis is rejected. Statistically, the independent variables do not improve the model fit. The Lagrange Multiplier test indicates that the independent variables are statistically insignificant. A variable is 'significant' where it improves the model fit. Variables that do not improve the model fit may be omitted. However, for quantiles 0.05, 0.90 and 0.95, the Lagrange Multiplier score is less. For the afore-mentioned quantiles, the test does not reject the null hypothesis. At these quantiles, which are extreme tails, the variables dataset likely contains significant outliers.

4.7 ALSI Returns prediction at different quantiles

Figure 4.7 shows the predicted residuals of ALSI returns based on the observations over the duration of the pandemic period. Although there is no apparent regression line, the plots indicate a general upward trend of predicted ALSI returns. This observation suggests that the pandemic outbreak did not negatively affect the ALSI returns beyond the event first few weeks.

Additionally, the plot diagrams show that the coefficient of the quantile regression model changes from negative to positive as the quantiles increase from 0.05 to 0.95. At the 0.50 quantile (median), there appears to be a balance between negative and positive returns. As the quantiles increase beyond the median, the ALSI returns changes overwhelmingly to positive. At these quantiles, the pandemic outbreak is not a factor in the ALSI returns. These results are consistent with Vengesai (2022), who found that during the pandemic period, the pandemic outbreak does not negatively affect the financial market returns. The negative impact is short-lived.

These results are similar to van der Westhuizen et al. (2022) analysis of the JSE and currency markets contagion dynamic in South Africa. According to van der Westhuizen et al. (2022), the COVID-19 induced uncertainty shock impact halved in 9 days in the financial markets and 15 days in the currency markets. Before the pandemic, the shock persistency half-life duration approximated 1 month in the financial markets and 6 months in the currency markets. The study covered FTSE/JSE ALSI from January 1979 to August 2021. On the contrary, however, Liu et al. (2021) when examining risk spill-over effects of COVID-19 across three continents (Asia, Europe and America), the COVID-19-induced shocks in global markets could last between 6 to 8 months measured from January 2020. Even this was the case, however, the “spill-overs frequencies” reverted to pre-pandemic levels after July 2020.

Another perspective from Bai et al. (2020) suggest that empirically a 2-year lag for the pandemic to exert a long-lasting volatility in stock markets. It is however noted Bai et al. (2020) data from USA, China, Japan and UK was from January 2005 to April 2020. COVID-19 was still about two months old in South Africa at the time.

Ricciardi & Simon (2000) suggests that behavioural finance theory departs from traditional finance by introducing “psychological considerations” including “emotions and anxiety” as influencers the investment decision. This is counter to Markowitz Morden Portfolio Theory and Efficient Market Hypothesis theories that postulate risks-averse investors operates in an information symmetry environment. The phycological and sociological considerations from proponents of behavioural finance theorists include fear, panic and herding behaviour when faced with uncertainty. The resultant financial markets uncertainty from COVID-19 induced shocks drew interest from various researchers to explore aspects of behavioural finance theory to explain the investor response to the pandemic.

According to Ampofo et al. (2023), USA and UK investors demonstrated herding behaviour. The USA investors demonstrated herding behaviour in both “bearish” and “bullish” market conditions whereas UK investors’ herding behaviour was only observed in the bullish market conditions. Apergis et al. (2023) observed abnormal VIX volatility when higher infections were reporting, to suggest investor fear from the uncertainty. Ashraf (2020) found COVID-19 deaths not to be statistically significant presumable due to the risk already priced in when infections were reported. Aggarwal et al. (2021), using the Coronavirus Panic Index which measure the “news chatter” in twelve countries suggest that the pandemic fear causes fear and panic where rational investors expect additional market risk premium.

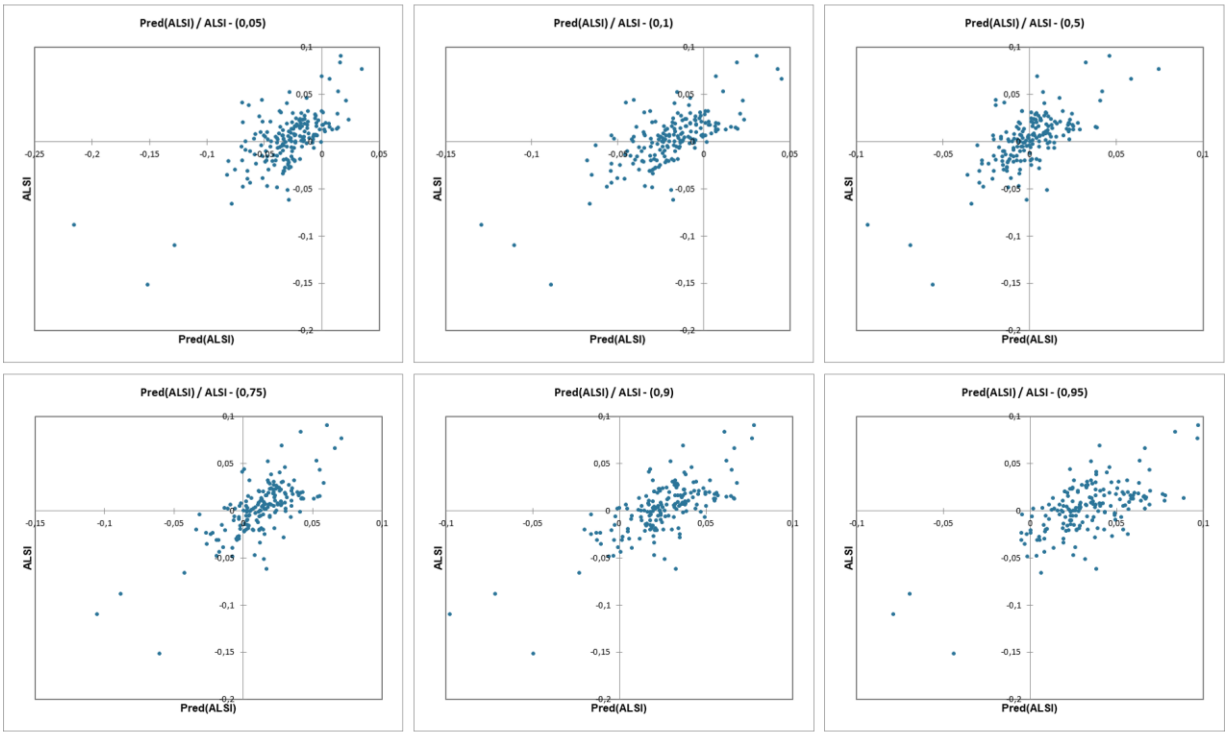

Figure 4.1: ALSI returns predicted at different quantiles

Figure 4.1 depicts the ALSI returns predicted at different quantiles. The structure of the returns transforms from negative in lower quantiles (which coincides with earlier stages of the pandemic outbreak) to positive in the higher quantiles.

4.8 Overall Findings against the independent variables

The behaviour of ALSI returns during the pandemic period was assessed against global financial markets variables represented by S&P 500 and Implied Volatility. Some collinearity and multicollinearity between the ALSI returns and global financial markets performance indicators was observed. The correlation between ALSI returns, S&P 500 and Implied Volatility is statistically significant at 0.716 and -0.600 respectively. This outcome indicates the deepened integration of the South African financial markets with the globe. The multicollinearity statistic also indicates that there is a contagion-like relationship between FTSE/ALSI and the global financial markets. The flight to safe havens was not observed in these results. This finding is pertinent as it suggests that the pandemic outbreak shock had a neutral effect in global and domestic financial markets, in the long term.

When contrasting the ALSI returns with the macroeconomic factors the relationship is statistically insignificant. The exchange rate was more sensitive to the government stringency measures as and when announced, including their impact on trade and global value chains as a result of tampering domestic and global supply and demand. However, such real economy disturbances do not appear to have been transmitted to the financial markets in the long term. Potential reasons may include the positive sentiments generated by the development of vaccines and the global rollout of vaccination programmes. Additionally, government interventions to stimulate the economy could have improve the investor sentiment. Other studies may explore this phenomenon further.

The mortality rate and the stringency measures had no impact on the JSE in the long term. Future studies may explore further the reasons why the ALSI recovered and outstripped the pre-pandemic levels during the pandemic period and whilst the stringency measures were still in place.

4.9 Chapter Summary

The chapter presents the outcome obtained through quantile regression analysis enabling conclusions to be drawn from the dataset. First the descriptive statistics provided the dataset characteristics including variables minimum and maximum values, median and standard deviation. Secondly, several tests assessing the relationship between the variables were conducted (including collinearity, correlations, goodness of fit, and quantile regression). The test outcomes indicate that the pandemic did not transmit to the financial markets. This is a significant finding for policy makers and investors as it provides valuable insights for determining suitable stringency measures and developing effective asset allocation strategies during global crises.

Chapter 5
Conclusion and Recommendations

5.1 Introduction

This chapter summarises key findings, conclusions, policy considerations and recommendations for future research. The study empirically explored the relationship between COVID-19 mortality rates, government-imposed stringency measures and JSE asset returns during the pandemic period. It also identifies avenues for further study, with particular attention to the impact of stringency measures, the implications of under-reported COVID-19 deaths, and comparisons across different regression frameworks in assessing financial market responses during the pandemic.

5.2 Summary and Conclusions

Using a quantile regression methodology, the study investigated whether COVID-19 exerted long-term influence on the JSE in South Africa. The research was motivated by a need to understand pandemic-era effects, with potential applications for investor portfolio and policymaker decisions concerning the nature, extent, and timing of interventions.

In analysing the ALSI returns marked by increasing mortalities and varying stringency measures across successive waves, no evidence of COVID-19 long-term transmission effect on South African financial markets was found. The standardised beta coefficients of macroeconomic and pandemic variables suggest a statistically insignificant relationship with ALSI returns during this period.

Moreover, macroeconomic performance – dampened by stringency measures, reduced productivity due to hospitalisations and quarantines, and disrupted global value chains – showed no significant long-term impact on the JSE. The Quantile ADF unit root test at higher quantiles (0.75 to 0.95) indicated stationarity, minimising the risk of spurious correlations throughout the pandemic outbreak and its subsequent waves.

5.3 Policy Recommendations

The study findings are relevant and valuable for investors and policy makers. Although each pandemic outbreak has different dynamics (extent, coverage, and economy state prior the onset), the insights from the study offer a foundational source of knowledge that can inform portfolio allocations, stringency measures and the management of economic downturns.

In South Africa, the fiscal policy interventions included income relief measures, supply side stimulation and extensive support of the health sector to manage the pandemic. From a policy perspective, the South African Reserve Bank interventions were supported by a well-coordinated international quantitative easing measure. Loewald (2021) suggests that the South Africa's monetary policy response included interest rates reduction (cumulative 275 basis points), liquidity injections in the money markets as and when needed, repurchasing of foreign-denominated bonds, macroprudential adjustments that entailed a capital relief through a guarantee facility for banks utilised for restructuring households debts. The effectiveness of these measures in stimulating the real economy require further investigation. Importantly, whether the pre-Covid employment rate was attained.

The study makes the following recommendations to policy makers and investors. (1) develop portfolio management strategies and asset allocations that will withstand the impact for the duration of the pandemic state, and (2) carefully balance the timing and the level of stringency measures and specific moments during the pandemic period. A balance is desirable between curbing the spread of the pandemic, stimulating the economy (stimulus packages) and hurting the economy (stringency measures).

5.4 Avenues for future studies

Much of the early research focused on the shock dynamic at the outbreak immediate aftermath. By contrast, this study explored effects over the entire pandemic duration, offering a more holistic view. Despite recurring waves, the findings suggest a sustained recovery in market performance – reinforcing the notion of a 'short-lived' effect, historically speaking

In alignment with Gormsen and Koijen's (2023) observations, future research could examine the unravelling of the "investor rationality theory" whereby investor fear decreased even as cases and deaths surged.

This observed “irrationality”, contrasting with findings from Ampoffo (2023, Apergis et al. (2023), Ashraf (2020), and Aggarwal et al. (2021) raises questions about the role of policy interventions in stabilising investor behaviour on the JSE in stabilising investor sentiment. Future studies may delve deeper into the drivers of the financial markets and the real economy decoupling dynamic. Was this apparent resilience a reflection of investor irrationality, or the result of decisive action by SARB, the Prudential Authority, and other governmental bodies?

COVID-19 deaths under-reporting emerged as a potential data limitation. The present study suggests that investor responses were driven more by public narratives than by muted communication around “excess natural deaths”. While this phenomenon is not pursued further here, it represents a compelling avenue for examining correlations between pandemic communication and policy efficacy.

Finally, given that the current analysis employed quantile regression, future research should consider comparing alternative frameworks to test whether the statistically insignificant relationship observed here remains consistent across various analytical methodologies.

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Appendix 1: Summary of Score Tests Output Table

Table below show the summary of the Wald test, Maximum likelihood and Lagrange Multiplier tests outputs. The Chi-Square table, at 6 degrees of freedom, with $\sigma = 0.05$, the critical value is 12.592.

Quantile regression / Results for variable ALSI:
Goodness of fit statistic:

Null hypothesis test H0: beta=0 (Quantile: 0,05):

	DF	Chi-square	Pr > Chi²
Maximum likelihood	6	3,091	0,797
Lagrange Multiplier	6	3,495	0,745
Wald	6	2,525	0,866

Null hypothesis test H0: beta=0 (Quantile: 0,1):

	DF	Chi-square	Pr > Chi²
Maximum likelihood	6	4,657	0,588
Lagrange Multiplier	6	12,891	0,045
Wald	6	1,612	0,952

Null hypothesis test H0: beta=0 (Quantile: 0,75):

	DF	Chi-square	Pr > Chi²
Maximum likelihood	6	3,786	0,706
Lagrange Multiplier	6	13,741	0,033
Wald	6	1,803	0,937

Null hypothesis test H0: beta=0 (Quantile: 0,9):

	DF	Chi-square	Pr > Chi²
Maximum likelihood	6	2,495	0,869
Lagrange Multiplier	6	5,002	0,544
Wald	6	1,640	0,950

Null hypothesis H0: beta=0 (Quantile: 0,5):

	DF	Chi-square	Pr > Chi²
Maximum likelihood	6	5,016	0,542
Lagrange Multiplier	6	14,038	0,029
Wald	6	1,472	0,961

Null hypothesis test H0 : beta=0 (Quantile: 0,95):

	DF	Chi-square	Pr > Chi²
Maximum likelihood	6	1,658	0,948
Lagrange Multiplier	6	1,511	0,959
Wald	6	1,894	0,929

Appendix 2

Coefficients (Quantile: 0,05):

	Value	Standard error	Lower bound	Upper bound
Intercept	-0,032	0,012	-0,055	-0,009
SPX	0,800	0,380	0,055	1,544
VIX	0,026	0,065	-0,101	0,154
EXC	-0,187	0,426	-1,023	0,648
BCO	0,100	0,122	-0,139	0,338
M_RATE	0,016	0,338	-0,646	0,677
STRI	-0,009	0,017	-0,041	0,024

Coefficients (Quantile: 0,1):

	Value	Standard error	Lower bound	Upper bound
Intercept	-0,018	0,006	-0,029	-0,006
SPX	0,549	0,188	0,180	0,917
VIX	-0,014	0,032	-0,077	0,049
EXC	-0,085	0,211	-0,499	0,328
BCO	0,050	0,060	-0,068	0,168
M_RATE	-0,139	0,167	-0,467	0,188
STRI	-0,006	0,008	-0,022	0,010

Coefficients (Quantile: 0,5):

	Value	Standard error	Lower bound	Upper bound
Intercept	0,001	0,003	-0,005	0,007
SPX	0,449	0,098	0,257	0,640
VIX	-0,034	0,017	-0,067	-0,002
EXC	0,039	0,110	-0,176	0,254
BCO	0,066	0,031	0,004	0,127
M_RATE	0,011	0,087	-0,159	0,182
STRI	-0,002	0,004	-0,011	0,006

Coefficients (Quantile: 0,75):

	Value	Standard error	Lower bound	Upper bound
Intercept	0,012	0,003	0,007	0,018
SPX	0,549	0,096	0,362	0,737
VIX	-0,031	0,016	-0,063	0,001
EXC	-0,050	0,107	-0,260	0,161
BCO	0,039	0,031	-0,021	0,099
M_RATE	-0,015	0,085	-0,181	0,152
STRI	0,000	0,004	-0,009	0,008

Coefficients (Quantile: 0,9):

	Value	Standard error	Lower bound	Upper bound
Intercept	0,022	0,005	0,013	0,031
SPX	0,437	0,154	0,136	0,738
VIX	-0,050	0,026	-0,102	0,001
EXC	0,015	0,172	-0,323	0,353
BCO	0,031	0,049	-0,065	0,128
M_RATE	0,116	0,137	-0,152	0,383
STRI	0,002	0,007	-0,011	0,016

Coefficients (Quantile: 0,95):

	Value	Standard error	Lower bound	Upper bound
Intercept	0,037	0,010	0,019	0,056
SPX	0,332	0,310	-0,276	0,939
VIX	-0,063	0,053	-0,167	0,042
EXC	-0,163	0,348	-0,845	0,519
BCO	0,060	0,099	-0,135	0,254
M_RATE	-0,065	0,276	-0,605	0,475
STRI	0,001	0,014	-0,026	0,028

Covariance matrix (Quantile: 0,05):

	Intercept	SPX	VIX	EXC	BCO	M_RATE	STRI
Intercept	0,000	0,000	0,000	-0,001	0,000	-0,003	0,000
SPX	0,000	0,144	0,015	0,043	-0,002	-0,003	0,001
VIX	0,000	0,015	0,004	-0,001	0,002	-0,002	0,000
EXC	-0,001	0,043	-0,001	0,182	0,004	0,011	0,001
BCO	0,000	-0,002	0,002	0,004	0,015	-0,002	0,000
M_RATE	-0,003	-0,003	-0,002	0,011	-0,002	0,114	0,000
STRI	0,000	0,001	0,000	0,001	0,000	0,000	0,000

Covariance matrix (Quantile: 0,5):

	Intercept	SPX	VIX	EXC	BCO	M_RATE	STRI
Intercept	0,000	0,000	0,000	0,000	0,000	0,000	0,000
SPX	0,000	0,010	0,001	0,003	0,000	0,000	0,000
VIX	0,000	0,001	0,000	0,000	0,000	0,000	0,000
EXC	0,000	0,003	0,000	0,012	0,000	0,001	0,000
BCO	0,000	0,000	0,000	0,000	0,001	0,000	0,000
M_RATE	0,000	0,000	0,000	0,001	0,000	0,008	0,000
STRI	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Covariance matrix (Quantile: 0,9):

	Intercept	SPX	VIX	EXC	BCO	M_RATE	STRI
Intercept	0,000	0,000	0,000	0,000	0,000	0,000	0,000
SPX	0,000	0,024	0,002	0,007	0,000	0,000	0,000
VIX	0,000	0,002	0,001	0,000	0,000	0,000	0,000
EXC	0,000	0,007	0,000	0,030	0,001	0,002	0,000
BCO	0,000	0,000	0,000	0,001	0,002	0,000	0,000
M_RATE	0,000	0,000	0,000	0,002	0,000	0,019	0,000
STRI	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Covariance matrix (Quantile: 0,1):

	Intercept	SPX	VIX	EXC	BCO	M_RATE	STRI
Intercept	0,000	0,000	0,000	0,000	0,000	-0,001	0,000
SPX	0,000	0,035	0,004	0,011	0,000	-0,001	0,000
VIX	0,000	0,004	0,001	0,000	0,000	0,000	0,000
EXC	0,000	0,011	0,000	0,044	0,001	0,003	0,000
BCO	0,000	0,000	0,000	0,001	0,004	0,000	0,000
M_RATE	-0,001	-0,001	0,000	0,003	0,000	0,028	0,000
STRI	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Covariance matrix (Quantile: 0,75):

	Intercept	SPX	VIX	EXC	BCO	M_RATE	STRI
Intercept	0,000	0,000	0,000	0,000	0,000	0,000	0,000
SPX	0,000	0,009	0,001	0,003	0,000	0,000	0,000
VIX	0,000	0,001	0,000	0,000	0,000	0,000	0,000
EXC	0,000	0,003	0,000	0,012	0,000	0,001	0,000
BCO	0,000	0,000	0,000	0,000	0,001	0,000	0,000
M_RATE	0,000	0,000	0,000	0,001	0,000	0,007	0,000
STRI	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Covariance matrix (Quantile: 0,95):

	Intercept	SPX	VIX	EXC	BCO	M_RATE	STRI
Intercept	0,000	0,000	0,000	0,000	0,000	-0,002	0,000
SPX	0,000	0,096	0,010	0,029	-0,001	-0,002	0,000
VIX	0,000	0,010	0,003	-0,001	0,001	-0,001	0,000
EXC	0,000	0,029	-0,001	0,121	0,003	0,007	0,001
BCO	0,000	-0,001	0,001	0,003	0,010	-0,001	0,000
M_RATE	-0,002	-0,002	-0,001	0,007	-0,001	0,076	0,000
STRI	0,000	0,000	0,000	0,001	0,000	0,000	0,000

Appendix 2 – Ordinary Least Squares

This appendix is included for comparative purposes between Quantile Regression results (median) and Ordinary Least Squares as explicated in section 4.7.

Regression of variable ALSI:

Goodness of fit statistics (ALSI):

Observations	179
Sum of weights	179
DF	172
R²	0,562
Adjusted R²	0,546
MSE	0,000
RMSE	0,020
MAPE	236,935
DW	2,335
Cp	7,000
AIC	-1393,326
AICC	-1392,671
SBC	-1371,014
PC	0,474

Analysis of variance (ALSI):

Source	DF	Sum of squares	Mean squares	F	Pr > F	p-values significat ion codes
Model	6,000	0,088	0,015	36,723	**<0,0001**	***
Error	172,000	0,069	0,000			
Corrected Total	178,000	0,157				

Computed against model Y=Mean(Y)
*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*

Model parameters (ALSI):

Source	Value	Standa rd error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)	p-values significat ion codes
Intercept	0,001	0,002	0,330	0,742	-0,003	0,005	°
SPX	0,523	0,068	7,705	**<0,0001**	0,389	0,657	***
VIX	-0,026	0,012	-2,268	**0,025**	-0,049	-0,003	*
EXC	-0,031	0,076	-0,411	0,681	-0,182	0,119	°
BCO	0,064	0,022	2,954	**0,004**	0,021	0,107	**
M_RATE	0,017	0,060	0,278	0,781	-0,102	0,136	°

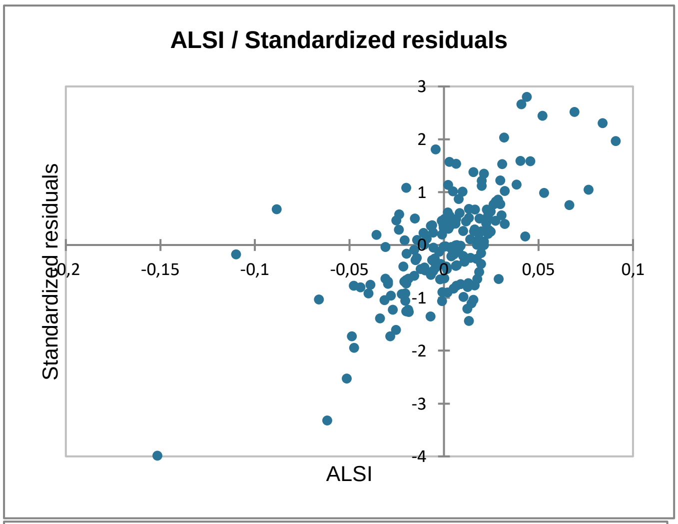
STRI	-0,002	0,003	-0,661	0,510	-0,008	0,004	°

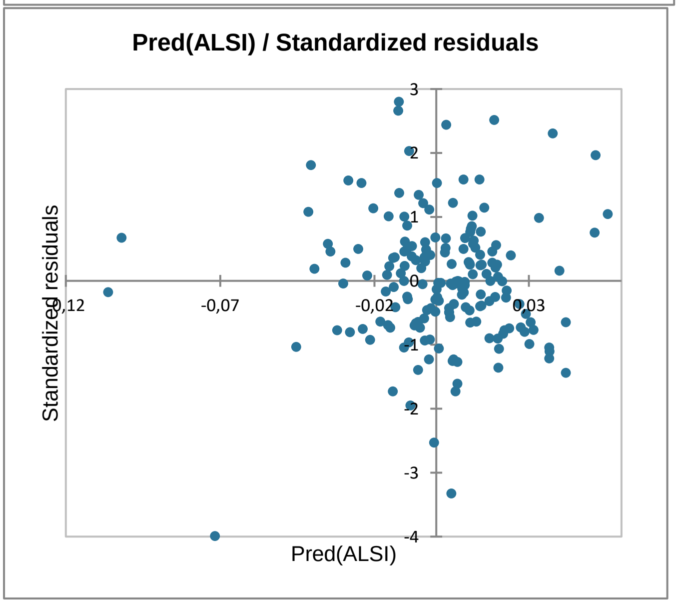
*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*

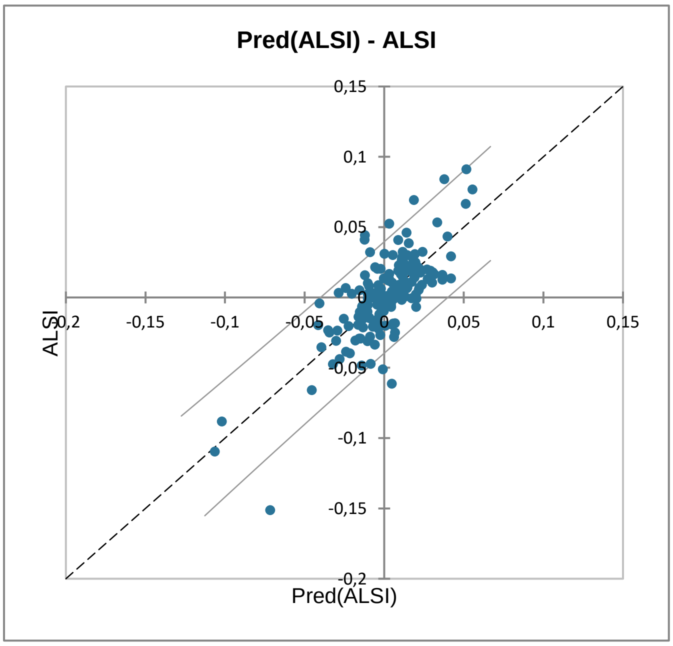
Standardized coefficients (ALSI):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)	p-values signification codes
SPX	0,551	0,071	7,705	**<0,0001**	0,409	0,692	***
VIX	-0,161	0,071	-2,268	**0,025**	-0,301	-0,021	*
EXC	-0,023	0,056	-0,411	0,681	-0,133	0,087	°
BCO	0,165	0,056	2,954	**0,004**	0,055	0,275	**
M_RATE	0,014	0,051	0,278	0,781	-0,086	0,114	°
STRI	-0,035	0,053	-0,661	0,510	-0,139	0,069	°

*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*






Pred(ALSI) - ALSI
0,15
0,1
0,05
0
-0,05
-0,1
-0,15
-0,2
-0,2
-0,15
-0,1
-0,05
0
0,05
0,1
0,15
ALSI
Pred(ALSI)