COVID-19 HEALTH RELATED NEWS AND SECTORAL STOCK RETURNS SENSITIVITY IN SOUTH AFRICA.

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by

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<u>DECALRATION BY THE SUPERVISOR</u>

I, **<u>Dr Sedjro Alovokpinhou</u>** have reviewed and am satisfied that the final report of **<u>Sbongiseni Zulu</u>**, student number **<u>715076</u>**, is ready for submission for marking.

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DECLARATION BY THE STUDENT

I, **Sbongiseni Zulu**, affirm that the minor thesis presented here for the Master of Commerce (MCom) in Economics at the University of Witwatersrand is entirely my own work. It has not been previously submitted by me for a degree at this university or any other tertiary institution.

Signature: ____________ Date: 12/03/2024
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ABSTRACT

The purpose of this study is to analyse the relevance of health news related to Covid-19 on South African sectorial stock returns. This is inspired by the global Covid-19 pandemic in predicting sectorial stock returns. This study examines the estimation of dynamic panel data using a dynamic common correlated effects estimator. It employs two pairwise forecast measures, specifically the Campbell & Thompson (2008) and Clark & West (2007) tests, to address the nested predictive models. Thus, this study begins by analysing the impact of health news relating to Covid-19 when control variables are not considered. This is following by when control variables are incorporated into the model. Lastly, the forecasting power of Models 3 and 4 is evaluated by comparing the two models with historical average or constant returns model (CR), for both with and without control variables.

The findings of this study reveals that the model incorporating health news indexes outperforms the constant returns model. This proves that health news is a valuable indicator for predicting stock returns, particularly in the wake of the pandemic, underscoring the importance of monitoring health-related information for investment decisions. This study further finds that considering the "asymmetry" effect and incorporating adjustments for macroeconomic factors enhances the predictive accuracy of the health news-driven model. The outcomes remain consistently strong across both the periods of in-sample and out-of-sample forecasts, demonstrating resilience to outliers and variations. These results have practical significance for a range of stakeholders, encompassing academics, practitioners like rational investors, portfolio managers and policymakers. The practical implications extend to aspects such as managing portfolio risk, realizing diversification advantages and exploring opportunities for the creation of innovative investment instruments within financial markets.

Keywords: Health news, Covid-19 pandemic, Sectorial stock returns, Predicting.

Paper type: Research paper.

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COVID-19 HEALTH RELATED NEWS AND SECTORAL STOCK RETURNS SENSITIVITY IN SOUTH AFRICA.

1. INTRODUCTION

1.1 Background

The world continues to face pandemics periodically. In the 21st century, several pandemics have emerged including swine flu (NIHI), Severe Acute Respiratory Syndrome (SARS), Middle East Respiratory Syndrome (MERS) and Ebola (Elsayed & Elrhim, 2021). On 11 March 2020, the global spread of Corona Virus Disease 2019 (Covid-19) was officially declared as pandemic by the World Health Organization (WHO, 2020) Covid-19 evolved into a global pandemic, leading to significant economic and financial implications (Rudden, 2020). Consequently, Covid-19 garnered substantial attention from news outlets. Generally, media reports tend to focus on high-impact events such as pandemic outbreaks inducing public panic (Young, King, Harper & Humphreys, 2013). News related to pandemics can startle and influence investor sentiments (Narayan, 2019). This results in health news related to pandemics being crucial in shaping investor decisions. Therefore, this means that news in general and news related to pandemics in particular cannot be disregarded when forecasting changes in economic or financial factors (Narayan, 2019). The decisions to buy or sell by individual investors depend on the available news content.

News is categorized into positive or negative (good or bad) news, and the impact of each type on economic or financial variables is a contentious topic among researchers (Salisu & Vo, 2020). Akinchi & Chahrour (2018) assert that only negative (bad) news influences investment decisions. However, Narayan (2019) argues that both positive and negative (good and bad) news plays a role in shaping investment decisions. It is against this backdrop that this research will be conducted. Numerous studies have explored the effects of news, including financial news, oil price news or earnings announcements, on stock market returns (Narayan & Bennigidadmath, 2015; Narayan, 2019; and Even-Tov, 2017). Motivated by the recent Covid-19 pandemic, this study will concentrate specifically on examining the influence of Covid-19 health-related news on the returns of South African sector-specific stocks.

1.2 Research Gap

Numerous global research has been conducted to evaluate the effects of the Covid-19 pandemic on economic or financial variables. Shahzad, Kristoufek & Saeed (2021) explored the impact of the Covid-19 pandemic on stock returns in the United States of America (USA), specifically focusing on equity sectors. While the study concentrated on the prominent and attractive market for investors, it overlooked the spillover effects on sectoral stock returns in other major markets across Asia, Europe and Africa. Shahzad et al., (2021) suggest that future research should extend to other leading stock markets to verify if the findings observed in the USA stock markets are applicable elsewhere. South Africa boasts the largest stock exchange on the African continent (Ncube, Sibanda & Matenda, 2023). Hence, this study will be conducted on the largest stock market in Africa, considering its prominence and influence in the region.

Equally, numerous research has been conducted in South Africa to evaluate the effects of the Covid-19 pandemic on economic or financial variables. For instance, Gbenga, Keji & Josue (2021) and Fasanya, Periola & Adetokunbo (2023) utilized the count of Covid-19 cases and fatalities as a proxy for Covid-19, overlooking the role of news pertaining to the health aspects of Covid-19. It is worth noting that individuals can be infected with Covid-19 and remain economically active, rendering the use of Covid-19 infections as a measure of its impact on economic and financial variables less precise. Few studies have specifically focused on the influence of health-related news regarding Covid-19 on economic or financial variables in South Africa. This research seeks to fill this existing void and is motivated by the recent Covid-19 pandemic. Most of the literature examining the effect of Covid-19 on returns in the stock market focuses on the company level, neglecting the sectoral perspective. Khatatbeh, Hani & Abu-Alfoul (2020) suggests that future research should investigate the significance of Covid-19 at the sectorial level, as the effects of pandemics are unevenly distributed, impacting some sectors positively and others negatively. Additionally, Salisu et al., (2020) assert that the exploration of health-related news to Covid-19 for forecasting stock returns is an area that has not been thoroughly investigated.

It is worth noting that while this study aligns with the methodology and presentation of results employed by Fasanya (2023) and Salisu et al., (2020), it diverges from them in the following aspects: Fasanya (2023) focused on determining the impact of uncertainty due to infectious disease (EMV-ID) on South African sectorial stock returns whereas, this study analyses the impact of significance or relevance of news related to the health aspects of Covid-19 on South African sectorial stock returns. While EMV-ID is a suitable index for measuring uncertainties stemming from the fear of the Covid-19 pandemic, it has garnered increased focus from researchers than health news related to Covid-19. Salisu et al., (2020) have asserted this, suggesting that news related to the health aspects of Covid-19 remains understudied. Furthermore, Fasanya (2023) examined the impact on each sector individually, while this study assesses the average impact of all sectors combined. Despite the varying effects on different sectors during a pandemic, understanding the overall impact is crucial for providing accurate policy recommendations.

Moreover, even though Salisu et al., (2024) analyses the impact of health news relating to Covid-19, only one search index is analysed. It is worth noting that negative and positive news affects stock returns differently (Narayan, 2019). Therefore, it is of utmost importance to analyse both negative and positive news impacts on stock returns. This study analyses three search index with the aim of analysing both positive and negative news. Additionally, Salisu et al., (2020) analyse only one sample period which is Covid-19 period. This study analyses three data samples which are full, pre Covid-19 and the Covid-19 samples. Analysing three data samples offers several advantages such as representativeness increase, enhancing robustness, diversity of perspectives, reduces bias and external validity, controlling for confounding factors and increasing precision. In summary, analysing three data samples instead of one can enhance the reliability, generalizability and robustness of research findings. It provides a more comprehensive view of the phenomenon under investigation and strengthens the validity of the study's conclusions.

1.3 Objectives

The primary objective of this research is to empirically evaluate the impact of health pandemic-related news associated with Covid-19 on the major sectors of the South African stock market. The overarching goal is to extract valuable lessons and implications from the Covid-19 experience, which may prove beneficial for other countries facing potential future pandemic crises. Given that the Covid-19 pandemic is health-related, this paper posits a hypothesis that health news related to Covid-19 will be utilized by investors to inform their decision-making processes, particularly in assessing the pandemic's severity and its implications for the global economy (Salisu et al., 2020).

This study aims to address the following key empirical analyses:

- Evaluate the impact of health news related to Covid-19 on South African sectorial stock returns.
- Examine health news related to Covid-19 as a potential predictor of South African sectorial stock returns during and after the Covid-19 pandemic.
- Assess both in-sample and out-of-sample forecast performance of the health news related to Covid-19-based predictive model for South African sectorial stock returns.
- Evaluate whether the forecast performance of the proposed model will be enhanced by controlling for macro-based predictors.

1.4 Research Questions

The objective of this study is to address the following question: Does health news related to Covid-19 influence trading activities in South African sectors? To explore this inquiry, this study considers the following questions:

- What is the impact of health news related to Covid-19 on South African sectorial stock returns?
- Can health news related to Covid-19 predict South African sectorial stock returns during and after the Covid-19 pandemic?
- What is the performance of both in-sample and out-of-sample forecasts of the health news related to Covid-19-based predictive model for South African sectorial stock returns?
- Does controlling of macro-based predictors enhance the forecast performance of proposed model?

1.5 Contribution.

The impact or value that this research brings is to offer evidence on the sensitivity of South African sectorial stock returns to health news related to Covid-19. This evidence aims to assist investors and policymakers in making informed decisions during pandemics, given that news related to pandemics can significantly influence investor decisions (Narayan, 2019). Therefore, understanding how sectorial stock returns respond to health news related to Covid-19 is crucial for several reasons. To begin with, investors decisions to buy or sell are increasingly dependent on available news content (Salisu et al., 2020). Additionally, the rise in the utilization of crowd wisdom and shared information on social media investment platforms plays a role in helping users make better decisions (Breitmayer, Massari & Pelseter, 2019). Salisu et al., (2020) asserts that the impact of health news on financial variables remains a contentious debate among researchers and this paper aims to contribute to that ongoing discourse.

Another notable contribution made by this study lies in its employed methodology which draws from predictive methods for panel data. This approach stands in contrast to the event study methodology used by Velasquez, Grinen & Henriquez (2022), the Autoregressive Conditional Heteroskedasticity (GARCH (1,1)) model employed by Onali (2020), and the Autoregressive Distributed Lag (ARDL) used by Fasanya et al., (2023). The selected model for this study is chosen for its suitability in handling short time periods, which is pertinent due to Google Trends limiting data. Additionally, opting for a panel data forecast as opposed to pooling individual forecasts from different markets with small T is expected to yield superior results, as advocated by Westerlund & Narayan (2016). In alignment with Westerlund et al., (2016) and for the sake of comprehensiveness, this study incorporates common factors such as New York Stock Exchange Returns (RNY), Crude Oil Price Returns (RCO), Interest Rate (ITR), Inflation Rate (IFR) and changes in nominal Exchange Rate (ΔEXR) in predicting stock returns. The benefits of considering such factors are widely acknowledged by Westerlund et al., (2016).

1.6 Significance

This study holds significance as it will furnish evidence on the sensitivity of sectorial stock returns to health news related to Covid-19 in South Africa. The findings from this research can prove valuable for policymakers, investors and academic professionals. In the context of policymakers who play a pivotal role in immediate responses during pandemic crises (The Organization for Economic Cooperation and Development (OECD), 2022), this study is particularly relevant. For the Covid-19 pandemic, this study will propose policy recommendations that can be utilized in future crises arising from pandemics. Investors, as highlighted by Akinchi et al., (2018), react to news, whether it is positive or negative, when making investment decisions. Understanding how health news impacts sectorial returns is crucial for making informed decisions about future investments in the event of pandemic attacks. It is noteworthy that the impact of certain news on financial variables such as sectorial stock returns, remains a subject of heated debate among researchers (Salisu et al., 2019). The significance of this paper also lies in its contribution to the ongoing debate about the impact of health news related to the recent pandemic, Covid-19, on South African sectorial stock returns.

The rest of this study will be structured as follows:

Section 2 will review the literature.
Section 3 will dissertate the econometric methodology and data employed by this study.
Section 4 will present and analyse the results of this study.
Section 5 will discourse the conclusion and policy recommendation.

2. LITERATURE REVIEW

2.1. Theoretical Background

2.1.1 The Efficient Market Theory (EMT)

Markowitz (1952) establishes that in the context of a portfolio, the relationship between beliefs and choice aligns with the relationship between expected returns and risk. This results in the formation of an efficient portfolio by investors based on the assumption that the efficient line starts with minimum risk. Markowitz (1952) posits that returns vary with risk, suggesting that investors cannot construct a portfolio solely based on the expectation of maximum return and minimum risk because diversification does not eliminate all risk. Lintner (1965) assumes that the fundamental condition for investors to create optimal investment portfolios is uncertainty. Under Lintner's (1965) assumption, when investors establish a portfolio with optimum returns, they are exposed to the risk of assets. This implies that the higher the expected return, the higher the associated risk. According to Fama (1970) and Souza & Gestao (2023), an efficient market is one in which the information that investors need is fully reflected in stock prices. Fama (1970) suggests that the basic concept of this theory revolves around the role of expected returns as a function of risk, indicating that higher risk corresponds to higher returns and this is converse to views by Markowitz (1952) and Lintner (1965).

Nevertheless, in contrast to the perspectives of Fama (1970) and Souza et al., (2023), Allen, Brealey & Myers (2011) characterize an efficient market as one in which an investor cannot achieve a higher return than the overall market return. Efficient markets typically rest on two foundational principles: (1) markets where all available information is already incorporated into stock prices and (2) markets where investors cannot attain a risk-adjusted excess return. Regarding the assimilation of information into prices, the Efficient Market Theory (EMT) is classified into three forms: (1) strong form, (2) semi-strong form, and (3) weak form (Fama, 1970, and Novickyte, 2014). The strong form contends that stock prices reflect all information available in the market, and insider information cannot be exploited for transactions. The semi-strong form posits that information about the company and publicly available information is fully reflected in stock prices. The weak form argues that information about past prices is completely incorporated into current stock prices (Fama, 1970).

The efficiency of markets is commonly influenced by various events and these effects vary in degree (Ozkan, 2021). Machmuddah, Utomo, Suhartono, Ali & Ghulam (2020) assert that market efficiency is gradually impacted by corporate actions such as warrants, right issues and splits. Nonetheless, unforeseen black swan occurrences, such as the Covid-19 pandemic, exert a substantial impact on market efficiency. Black swan events, like the Covid-19 pandemic, induce widespread panic, often resulting in asset prices deviating from their fundamental values and causing a breakdown in the EMT (Lalwani & Meshram, 2020). These structural shifts in both commodity and financial markets have asymmetrical consequences on market efficiency, volatility spillovers, and portfolio allocations (Aslam, Aziz, Nguyen, Mughal & Khan, 2020). In response to the Covid-19-induced financial challenges, most central banks swiftly adapt their monetary frameworks to address the interplay of exchange rate movements and capital outflows, with the aim of minimizing the financial setbacks (Machmuddah et al., 2020).

Several pieces of literature have delved into the existence of the EMT, with some supporting and others challenging it. Critics of EMT, such as Shiller (2013), label it as "half true." Mnif & Jarboui (2021) find that the bitcoin market is not efficient during the Covid-19 period, and herd behaviour is reduced by Covid-19. Wang & Wang (2021) assert that the efficiency of the US$ Index, S&P 500 Index, Bitcoin and Gold decreases during the Covid-19 event. Pilai & Pilai (2021) discover that the Indian markets were inefficient during the Covid-19 pandemic, presenting several opportunities to make abnormal profits. On the supportive side of EMT, Shleifer (2000) investigates aggregate data on investor reactions to corporate news, revealing that price adjustments align with the semi-strong form of EMT. In agreement with Shleifer (2000), El (2019) reports semi-strong efficiency in the CAC 40 Index. Gupta & Gedam (2022) report that the Indian market is weakly efficient. It is noteworthy that, although criticism of EMT has lessened its popularity, the idea of market efficiency remains relevant in modern finance.

The literature above underscores the considerable attention that market efficiencies are receiving from financial researchers. However, it is essential to acknowledge that the definition of EMT is very general, making it challenging to test. Abdullahi (2021) notes that for EMT to be testable, price information must be specified in detail. The debate about the existence of EMT persists. In essence, EMT elucidates the phenomenon wherein stock returns are positively correlated with risk (Budiarso, Hasyim, Soleman, Zam & Pontoh, 2020). This perspective is supported by Wolski (2017), who asserts that stock returns and risk exhibit a positive correlation. Therefore, according to these viewpoints, EMT can be employed as a hypothesis to explain the positive relationship between stock returns and Covid-19.

2.1.2. The Prospect Theory (PT)

According to Lintner (1965) and Fama (1970), within the behavioural finance concept, the utility function serves as the constraint of the EMT. This concept was further developed by Kahneman & Tversky (1979) into the establishment of Prospect Theory (PT) after realizing that the Morgenstern & Von Neumann (M&VN) (1953) utility model did not adequately describe situations in which individuals make choices when faced with risk. PT places emphasis on how investors set aside and decide on portfolios under risk. Kahneman et al., (1979) demonstrates that investors exhibit a greater inclination to take risks to avoid losses rather than to take risks for an equivalent gain. This suggests that, in the context of gains, investors tend to be risk-averse, while in the context of losses, investors are risk-seeking. This is supported by Alam, Mahmudul & Abu (2022), who asserts that investors detest losses more than gains of equal size. Zhang (2014), in line with Kahneman et al., (1979), asserts that when faced with two options, given the choice between a definite loss and the prospect of a gamble that could either amplify or diminish a certain loss, investors are more inclined to opt for the gamble.

The utility is derived from "gains" and "losses" experienced by individuals concerning a reference point. However, it is not clear in the given context what constitutes gains or losses, as there is limited information explaining how the reference point was determined (Berberis, 2012). Studies on loss aversion for both small and large firms indicate a tendency toward modest risk aversion (Rabin, 2000). PT serves as a formal theory for risk aversion (Kahneman & Tversky, 1992). Analysing loss aversion involves determining the utility of gains and losses simultaneously. The challenge lies in measuring utility, assuming that gains and losses probabilities are weighted differently. PT posits that risk is the outcome of uncertainty, rendering decisions risky. The higher the degree of uncertainty, the riskier the decision (Jalonen, 2011). PT is characterized by probability weighing, diminishing utility, loss aversion and reference dependence. Despite claims of making logical decisions, individuals are highly susceptible to cognitive biasness and sometimes overlook the logical choice (Tapas & Pilai, 2022).

The Covid-19 pandemic altered the conventional way in which businesses operate (Tapas et al., 2022). It led to businesses making decisions under challenging conditions that deviate from the normal state. Firms had to employ non-traditional mechanisms to ensure stability and resilience during Covid-19, prompting investors to set aside and make decisions on investment portfolios under risk (Liu & Zhang, 2022). Linter (1965) demonstrates that in the presence of anomalies, investors become more averse to risk. Linter's (1965) point suggests that the existence of anomalies in investors investment decisions poses a challenge to EMT. In agreement with Linter (1965), Fama (1970) asserts that the difficulty in testing EMT lies in the assumption that prices incorporate all available information and that investors are risk-averse, as this assumption forms the basis of investment decisions.

Just like EMT, there are researchers both against and in support of PT. Opponents of PT include Nwogugu (2005), who argues that PT fails to consider the opportunity cost arising from decisions. Brockner (2018) asserts that the study by David & Bobko (1986) supports self-justification more than it supports PT, as they found that individuals who initiated the action are more likely to persist with a failing course of action. It is worth noting that PT also does not address the existence of liabilities arising from the selection of outcomes (Baird & Morrison, 2010). The study used in deriving PT failed to analyse negotiations (Ballestro, 2022). Supporters of PT include Cameron & Shah (2015), who claim that individuals who have experienced a black swan event previously are more risk-averse to losses than those who have not experienced the event. Destinations perceived as unsafe fail to attract travellers (Kiu & Pratt, 2017). In agreement with Kiu et al., (2017), Li, Gong, Gao & Yuan (2021) find that tourists avoid visiting areas with higher confirmed cases of Covid-19 compared to their places of origin.

Fama (1998) confirms that anomalies such as under and over-reaction of investors are still consistent with EMT. PT is based on risk-averse investors and anomalies, resulting in a negative relationship between stock returns and risk, as confirmed by Jin (2022). Han (2005) asserts that this behaviour is a form of mental accounting. Daniel & Hirshleifer (2015) confirm consistency with PT. Daniel et al., (2015) asserts that high-earning investors are risk-averse, exhibiting a positive relationship between returns and risk when targeted earnings are above the level. Conversely, low-earning investors are risk-seeking and their relationship between returns and risk is negative when targeted earnings that are below the level. Therefore, based on the analyses above, PT can be used as a hypothesis to explain the negative relationship between stock returns and Covid-19.

2.2 Empirical Evidence

Researchers have employed event study methodology to analyse the impacts of pandemics on stock returns. Wang, Yang & Chan (2006) found that due to statutory infectious epidemics, there is a significant positive abnormal return on biotechnological companies shares in Taiwan after the announcements of four infectious diseases outbreaks, namely Enterovirus 71, Dengue Fever, SARS and H1N1. The study applies the event study methodology and examines the four announcement dates, which are 27 May 1998, 14 July 2002, 27 April 2003 and 30 July 2009 for the outbreaks, respectively. During pandemics, the demand for biotechnological products increases as society relies on such products to protect themselves from the pandemic.

However, not all sectors of the economy experience abnormal positive returns during pandemics. Chen, Jang & Kim (2007) found that the earnings and stock prices of seven Taiwanese hotels declined during the SARS pandemic. During the day of the SARS outbreak announcement and the subsequent day, the seven hotels in Taiwan experienced notably negative Cumulative Mean

Abnormal Returns (CMAR). The research utilized the event study methodology to examine the announcement event of the SARS pandemic in Taiwan which occurred on 27 April 2003, on the stock returns of the seven Taiwanese hotels. This is not surprising, as destinations perceived as unsafe fail to attract travellers (Kiu et al., 2017). In agreement with Kiu et al., (2017), Li et al., (2021) found that tourists avoid visiting areas with higher confirmed cases of Covid-19 compared to their places of origin. Additionally, when a pandemic is announced, governments resort to measures intended to slow down the spread of the pandemic such as national lockdowns. This prevents travellers from visiting their desired destinations during pandemic outbreaks.

Concurring with the findings of Wang et al., (2006) and Chen et al., (2007), Chong, Lu & Wong (2010) found that the pharmaceutical sector is positively affected by the SARS announcement outbreak, while the tourism sector is negatively affected by the SARS announcement outbreak in China. This indicates that the pharmaceutical sector experiences positive abnormal returns during SARS pandemics, while the tourism sector experiences negative abnormal returns during SARS pandemics. The study employed the event study methodology and analysed the events of 27 June 2003 when China announced the outbreak of SARS and 20 April 2003 when WHO announced that the world is free of SARS. Five leading companies for each sector were analysed. The results in China for the tourism and medical-related sectors, such as biotechnological and pharmaceutical, align with the results found by both Wang et al., (2006) and Chen et al., (2007). The increase in demand for medical products during pandemics and measures taken by governments, actions like lockdowns lead to both positive and negative correlations between pandemics and stock returns in the medical-related sector and tourism sector, respectively.

Some sectors of the economy are interconnected, and the expectation is that if one sector performs poorly, the negative impact will spill over to other connected sectors. This is supported by Sheikh & Kanungo (2023), who found that the stock returns of Indian aviation companies dropped following the declaration of the Covid-19 pandemic. The study analysed the impact of Covid-19 on the stock returns of the top four Indian aviation companies, covering the period from 1 January 2019 to 3 May 2020 to include both pre- and during-Covid-19 periods. The study applied the event study methodology. The tourism and aviation sectors are mutually supportive, as air travel is a common mode of transportation between countries, and many individuals travel for tourism purposes. Therefore, when governments implement lockdowns and restrict tourist entry to manage the dissemination of Covid-19, the aviation sector also experiences negative consequences.

The USA, having the largest global stock market, was not exempt from the analysis of pandemics effects on its stock market. Ichev & Maric (2017) investigated whether the geographic closeness of information regarding the 2014-2016 Ebola outbreak, coupled with widespread media attention, impacts stock prices in the United States. The research indicated that information about the Ebola outbreak held greater relevance for companies situated closer geographically to both the outbreak's origin and the financial markets. As a result, companies with exposure to West African Countries (WAC) and the USA for their operations were most affected. The analysis encompassed 103 Ebola events occurring in various locations such as the USA, Europe and WAC. The study utilized reports from the WHO and USA Newspapers Ebola Outbreak News, spanning from January 2013 to June 2016, employing event study methodology and regression-based methodologies. The study's findings suggest that the closer a company is to a pandemic, the more significant the impact, as investors and governments are more likely to respond promptly to a pandemic that is closer to their geographic locations.

While the literature discussed above focuses on studying one country at a time, the event study methodology can be applied to assess the impact of pandemics on stock returns across multiple countries simultaneously. Khatatbeh et al., (2020) discovered that investors in Belgium, China, France, Germany, Italy, Netherlands, South Korea, Spain, Switzerland, the United Kingdom and the USA anticipated adverse economic consequences of Covid-19, and this expectation was reflected in their respective stock markets. The study also identified an underreaction of investors from the studied countries to the Covid-19 pandemic announcement. Using the event study methodology, the research examined the immediate reaction of each country's stock market indices to the confirmed first case of Covid-19 and the declaration of Covid-19 as a pandemic by the WHO on 11 March 2020. As economic conditions change, investors make decisions to buy or sell, and since Covid-19 impacts economies, these effects are reflected in stock prices. The underreaction observed may be attributed to the event occurring far from the investor countries, with minimal impact on their decision-making.

The BRIC (Brazil, Russia, India, and China) group, with three countries (India, Brazil, and Russia) ranking among the top 10 most affected countries by Covid-19 and including the country where Covid-19 was initially discovered (China) (WHO, 2023), has garnered significant attention from researchers. In their analysis of the impact of WHO announcements on H1N1 and Covid-19 pandemics (11 June 2009 and 11 March 2020, respectively) on BRIC stock markets, Velasquez et al. (2022) found that these announcements had negative effects on the daily returns of stock market indices in BRIC countries. This suggests that investors recognize pandemic announcements as legitimate market signals. The study employed the event study methodology and the price indices of countries covered a period from 2005 to 2020. Given the economic disruption caused by Covid-19 in BRIC countries, the results align with expectations.

In examining the influence of announcements regarding both Covid-19 and the Russian invasion of Ukraine on the stock markets of 11 advanced emerging markets (Brazil, Czech Republic, Greece, Hungary, Malaysia, Mexico, Poland, South Africa, Taiwan, Thailand, and Turkey), and evaluating if these nations experienced similar effects, Pretorius (2023) determined that the stock markets of advanced emerging economies were notably more adversely affected by the Covid-19 pandemic than by the Russian invasion of Ukraine. The study employed the event study methodology and focused on two events: the first event on 20 January 2020, when the Chinese spokesperson acknowledged that Covid-19 could be transmitted among humans through contact and the second event on 24 February 2022, when Russia invaded Ukraine. The announcement regarding Covid-19, with its potential to quickly spread globally, triggered significant investor panic. In contrast, the Russian invasion of Ukraine being a more localized event, had a lesser impact on the stock returns of the studied countries.

While most studies focus on countries outside of Africa, Ncube et al. (2023) investigates how sub-Saharan African stock markets are influenced by announcements related to the Covid-19 pandemic. Employing the event study methodology followed by panel data regression, the study aims to ascertain the cause-and-effect connection between Covid-19 and abnormal stock returns, the examination encompasses four African stock exchanges, encompassing the two largest ones, namely the Johannesburg Stock Exchange (JSE) and the Nigerian Stock Exchange (NSE), along with two burgeoning markets: the Zimbabwe Stock Exchange (ZSE) and Lusaka Stock Exchange (LSE). The research delves into stock returns, trade volumes, Covid-19 cases, and Covid-19 deaths. Results indicate that government lockdown measures negatively impacted the overall performance of various sectors in markets within sub-Saharan Africa, as expected, due to the halt in economic activities. Moreover, the research indicates that government economic stimulus packages did not have a favourable influence on stock market performance, except in the case of South Africa.

While the event study methodology is preferred by some researchers to analyse the impact of extreme events on stock returns, there are alternative methodologies equally capable of examining the effects of pandemics on stock returns. For instance, Jiang, Zhang, Ma, Wang, Xu, Donavan, Ali & Sun (2017) employs an Analyses of Variance (ANOVA) and a distributed lag non-linear model (DLNM) to investigate the relationship between reported cases of Asian Lineage Avian Influenza (H7N9) and sector price indices in China. The study covers the period from 19 February 2013 to 31 March 2014 and focuses on five medical-related sectors. Results indicate that the emergence of H7N9 leads to economic loss reflected in stock price movements, with a negative relationship existing between reported H7N9 cases and stock indices in China. It proposes that because H7N9 does not have the potential to escalate into a worldwide pandemic that would boost medical demand, the stock prices of biomedicine-related companies are influenced in a manner akin to other sectors, declining with an increase in the number of patients. If H7N9 had spread to other countries like Covid-19, it might have led to an increased medical demand, resulting in different outcomes.

Also departing from the event study methodology, Lee, Jais & Chan (2020) utilize Ordinary Least Squares (OLS) regression with three diagnostic checks, including Variance of Inflation (VI) for multicollinearity testing, Durbin-Watson statistics for autocorrelation testing and the Cook and Weisberg test for heteroscedasticity testing. This study aims to examine the influence of the Covid-19 pandemic on the stock markets in Malaysia. The research encompasses the period from 31 December 2019 to 18April 2020, utilizing the Kuala Lumpur Composite Index (KLCI), 13 sector-specific indices, and reported Covid-19 cases. The results indicate that the rise in the number of Covid-19 cases in Malaysia has a detrimental impact on the performance of the KLCI index and all other sector-specific indices, except for the Real Estate and Investment Fund (REIT) index. The study identifies an adverse correlation between Covid-19 cases in Malaysia and all sector-specific indices and KLCI, with the exception of the plantation sector. This exception is attributed to essential sectors like plantations being permitted to operate during pandemics thereby avoiding negative impacts.

In the USA, Onali (2020) employs the GARCH (1,1) model to examine the impact of reported cumulative Covid-19 cases and deaths on stock market returns. The study spans from 8 April 2019 to 9 April 2020 and concludes that changes in the number of cumulative cases and deaths in the USA do not influence stock markets. However, Sansa (2020) reports a positive relationship between confirmed Covid-19 cases and financial markets in the USA, using a simple regression method. These findings are challenged by Xu (2021), who utilizes a bivariate structural GARCH-in-Mean VAR approach to investigate the impact of the Covid-19 pandemic on the stock markets of the USA and Canada. Data covers the periods from 21 January 2020 to 2 July 2020, for the

USA and from 27 January 2020 to 2 July 2020, for Canada. Xu (2021) study reveals a negative relationship between stock markets and the increase in the number of Covid-19 cases and deaths. Yousfi, Younes, Nidhaleddine, Bechir & Houssem (2021) argue that additional measures such as lockdowns and social distancing have exacerbated the negative impact of Covid-19 on stock market returns in the USA and Canada compared to previous pandemics.

During pandemics, uncertainty becomes a prevailing factor influencing investor decisions to buy or sell. The World Pandemic Uncertainty Index (WPUI) serves as a comprehensive measure of this uncertainty. Athari, Krikkaleli & Adebayo (2022) argues that the WPUI is an effective gauge for assessing the impact of pandemics on stock market indexes. In their study, they utilize the Markov regime-switching and Fourier-based approaches (including Fourier Augmented Dickey-Fuller Unit Root, Fourier Engle-Granger Cointegration, Bayer-Hanch Cointegration, and Markov switching regressions) to investigate the effect of WPUI on the DAX index in Germany. The data spans from 1996Q1 to 2020Q2 and the study controls for other macroeconomic variables such as Real Effective Exchange Rate (REER), Consumer Price Index (CPI) and Industrial Production Index (IPI). The findings indicate a significant long-term impact on German stock markets when considering the combined influence of WPUI, REER, CPI and IPI variables. The study further reveals a negative relationship between WPUI and REER with the German stock market index in both high and low volatile regimes, while the effects of CPI and IPI are positive.

In China, Jin (2022) employs the Autoregressive-Distributed Lag (ARDL) model to investigate the co-integration, short-run and long-run relationship between new infection rates of Covid-19 and stock price volatility. The study utilizes daily time series data spanning from 1 July 2020 to 31 October 2021. Separate empirical models are employed to estimate inner-day and inter-day volatility, with control for the Inter-bank overnight lending rate to consider the effects of liquidity and investment cost. The findings reveal a negative correlation between the new infection rate of Covid-19 and stock prices in the short term at the beginning of the pandemic in 2020. After the outbreak in 2021, the study indicates that new Covid-19 infections initially depress inner-day volatility in the short term but contribute to increased stock prices in the long term. Jin (2022) argues that these phenomena result from investor concerns about the withdrawal of monetary easing and fiscal stimulus measures introduced to combat the economic impact of the Covid-19 pandemic.

Another study utilizing ARDL is conducted by Fasanya et al., (2023), which analyses the potential relationship between the Covid-19 pandemic and stock prices in selected countries namely China, France, Italy and the USA. The study uses daily data from 1 January 2020 to 3 December 2021, covering Covid-19 reported cases, stock market indices, oil price volatility and financial volatility for each country. The findings indicates that the impact of Covid-19 reported cases on stock prices varies among countries and is limited. The study concludes that both short and long run relationships exist in the models. In the short run, there is a negatively significant relationship between Covid-19 reported cases and stock prices in the investigated countries, except for Italy where there is no significant relationship. In the long run, Covid-19 cases have a negative relationship with the stock indices of France and Italy. The application of the same econometric methodology to countries with different economic backgrounds leads to diverse results, resulting in heterogeneous findings among the countries under investigation.

Researchers also employ predictive models as demonstrated by Kim, Lucivjanska, Molnar & Villa (2018). They use a predictive model to investigate whether Google Searches can explain current and predict future abnormal returns, trading volume and volatility of the largest companies in Norway. The study spans from 2 January 2012 to 2 January 2017. The study initiates by regressing abnormal stock returns with the abnormal Google Search volume index (ASVI) and a set of control variables. Subsequently, it regresses abnormal volume (ATV) against lagged trading volume, ASVI, volatility and abnormal returns. The study further analyses whether the relationship between ASVI and volatility is contemporary. Predictive models are constructed similarly, utilizing only lagged variables as potential predictors. The findings reveal that Google Searches are not correlated with current abnormal returns and cannot predict future abnormal returns in Norway. However, the increase in Google Searches predicts higher volatility and increased trading volume in the future. Consequently, Google Searches exhibit a stronger connection to future trading activity than to current trading activity in Norway.

The study conducted by Kim et al. (2018) focused on normal economic conditions. During pandemic periods, Salisu & Akani (2020) propose the Global Fear Index (GFI) as the best predictor for OECD (developed markets) and BRICS (developing markets) stock returns, utilizing a single-factor predictive model. To address the issue of zero weights, particularly concerning the number of deaths, the starting date is chosen as 14 days after the report of 10 death cases due to Covid-19, aligning with 10 February 2020 as the commencement for deriving GFI. The predictive efficacy of GFI is comparatively assessed against other potential forecasting models for stock returns. To accommodate the day-of-the-week effects, the estimation is extended by adjusting the stock returns series to account for potential anomalies related to different days of the week. The study illustrates how the model utilizing the GFI as the predictor outperforms the benchmark model. Additionally, it suggests that improving the forecast performance of the GFI-based predictive model might require addressing "asymmetry effects" and incorporating macro common factors. Finally, the study indicates that GFI serves as a superior predictor of panic/fear compared to existing fear indices in the stock market.

Although Salisu et al., (2020) propose that the GFI is a superior predictor of market returns due to its incorporation of both Covid-19 reported cases and deaths, Li, Liang, Ma & Wang (2020) argue that the WPUI may possess additional predictive ability for the Realized Volatility (RV) of European stocks during the Covid-19 pandemic. The study covers the period from 2 February 2000 to 15 April 2020 and focuses on three European countries: France, the UK and Germany. The benchmark model employed by the study is the Heterogeneous Autoregressive Realized Volatility (HAR-RV), known for effectively capturing volatility characteristics and being estimated with Ordinary Least Squares (OLS). To assess the role of WPUI, the XIV components in the HAR-USRV-VIX model are replaced with the HAR components of WPUI. The findings suggest that WPUI exhibits stronger predictive power for stock market volatilities in France and the UK during the Covid-19 pandemic. Additionally, VIX demonstrates stronger predictive ability for the three analysed European stock markets during the same period.

In South Africa, Fasanya (2023) develops a predictive model that explores the relationship between the Infectious Disease Equity Market Volatility (IDEM) and eight South African sectorial stock returns. The study encompasses daily data from 8 February 2016 to 7 May 2021, spanning both pre-Covid-19 and during the Covid-19 period. The IDEM is employed as the predictor in the model. The study initiates by assessing IDEM predictability as a potential indicator before and during the Covid-19 pandemic. Given the heterogeneity of the eight South African sectors, the study hypothesizes that IDEM impact on market volatility may differ across sectors. Subsequently, the study evaluates both in-sample and out-of-sample IDEM forecast performance for stock returns across sectors. Finally, the research tests whether the forecast performance of the proposed model can be enhanced by incorporating other macroeconomic predictors. The findings indicate that IDEM significantly and negatively affects the returns of the sectors under investigation, suggesting that as the pandemic becomes more noticeable, the stock returns of the eight sectors decline. Although the single predictor model outperforms the historical average model for both in-sample and out-of-sample analyses, the forecast accuracy of IDEM is improved by considering other macroeconomic variables.

Lastly, Tuna (2022) investigates the health news related to Covid-19 as a predictor in financial markets. The study utilizes daily data from 19 March 2020 to 27 July 2020, analysing index values derived from Covid-19 deaths, Covid-19 cases and health news related to Covid-19 as predictors for 11 different sectors in both Islamic and conventional stock markets. Google Search Volume (GSV) values obtained from Google Trends are employed to calculate indices for the news variable. The study adopts the methodology applied by Salisu et al., (2020), predicting returns by using historical return values for each sector index in Islamic and conventional stock markets. The findings reveal that employing Covid-19 deaths, Covid-19 cases and health news related to Covid-19 as predictors outperforms historical return values in all sectors of both Islamic and conventional financial markets. Consequently, these variables can serve as effective predictors in Islamic and conventional financial markets.

Table 1: Summary of empirical results

Author/ Year	Country/ies	Period	Methodology	Variables	Conclusion
Wang et al., (2006)	Taiwan	27 May 1998, 14 July 2002, 27 April 2003, 30 July 2009	Event study approach	Events dates, Stock Returns.	There is a significant abnormal return on companies' shares.
Chen et al., (2007)	Taiwan	27 April 2003	Event study approach	Event date, Stock prices.	The earnings and stock price of the 7 Taiwanese hotels declines during SARS
Chong et al., (2010)	China	24 February 2003 to 25 June 2003.	Event study approach	Events dates, Stock Prices	Pharmaceutical sector is positively affected by SARS and tourism sector is negatively affected by SARS.
Jiang et al., (2017)	China	19 February 2013 to 31 March 2014.	ANOVA and DLNM	H7N9 cases and biomedical related firms stock prices.	Emerging of H7N9 cause economic loss that is reflected in the movements in stock prices, concluding that there is a reverse and significant relationship between daily cases of H7N9 and stock indices in China.
Ichev et al., (2017)	USA	January 2013 to June 2016.	Event study approach	Ebola outbreak events, Stock prices	The results suggests that the Ebola outbreak information

					is more relevant for companies that are geographically closer to both the birthplace of the Ebola outbreak events and the financial markets.
Kim et al., (2018)	Norway	02 January 2012 to 02 January 2017	Predictive model	Google search volume, Stock returns.	The study shows how the model that employs GFI as the predictor outperforms the benchmark model. The study further reveals that in order to improve the forecast performance of GFI based predictive model, they may be a need to account for “asymmetry effects” and macro common factors. Finally, the study shows that the GFI is better predictor of panic/ fear than the existing fear index in the stock market.

Khatatbeh et al., (2020)	Belgium, China, France, Germany, Italy, Netherlands, South Korea, Spain, Switzerland, United Kingdom, USA and uses the World Benchmark	Confirmed Covid-19 case for each country and 11 March 2020.	Event study approach.	Event dates and Stock prices.	The investors expect adverse economic consequences of Covid-19 and that expectation was capture in stock markets. There is underreaction of investors to the Covid-19 pandemic announcement.
Lee et al., (2020).	Malaysia	31 December 2019 to 18 April 2020	OLS, VI, Durbin Watson and Cook & Wiesberg test.	Covid-19 cases, KLCI and Sectorial Indices.	The increase in the number of Covid-19 cases in Malaysia adversely affects the performance of the KLCI index and all other sectorial indices, except the real estate and Investment Fund (REIT) index
Onali (2020)	USA	8 April 2019 to 9 April 2020	GARCH (1,1)	Covid-19 cumulative cases, Covid-19 deaths and Stock prices	The changes in the number of cumulative cases and deaths in the USA does not have any impact on stock markets.
Sansa (2020)	USA and China	1 March 2020 to 25 March 2020.	Regression	Covid-19 cases and Stock returns.	There is a positive relationship between Covid-19 confirmed

					cases on studied financial markets.
Saliso et al., (2020)	OECD and BRICS	10 February 2020	Predictive model	GFI, Stock Returns	The study shows how the model that employs GFI as the predictor outperforms the benchmark model. The study further reveals that in order to improve the forecast performance of GFI based predictive model, they may be a need to account for “asymmetry effects” and macro common factors. Finally, the study shows that the GFI is better predictor of panic/ fear than the existing fear index in the stock market.
Xu (2021)	USA and Canada.	21 January 2020 to 2 July 2020 for USA and 27 January 2020 to 2 July 2020 for Canada.	GARCH-in-Mean VAR.	Covid-19 cases and deaths, Stock returns.	The stock markets are negatively impacted by the increase in Covid-19 cases and deaths, while the measures taken by

					governments to strengthen the economy such as stimulus packages, assisted the stock markets to recover.
Velasquez et al., (2022)	BRIC	11 June 2009 and 11 March 2020	Event study approach	Event dates and stock returns of BRIC countries.	The announcements by WHO has negative effects on daily returns of stock market indices of BRIC countries
Athari (2022)	Germany	1996Q1 to 2022Q2	Markov regime-switching and Fourier based approaches	WPUI, Stock Market indices, REER, CPI and IPI.	There exist a long run cointegration between stock market index and WPUI, REER, CPI, and IPI suggesting that the combination of the above variables significantly affects the German stock markets in long run. In both high and low volatile regimes, the exist the negative relationship between WPUI, REER and German stock market index while CPI, IPI effects is positive.

Tuna (2022)	Islamic Countries	19 March 2020 to 27 July 2020	Predictive Model	Health News related to Covid-19 and Stock returns.	Employing Covid-19 deaths, Covid-19 cases, and health news related to Covid-19 as predictors outperforms historical return values in all sectors of both Islamic and conventional financial markets. Consequently, these variables can serve as effective predictors in Islamic financial markets.
Jin (2022)	China	1 July 2020 to 31 October 2021.	ARDL	Covid-19 infection rate and Stock prices.	There is negative correlation between the new infection rate of Covid-19 and stock-prices in a short-term. After the Covid-19 pandemic outbreak (2021), Covid-19 new infections depressed the inner-day volatility in a short-term, while it increased the stock prices in a long-term

Pretorius (2023)	Brazil, Czech Republic, Greece, Hungary, Malaysia, Mexico, Poland, South Africa, Taiwan, Thailand and Turkey	20 January 2020 and 24 February 2022.	Event study approach.	Event dates and each countries stock market index.	The Covid-19 pandemic had much more negative impact on the advanced emerging stock markets compared to the Russian invasion of Ukraine. For the Ukraine invasion, regional and country-specific factors were more relevant, with Eastern European countries affected the most. There is no indication of herd behaviour by investors.
Ncube et al., (2023)	South Africa, Nigeria, Zimbabwe and Zambia.	160 days before the case of Covid-19 un each country and 150 days after the first of Covid-19 was reported in each country.	Event study approach.	Pre and Post Covid-19 dates for each country and Stock returns.	The lockdown measure by governments had a negative impact in the performance of most sectors sub-Saharan African markets, while the economic stimulus packages by governments has no positive impact on stock markets

					performance except in South Africa.
Fasanya et al., (2023)	China, France, USA, and Italy.	1 January 2020 to 3 December 2021.	ARDL	Countries Covid-19 cases and stock market indices, financial volatility, and Oil-price volatility.	The short-run estimates revels that the Covid-19 reported cases have a negative significant relationship with stock prices of the countries under investigation, except for Italy where there is no significance relationship. In long-run, Covid-19 cases have a negative relationship with the France and Italy stock indices.
Fasanya (2023)	South Africa	8 February 2016 to 7 May 2021	Predictive Model	IDEM and Stock Returns.	IDEM exerts a detrimental and statistically noteworthy impact on various sector returns, suggesting that the returns of sector stocks decrease with the escalation of the pandemic outbreak. Although the sole predictor model

consistently surpasses the historical average model in both in-sample and out-of-sample scenarios, incorporating other macroeconomic variables enhances the forecast accuracy of uncertainty related to infectious diseases.

3. RESEARCH METHODOLOGY AND DATA
3.1 Methodology

This study establishes a predictive model to explore the relationship between health news related to Covid-19 and South African sectorial stock returns. The model utilizes health news as a predictor and evaluates its predictive power in comparison with other plausible forecast models for stock returns. The chosen sectorial stocks provide a representative sample of the South African stock markets and the outcomes are expected to offer insights into other stock markets (Rapach & Wohar, 2004). The pooling of sector stock data ensures an adequate number of observations, avoiding inefficiency issues (Fasanya, 2023). Employing a panel regression has advantages over cross-sectional and time series estimation (Baltagi, 2013). The methodology of constructing the predictive model follows the framework outlined by Salisu et al., (2020).

The analysis in this study initiates with a baseline model that incorporates a historical average or constant return (CR) , disregarding any potential stock predictor. The model is specified as follows:

$$r_{it} = \alpha_1 + e_{it} \quad ; t = 1,2,3, \dots, T \, ; i = 1,2,3, \dots., N \tag{1}$$

In equation (1) r_{it} represents aggregate return of a portfolio of different stocks calculated as log returns using $r_{it} = log\left(\frac{p_t}{p_{t-1}}\right) * 100$, α_1 is a constant parameter and e_{it} is the error term. The CR model is then enhanced with health news as a single predictor, leveraging the Investor Recognition Hypothesis (IRH) (Merton, 1987). The IRH posits that incomplete market information leads to investors being unaware of all information about securities. According to the IRH, news influences the investors decisions, resulting in them selecting only familiar stocks when constructing portfolios (Zhu & Jiang, 2018). The predictability model, incorporating only health news as a predictor of stock returns, is represented as follows:

$$r_{it} = \alpha_1 + \delta_1 HN_{i,t-1} + \delta_2 HNP_{i,t-1} + \delta_3 HNV_{i,t-1} + e_{it} \tag{2}$$

In equation (2), the variables *HN*, *HNP* and *HNV* represents the "health news" search index, "Covid-19 prevention" search index and "Covid-19 vaccine" search index respectively, as utilized by Salisu et al., (2020), Rovetta & Bhagavathula (2020) and Hernandez-Garcia & Gimenez-Julvez (2020), expressed in natural logs. The δ_1, δ_2 and δ_3 are coefficients. Unlike Salisu et al., (2020), this study employs weekly data due to the unavailability of daily sufficient data from Google Trends. Consequently, the "day-of-the-week" effects are not considered in this study, as opposed to Salisu et al., (2020). It's important to note that the weekly data collected for this study is adjusted closing prices, therefore:

$$r_{it} = r_{it}^{adj} \tag{3}$$

The next step involves substituting the adjusted weekly stock returns (r_{it}^{adj}) to equation (2). As a result, equation (2) becomes:

$$r_{it}^{adj} = \alpha_1 + \delta_1 HN_{i,t-1} + \delta_2 HNP_{i,t-1} + \delta_3 HNV_{i,t-1} + e_{it} \tag{4}$$

The adjusted weekly stock returns denoted as r_{it}^{adj} are calculated from equation (4). The regressions without control variables is then conducted, where HN is the single predictor ($\delta_2 = \delta_3 = 0$), followed by a regression with HNP as a single predictor ($\delta_1 = \delta_3 = 0$) and lasty, a regression with HNV as a single predictor ($\delta_1 = \delta_2 = 0$) (Model 1). Subsequently, all predictors (HN, HNP, and HNV) are regressed simultaneously against r_{it}^{adj} (Model 3).

Following the approach of Shin & Greenwood-Nimmo (2014), this study addresses "asymmetry" by decomposing the health news indicators (HN, HNP and HNV) into positive and negative changes, which are computed as partial sums defined as:

$$HN_t^+ = \sum_{j=1}^{t} \Delta HN_j^+ = \sum_{j=1}^{t} \max(\Delta HN_j, 0) \qquad HN_t^- = \sum_{j=1}^{t} \Delta HN_j^- = \sum_{j=1}^{t} \min(\Delta HN_j, 0) \tag{5}$$

$$HNP_t^+ = \sum_{j=1}^{t} \Delta HNP_j^+ = \sum_{j=1}^{t} \max(\Delta HNP_j, 0) \qquad HNP_t^- = \sum_{j=1}^{t} \Delta HNP_j^- = \sum_{j=1}^{t} \min(\Delta HNP_j, 0)$$

$$HNV_t^+ = \sum_{j=1}^{t} \Delta HNV_j^+ = \sum_{j=1}^{t} \max(\Delta HNV_j, 0) \qquad HNV_t^- = \sum_{j=1}^{t} \Delta HNV_j^- = \sum_{j=1}^{t} \min(\Delta HNV_j, 0)$$

The equations (5) represents the positive and negative partial sums of HN, HNP and HNV respectively ($HN_t^+, HN_t^-, HNP_t^+, HNP_t^-, HNV_t^+$ and HNV_t^-). Therefore, the re-specified predictive model that takes these asymmetries into account is as follows:

$$\begin{aligned} r_{it}^{adj} = {} & \alpha_1 + \beta_1^+ HN_{i,t-1}^+ + \beta_2^- HN_{i,t-1}^- + \beta_3^+ HNP_{i,t-1}^+ + \beta_4^- HNP_{i,t-1}^- + \beta_5^+ HNV_{i,t-1}^+ \\ & + \beta_6^- HNV_{i,t-1}^- + e_{it} \end{aligned} \tag{6}$$

In equation (6), $\beta_1^+, \beta_2^-, \beta_3^+, \beta_4^-, \beta_5^+$ and β_6^- represents the coefficients of the positive and negative asymmetry parameters, respectively. From equation (6) the regressions without control variables are run, in which $HN_{i,t-1}^+$ is the only predictor ($\beta_2^- = \beta_3^+ = \beta_4^- = \beta_5^+ = \beta_6^- = 0$) and also $HN_{i,t-1}^-$ as a single predictor ($\beta_1^+ = \beta_3^+ = \beta_4^- = \beta_5^+ = \beta_6^- = 0$). This is followed by a regression in which HNP_t^+ is the single predictor ($\beta_1^+ = \beta_2^- = \beta_4^- = \beta_5^+ = \beta_6^- = 0$) and also $HNP_{i,t-1}^-$ as a single predictor ($\beta_1^+ = \beta_2^- = \beta_3^+ = \beta_5^+ = \beta_6^- = 0$). Lastly, the regression is run in which

$HNV_{i,t-1}^{+}$ is a single predictor ($\beta_1^+ = \beta_2^- = \beta_3^+ = \beta_4^- = \beta_6^- = 0$) and also $HNV_{i,t-1}^{-}$ as a single predictor ($\beta_1^+ = \beta_2^- = \beta_3^+ = \beta_4^- = \beta_5^+ = 0$) (Model 2). Also, all asymmetries are regressed simultaneously against r_{it}^{adj} (Model 4).

Finally, the Arbitrage Pricing Theory (APT) serves as the basis for integrating systematic or macroeconomic risks into the predictability of stock returns for both regressions (with and without asymmetry). Consequently, this paper also considers other significant factors influencing stock returns. Following the incorporation of systematic or macroeconomic risks, the regressions, both with and without asymmetry, are as follows in equations (7) and (8) below, respectively:

$$r_{it}^{adj} = \alpha_1 + \delta_1 HN_{i,t-1} + \delta_2 HNP_{i,t-1} + \delta_3 HNV_{i,t-1} + \phi_1 RNS_{i,t-1} + \phi_2 RCO_{i,t-1} + \phi_3 \Delta EXR_{i,t-1} + \phi_4 ITR_{i,t-1} + \phi_5 IFR_{i,t-1} + e_{it} \tag{7}$$

and

$$r_{it}^{adj} = \alpha_1 + \beta_1^+ HN_{i,t-1}^+ + \beta_2^- HN_{i,t-1}^- + \beta_3^+ HNP_{i,t-1}^+ + \beta_4^- HNP_{i,t-1}^- + \beta_5^+ HNV_{i,t-1}^+ + \beta_6^- HNV_{i,t-1}^- + \phi_1 RNS_{i,t-1} + \phi_2 RCO_{i,t-1} + \phi_3 \Delta EXR_{i,t-1} + \phi_4 ITR_{i,t-1} + \phi_5 IFR_{i,t-1} + e_{it} \tag{8}$$

In equation (7) and (8) RNS, RCO, EXR, ITR and IFR represents New York Stock Exchange Returns (RNS), Crude Oil Returns (RCO), Interest Rate (ITR), Inflation Rate (IFR) and changes in nominal Exchange Rate (ΔEXR). The (K*1) vector of parameters for K regressors are represented by $\phi_1, \phi_2, \phi_3, \phi_4$ and ϕ_5 respectively. To circumvent having so many parameters in the predictive model, and adopting the same procedure employed by Westerlund, Karabiyik & Narayan (2016), the return series is regressed on the selected macro variables, resulting in:

$$r_{it} = \vartheta + \phi_1 RNS_{i,t-1} + \phi_2 RCO_{i,t-1} + \phi_3 \Delta EXR_{i,t-1} + \phi_4 ITR_{i,t-1} + \phi_5 IFR_{i,t-1} + u_{it} \tag{9}$$

Following that, the macro-adjusted return series is subjected to regression with health news for all Models 1,2,3 and 4. Ideally, the comparative forecast performance of r_{it} and r_{it}^{adj} from the single predictors case will guide the selection of the return series. Finally, two pairwise forecast evaluation measures are considered. The evaluation employs the Campbell & Thompson (2008) and Clark & West (2007) examinations, which demonstrate significant utility, particularly in the evaluation of nested predictive models. The structure of the Campbell & Thompson (2008) test is articulated as follows:

$$CT = 1 - \left(\frac{M\hat{S}E_u}{M\hat{S}E_r}\right) \tag{10}$$

In equation (10), $M\hat{S}E_u$ is the mean square error from unrestricted model, in the case of health-news relating to Covid-19 predictor (Equation 2) and $M\hat{S}E_r$ is the mean square error from the restricted model (Equation 1). If $CT > 0$ then Equation 2 outperforms Equation 1 and vice-versa. The Clark & West (2007) is convenient in establishing the statistical significance of the forecast evaluation in Campbell & Thompson (2008). The Clark & West (2007) for a forecast of horizon h is specified as follows:

$$\hat{f}_{t+h} = M\hat{S}E_r - (M\hat{S}E_u - adj) \tag{11}$$

In equation (11) $\hat{f}_{t+h}$ is the forecast horizon, $M\hat{S}E_r$ is the mean square error of restricted model, $M\hat{S}E_u$ is the mean square error for unrestricted model, respectively calculated as follows:

$$P^{-1}\sum(r_{i,t+h} - \hat{r}_{ri,t+h})^2 \qquad \& \qquad P^{-1}\sum(r_{i,t+h} - \hat{r}_{ui,t+h})^2 \tag{12}$$

Additionally, in equation (11), the term adj represents an adjustment factor, and its role is to compensate for the noise in the unrestricted model. The adjustment term (adj) is defined by the expression:

$$P^{-1}\sum(\hat{r}_{ri,t+h} - \hat{r}_{ui,t+h})^2 \tag{13}$$

In equation (13) P represents the quantity of predictions for which the averages are calculated. Lastly, the statistical significance of regression $\hat{f}_{t+h}$ on a constant confirms the CT. This means that conducting a regression analysis where the dependent variable is denoted as $\hat{f}_{t+h}$ against a constant term, the confirmation of CT is contingent upon achieving statistical significance. In simpler terms, the validation or support for the conceptual framework is determined by whether the regression results are statistically significant when examining the relationship between $\hat{f}_{t+h}$ and a constant term.

3.2 Data

This study examines 10 South African sectors namely: Automobiles & Parts, Beverages, Construction & Materials, Consumer Goods, Consumer Services, Financials, Mining, Pharmaceuticals & Biotechnology, Technology and Telecommunications. Additionally, the South African All Share Index and Top 40 Index are considered. Closing prices for the 10 sectors, All-Share Index and Top 40 Index are sourced from Thompson Reuters DataStream. Notably, certain sectors operated fully (Pharmaceuticals & Biotechnology), some experienced reduced operations (Beverages) and others had their operations halted (Construction & Materials) during government-imposed lockdowns to curb the spread of Covid-19. The diverse data used in this study covers sectors that were impacted differently by Covid-19, providing a comprehensive understanding of its effects on South African sectorial stock markets. Even though different sectors were affected differently during Covid-19, this study will analyse the aggregate impact of all sectors, as Fasanya (2023) has already studied the impact of Covid-19 on different sectors of South African economy.

The All-Share Index and Top 40 Index are included because they are the broad indicators of the overall performance of the markets, which includes companies from all sectors of the economy. All-Share Index represents nearly all companies listed in JSE while Top 40 Index represents the largest and most liquid companies, majority which are leading representatives of different sectors. It is therefore worth noting that both indices give an indication of how companies which dominates their sectors are impacted by health news relating to Covid-19. Therefore, by including All-Share Index and Top 40 Index indices together with sectors, the analysis of this study captures the aggregate impact of broad economic factors, thus ensuring the more overarching view of the economy beyond individual sectors.

In this study, health news related to Covid-19 is considered as a proxy for Covid-19, using search indexes for *HN*, *HNP* and *HNV* to measure the search volume of this health-related information, obtained from Google Trends. Control variables includes RNS, RCO, EXR , ITR and IFR and the variables are explained in methodology. Crude oil consumption correlates with economic activity, influencing other commodity prices (IMF, 2020), justifying its use as a control for a global variable. The closing prices for crude oil are sourced from Yahoo Finance.The NYSE stock market, being the world's largest, is included as a control, with closing prices sourced from Global Financial Data (GFD). The EXR exhibits asymmetric effects on stock returns (Amanda, Akhyar & Ilham, 2023), and changes in interest rates impact stock returns (Kumar, Kumar & Singh, 2023). Investors use inflation to assess necessary returns from investments to maintain their standard of living (Siegel, 2021). Data for EXR , ITR and IFR is harvested from the South African Reserve Bank (SARB).

It is worth noting that the consumer price inflation is released monthly by Stats SA, therefore, the monthly data is available and not the weekly data applied by this study. This study estimates the weekly IFR by interpolating the monthly IFR data provided by SARB. This study assumes that the build-up of inflationary pressures is at a relatively constant rate within a month. This implies that the monthly IFR is disaggregated into weekly intervals, based on historical patterns of market activity and price changes. This paper assumes that the frequent price changes occur more at specific periods within the month, and therefore, the weekly IFR can be estimated accurately by using such patterns. This allows for a smooth approximation of weekly changes based on monthly data. Therefore, this study assumes that the IFR is constant throughout the month

The study encompasses weekly data spanning 5 years, from 7 September 2018 to 5 May 2023. To ensure robustness, the sample is divided into three data subsets: (1) The full sample (7 September 2018 to 5 May 2023), (2) The pre-Covid-19 sample (7 September 2018 to 10 March 2020) and (3) The Covid-19 sample (11 March 2020 – 5 May 2023). The determination of pre and Covid-19 periods is based on WHO (2023) information. Covid-19 was declared a pandemic on 11 March

2020 and was no longer declared a pandemic on 5 May 2023 (WHO, 2023). This breakdown provides a comprehensive understanding of the impact of Covid-19 on sectorial stock returns.

Pre-Covid 19 sample is included to act as a baseline, thus helping in distinguishing any shifts in HN, HNP and HNV that may have occurred because of a pandemic. By comparing the Full sample, pre-Covid 19 sample and Covid-19 sample, this will provide a clear view of how visibility and perceptions evolved during Covid-19 pandemic. Additionally, even though during the pre-Covid 19 sample, the Covid-19 was not in public awareness, the pattens and trends of health news before any pandemic outbreak can reveals a typical state of the visibility and perceptions of health news. This assists in comparing the pandemic impact to the time of “normal” health news related to Covid-19. Lastly, including the pre-Covid 19 sample increases the data sample and increases the statistical power of the analyses. Therefore, this may improve the robustness of findings and allow for more comprehensive conclusion.

Table 2: Description of Variables.

Variable	Description	Source
HN, HNP and HNV	Measures the volume search of the health news relating to Covid-19, expressed in natural logs.	Google trends
r_{it} (Stock Returns)	Measures the stock returns of 10 South African sectors, All Shares and Top40	Thompson Reuters DataStream
RCO	Measures the stock returns of Crude-oil.	Yahoo Finance
RNS	Measure the stock returns of NYSE	Global Financial Data
ΔEXR	Measures changes South African nominal exchange rate (USD/ZAR)	South African Reserve Bank
ITR	Measures South African nominal interest rate	South African Reserve Bank
IFR	Measures South African inflation rate	South African Reserve Bank

4. EMPERICAL RESULTS

4.1. Descriptive Statistics

Table 3: Descriptive Summary Statistics

An overview of the descriptive summary statistics for the different variables is given in Table 3. SR has a mean of 0.02, indicating a relatively low average, with a standard deviation of 1.81, suggesting considerable variability. The minimum and maximum values are -13.64 and 11.04, respectively. The 1st percentile is -5.12, and the 99th percentile is 4.73. The skewness is negative (-0.51), implying a slight leftward skew and the kurtosis is 8.87, indicating a distribution with heavier tails and a more pronounced peak. RCO has a mean is 0.04 and the standard deviation is 2.92, pointing to a wider range of values. The data's distribution is characterized by a minimum of -15.06 and a maximum of 11.98. The 1st percentile is -9.54, and the 99th percentile is 9.72. The skewness is negative (-0.53), indicating a slight leftward skew, and the kurtosis is 7.99, suggesting heavier tails and a more peaked distribution. RNS and has a mean is 0.04, with a standard deviation of 1.26. The data ranges from -7.49 to 5.20, with a skewness of -1.06 and kurtosis of 10.96, suggesting a distribution with a pronounced negative skew and heavy tails.

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
SR	3120	0.02	1.81	-13.64	11.04	-5.12	4.73	-0.51	8.87
RCO	3120	0.04	2.92	-15.06	11.98	-9.54	9.72	-0.53	7.99
RNS	3120	0.04	1.26	-7.49	5.20	-5.26	2.98	-1.06	10.96
ΔEXR	3120	0.01	0.40	-1.09	1.72	-0.81	1.60	0.83	5.96
ITR	3132	8.86	1.62	7.00	11.75	7.00	11.75	0.10	1.48
IFR	3132	4.92	1.48	2.10	7.80	2.10	7.80	0.30	2.27
HN	2352	1.02	0.50	0.00	2.00	0.00	1.91	-0.09	2.05
HNP	3132	0.41	0.49	0.00	2.00	0.00	1.60	0.89	2.66
HNV	3132	0.64	0.51	0.00	2.00	0.00	1.85	0.47	2.28

Note (s): SR, RCO and RNS represents sectors returns, crude oil returns and NYSE returns calculated as $r_{it} = log\left(\frac{p_t}{p_{t-1}}\right) * 100$, ΔEXR represents South African nominal exchange rate change, ITR and IFR represents South African interest rate and inflation rate respectively. *HN*, *HNV* and *HNV* represents search indexes of health news, Covid-19 prevention and Covid-19 vaccine expressed as natural logs.

ΔEXR has a mean of 0.01, the standard deviation is 0.40, and the data ranges from -1.09 to 1.72. The skewness is positive (0.83), indicating a rightward skew and the kurtosis is 5.96, suggesting a distribution with somewhat heavy tails and a moderate peak. ITR and IFR represent variables with 3132 observations each. ITR has a mean of 8.86, the standard deviation is 1.62 and the range is from 7 to 11.75. The skewness is positive (0.10) and the kurtosis is 1.48. IFR has a mean of 4.92, a standard deviation of 1.48 and a range from 2.10 to 7.80. The skewness is positive (0.30) and the kurtosis is 2.27. These variables suggest relatively moderate variability with positive skewness and kurtosis indicating a distribution with slightly heavier tails and peaks. Finally, *HN*, *HNP* and *HNV* with 2352 observations each, *HN* has a mean of 1.02, a standard deviation of 0.50, and a range from 0.00 to 2.00. The skewness is negative (-0.09), and the kurtosis is 2.05. *HNP* and *HNV* have means of 0.41 and 0.64, standard deviations of 0.49 and 0.51, and ranges from 0.00 to 2.00. All three variables exhibit positive skewness and kurtosis, suggesting distributions with slightly heavier tails and peaks.

4.2. Presentation of Results

4.2.1 Predictability results of sectorial stock returns: Results related to first and second questions.

This study follows Fasanya (2023) and Salisu et al., (2020) in presenting the results. The results are organized into three tables, namely: Tables 4, 5 and 6. Each table represents the period analysed, as explained in the data section above. Table 4 represents the results for full sample analyses. This is followed by Table 5, representing the results for the pre-COVID-19 period, and lastly, Table 6 follows, which represents the results for the COVID-19 period. Even though this study follows Fasanya (2023) and Salisu et al., (2020) in presenting the results, it is worth noting that Salisu et al., (2020) did not analyse the full sample and pre-COVID-19 period. However, Fasanya (2023) did analyse all sample periods analysed by this study.

Each table is divided into two parts: (1) Without control variables, and (2) With control variables. Without control variables represents results in which control variables were neglected, while with control variables represents results in which control variables are included. Each part contains the analyses of four models namely: Models 1, 2, 3 and 4 respectively. The models are explained in the methodology. For Models 1 and 3 respectively, the first column represents the health news predictor or asymmetries of the predictors. The second, third and fourth columns represents $\alpha_1, \delta_1, \delta_2$ and δ_3 respectively and the parameters and coefficients are explained in methodology. For Models 2 and 4, the first column represents the health news predictor or asymmetries of the predictors. This is followed by columns representing $\alpha_1\ \beta_1^+, \beta_2^-, \beta_2^-, \beta_3^+, \beta_4^-, \beta_5^+$ and β_6^- respectively, which are parameters and coefficients as explained in methodology. All values for parameters and coefficients are presented with their standard errors and their statistically significance level, as explained at the end of the tables below.

4..2.2. In-sample and out-of-sample forecast evaluation: Results related to third and fourth questions.

The forecast evaluation results are presented in Tables 7,8 and 9 for full sample, pre Covid-19 sample and Covid-19 sample respectively. Each table is divided into two parts: (1) Without control variable and (2) With control variables analyses respectively. Each analysis (without or with control variables) is further divided in two: (1) in-sample and, (2) out-of-sample evaluations respectively. For each evaluation, the first column represents the models being compared. Two models are compared with CR model (Model 3 vs CR and Model 4 vs CR). The second columns represent the C-T constant while the third column represents the Clark and West test results (coefficient). The Clark and West coefficient are presented with its standard error and the level of statistical significance level, as explained at the end of each table.

Table 4: Predictability results of sectorial stock returns: Full Sample Results

Full Sample
Without Control Variables

Model 1 and Model 3:

$$r_{it}^{adj} = \alpha_1 + \delta_1 HN_{i,t-1} + \delta_2 HNP_{i,t-1} + \delta_3 HNV_{i,t-1} + e_{it}$$

Model 2 and Model 4:

$$r_{it}^{adj} = \alpha_1 + \beta_1^{+} HN_{i,t-1}^{+} + \beta_2^{-} HN_{i,t-1}^{-} + \beta_3^{+} HNP_{i,t-1}^{+} + \beta_4^{-} HNP_{i,t-1}^{-} + \beta_5^{+} HNV_{i,t-1}^{+} + \beta_6^{-} HNV_{i,t-1}^{-} + e_{it}$$

Model 1

Variables	α_1	δ_1	δ_2	δ_3
$HN_{i,t-1}$	-0.01 (0.89)	-0.25** (0.10)		
$HNP_{i,t-1}$	-0.63 (0.04)		0.19*** (0.07)	
$HNV_{i,t-1}$	-0.07 (0.05)			0.13** (0.06)

Model 3

Variables	α_1	δ_1	δ_2	δ_3
$HN_{i,t-1}$	0.00 (0.09)	-0.26** (0.10)		
$HNP_{i,t-1}$	0.00 (0.09)	-0.26** (0.10)	0.21 (0.14)	
$HNV_{i,t-1}$	0.00 (0.09)	-0.26** (0.10)	0.21 (0.14)	0.21** (0.09)

Model 2

Variables	α_1	β_1^{+}	β_2^{-}	β_3^{+}	β_4^{-}	β_5^{+}	β_6^{-}
$HN_{i,t-1}^{+}$	0.24 (0.71)	-0.27* (0.16)					
$HN_{i,t-1}^{-}$	0.14 (0.70)		0.06 (0.04)				
$HNP_{i,t-1}^{+}$	0.40 (0.76)			0.56* (0.35)			
$HNP_{i,t-1}^{-}$	0.14 (0.70)				-0.05* (0.03)		
$HNV_{i,t-1}^{+}$	0.29 (0.71)					0.04* (0.02)	
$HNV_{i,t-1}^{-}$	0.24 (0.71)						-0.19* (0.16)

Model 4

Variables	α_1	β_1^{+}	β_2^{-}	β_3^{+}	β_4^{-}	β_5^{+}	β_6^{-}
$HN_{i,t-1}^{+}$	0.43 (0.81)	-1.43*** (0.43)					
$HN_{i,t-1}^{-}$	0.43 (0.81)	-1.43*** (0.43)	0.42*** (0.16)				
$HNP_{i,t-1}^{+}$	0.43 (0.81)	-1.43*** (0.43)	0.42*** (0.16)	0.34** (0.14)			
$HNP_{i,t-1}^{-}$	0.43 (0.81)	-1.43*** (0.43)	0.42*** (0.16)	0.34** (0.14)	-0.14 (0.09)		
$HNV_{i,t-1}^{+}$	0.43 (0.81)	-1.43*** (0.43)	0.42*** (0.16)	0.34** (0.14)	-0.14 (0.09)	0.52 (0.35)	
$HNV_{i,t-1}^{-}$	0.43 (0.81)	-1.43*** (0.43)	0.42*** (0.16)	0.34** (0.14)	-0.14 (0.09)	0.52 (0.35)	-0.65** (0.32)

With Control Variables

Model 1:

$HN_{i,t-1}$	0.09***	-0.10***		
	(0.02)	(0.01)		
$HNP_{i,t-1}$	-0.0.3***		0.12***	
	(0.01)		(0.01)	
$HNP_{i,t-1}$	0.03***			0.26***
	(0.01)			(0.01)

Model 2:

$HN_{i,t-1}^{+}$	0.69***	-0.79***					
	(0.11)	(0.01)					
$HN_{i,t-1}^{-}$	0.37***		0.14***				
	(0.10)		(0.01)				
$HNP_{i,t-1}^{+}$	0.69***			0.06***			
	(0.12)			(0.01)			
$HNP_{i,t-1}^{-}$	1.45***				-0.10***		
	(0.12)				(0.00)		
$HNV_{i,t-1}^{+}$	1.03***					0.07***	
	(1.21)					(0.01)	
$HNV_{i,t-1}^{-}$	0.84***						-0.05***
	(0.11)						(0.00)

Model 3:

$HN_{i,t-1}$	0.035***	-0.26***		
	(0.02)	(0.02)		
$HNP_{i,t-1}$	0.035***	-0.26***	0.27***	
	(0.02)	(0.02)	(0.02)	
$HNP_{i,t-1}$	0.035***	-0.26***	0.27***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)

Model 4

$HN_{i,t-1}^{+}$	0.54***	-0.42***					
	(0.12)	(0.06)					
$HN_{i,t-1}^{-}$	0.54***	-0.42***	0.43***				
	(0.12)	(0.06)	(0.02)				
$HNP_{i,t-1}^{+}$	0.54***	-0.42***	0.43***	0.11***			
	(0.12)	(0.06)	(0.02)	(0.02)			
$HNP_{i,t-1}^{-}$	0.54***	-0.42***	0.43***	0.11***	-0.24***		
	(0.12)	(0.06)	(0.02)	(0.02)	(0.01)		
$HNV_{i,t-1}^{+}$	0.54***	-0.42***	0.43***	0.11***	-0.24***	0.25***	
	(0.12)	(0.06)	(0.02)	(0.02)	(0.01)	(0.05)	
$HNV_{i,t-1}^{-}$	0.54***	-0.42***	0.43***	0.11***	-0.24***	0.25***	-0.24***
	(0.12)	(0.06)	(0.02)	(0.02)	(0.01)	(0.05)	(0.01)

Note (s): Model 1 represents the single predictor model in which the Health News relating to Covid-19 (HN, HNP and HNV) is the single predictor, Model 2 represents a model in which all Health News to Covid-19 (HN, HNP and HNV) are all predictors simultaneously, Model 3 represents Model 1 with asymmetry and lastly, Model 4 represents Model 2 with asymmetry. Values in parenthesis are standard errors.

*** Indicates statistical significance at 1%

** Indicates statistical significance at 5%

* Indicates statistical significance at 10%

Table 5: Predictability results of sectorial stock returns: Pre Covid-19 Period Results

Pre Covid-19 Sample
Without Control Variables

Model 1 and Model 3:

$$r_{it}^{adj} = \alpha_1 + \delta_1 HN_{i,t-1} + \delta_2 HNP_{i,t-1} + \delta_3 HNV_{i,t-1} + e_{it}$$

Model 2 and Model 4:

$$r_{it}^{adj} = \alpha_1 + \beta_1^{+} HN_{i,t-1}^{+} + \beta_2^{-} HN_{i,t-1}^{-} + \beta_3^{+} HNP_{i,t-1}^{+} + \beta_4^{-} HNP_{i,t-1}^{-} + \beta_5^{+} HNV_{i,t-1}^{+} + \beta_6^{-} HNV_{i,t-1}^{-} + e_{it}$$

Variables	α_1	δ_1	δ_2	δ_3
Model 1				
$HN_{i,t-1}$	-0.76	-1.41***		
	(0.68)	(0.48)		
$HNP_{i,t-1}$	0.19		3.78**	
	(0.67)		(1.80)	
$HNV_{i,t-1}$	-0.76			2.77***
	(0.68)			(0.68)
Model 3				
$HN_{i,t-1}$	-0.90	-0.24***		
	(0.63)	(0.49)		
$HNP_{i,t-1}$	-0.90	-0.24***	8.56***	
	(0.63)	(0.49)	(1.82)	
$HNV_{i,t-1}$	-0.90	-0.24***	8.56***	4.30**
	(0.63)	(0.49)	(1.82)	(0.73)

Variables	α_1	β_1^{+}	β_2^{-}	β_3^{+}	β_4^{-}	β_5^{+}	β_6^{-}
Model 2							
$HN_{i,t-1}^{+}$	4.80	-3.44***					
	(1.10)	(0.80)					
$HN_{i,t-1}^{-}$	2.45***		0.21***				
	(0.87)		(0.07)				
$HNP_{i,t-1}^{+}$	-			-			
$HNP_{i,t-1}^{-}$	12.12***				-7.38***		
	(1.82)				(1.10)		
$HNV_{i,t-1}^{+}$	3.61***					0.21**	
	(1.23)					(0.10)	
$HNV_{i,t-1}^{-}$	1.26						-0.21**
	(1.06)						(0.10)
Model 4							
$HN_{i,t-1}^{+}$	11.01***	-1.55					
	(1.92)	(2.03)					
$HN_{i,t-1}^{-}$	11.01***	-1.55	0.27				
	(1.92)	(2.03)	(0.40)				
$HNP_{i,t-1}^{+}$	-	-	-	-			
$HNP_{i,t-1}^{-}$	11.01***	-1.55	0.27	-	-6.35***		
	(1.92)	(2.03)	(0.40)		(0.35)		
$HNV_{i,t-1}^{+}$	11.01***	-1.55	0.27	-	-6.35***	0.21	
	(1.92)	(2.03)	(0.40)		(0.35)	(0.54)	
$HNV_{i,t-1}^{-}$	11.01***	-1.55	0.27	-	-6.35***	0.21	-0.41
	(1.92)	(2.03)	(0.40)		(0.35)	(0.54)	(0.53)

With Control Variables

Model 1:

$HN_{i,t-1}$	0.43***	-0.50***		
	(0.17)	(0.10)		
$HNP_{i,t-1}$	0.51***		2.11***	
	(1.16)		(0.43)	
$HNP_{i,t-1}$	0.17			0.90***
	(0.17)			(0.17)

Model 2:

$HN^{+}_{i,t-1}$	4.11***	-2.95***					
	(0.21)	(0.15)					
$HN^{-}_{i,t-1}$	2.41***		0.21***				
	(0.18)		(0.01)				
$HNP^{+}_{i,t-1}$	-			-			
$HNP^{-}_{i,t-1}$	2.95***				-1.82*** (0.24)		
	(0.41)						
$HNV^{+}_{i,t-1}$	2.26***					0.16***	
	(0.25)					(0.02)	
$HNV^{-}_{i,t-1}$	2.24***						-0.12***
	(0.23)						(0.01)

Model 3:

$HN_{i,t-1}$	0.11	-1.30***		
	(0.13)	(0.10)		
$HNP_{i,t-1}$	0.11	-1.30***	3.89***	
	(0.13)	(0.10)	(0.36)	
$HNP_{i,t-1}$	0.11	-1.30***	3.89***	1.60***
	(0.13)	(0.10)	(0.36)	(0.15)

Model 4

$HN^{+}_{i,t-1}$	2.90***	-3.24***					
	(0.36)	(0.39)					
$HN^{-}_{i,t-1}$	2.90***	-3.24***	0.24***				
	(0.36)	(0.39)	(0.08)				
$HNP^{+}_{i,t-1}$	-	-3.24***	0.24***	-			
		(0.39)	(0.08)				
$HNP^{-}_{i,t-1}$	2.90***	-3.24***	0.24***	-	-1.05*** (0.26)		
	(0.36)	(0.39)	(0.08)				
$HNV^{+}_{i,t-1}$	2.90***	-3.24***	0.24***	-	-1.05*** (0.26)	0.42***	
	(0.36)	(0.39)	(0.08)			(0.10)	
$HNV^{-}_{i,t-1}$	2.90***	-3.24***	0.24***	-	-1.05*** (0.26)	0.42***	-0.47***
	(0.36)	(0.39)	(0.08)			(0.10)	(0.10)

Note (s): Model 1 represents the single predictor model in which the Health News relating to Covid-19 (HN, HNP and HNV) is the single predictor, Model 2 represents a model in which all Health News to Covid-19 (HN, HNP and HNV) are all predictors simultaneously, Model 3 represents Model 1 with asymmetry and lastly, Model 4 represents Model 2 with asymmetry. Values in parenthesis are standard errors.

*** Indicates statistical significance at 1%

** Indicates statistical significance at 5%

* Indicates statistical significance at 10%

Table 6: Predictability results of sectorial stock returns: Covid-19 Results

Covid-19 Sample
Without Control Variables

Model 1 and Model 3:

$$r_{it}^{adj} = \alpha_1 + \delta_1 HN_{i,t-1} + \delta_2 HNP_{i,t-1} + \delta_3 HNV_{i,t-1} + e_{it}$$

Model 2 and Model 4:

$$r_{it}^{adj} = \alpha_1 + \beta_1^+ HN_{i,t-1}^+ + \beta_2^- HN_{i,t-1}^- + \beta_3^+ HNP_{i,t-1}^+ + \beta_4^- HNP_{i,t-1}^- + \beta_5^+ HNV_{i,t-1}^+ + \beta_6^- HNV_{i,t-1}^- + e_{it}$$

Model 1

Variables	α_1	δ_1	δ_2	δ_3
$HN_{i,t-1}$	0.07	-0.19		
	(0.11)	(0.12)		
$HNP_{i,t-1}$	0.12		-0.18*	
	(0.11)		(1.80)	
$HNV_{i,t-1}$	0.07			-0.22*
	(0.11)			(0.13)

Model 2

Variables	α_1	β_1^+	β_2^-	β_3^+	β_4^-	β_5^+	β_6^-
$HN_{i,t-1}^+$	0.10	-0.10					
	(0.94)	(0.08)					
$HN_{i,t-1}^-$	0.52		-0.33				
	(0.98)		(0.24)				
$HNP_{i,t-1}^+$	0.10			-0.08			
	(0.94)			(0.06)			
$HNP_{i,t-1}^-$	0.21				-0.05		
	(0.94)				(0.04)		
$HNV_{i,t-1}^+$	0.10					-0.05	
	(0.97)					(0.05)	
$HNV_{i,t-1}^-$	0.52						-0.33
	(0.98)						(0.23)

Model 3

Variables	α_1	δ_1	δ_2	δ_3
$HN_{i,t-1}$	0.09	-0.20*		
	(0.11)	(0.13)		
$HNP_{i,t-1}$	0.09	-0.20*	-0.12	
	(0.11)	(0.13)	(0.12)	
$HNV_{i,t-1}$	0.09	-0.20*	-0.12	-0.15
	(0.11)	(0.13)	(0.12)	(0.15)

Model 4

Variables	α_1	β_1^+	β_2^-	β_3^+	β_4^-	β_5^+	β_6^-
$HN_{i,t-1}^+$	1.85*	-1.39***					
	(1.20)	(0.51)					
$HN_{i,t-1}^-$	1.85*	-1.39***	-1.16***				
	(1.20)	(0.51)	(0.44)				
$HNP_{i,t-1}^+$	1.85*	-1.39***	-1.16***	-0.29*			
	(1.20)	(0.51)	(0.44)	(0.16)			
$HNP_{i,t-1}^-$	1.85*	-1.39***	-1.16***	-0.29*	-0.01		
	(1.20)	(0.51)	(0.44)	(0.16)	(0.12)		
$HNV_{i,t-1}^+$	1.85*	-1.39***	-1.16***	-0.29*	-0.01	-0.54	
	(1.20)	(0.51)	(0.44)	(0.16)	(0.12)	(0.47)	
$HNV_{i,t-1}^-$	1.85*	-1.39***	-1.16***	-0.29*	-0.01	-0.54	-1.00**
	(1.20)	(0.51)	(0.44)	(0.16)	(0.12)	(0.47)	(0.47)

With Control Variables

Model 1:

$HN_{i,t-1}$	0.07**	-0.07**		
	(0.27)	(0.03)		
$HNP_{i,t-1}$	0.04		-0.12***	
	(0.02)		(0.03)	
$HNP_{i,t-1}$	0.03			-0.06***
	(0.02)			(0.02)

Model 2:

$HN^{+}_{i,t-1}$	0.65***	-0.07**					
	(0.22)	(0.02)					
$HN^{-}_{i,t-1}$	0.71***		-0.02***				
	(0.22)		(0.01)				
$HNP^{+}_{i,t-1}$	0.65***			-0.05***			
	(0.22)			(0.01)			
$HNP^{-}_{i,t-1}$	0.50**				-0.01**		
	(0.21)				(0.00)		
$HNV^{+}_{i,t-1}$	0.69***					-0.04***	
	(0.23)					(0.01)	
$HNV^{-}_{i,t-1}$	0.35						-0.31***
	(0.23)						(0.06)

Model 3:

$HN_{i,t-1}$	0.05**	-0.04		
	(0.03)	(0.03)		
$HNP_{i,t-1}$	0.05**	-0.04	-0.11***	
	(0.03)	(0.03)	(0.03)	
$HNP_{i,t-1}$	0.05**	-0.04	-0.11***	-0.17***
	(0.03)	(0.03)	(0.03)	(0.03)

Model 4

$HN^{+}_{i,t-1}$	0.03	-0.64***					
	(0.28)	(0.12)					
$HN^{-}_{i,t-1}$	0.03	-0.64***	-0.77***				
	(0.28))	(0.12)	(0.10)				
$HNP^{+}_{i,t-1}$	0.03	-0.64***	-0.77***	-0.31***			
	(0.28)	(0.12)	(0.10)	(0.04)			
$HNP^{-}_{i,t-1}$	0.03	-0.64***	-0.77***	-0.31***	-0.14***		
	(0.28)	(0.12)	(0.10)	(0.04)	(0.03)		
$HNV^{+}_{i,t-1}$	0.03	-0.64***	-0.77***	-0.31***	-0.14***	-0.37***	
	(0.28)	(0.12)	(0.10)	(0.04)	(0.03)	(0.12)	
$HNV^{-}_{i,t-1}$	0.03	-0.64***	-0.77***	-0.31***	-0.14***	-0.37***	-0.43***
	(0.28)	(0.12)	(0.10)	(0.04)	(0.03)	(0.12)	(0.11)

Note (s): Model 1 represents the single predictor model in which the Health News relating to Covid-19 (HN, HNP and HNV) is the single predictor, Model 2 represents a model in which all Health News to Covid-19 (HN, HNP and HNV) are all predictors simultaneously, Model 3 represents Model 1 with asymmetry and lastly, Model 4 represents Model 2 with asymmetry. Values in parenthesis are standard errors.

*** Indicates statistical significance at 1%

** Indicates statistical significance at 5%

* Indicates statistical significance at 10%

Table 7: In-sample and out-of-sample forecast evaluation: Full sample.

Models	In-sample		Out-of-sample	
	C-T stat	Clark and West	C-T stat	Clark and West
Without Control Variables				
Model 3 vs CR	0.06	3.53*** (0.18)	0.01	2.34*** (0.22)
Model 4 vs CR	0.09	3.37*** (0.17)	0.03	2.91*** (0.48)
With Control Variables				
Model 3 vs CR	0.10	3.56*** (0.18)	0.91	2.39*** (0.23)
Model 4 vs CR	0.18	3.43*** (0.17)	0.97	2.44*** (0.34)

Note (s): CR is the historical advantage model. Without control variables refer models without control variables, With control variables refer to models with control variables, Model 3 is a model in which all health news indicators are predictors, Model 4 is a model in which all partial sums are predictors. Assessing and comparing the performance of the variant models (MD3 and MD4) is done by forecasting, and their results are juxtaposed with the performance of the historical average. Standard errors are presented within parentheses.

*** Indicates statistical significance at 1%

Table 8: In-sample and out-of-sample forecast evaluation: pre Covid-19 period.

Models	In-sample		Out-of-sample	
	C-T stat	Clark and West	C-T stat	Clark and West
Without Control Variables				
Model 3 vs CR	0.02	3.12*** (0.69)	0.01	4.05*** (0.96)
Model 4 vs CR	0.14	3.00*** (0.41)	0.04	3.84*** (0.63)
With Control Variables				
Model 3 vs CR	0.79	3.32*** (0.71)	0.58	4.08*** (0.97)
Model 4 vs CR	0.95	6.16*** (0.40)	0.86	4.25*** (0.99)

Note (s): CR is the historical advantage model. Without control variables refer models without control variables, With control variables refer models with control variables, Model 3 is a model in which all health news indicators are predictors, Model 4 is a model in which all partial sums are predictors. Assessing and comparing the performance of the variant models (MD3 and MD4) is done by forecasting, and their results are juxtaposed with the performance of the historical average. Standard errors are presented within parentheses.

*** Indicates statistical significance at 1%

Table 9: In-sample and out-of-sample forecast evaluation: Covid-19 period.

Models	In-sample		Out-of-sample	
	C-T stat	Clark and West	C-T stat	Clark and West
Without Control Variables				
Model 3 vs CR	0.05	3.66*** (0.21)	0.02	2.24*** (0.30)
Model 4 vs CR	0.08	4.59*** (0.23)	0.07	2.68*** (0.42)
With Control Variables				
Model 3 vs CR	0.20	3.67*** (0.21)	0.43	2.32*** (0.32)
Model 4 vs CR	0.31	3.67*** (0.20)	0.98	2.45*** (0.34)

Note (s): CR is the historical advantage model. Without control variables refer models without control variables, With control variables refer models with control variables, Model 3 is a model in which all health news indicators are predictors, Model 4 is a model in which all partial sums are predictors. Assessing and comparing the performance of the variant models (MD3 and MD4) is done by forecasting, and their results are juxtaposed with the performance of the historical average. Standard errors are presented within parentheses.
*** Indicates statistical significance at 1%

4.3 Discussion of results

4.3.1 What is the impact of health news related to Covid-19 on South African sectorial stock returns?

Tables 4,5 and 6 summarizes the predictability results of four models for full sample. Four models are analysed for without and with control variables, as outlined in the methodology. When full sample without control variables considered is analysed, the estimated coefficients for Models 1 and 2 are correctly signed and statistically significant following the a priori expectation. The results reveal that HN impacts SR negatively and is statistically significant at 5% level of significance, while HNP and HNV both impacts SR positively and are statistically significant at 1% and 5% level of significance respectively. Analyses of Model 2 reveal that HN^{+}, HNV^{-} and HNP^{-} impacts SR negatively respectively and are all statistically significant at 10% level of significance. HNV^{+} and HNP^{+} both affects SR positively respectively and are also statistically significant at 10% level of significance.

Model 3 results reveal similar results to Model 1, except for the statistical insignificant of one variable. HN and HNV impacts SR negatively and positively respectively and are both statistically significant at 5% level of significance. Model 4 results concurs with that of Model 2 also. The HN^{+} and HNV^{-} both impacts SR negatively and are both statistically significant at 10% level of significance. Also, HN^{-} and HNP^{+} both affects SR positively and are both statistically significant at 10%. Therefore, as expected, Model 1 and Model 3 results concurs with each other while Model 2 and Model 4 results concurs with each other also. Therefore, for all our Models 1,2,3 and 4, the estimated coefficients are correctly signed and statistically significant following the a priori expectation.

When control variables are considered and all Models 1,2,3 and 4 are re-examined, Model 1 results are still analogous to when control variables were neglected, however they become more significant. HN impacts SR negatively while , HNP and HNV both impacts SR positively and all health news predictors (HN, HNP and HNV) are statistically significant at 1% level of significance. The Model 2 results are also analogous to when control variables were neglected, however, statistical significance improves. HN^+, HNP^- and HNV^- all affects SR negatively, while HN^-, HNP^+ and HNV^+ all affects SR positively. All asymmetric variables are statistically significant at 1% level of significance. It is transspecies that the addition of control variables to our models improves the statistical significance of our variables.

Models 3 and 4 with control variables yields similar results also to when control variables were neglected, however statistical significance improves. Model 3 results indicates that HN impacts SR negatively while HNP and HNV impacts SR positively respectively. All variables are statistically significant at 1% level of significance. Model 4 results shows that HN^+, HNP^- and HNV^- all affects SR negatively while HN^-, HNP^+ and HNV^+ all affects SR positively. All asymmetric variables are statistically significant at 1% level of significance. It is worth noting that the full sample results are similar in terms of the impacts for both with and without control variables, however, the statical significance improves with the addition of control variables. Therefore, this implies that the control variables are contributing valuable information and helping to better explain the variation in the SR.

The pre Covid-19 sample results are analogous to that of a full sample, except for statistical significance of some variables. When control variables are neglected Model 1 results indicates that HN impacts SR negatively while HNP and HNV both affects SR positively and all variables are statistically significant at 1% level of significance. Model 2 results shows that HN^+, HNP^- and HNV^- all affects SR negatively while HN^- and HNV^+ both affects SR positively and all asymmetric variables are statistically significant at 1% level of significance. Model 3 and Model 4 results also simulates that of full sample. HN impacts SR negatively while HNP and HNV both affects SR positively and all variables are statistically significant at 1% level of significance. When all asymmetries are regressed simultaneously, HNP^- affects SR negatively and is statistically significant at 1% level of significance.

When control variables are incorporated in the Models, Model 1 results are analogous to when regressions are conducted without control variables. HN impacts SR negatively while HNP and HNV both affects SR positively and all variables are statistically significant at 1% level of significance. Model 2 results shows that HN^+, HNP^- and HNV^- all affects SR negatively while HN^- and HNV^+ all affects SR positively and all asymmetric variables are statistically significant at 1% level of significance. Model 3 results indicates that HN impacts SR negatively while HNP and HNV both affects SR positively and all variables are statistically significant at 1% level of significance. Also, Model 4 results are as follows: HN^+, HNP^- and HNV^- all affects SR negatively while HN^- and HNV^+ all affects SR positively and all asymmetric variables are statistically significant at 1% level of significance.

The focus and most important period for this study is Covid-19 period. Full sample and pre Covid-19 sample are analysed for robustness purposes. When control variables are ignored, Model 1 reveals that HNP and HNV impact SR negatively and both are statistically significant at 10% level of significance. The analyses of Model 3 shows that HN negatively impacts SR and it is statistically significant at 10% level of significance. Lastly, Model 4 analyses reveals that HN^{+} and HN^{-} negatively impacts SR, and both are statistically significant at 1% level of significance. HNP^{+} and HNV^{-} also impacts SR negatively and are statistically significant at 10% and 5% level of significance respectively.

When control variables are taken into consideration, Model 1 results shows that all health news predictors (HN, HNP and HNV) impacts SR negatively and are all statistically significant at 1% level of significance. Model 2 revels the same results also except the less statistical significance of HN^{+}. All asymmetric variables (HN^{+}, HN^{-}, HNP^{-}, HNP^{+}, HNV^{-} and HNV^{+}) affects SR negatively and HN^{+} is statistically significant at 5% level of significance. All other variables are statistically significant at 1% level of significance. The Model 3 results revels the same results. The health news predictors HN and HNV impacts SR negatively and are both statically significant at 5% and 1% level of significance respectively. Lastly, Model 4 results are no different to when control variable are ignored, except the increased statistical significance of asymmetric variables. The asymmetric variables HN^{+}, HN^{-}, HNP^{-}, HNP^{+}, HNV^{-} and HNV^{+} impacts SR negatively and all variables are statistically significant at 1% level of significance.

This study reveals that the impact of health news related to Covid-19 differs during mixed period (full sample which contains both pre Covid-19 and Covid-19 period), pandemic free period (pre Covid-19 period) and pandemic period (Covid-19 period). However, one of the challenges that this study faced is the scarcity of studies that examined the mixed and free pandemic periods. Most studies focused only on Covid-19 period. The HN impacts SR negatively for all periods, while HNP and HNV impacts SR positively for mixed and pandemic free period and impacts SR negatively for a pandemic period. HN^{+}, HNP^{-} and HNV^{-} all affects SR negatively while HN^{-}, HNP^{+} and HNV^{+} all affects SR positively for mixed and pandemic free period. All asymmetries affect SR negatively for a pandemic period.

It is worth noting that it is not unusual for variables impact to change for different periods. Fasanya (2023) finds that IDEM impacts technology sector returns negatively for full sample and pre Covid-19 while the impact is positive for a Covid-19 period. The hedging characteristics of the stock before the onset of the COVID-19 crisis provide additional clarification for the positive impact of HNV and HNP on financial stocks during the full and pre-COVID period (Fasanya, 2023). In addition, the overall negative impact of health news relating to Covid-19 on SR indicates that irrespective of fluctuations in health news (HN, HNP and HNV), its influence on stock returns is detrimental throughout the pandemic (Salisu et al., 2020).

It is worth noting that the Covid-19 was first detected in China in December 2019 (WHO, 2020). The news of its deadly nature and possible spread to other countries quickly spread thought the globe. The first case of Covid-19 in South Africa was detected on 5 March 2020 (National Institute of Health (NIH), 2020). A week later, the WHO (2020) declared Covid-19 as a pandemic on 11 March 2020. With the detection of COVID-19 in China, it is noteworthy that investors had proactively factored in the implications of the pandemic into their decision-making processes. By the time COVID-19 reached South Africa, its potential impact on various sectors had already been considered by market participants, resulting in some health news predictors being insignificant. It is also worth noting that the inclusion of control variables enhances the precision of coefficient estimates by reducing standard errors. This resulted in health news indicators being significant when control variables are considered.

The results of this study concurs with a number of studies including Fasanya et al., (2023) who finds that the short-run estimates revels that the Covid-19 reported cases have a negative significant relationship with stock prices of the countries under investigation, except for Italy where there is no significance relationship. In long-run, Covid-19 cases have a negative relationship with the France and Italy stock indices. Additionally, Pretorius (2023) finds that news/events relating to Covid-19 pandemic had much more negative impact on the advanced emerging stock markets. Also, Jin (2022) observes that there is negative correlation between the new infection rate of Covid-19 and stock-prices in a short-term. After the Covid-19 pandemic outbreak (2021), Covid-19 new infections depressed the inner-day volatility in a short-term, while it increased the stock prices in a long-term, indicating negative relationship between news relating to Covid-19 and SR. Lastly, Salisu et al., (2020) observe that seeking more information on health issues since the pandemic outbreak, as reflected in health news, is associated with a statistically significant and adverse impact on stock returns. This implies that stock returns tend to decrease as the demand for health-related information increases in the wake of the pandemic.

4.3.2 Can health news related to Covid-19 predict South African sectorial stock returns during and after the Covid-19 pandemic?

This study delves into the intricate relationship between health news searches and the SR of South African sectors, with a specific focus on the Covid-19 period. The findings illuminate a nuanced dynamic, indicating a negative impact on SR attributed to an increase in health news searches during the Covid-19 era. While the influence of some health news searches during non-Covid-19 periods is discerned to have a positive impact on SR, the overall effect during the pandemic is notably negative. This outcome aligns seamlessly with our a priori expectations, affirming the heightened sensitivity of the stock market to health-related information during the unique circumstances posed by the global health crisis.

Moving beyond the impact assessment, the study also undertakes a comprehensive evaluation of forecasting performance using health news as a predictor for stock returns. Both in-sample and out-of-sample evaluations consistently demonstrate the outperformance of the health news predictive model over the conventional CR model. The application of the Campbell & Thompson (2008) and Clark and West Test (2007) confirms the superiority of the health news predictive model, emphasizing its ability to enhance predictive accuracy in comparison to the benchmark CR model. Remarkably, this outperformance extends across both long and short forecasting horizons, indicating the robustness of the health news predictive model and its applicability across diverse timeframes. This observation carries significant implications, suggesting that the incorporation of health news as a predictor can yield reliable predictions regardless of the specific forecast timeframe, catering to the varied needs of investors, practitioners, and policymakers.

Considering these findings, the study unveils a compelling conclusion regarding the predictive utility of health news related to Covid-19 in forecasting South African sectorial stock returns. The robustness of the health news predictive model, especially during the pandemic, suggests its potential applicability beyond the immediate crisis, extending into the post-Covid-19 period. As a result, this study not only contributes to our understanding of the complex interplay between health news and stock returns but also provides practical insights for stakeholders. Investors, practitioners and policymakers can leverage the predictive power of health news in navigating the evolving landscape of South African sectorial stock returns, both during and in the aftermath of the Covid-19 pandemic.

4.3.3 What is the performance of both in-sample and out-of-sample forecasts of the health news related to Covid-19-based predictive model for South African sectorial stock returns?

Tables 7, 8 and 9 assess the predictive accuracy of each competing model, encompassing the CR model and different health-news predictability models (Models 3 and 4) for both without and with control variables. The assessment of predictive accuracy is conducted for both in-sample and out-of-sample forecast periods, employing two pairwise forecast evaluation methods: the Campbell & Thompson (2008) test and the Clark and West (2007) test. The Campbell & Thompson (2008) (C-T (2008)) statistic compares the Mean Square Error (MSE) or Root Mean Square Error (RMSE), which measures the deviation of the forecast from the actual values, among competing models. A model is considered superior to another when the C-T statistic is positive, indicating that its $M\hat{S}E_u$(numerator) outperforms the $M\hat{S}E_r$ of the other model (denominator), in this case the unrestricted and restricted models. Conversely, a negative C-T (2008) statistic suggests inferior performance. On the other hand, the Clark and West (2007) test serves as a formal procedure to determine the statistical significance of the disparities in observed forecast errors. If the constant parameter in the Clark and West (2007) test regression is positive and significant, it implies better forecast performance of the model with adjusted-MSE compared to the one without adjustment (refer to methodology).

For all our samples (full, pre Covid-19 and Covid-19 periods), the C-T (2008) statistics are all positive. In addition to that, the Clark and West (2007) coefficients are positive and are statistically significant at 1% for both in sample and out of sample. This is an indication of Models 3 and 4 outperforming the CR model. As a result, this implies the following: (i) The health news predictors model, when all health news predictors are regressed simultaneously without control variables, outperforms the CR model, (ii) The health news predictors model, when all health news predictors are regressed simultaneously with control variables, outperforms the CR model (iii) The health news asymmetric predictors model, when all health news asymmetric predictors are regressed simultaneously without control variables, outperforms the CR model, (iv) The health news asymmetric predictors model, when all health news asymmetric predictors are regressed simultaneously with control variables, outperforms the CR model., (v) The predictability of stock returns is influenced by the asymmetry observed in health-news searches and lastly, (vi) The inclusion of macroeconomic variables enhances the forecasting accuracy of predicting stock returns.

The results from forecasting evaluation concurs with Salisu et al., (2020) and Tuna (2022) who finds that positive C-T (2008) statistics and Clark and West (2007) coefficients, along with their statistical significance, in both in-sample and out-of-sample data sets, signify that the models excel in comparison to the CR predictor. Salisu et al., (2020) and Tuna (2022) further asserts that: (i) The stock returns model with the health-news index as the sole predictor demonstrates superior performance compared to the CR model, (ii) Considering the day-of-the-week effect and adjusting the stock returns series proves to be pertinent, enhancing the predictive accuracy of the single predictor model, (iii) The asymmetry in health-news searches plays a significant role in predicting stock returns, where heightened searches for health news exert a more pronounced negative impact on stock returns and lastly, (iv) Incorporating control for macroeconomic variables enhances the overall forecasting performance of stock returns predictability.

In addition to Salisu et al., (2020) and Tuna (2022), the result of this study also concurs with Fasanya (2023) who notes that, across all sample sets and at both forecast horizons, both the IDMV and the control predictive models for stock returns exhibit superior performance compared to the CR model. The consistent outperformance in out-of-sample predictions, coupled with the evidence of in-sample predictability, underscores the effectiveness of incorporating IDMV in the predictive model for stock returns. This improvement in predictive accuracy is evident when comparing our model to the CR model benchmark. Additionally, the consistent outperformance holds true for both long and short horizons, suggesting that the results remain consistent regardless of the forecast horizon under consideration. The result of this study concurs with the expected results and results of other conducted studies (Salisu et al., 2020 and Tuna.,2022).

4.3.4 Does controlling of macro-based predictors enhance the forecast performance of proposed model?

The evaluation of forecasting performance, as presented in Tables 7, 8, and 9, the results reveal valuable insights into the effectiveness of the models under consideration. Notably, the positive C-T (2008) constants and Clark and West (2007) coefficients respectively with the latter statistical significance observed in both Models 3 and 4 suggest a superior performance compared to the CR model. This superiority is evident in both in-sample and out-of-sample evaluations, demonstrating the robust predictive capabilities of these models. The positive coefficients indicate that the proposed models outperform the baseline CR model, reinforcing their reliability in forecasting. Therefore, this indicates that Models 3 and 4 are better forecasting than CR model.

A critical observation arises when comparing analyses conducted with and without control variables. The C-T (2008) constants, serving as crucial indicators of forecasting performance, exhibit nuanced behaviour in this context. Interestingly, the analyses without control variables yield smaller C-T (2008) constants than those with control variables. This divergence implies that the introduction of control variables contributes to an increase in the C-T (2008) constant. In a theoretical sense, a larger C-T (2008) constant signifies improved forecasting performance. Therefore, the incorporation of control variables evidently enhances the predictive capabilities of our proposed models. This result underscores the importance of considering and incorporating relevant control variables for a more accurate and robust forecasting model.

The findings regarding the C-T (2008) constants carry important theoretical implications for forecasting methodologies. The discernible enhancement in forecasting performance when control variables are integrated into the models suggests that a comprehensive approach, accounting for additional factors, yields more accurate predictions. This implies that, beyond the core variables, certain external factors captured by control variables contribute significantly to the model's forecasting efficacy. Consequently, this study not only reinforces the superiority of Models 3 and 4 over the CR model but also underscores the practical importance of refining forecasting models by judiciously incorporating relevant control variables, ultimately enhancing their overall predictive power.

5. CONCLUSSION AND POLICY RECOMMENDATION

This study examines the role of health news relating to Covid-19 on predictability of South African sectors stock returns. This is motivated by the recent Covid-19 pandemic. The analyses cover 10 South African different sectors namely Automobiles & Parts, Beverages, Construction & Materials, Consumer Goods, Consumer Services, Financials, Mining, Pharmaceuticals & Biotechnology, Technology and Telecommunications. In addition to that, South African All Share Index and Top 40 Index are added. The empirical literature is filled with research studies investigating how news and information can predict economic and financial variables (Chen et al., (2007); Jiang et al., (2017); Khatatbeh et al., (2020); Lee et al., (2020); Salisu et al., (2020); Velasquez et al., (2022); Pretorius (2023) and Fasanya et al., (2023)). Nevertheless, the impact of health news on return predictability has received limited attention (Salisu et al., 2020). This constitutes the primary contribution of the study.

This study utilizes a panel data forecasting method to analyse the performance of health news relating to Covid-19 on stock return predictability in South Africa. For robustness, this study analyses the full and pre Covid-19 samples, the asymmetry effect and account for common macroeconomic factors in the pandemic-based predictive model for South African sectoral stock returns. The discovery of this study reveals that the pursuit of health-related news is associated with a negative and statistically significant impact on South African stock returns, implying a decline in stock returns amid increased interest in health news following the pandemic outbreak. The model using a health news predictor consistently performs better than the CR model, both in-sample and out-of-sample. Additionally, controlling for other macroeconomic variables and the "asymmetry" effect, enhances the forecast accuracy of health news.

These findings carry practical implications for various stakeholders, including academics, practitioners such as rational investors, portfolio managers, and policymakers. The implications extend to areas such as portfolio risk management, diversification benefits, and the potential development of new investment tools within financial markets. Investors should consider the potential impacts of global pandemics when assessing risk-adjusted returns for stocks, and this consideration may also apply to the broader diversification of financial assets. This conclusion aligns with the growing body of literature highlighting the stock market's vulnerability to the COVID-19 pandemic. For future research endeavours, it would be intriguing to explore the diversification properties of other financial markets, such as cryptocurrencies, commodities, foreign exchange, bonds, money markets, and real estate. A particular focus on examining the effects of uncertainties arising from pandemics and epidemics could contribute further to the existing literature. It is important to note that a limitation of this study is the omission of the role played by government and market regulators. Thus, future studies may benefit from incorporating the influence of government policies and relevant market regulatory measures when modelling the financial sector's response to pandemics.

The future studies can improve this study by pooling together several countries other than analysing one country. Pooling together different countries will bring the average date closer to 11 March 2020 which is the date in which Covid-19 was declared a pandemic by WHO (2020). Some countries discovered Covid-19 before 11 March 2020 (e.g. China), while others discovered Covid-19 after 11 March 2020 (e.g. South Africa). Therefore, pooling together such countries will results to the results that are more accurate and more statistically significant. In addition to that, Oanh (2022) asserts that the impact of Covid-19 is different for developing countries and developed countries. Therefore, future studies can consider having two groups of countries, pooling together developing and developed countries and analyses be based on those two groups.

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