INVESTOR ATTENTION AND STOCK MARKET PERFORMANCE DURING COVID-19 PANDEMIC: EVIDENCE FROM MALAYSIA

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APRIL 2021

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A final year project summitted in partial fulfilment of the requirement for the degree of the

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DECLARATION

We hereby declare that:

(1) This undergraduate Final Year Project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this Final Year Project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the Final Year Project.

(4) The word count of this report is 13,021 words.

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Date: 5th April 2021

ACKNOWLEDGEMENT

First of all, we would like to take this opportunity to deliver our utmost gratitude to University Tunku Abdul Rahman (UTAR) for providing us a precious opportunity to conduct this research project. This is a great opportunity for us to enhance our knowledge and experiences that may improve our understanding in the areas that we may participate in the near future. We would like to express our appreciation for the facilities provided by UTAR library to enable us to get information and journal articles that needed for our research.

Besides, we would like to express our special thanks to our supervisor, Mr Lee Chee Long for guiding and giving as a lot of ideas and suggestion on our research. He always presented us with a clear path and advices while we encountered issues or problems. We appreciate his advices and encouragement from beginning until end of our research project. Without his support and guidance, our project will not be done successfully. We sincerely thank Mr Lee for his precious time and effort put on our project. His support and guidance help us a lot in our completion of research project.

Last but not least, we would like to convey our appreciation to our family members, friends, and course mates who giving us support and encouragement in these few months. Most importantly, a great thank you to all the members for paying efforts to accomplish the research. Everyone is important in completing this research project and thank you for the contribution and valuable time by group members in completing this research.

DEDICATION

Dedicated to

Mr Lee Chee Long

Mr Lee Chee Long, our supervisor of this research project for his patient, and valuable guidance and support throughout this research project.

Friends and Family Members

They have given us greatest encouragement and endless support when we conducting this research project.

Future Researchers

Those potential and future researchers who are interested in related topics we hope this research could assist them in the future studies.

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LIST OF ABBREVIATIONS

CMCO	Conditioned Movement Control Order
EMH	Efficient Market Hypothesis
GSVI	Google Search Volume Index
IRF	Impulse Response Function
KLCI	Kuala Lumpur Composite Index
RMCO	Recovery Movement Control Order
WHO	World Health Organization

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PREFACE

Investor attention is a scarce resource; investor have limited attention to focus on huge amount of the financial information. The new era of technology provides a faster way to access the information globally. Due to the rapid flow of information, investor is more likely to pay attention on the stocks information that grabs their attention. In this study, our aim is to study the attention of investor during the Covid-19 pandemic in Malaysia as Covid-19 is the first financial crisis contributed by the pandemic in history. Our study is focus on FTSE Bursa Malaysia KLCI stock market performance in the whole year 2020. Meanwhile, the Google Search Volume Index (GSVI) is used in our study as an indicator for investor attention. Thus, our study will focus on the impacts on investor attention towards the FTSE KLCI stock return, trading volume and stock return volatility. Thereby, our study aims to provide significant information and direction for future study towards Malaysia stock market.

ABSTRACT

In this research, we indicate the relationship of investor attention proxied by Google Search Volume Index (GSVI) and Malaysia Stock Market Performance on Covid-19 pandemic. Since the Covid-19 pandemic is a new phenomenon, it has led to the first financial crisis contributed by the pandemic in history. In this study, search queries of "Coronavirus" and "Covid-19" is indicated. Results revealed that keyword "Coronavirus" has no insignificant results to the Kuala Lumper Composite Index (KLCI) performance and keyword "Covid-19" is tested to be significant to indicate the relationship between investor attention and the Malaysia stock market performance. To indicate the validity of the regression model, various test like Augmented Dickey-Fuller test, Philips-Perron test, Breusch-Godfrey LM test, Jacque-Bera test, White heteroscedasticity test has been carried out in this research project. The results had revealed that the model have no existence of unit root, autocorrelation and heteroscedasticity problems in the model and the error term is normally distributed. Granger causality test has been carried out and results that three dependent variables have no granger causal relationship with GSVI Covid-19. To indicate the short and long run effect on the model, Impulse Response Function has been carried out and proven that there have no impacts on the both short and long runs between the dependent variables and GSVI Covid-19. This study found out that insignificant relationship between investor attention proxied by GSVI with stock market return and stock market volatility. The empirical results support efficient market hypothesis (EMH) which stated that the Malaysian stock market is efficient and hence, there is no arbitrage opportunities for investors since stock prices fully reflect all information.

CHAPTER 1: RESEARCH OVERVIEW

1.1 Research Background

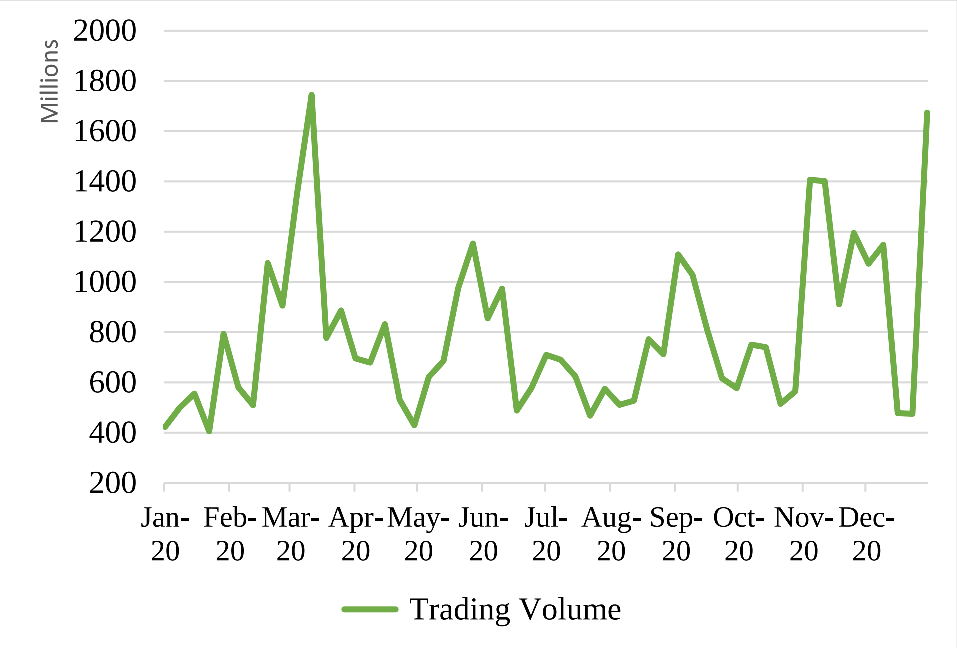
1.1.1 COVID-19 Pandemic

The COVID-19 pandemic is a multidimensional phenomenon, not only from the medical dimension, but also from the financial aspect. Initiated in Wuhan, Hubei Province of China, the COVID-19 outbreak has led to the first financial crisis contributed by the pandemic in history. The COVID-19 pandemic has then spread rapidly to other countries including Singapore, Italy, USA and UK (Elengoe, 2020). Due to the severity and alarming levels of spread, the World Health Organization (WHO) announced the COVID-19 as pandemic on 11 March 2020 (The World Health Organization, 2020). As of 30 December 2020, the COVID-19 has caused over 1.8 million deaths worldwide (Worldometer, 2021). On 24 January 2020, Malaysia recorded the first case of COVID-19 while in year 2020 alone, Malaysia recorded 113,010 confirmed cases of COVID-19 and 471 death cases (Ng, 2020; Worldometer, 2021).

1.1.1.1 The Impact of COVID-19 on the Stock Market

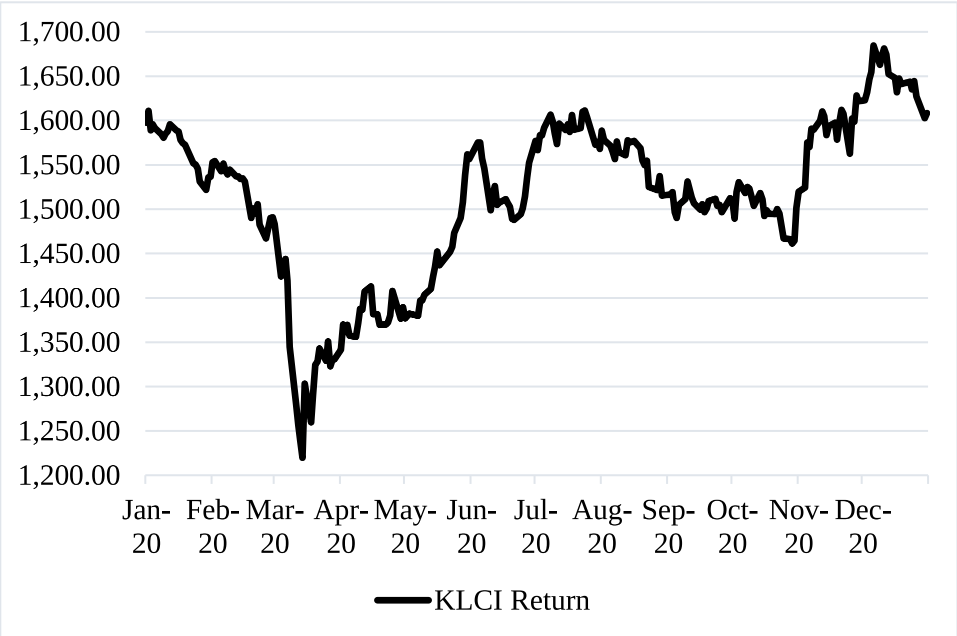
During the crisis, the stock market has been experienced one of the greatest volatilities in the history (Baker et al., 2020). Major indices such as the S&P 500 Index and the Dow Jones Industrial Average have plunged sharply and recorded its lowest point since 2008. Asia-Pacific stock markets such as Nikkei 225 has also fell more than 20% amid coronavirus fear while the European stock markets drop by around 11%. Meanwhile, the trading volume in Bursa Malaysia has reached its highest record in history. As shown in figure 1.1, Bursa Malaysia trading volume reached a new-time high, recorded 6.61 billion shares traded in April 2020 (The Edge Market, 2020). The high record of trading volume maintained throughout the year. Amid the heavy trading volume, the FTSE Bursa Malaysia KLCI return dropped to its lowest point after 11 years in March, recorded less than 1250.00 as shown in figure 1.2. The massive losses in the market are believed to be influenced by the investors fear due to the movement control order and losses on key index such as Genting Berhad (Bernama, 2020). The KLCI return then gradually rose to more than 1,500.00 return at the beginning of June but the index dropped again at the end of the year amid the coronavirus fear.

Figure 1.1 Weekly FTSE Bursa Malaysia Trading Volume in Year 2020



Source: MarketWatch

Figure 1.2 Weekly FTSE Bursa Malaysia KLCI Return in Year 2020



Source: MarketWatch

1.1.2 Investor Attention

According to Baker et al. (2020), the extreme fluctuations that have been experienced by the stock markets is probably due to the rapid information flows during the COVID-19 pandemic. During the pandemic, the investor attention towards the COVID-19 related information have risen sharply. This investor attention brings impact to the stock market and this is proven by the previous studies (Tan & Tas, 2018; Zhang et al., 2020; Iyke & Ho, 2021; Ekinci & Bulut, 2021). In fact, it can be related to the efficient market hypothesis (EMH). In EMH, it is assumed that the stock prices incorporate and reflect all available information including news in an instantaneous way. Therefore in this hypothesis, it is assumed that the market is efficient and hence, the COVID-19 related news are all reflected on the Malaysia stock market. In the EMH, the investors are also assumed to be rational when responding to the COVID-19 related news. Therefore, when EMH is applied in the case of investor attention, it suggests that the stock market volatilities can be figured out by looking into the internet searches as it serves as the reflection of investor attention. The internet searches enhance the speed of information dissemination among individual investors and thus, helping investors to make more accurate investment decisions.

However, investor attention is a scarce resource and it is a constraint (Barber & Odean, 2008; Da et al., 2009; Kahneman, 1973). According to Chen and Yu (2013), attention is a cognitive process at which an individual is focusing on a subject but ignoring other subjects. The investor attention is constrained especially to the individual investors. This is due to individual investors have less access to professional information sources such as Bloomberg compared to institutional investors. Therefore, searching for information on the internet becomes the direct tool for individual investors to gain information. However, internet searches produce large amount of information and this is difficult for the investors to produce all information.

From the aspect of behavioral finance, it is found that the investors are irrational and tend to be affected by some psychological and emotional biases when making investment decisions. According to Barber & Odean (2008), investors have the tendency to buy the stocks that are attention-grabbing among large amount of stock available. In this case, information search query about the particular keywords clearly reflects that the person is paying attention to that subject. Therefore, investor attention becomes one of the variables which is correlated to the stock market movement.

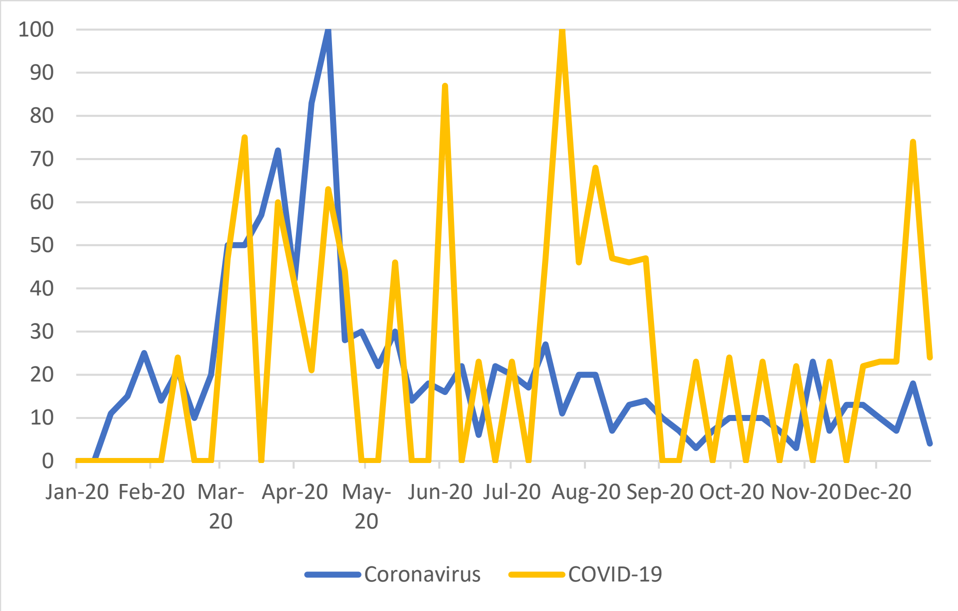
1.1.2.1. Google Search Volume Index (GSVI)

With the rising of information technology and social media, the internet becomes one of the fundamental pathways of individual investors to obtain financial information. Nowadays, online platforms such as Google, Yahoo and Baidu have been highly utilized by investors to obtain financial information. Among them, Google is the most used in Malaysia and it owns 98.57% of search engine market share in Malaysia, compared to bing (0.88%), Yahoo (0.44%), DuckDuckGo (0.05%), Baidu (0.02%) and Ecosia (0.01%) (StatCounter. 2020). Therefore, Google is taken as the direct measure of investor attention in Malaysia. In fact, Google search volume is used as the indicator of investor attention in many previous studies done (Joseph, Wintoki, & Zhang, 2011; Mondria & Wu, 2011; Preis, Moat, & Stanley, 2013; Vozlyublennaia, 2014). Therefore in this study, we attempt to look into the investor attention through the lens of Google search volume index (GSVI).

1.1.2.2 Trend of Google Search Volume Index (GSVI) on COVID-19 Related Keywords

As shown in figure 1.3, the weekly Google search volume index (GSVI) on the keyword "Coronavirus" in Malaysia has started to increase since January. The GSVI reached its peak at April with the scale of 100 and gradually decreased through the year 2020. Meanwhile, the GSVI on the keyword "COVID-19" started to increase since February, which is after the announcement on the official name of the coronavirus disease 2019 with the abbreviation of COVID-19 by the World Health Organization (Centers for Disease Control and Prevention, 2020). After the announcement of the implementation of the Movement Control Order (MCO) on 18 March 2020, the GSVI spiked to the scale of 75. It then reached its peak with the scale of 100 at July. Between March and July, the trends of GSVI on the keyword "COVID-19" has been fluctuating significantly. After rocketing to the peak at July, the trend of GSVI on the keyword "COVID-19" then show a downward trend, but it climbs to the scale of 75 again at the end of the year 2020. During the early stage of the COVID-19 outbreak, the keyword "Coronavirus" is highly searched in the Google search engine but the searching trend of keyword "COVID-19" surpassed it after the coronavirus was officially named.

Figure 1.3 Weekly Google Search Volume Index on Keywords "COVID-19" and "Coronavirus" in Malaysia (Investing Category)



Source: Google Trends

1.2 Research Problem

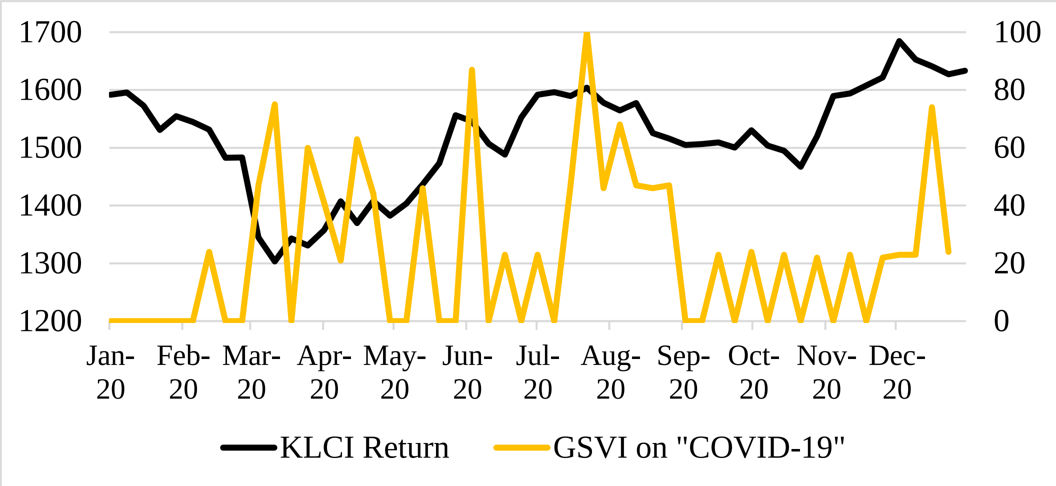
During the COVID-19 outbreak, the FTSE Bursa Malaysia KLCI returns has been going through significantly high volatilities. The Bursa Malaysia trading volume has reached all time high records amid the outbreak. The extreme volatility in the Malaysian stock market is significantly high compared to other emerging markets. Therefore, Malaysia is a good research focus to study the impact of COVID-19 attention on the stock market performances. According to Nguyen et al. (2019), the Google search volume have potentials to impact the stock market performances in emerging markets such as Thailand, Vietnam and Malaysia indirectly. By comparing the trends between KLCI return, Bursa Malaysia trading volume and Google search volume index, it is found out that the stock market return and volatility in Malaysia vary depend on the investor attention.

As shown in the figure 1.5, the KLCI return recorded the lowest point when the GSVI on “Coronavirus” is at its highest point in March. For the months following, the GSVI on “Coronavirus” shows a downward trend while the KLCI return shows an overall upward trend. It is clearly shown that the movement of the KLCI return and the GSVI on “Coronavirus” is on opposite direction. The downward trend of GSVI on the keyword “Coronavirus” might be due to the announcement of official name of “COVID-19” on March. The keyword “COVID-19” then becomes the new keyword that is highly searched. On the other side, the correlation between the GSVI on “COVID-19” and the KLCI return shown positive relationship despite some fluctuation amid the months. In figure 1.4, the KLCI return recorded the lowest point when the GSVI on “COVID-19” spike to the first new high point in March. The trends of GSVI on “COVID-19” and the KLCI return then shown positive relationship for the following months.

From the point of view of Bursa Malaysia trading volume, it is shown that the Bursa Malaysia trading volume increases when the GSVI on “COVID-19” and “Coronavirus” increases. As shown in the figures 1.6 and 1.7, when the GSVI on “COVID-19” rises sharply, the Bursa Malaysia trading volume reached a high point as well. After that, both Bursa Malaysia trading volume and GSVI on “COVID-19” show decreasing trends. Meanwhile, the relationship between the GSVI on “Coronavirus” and the Bursa Malaysia trading volume shows the similar trends. During the first three months in 2020, the Bursa Malaysia trading volume shown an increasing trend when the GSVI on “Coronavirus” gradually increases. In short, the chart portraits that the GSVI on “COVID-19” and “Coronavirus” and Bursa Malaysia trading volume move in the same direction.

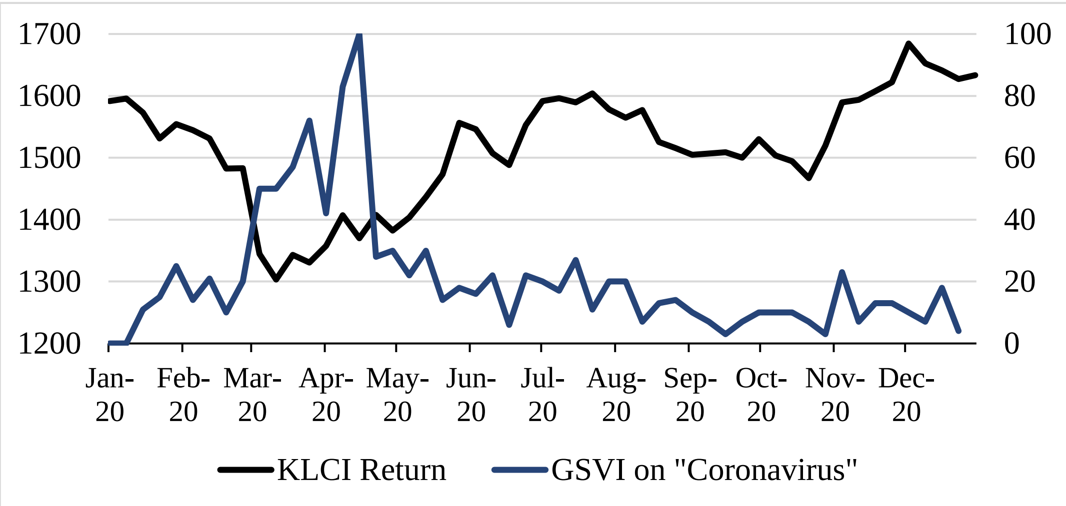
The positive correlations between the GSVI on keywords “COVID-19” and “Coronavirus” could be explained by the efficient market hypothesis (EMH). This is due to the keywords “COVID-19” and “Coronavirus” become good news when the news of COVID-19 vaccine was announced, and this brings new hopes to the investors. The stock market has incorporated this good news and hence, bringing positive impacts on the stock market.

Figure 1.4: The Relationship between Weekly KLCI return and Weekly Google Search Volume Index (GSVI) on Keyword "COVID-19" in Year 2020



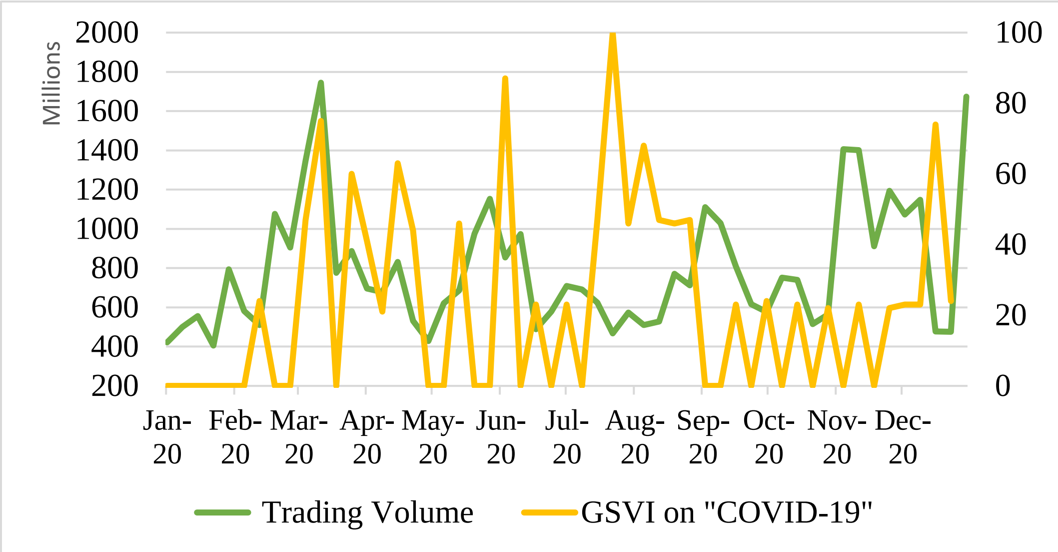
Source: MarketWatch and Google Trends

Figure 1.5: The Relationship between KLCI Return and Google Search Volume Index (GSVI) on Keyword "Coronavirus" in Year 2020



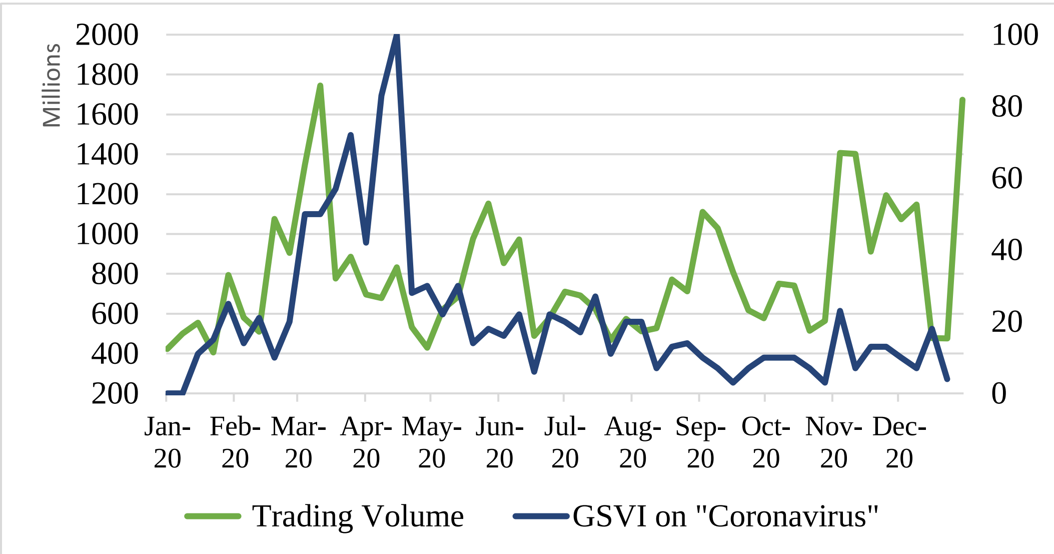
Source: MarketWatch and Google Trends

Figure 1.6: The Relationship between Bursa Malaysia Trading Volume and Google Search Volume Index (GSVI) on Keyword "COVID-19" from January to August,2020



Source: Yahoo Finance and Google Trends

Figure 1.7: The Relationship between Bursa Malaysia Trading Volume and Google Search Volume Index (GSVI) on Keyword "Coronavirus" in Year 2020



Source: MarketWatch and Google Trends

The FTSE Bursa Malaysia KLCI returns has experienced extreme fluctuations during the pandemic. The past study done by Padungsaksawasdi et al. (2019) linked the stock volatilities to the search volume index and the stock volatilities. Therefore, it is important to find that whether there are associations between the Bursa Malaysia trading volume and GSVI on “Coronavirus” and “COVID-19” and between the KLCI return and the GSVI on “Coronavirus” and “COVID-19”. However, there is still a lack of studies to look into the impact of investor attention on the Malaysian stock market during pandemic. Hence in this dissertation, the relationship between investor attention and the Malaysia stock market performance is investigated. The stock market performance is measured in terms of return, volatility and trading volume by referring to the FTSE Bursa Malaysia KLCI. Meanwhile, investor attention is indicated by the Google Search Volume Index (GSVI).

1.3 Research Objectives

1.3.1 General Research Objective

To investigate the relationship between investor attention and stock market performance in Malaysia.

1.3.2 Specific Research Objectives

i. To study the influence of COVID-19 attention on the stock market return in Malaysia.
ii. To investigate the impact of COVID-19 attention on the stock market volatility in Malaysia.
iii. To study the relationship between the COVID-19 attention and the Bursa Malaysia trading volume.

1.4 Research Significance

Our dissertation contributes to the growing body of literature in investigating the impact of investor attention on the Malaysian stock market during COVID-19 pandemic. Since the COVID-19 pandemic is quite a new phenomenon, there is a lack of studies to investigate the investors' behaviour on investment decisions during this health crisis. Also, although there are lots of studies done previously in investigating the behavioural finance during the financial crisis in countries like US and China, there are still a lack of studies to investigate the impact of investor attention on the stock market performance in Malaysia. Malaysia is chosen in this study as the Bursa Malaysia has recorded one of its highest trading volumes during the COVID-19 pandemic. This shows that investor attention has been reflected in the volatility of the stock market compared to other emerging markets. Therefore, Malaysia is suitable to be studied on the impact of COVID-19 attention on its stock market.

1.4.1 Investors

From this study, investors will understand the impact of the investor attention on the stock market and thus, used it as an efficient indicator to predict the stock market movement in future. By analysing the trends of the investor attention on the stock market, investors can tailor their investment strategy when setting up a portfolio. For example, a past study done by Iyke and Ho (2021) shows that there is a positive relationship between investor attention and the stock return in Botswana, Zambia and Nigeria but there is a negative relationship between investor attention and the stock return in Tanzania and Ghana. This indicates that the investor attention might to be used as the hedging instrument in a portfolio by analysing the investor attention. In short, this study is helpful to investor in making timing selection when making investments in the stock market.

1.4.2 Policy makers

The results of this study will be a useful reference for policy makers and regulators such as the Securities Commission (SC) to supervise and to monitor the stock market from the impact of crisis. By tracking the trends of the investor attention, the policy makers and government can maintain the financial market vulnerabilities by imposing relevant regulations as response to the crisis. For example, the Securities Commissions has suspended the activities of short selling from March 2020 until the end of year 2020, in order to minimize the stock market volatilities from the impact of COVID-19 pandemic (The Star, 2020). Therefore, the results of study can contribute to the regulators and governments to respond to the uncertainties resulted from the crisis. This is important to ensure the stability and the soundness of the stock market yet, strengthening the financial market in the loss-absorbing capacity during crisis (Couppey-Soubeyran, 2010).

1.4.3 Researchers

From the behavioral finance aspect, the results of this study will be helpful to researchers by giving them more insight into the influence of investor attention on the stock market performance. According to Smales (2021), it is found out that when the there is a negative relationship between investor attention and stock returns but positive relationship with the price volatility. However, the study done by Iyke and Ho (2021) shows that there is a positive relationship between investor attention and the stock return in Ghana and Tanzania. These 2 studies shown completely different results and hence, this study which is focus in Malaysia may give future researches more understandings on the role of investor attention on the stock market performances.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

In this chapter, we focus on the underlying theories and review of empirical results. Literature review can be defined as the topic that has been released by accepted researchers previously. Enormous research had been studies and the past studies enable us to perform our research. This chapter will be discussed to few theories which related to our research topic. The independent variable is investor attention, as proxied by Google Search Volume Index (GSVI) on keyword "COVID-19" and "Coronavirus". The dependent variables are stock market return and stock market volatility by referring to the FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLCI) in Malaysia.

2.1 Underlying Theories

2.1.1 Efficient Market Hypothesis

Efficient market hypothesis (hereafter EMH) is one of the traditional financial theory that developed by Eugene Fama. The concept of this theory is reported that share or security prices in financial market is fully affected by all the relevant information (Fama, 1970). The price of securities is fair when the capital is efficient. In the EMH, investors are assumed as rational people in financial market. This efficient market theory is also known as Random Walk Theory. According to Kisaka (2015), random walk is a financial theory suggests that the past movement of stock prices or market is impossible to predict the future movement of stock prices and believes that the stock market prices are random.

Fama (1970) identified weak form, semi-strong form and strong form are the three forms of market efficiency measurement. According to Nada (2013), in weak form efficiency, the author stated that the security prices fully reflect all available past information. Such examples of the past information are the prices, trading volume, past financial report, news, stories of the company etc. If such information were accessed by people, then weak form market is said to be efficient. However, Nada presented that there is no chance to have arbitrage opportunities or profits for investors by just referring to such historical information. Hence, the outdated information would be useless to an analyst due to the historical prices are reflected in current prices, but not future prices. The explanation for weak form market efficiency is similar known as the random walk theory since random walk theory defined that the stock price movements are unpredictable.

In semi-strong form efficiency, Nada (2013) pointed that all publicly available information (historical and current) is incorporated in the stock prices. Not only the past data, but everyone can also access to the current or new information. However, individual investor is also no chance to earn superior returns in semi-strong form efficient market, and this argument also supported by Subash (2012). This is because that information already been affecting the stock prices. For example, the public announcements of balance sheet, income statements, dividends, earnings, stock split and so on can result in the changing of stock prices.

In strong form of EMH, scholars proposed all available, public and private information are incorporated in the security prices. There is assumption that the private information is less important because the inside information would not much more help in making higher returns for investors (Subash, 2012). Strong form is difficult to accept and market cannot be completely efficient, and the actual financial markets relatively supports the weak and semi-strong forms (Nada, 2013).

Past researcher, Smales (2021) have examined the available information influence the security prices. The EMH is applied in the case of investor attention. Attention is known to play an important role in investors learning and trading behaviours. By testing EMH, Smales indicates the negative relationship between GSVI and global stock returns during the pandemic crisis. Besides, Smales found a positive relationship in GSVI to the stock volatility. Evidence proved that a high speed of information dissemination causes the number of internet searches increase, and people are rational to be more attentive to the news event. Eventually, it induces a price response and higher return volatility.

However, few scholars examined there is problem and limitation with EMH. Barber & Odean (2008) and Kahneman (1973) found out attention is a scarce cognitive resource. Also, Yung & Nafar (2017) and Nada (2013) said that investors have bounded rationality, which means investors is limited by the information they have. They reported that individuals have limited attention to produce with the massive information. Therefore, investors are suggested go for the stocks that can grab their attention. Moreover, study done by Bui & Nguyen (2019) documented that individual investors are having difficulty to come up with an optimal choice by analysing hundreds of stocks in full details. Arguments above can be concluded that the stock prices may not immediately adjust to reflect its true value. Hence, investor attention and stock market performance by testing EMH might be not significant related.

2.1.2 Behavioral Finance Theory

From the past to the present, financial economists started to assume that investors are irrational and normal in the financial environment. Hence, behavioral finance came into picture. The behavioral finance is interaction between financial activity and psychology. This theory claims that investors propensity to have some psychological effects and emotional biases on financial decision making and on financial market. The response reactions to the new information and good-bad news can be explained by this theory. Findings pointed that the psychologic factors would make changing in the stock price (Nada, 2013; Subash, 2012 and Yildirim, 2017).

Behavioral finance focuses on limited cognitive person rather than cognitive person. The limited cognitive person is influenced by psychologic bias when they are making investment decision from the massive information. The related psychologic bias leads investors to have irrational behaviour (Yildirim, 2017; Subash, 2012). One example of the irrational behaviour is representativeness. Representativeness described the individuals make judgements based on the similarity of an event to predict the occurrence of an event, as they are trying to avoid uncertainty issue arises. It can be useful when people are trying to make a quick decision, but the limitation for this is it would lead to close-mindedness. In the study of Yildirim said that investors pay attention to averaged success of security in that moment and they are willing to buy the security that moment. In that moment, they do not consider long run income for security and no desire to invest in security which have a good long-term performance.

Yildirim and Subash also pointed the herding behaviour is another example of irrational behaviour. Herding behaviour can be explained by information cascade. It suggests that investors believe other people's choices are optimal level. Investors ignore their own preference and their own personal knowledge, then will implement others' opinion or decision. It occurs when there is a lack of information, fear of reputation and wage levels etc. Investor is easier to accept a good attention from others and continue to spread the information via online. Investors are then willing to invest in the securities which support by other people's choices. Hence, this can be linked to the herding behaviour make high trading volume in stock market, then causes higher volatility, and therefore increase in investor attention.

Other than that, overconfidence, avoidance of regret etc. known as the examples of irrational behaviour which significant to study as the related psychologic bias might impact on the stock market performance, evidence proven by the study of (Nada, 2013; Subash, 2012 and Yildirim, 2017). People with overconfidence bias behave to overestimate their knowledge and underestimate their risks. Psychological findings state that the behavioural of avoidance of regret related to investors do not sell their stocks when the price is low due to the fear of making loss, but willing to sell the stocks when the price started to increase.

2.1.3 Price Pressure Hypothesis

According to Price Pressure Hypothesis, few researchers examined investors are more likely to consider on buying in the options that have first caught their attention among the massive information available. The reason proved by Barber Odean (2008); Swamy, et al. (2019) and Yung & Nafar (2017), they founded that individual investors have limited time or resources to consider among the thousands of stocks in the market. Majority investors are attracted to the news attention because of the news have reported as an example of attention-grabbing event. Furthermore, Barber and Odean indicated that individual investors are net buyers of attention-grabbing stocks, hence; the stocks will experience in high abnormal trading volume.

Two empirical conceptual frameworks in explaining how investor attention generates price pressure have been done by Swamy, et al. (2019) and Smales (2021). There are information discovery hypothesis and asymmetry of the choices hypothesis. The information discovery hypothesis argues that if more abundant news information will help investors in reducing information asymmetry. That information related to stocks are easy for investors to access through Google search. In the study of Smales support the information discovery hypothesis indicate that COVID-19 attention is associate with a negative stock return.

For asymmetry of the choices hypothesis, Barber and Odean (2008) supposed price pressure hypothesis generated when only the attention-grabbing stocks are chosen and purchased by investors. The authors also pointed out the problem about investors have only limited resources and time to analyse on the large amounts of possible investments, this argument also proven by Smales (2021). It also explained by the concept of a rises of search query will create investors' buying attention on the security. Conversely, there is no such search problem exist in the condition of selling stocks from retail investors because the person is typically only able to see the stocks they already own. Summarize, a rising number of attentions will increase buying and temporarily push the prices up, but no impact on selling frequency.

In support of this theory, a research paper done by Swamy et al. (2019) found that there is relationship between investor's attention and stock market performance. For instance, Fehle et al., (2005) stated there is a positive effect on the company's stock prices in which the company was mentioned in the American daily newspaper of New York Times; as well as the example from Takeda and Yamazaki (2005) stated there is increase in the company's stock prices after the broadcast on the Japanese TV program. Moreover, Barber and Odean (2008) suggests the direct measurement of GSVI reflects the retail investors' attention by testing the attention-induced price pressure hypothesis. Other than that, Adachi et al. (2017) examined the raising stock liquidity and trading activity if there is an increase in search queries. Study of Tan & Tas (2019) also provide evidence that an increase in average search volume index generates higher future returns.

2.2 Review of Empirical Results

2.2.1 The Concept and Measurement of Investor Attention

Odean (1999) explained that investor could solve the problems of selecting from thousands of potential stocks to invest by restricting their selection to the stocks that have recently gets their interest. Investor are likely to purchase attention-grabbing stocks and the preference of investors indicate their decisions after the choices has been determined by attention. The search for details of a specific topic clearly shows that one pays attention on the matter. Papadamou et al. (2020) stated that internet searches are one significant medium by which investors deliver their information requirement in the way that are more direct and transparent. Hence, Google Search Volume Index (GSVI) offers a direct and timely indicator of the attention and could reflect the general population’s searching behaviour. Da et al. (2011) was the first to implement the Google Search Volume Index (GSVI) as the indicator for investor attention.

The search on the Internet reflects the intention of investor to look for information in the search queries. The online search platform currently leads by Google and its partner networks like Yahoo, Bing and Baidu, comprising over 95% of the online searching (Nawaz, 2014). Google search query has been widely used on the literature throughout variety of field study. Internet provides huge amount of available information and easily to be access globally. Google reflects the search behaviours of Internet users as users will search for the particular terms while they paying attention to it (Smales, 2020). The GSVI could obtained from Google Trend, which tracks the cumulative number of searches of the term scaled by its time-series average and is generated weekly using the aggregate search frequency of Google. The results index is normalised from 0 to 100, term that obtained 100 of search volumes indicates a highly researched during the timeline and chosen geographical area, while the 0 scaled search volume indicate no researched or few researched at that timeline (Yung & Nafar, 2016; Lyke & Ho, 2021).

Many researchers have examined the investor attention on Covid-19 by using the GSVI to reveal a significant effect on the financial stock market. The research of Lyke & Ho (2021) stated that Google Trends enables the users using search volume index to indicate search frequency related to Covid-19 to analyse the impacts of attention to the Africa stock market and the results proved that GSVI is significant measurement for attention. The search queries for the Covid-19 related keywords are act as the proxied to indicate the investor attention on the Africa stock market on Covid-19 pandemic. The study found that a rapid flow of Covid-19 related information has grab the attention of investors, the Google Trends show a sharp increase on the Covid-19 related terms proved by Smales (2020). The study indicates that when investors paying high attention to the Covid-19 related information contribute greater exploration of information.

The Covid-19 pandemic create enormous uncertainty to the global stock market that could directly affects the financial economics. The widely use of technology provide the platform for investors to look for the stock trading patterns and make actively trading in stock markets during the era of Covid-19. Swamy & Dharani (2019) indicate GSVI could be a reliable measurement of direction and magnitude on excess returns and GSVI has been proved useful towards the strategies on profitable trading. Study on Papadamou et al. (2020) reveal that the GSVI could be significant determinant of attention on coronavirus to the stock market. The study examined the synthetic index on the term and theme of “Coronavirus” to capture the attention. The study reveals an increase on risk-aversion in stock market to the contagion effects of google based anxiety towards Covid-19 pandemic.

Several studies proved that GSVI act as indicator for attention are applicable to predict future trading activity as compared to current. GSVI is significant to forecast the trading volume and volatility, which are consistent with market efficiency as study stated that nearly 90% of the internet searches are performed by Google's search engine. GSVI could recognise the future trading patterns by the search queries act as the proxied for the attention (Kim et al., 2018). Tan and Tas (2021) results that increase in GSVI is linked to higher future returns. The study further mentioned that firms receiving abnormally high attention are earning higher returns and the results revealed stronger price pressure effect of GSVI among small stocks.

2.2.2 Investor Attention and Stock Market Return

The attention theory proposed by Barber and Odean (2008) stated that investors make investment decision on stocks that attract their attention as they found difficulty to search on the huge amount of potential stocks they can buy, results only those stocks that could get investors' attention are purchased that will directly impacts the stock market trading. Recent studies on the attention on Covid-19 found that the increase on investor attention results a negative stock market return. Shear et al. (2021) study on investor attention on Covid-19 to the 34 countries stock market returns and found out that the high investors' attention is expected to generate greater selling pressure from shareholders. This is due to the disposition effect or rebalance of portfolio requirements as COVID-19 created enormous uncertainty and raised economic uncertainty. Research on Smales (2020) show that the shareholders are intends to sell out high risk stocks to reduce uncertainty that could give negative impact the stock market return.

The studies demonstrate that investors may highly relying on the news attention as their primary source of information and would make their investment decision based on the news attentions. The study of Engelhardt et al. (2020) indicates the investor attention on corona-crash of a total of 64 countries stock market and found that the enormous uncertainty that created by Covid-19 pandemic results a significant negative stock market return. The effects of Covid-19 pandemic on the financial market are an emerging strand. Investors pay more attention on the negative information and results a decline on stock return with higher attention to reduce potential losses. Smales (2020) study on the investor attention on Covid-19 to U.S. stock market. The research reflects that during financial crisis period, investors are giving higher attention on stock that catch their attention and holding stocks, investors likely to reduce uncertainty and created selling pressure on risky stocks instead of buying on new stocks as Covid-19 created a decline phenomenon on the stock market.

Moreover, previous studies also revealed that the role of investor attention creates a new window for researching the predictability of future stock market. The study of Yoshinaga and Rocco (2020) on 57 Brazilian stocks by analyzing weekly GSVI from 2014 to 2018. The results demonstrate a greater effect on high trading volume stocks and revealed a lower stock return. The rises in the attention may expose the stock to higher risk and this is consistent with the theory that greater interest from individual investors contributes to lower subsequent returns. This meaning that growing popularity causes stock prices to deviate from their basic valuation, resulting a negative return on stock. Kou et al. (2017) found that the greater predictive strength of the search frequency is from PC-based searches and not from smartphone searches that could forecasts greater positive and negative returns on futures markets.

In contrast, there are few studies showed that the increase on the investor attention results a positive stock return. The study of Zhang et al. (2020) investigates on the investor attention and the mask concept stock under the Covid-19 outbreak and found that they have positively significant impacts. The establishment of the model of panel fixed effect analyze that since the Covid-19 outbreak, high production of the mask rises the attention of investors on the mask concept stock. Investor access to information to the mask concept stocks revealed a high attention and results in a positive return on the mask concept stocks. The study on Swamy et al. (2019) found that the GSVI and stock return are significant and positively related as the higher attention forecast higher stock returns. Investors' trading behavior can be capture from the GSVI to determine the investors' attention and the stock-related information from Google is useful for financial decision. Investors are making decision on the access information as compared with make decision on the basis of experience. The results show that while investors paying more attention on the stock prices results a positive stock returns in subsequent three weeks (Swamy, 2019).

2.2.3 Investor Attention and Stock Volatility

The rapid development of the Internet created a platform for investors to capture stock information and financial news for analysis and make prediction on the stock market and could be directly affecting the stocks trading activity (Zhang et al., 2020). Several researches have studied on the impacts on investor attention on the stock trading volume and volatility to investigate the prove that attention is correlated to the volatility in the stock markets. The research on Zhang et al. (2020) found that the higher attention on the stock market is significantly related to the stock volatility. The research studied on mask-related stock market during Covid-19 pandemic. Investors could access the information through search volume and big data, investors make investment decision based on the information obtained and attentions focused on stocks that caught their attention and cause buying and selling pressure. The buy and sell of stocks reflect the stock price fluctuation and high volatility of the stock markets and results the increase number of the search volume on the stock market reflects a higher trading volume and greater volatility on the stocks (Smales, 2020).

The increase in the internet searches triggers a rapid flow of information into the financial markets, that could generate a higher volatility of the stocks. Smales (2020) studied on the investor attention and global stock market on Covid-19 period and found that the increase on investor attention would results higher stock volatility. The investor reflects their trading activity behavior based on their attention on the stock's information that could create a shock to the market. The rapidly fast dissemination of news on Covid-19 pandemic causing stock market fluctuate is larger than at any other time of history (Papadamou et al., 2020). Investors' attention is focused on the stock's performance that could reduce their uncertainty about fears during the crisis. Thus, the stocks markets result a greater trading activity and greater volatility.

Study also proved that increasing on the investor attention shows an increase stock volatility even after controlling the impact of the financial crisis (Aouadi et al., 2013). Study shows that the investor attention is highly associated with trading activity and is a major determinant of stock market performance. Aouadi examined the France stock market illiquidity and volatility and results a significant positive relation between the investor attention and stock volatility even after monitoring the effects of financial crisis. The results show robust after including the crisis effects and a strong correlation is revealed between the investor attention to the France stock market volatility. Online searches reflect the investment behaviours of investors and proved that online searches are highly correlated to the trading volume and stock volatility where shows the correlation of SVI and volatility are significant and positive (Chen & Lo, 2018).

The google search queries has predictive potential for the stock volatility while investor exposure to the stock market results in a high market movement. The research of Brochado (2016) proved that rising on the investor attention results greater stock volatility. The research examined the Portuguese stock market return and volatility to the investor attention by using GSVI. The strong correlation is found when the stocks are gaining more attention from investor, it will be comparatively more traded as compared to those that draw lesser attention. The price fluctuation results a greater volatility on the Portuguese stock market. The study on Bui and Nguyen (2019) proved that the investor attention is significantly positive to the Vietnam stock market volatility on the VN-100 stocks from 2014 to 2018. Bui and Nguyen reveal that the high attention on the stock market leads to the more uncertainty and rising on the access on online information could resulting in overtrading and the greater price fluctuation. Thus, the results revealed that investor attention is significant for forecasting the stock market return volatility.

2.3 Conclusion

In this chapter, the previous studies found that the investor attention and stock market performance have either positive, negative or no relationship. Although there have many researchers studied on the impacts of investor attention on stock market in the developed countries like U.S. and China, there are still lack of research on developing countries like Malaysia. During period of Covid-19, we found a record of highest trading volume on Malaysia stock market as compared with other emerging market. This reflects that the pandemic has cause volatility on the Malaysia stock market and our study aim to know how the pandemic react towards the FTSE Bursa Malaysia KLCI stock performance. Malaysia is an emerging market with rapid growth and development as compared with other developing countries; therefore, we aim to study on the Malaysia stock market. In our research, we focusing on the Malaysia stock market by using the latest data on Covid-19 pandemic. Since Covid-19 is a new phenomenon, therefore, our study period is from January to December 2020 towards Malaysia stock market. The research will then continue in following chapters to identify the outcome from the previous studies with the research methodology and test will be carried out in the next chapter.

CHAPTER 3: METHODOLOGY

3.0 Research Design

This research is focusing on secondary data, historical data and time-series data is used. The dependent variables, stock returns and trading volume is found to be having a relationship with the independent variables, google search volume index.

3.1 Data Collection Methods

3.1.1 Google Search Volume

In this study, the data on Google search volumes are used to indicate the investor attention as the search volume is the direct way to capture attention. The Google search volumes are obtained from Google Trends. Google Trends is a Google website which reflects the search volume of particular keywords from all over the world on Google. The data on Google Trends are normalized and scaled on a range of 0 to 100 based on the relative popularity. Daily, weekly and monthly data are available on Google Trends since year 2004. In this study, weekly data is obtained from the Google Trends as daily data might be affected by seasonal effects and thus, decreasing the accuracy when reflecting the investor attention. It is also difficult to capture the investor attention using monthly data. Since this study is focused on investor, the category of finance is chosen when obtaining data on Google search volumes (Tan & Tas, 2019). The keywords use include "Coronavirus" and "COVID-19", the geographical area covered is Malaysia and we focused on searches in investing under finance category. The data is collected for the period from January 2020 to December 2020 as 24 January 2020 is the data at which the first case of COVID-19 in Malaysia as detected (World Health Organization, 2020).

$$GSVI_t = \frac{GSVI_t - \frac{1}{n}\sum_{i=1}^{n} GSVI_i}{\sigma_{GSVI}}$$

$n = GSVI\ observation\ (weeks)$

$\sigma_{GSVI} = standard\ deviation\ of\ GSVI$

3.1.2 Stock Market Return & Trading Volume

The data on the FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLCI) is used to indicate the aggregate stock return. The KLCI is the capitalization-weighted stock market index which represents the 30 largest companies listed on the main market of Bursa Malaysia. The KLCI is the benchmark of stock market in Malaysia based on the market capitalization. In order to be eligible listed stock in FTSE KLCI, the companies have to fulfil 2 requirements including (1) have a minimum free float of 15% and (2) have enough liquidity to be traded in the market. It composes of different sectors including banking, plantation, food and beverages, automotive, health care, transportation and logistics services (Bursa Malaysia, n.d.). The KLCI index are collected from Yahoo Finance. In order to obtain the stock return, we run calculation on the KLCI index to derive the return in percentage.

$$KLCI\ Return = \left(\frac{KLCI\ Index_1 - KLCI\ Index_0}{KLCI\ Index_0}\right) * 100\%$$

Trading volume of KLCI is also being collected for our research. Data of trading volume is collected from January 2020 to December 2020, a total of 52weeks.

3.1.3 Analytical Tool – EViews

The analytical tool that our research has chosen is EViews. This software allows us to input our data and run numerous tests that is required to complete our research. EViews offers data analysis, regression and forecasting tools, allowing users to generate statistical relation from data set imported and utilising the result generated for future values forecast.

3.2 Empirical Framework

<u>Equation 1</u>

$$KLCI\_Return_t = A_0 + A_1 GSVI\_Covid\_19_t + A_2 GSVI\_Coronavirus_t + \varepsilon_t$$

<u>Equation 2</u>

$$Trading\_Volume_t = A_0 + A_1 GSVI\_Covid\_19_t + A_2 GSVI\_Coronavirus_t + \varepsilon_t$$

<u>Equation 3</u>

$$KLCI\_Risk_t = A_0 + A_1 GSVI\_Covid\_19_t + A_2 GSVI\_Coronavirus_t + \varepsilon_t$$

In Equation 1, the dependent variable is stock market return derived from stock market index of Malaysia' KLCI. Trading volume of Malaysia's KLCI is the dependent variable for Equation 2. Lastly, we used the conditional variance obtained from KLCI stock return and named it as KLCI_Risk to be the dependent variable of Equation 3. All three models will be having GSVI indexes of two searches, 'Covid_19' and 'Coronavirus'.

3.3 Unit root test

Unit root is the factor that helps in determining the stationarity of a time series. With the present of unit root in a time series, it is said to be non-stationary. Before carrying out Granger Causality test, unit root test shall be performed as the requirement to run granger causality test is for the time series to be stationary (Chaudhary, 2020).

3.3.1 Augmented Dickey-Fuller test (ADF test)

By including more differencing terms into Dickey-Fuller test for it to contain regressive process that is higher in order, Augmented Dickey-Fuller test is generated and being chosen for this research. ADF test is able to perform on time series data that is larger and have a higher complexity. The equation of Augmented Dickey-Fuller unit root test is written as:

In this equation,

$$\Delta y_t = \alpha + \delta_t + \beta y_{t-1} + \Sigma_{(i=1 \to k)} \gamma_i \Delta y_{t-i} + \varepsilon_t$$

Null hypothesis suggests that a unit root is present or the time series is non-stationary whereas alternative hypothesis suggests that no unit root is present or the time series is stationary. The null hypothesis will be rejected when p-value obtained is smaller than the significance level set (may it be at 10% , 5% or 1%), by rejecting the null hypothesis, the time series is now being analysed to be stationary (Chaudhary, 2020).

3.3.2 Phillips-Perron Test (PP test)

Besides running ADF test, PP test is being adapted to our research as an alternative test. Phillips-Perron test is able to corrects the time series statistics and has robustness to heteroscedasticity and any unspecified correlation present in error terms. PP test has an additional advantage compared to ADF test, lag length need not to be specified while running the regression for the prior but requires for the later (Bath, n.d.)

$$\Delta y_t = \beta' D_t + \rho Y_{t-i} + \varepsilon_t$$

Null hypothesis for PP test is identical to ADF test, where unit root is present in time series, alternative hypothesis for both tests is no unit root present in the time series, indicating a stationary time series.

3.4 E-GARCH model

Asymmetric shocks existing on volatility can be captured using E-garch model (Nelson, 1991). The E-garch model is applied to study volatility of the stock market return.

$$\lg(\sigma_t^2) = \lambda_0 + \lambda_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \gamma_E \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \lambda_3 \lg(\sigma_t^2)$$

Where $\lambda_0 = constant$

$\lambda_1 = ARCH\ effects$

$\gamma_E = Asymmetric\ effects$

$\lambda_3 = GARCH\ effects$

If $\gamma_E < 0$, it implies that negative relationship exist. Volatility is higher for bad news than good news.

For our research, we will be looking at the volatility of KLCI_Return. The data collected will be run and interpreted to see find leverage effect. Furthermore, we will find the conditional variance for KLCI_Return through E-Garch. Conditional variance represents the financial risks within the stock returns of KLCI. The conditional variance set of data will be applied into the following Granger causality test as well. The adjusted data will form another model with the independent variable, GSVI_Covid_19 to look into the relationship between volatility of KLCI_Return and GSVI_Covid_19.

3.5 Diagnosis checking

3.5.1 Autocorrelation

The time intervals in our data collected is successive, thus we will need to perform LM test to check if there is any serial correlation in the data set. Autocorrelation enables us to view the trend of past data and able to use for prediction for future data. Besides, it is able to determine the pattern of changes in the stock returns, helping to determine whether the changes in stock returns is following a pattern or were under influence caused by other factors (CFI, 2021). Breusch Godfrey Test is developed by Breusch (1978) and Godfrey (1978a, 1978b) and among all LM test, it was most widely used for autocorrelation checking (Toor & UI Islam, 2019). In this research we will be applying this LM test to determine whether autocorrelation exists in our time series.

When the autocorrelation is positive, we can tell that the changes in pattern is likely to be the same over period of time. Negative correlations may tell us that there are changes in the disturbance term where the signs migrates between positive to negative throughout the Time period. Null hypothesis will be no autocorrelation existence while alternative hypothesis will be autocorrelation exists. If the p-value is lesser than significance level used (may it be 10%, 5% or 1%), null hypothesis will be rejected and the time series data is not auto-correlated. Otherwise, the null hypothesis will not be rejected.

3.5.2 Normality of Residual Test

Jarque-Bera test will be performed to help testing the normality of the residuals for our data. Results from JB test, skewness and kurtosis are the indicators in comparing if the normal distribution's skewness and kurtosis matches with our data set.

$$JB = \frac{n}{6}[S^2 + \frac{(K-3)^2}{4}]$$

$$n = nample\ size\ ; S = skewness\ ; K = kurtosis$$

Null hypothesis of JB test is error term is normally distributed and alternative hypothesis will be error term is not normally distributed. If the p-value obtained is smaller than the level of significance, null hypothesis will be rejected. Otherwise, null hypothesis is not rejected and normality in error term is proven.

3.5.3 Heteroscedasticity

White test for heteroscedasticity will be performed in Eviews. White test is more general than Breusch-Pagan case as it includes more terms which allows different types of heteroscedasticity to be tested. Squares of regressors are added in this test, which helps in detecting nonlinearities (Williams, 2020). Null hypothesis for White test is homoscedasticity exists among error terms (constant variance), while alternate hypothesis suggest heteroscedasticity exists among error terms (variance not equal). We will reject the null hypothesis and accept the alternate hypothesis if the p-value that we obtained is lesser than significance level of 5%, otherwise we do not reject the null hypothesis. If the null hypothesis is being rejected, it can be said that there are heteroscedasticity problem occurring in the model.

3.6 Granger Causality

The relationship between GSVI and stock market performance is tested by using Granger causality test. The test is used to examine the Granger causality's causal direction between the two variables. It is able to capture the relationship of the past values of one variable to another variable's current value. Vector autoregressive (VAR) model can be applied in linear Granger causality test when the variables are stationary (Li et al., 2019).

VAR model

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t$$

$y_t = Dependent\ variable$

$A_0 = intercept\ vector$

$A_p = matriks\ for\ coefficients$

$\varepsilon_t = \varepsilon_t \sim (0, \Sigma)\ disturbance\ terms$

$$H_0: Ap(j, i) = 0, p = 1, \dots, q$$

$$H_1: Ap(i, j) = 0, p = 1, \dots, q$$

The equation will run from i to j and vice versa respectively. The null hypothesis will be rejected if the result contains of at least one element that is not significantly equals to zero. It will conclude that past value and the present value did have a relationship, implies that x and y are related.

3.7 Impulse-response function

Interactions between different variables in a vector autoregressive (VAR) model can be determined by applying impulse response functions. Reactions from variables to shocks can be captured using this function (Lutkepohl, 2018). Variables in VAR model interact with and depends on each other, making it difficult to determine the reaction of the model when shock is applied as the information given is too limited. Hence, this function is very useful in econometric analysis since it is able to trace every single shock transmission within a complicated system of equation (Mohr, 2020). When a brief input signal, also known as impulse is generated in signal processing, an impulse response function (IRF) will be the output. The response given by the model when there are external changes such as shocks and impulse is generally known as IRF. When running impulse-response function, it will generate a graph that allows us to see the pattern on how the output is moving in the time domain and allow us to make predictions on the possible future movements.

3.8 Variance Decomposition

Variance decomposition is carried out as it allows us to find out to what extend that a dependent variable's variability is lagged by its own term. It helps in showing which independent variables have more impact on the variability of the dependent variables over time (Omet, 2017). It is a method used in multivariate analysis, to uncover simplifying structures among a huge set of variables. Forecast error variance decomposition is a more precise name for variance decomposition. This analysis is performed on the vector autoregressive (VAR) model. Sims (1980) advocated these models and being utilised by numerous economists to solve classical simultaneous equations models (Lütkepohl, 2010).

CHAPTER 4: DATA ANALYSIS

4.0 Data Collection

4.1 Descriptive Statistics

Table 4.1: Descriptive Statistics

	Trading Volume (Log)	KLCI_return	GSVI_Covid_19	GSVI_Coronavirus
Mean	8.854311	0.050802	22.82692	26.78846
Median	8.840777	-0.503363	0.000000	21.50000
Maximum	9.241744	5.639230	100.0000	100.0000
Minimum	8.607922	-9.328432	0.000000	0.000000
Std. Dev.	0.156850	2.542474	29.99067	23.86427
Skewness	0.448641	-0.503738	0.897396	1.557542
Kurtosis	2.361740	5.195612	2.719557	5.138132
Jarque-bera	2.627067	12.64406	7.149844	30.92993
Probability	0.268868	0.001796	0.028018	0.000000
Sum	460.4242	2.641716	1187.000	1393.000
Sum Sq. Dev	1.254702	329.6728	45871.44	29044.67
Observations	52	52	52	52

Table 4.1 records the descriptive statistics of four variables, i.e., Trading_volume, KLCI_return, GSVI_covid_19 and GSVI_coronavirus. Descriptive statistics provides all relevant information that we require before running any sort of regression analysis. It allows us to have a clear picture about our data. Trading volume after log have a mean of 8.8543, the skewness close to 0 do supports that there is normality for this variable, however the kurtosis and Jarque-Bera probability do not propose normality. The mean for KLCI_return is 0.050802, about 5% for the 52 weeks. The skewness is close to zero and kurtosis reading is more than 3, the Jarque-Bera probability supports that this variable is normally distributed. There are an average of approximately 22 searches of GSVI_Covid_19 weekly throughout 52 weeks. Kurtosis less than 3 do not suggest normality however the skewness and Jarque-Bera probability do suggest the data to be normally distributed. Lastly, GSVI_Coronavirus records approximately 26 searches every week in Year 2020. Skewness of 1.5575 do not suggest the data to be normally distributed while Kurtosis of 5.1381 and probability of 0.0000 shows possibility. Looking at the skewness, log_trading_volume, GSVI_covid_19 and GSVI_coronavirus is skewed towards the left side, as 3 of the variables are positive numbers. KLCI_return that has a skewness less than zero is skewed towards to the right. Volatility of KLCI_return and GSVI_coronavirus are considered to be high, both kurtosis reading is higher than 3 ; GSVI_covid_19 and Log_trading_volume are less volatile as both kurtosis reading is lower than 3.

4.2 Unit Root Test

4.2.1 Augmented Dickey-Fuller Test

Table 4.2.1: Augmented Dickey-Fuller Test

	ADF					
	At level			1st diff		
Variables	T-stat	p-value*	Result	T-stat	p-value*	Result
Coronavirus	-2.5386	0.1126	Non-stationary	-8.6782	0.0000	Stationary
Covid-19	-6.5296	0.0000	Stationary	-9.1969	0.0000	Stationary
KLCI returns	-6.2983	0.0000	Stationary	-11.2930	0.0000	Stationary
Trading Volume (Log)	-3.9061	0.0039	Stationary	-8.1164	0.0000	Stationary

Note: The null hypothesis will be rejected if the p-value <0.05. Significance level is at 5%.

Table 4.2.1 records the results of ADF test applied on four of the variables, GSVI on coronavirus, GSVI on covid-19, KLCI returns and Trading volume. We run ADF test at level and found that GSVI on coronavirus do has unit roots, while KLCI returns, GSVI on covid-19 and trading volume have no existence of unit roots. By taking the test in 1st first difference, all four variables are proved to be stationary, as null hypothesis is rejected, implying that no unit roots existed for the variables in 1st difference.

4.2.2 Phillips-Perron Test

Table 4.2.2: Phillips-Perron Test

	PP					
	At level			1st diff		
Variables	t-stat	p-value*	Result	t-stat	p-value*	Result
Coronavirus	-2.507291	0.1197	Non-stationary	-8.861423	0.0000	Stationary
Covid-19	-6.617980	0.0000	Stationary	-19.08153	0.0001	Stationary
KLCI returns	-6.298326	0.0000	Stationary	-32.78647	0.0001	Stationary
Trading volume (Log)	-3.824622	0.0049	Stationary	-8.288448	0.0000	Stationary

Note: The null hypothesis will be rejected if the p-value <0.05. Significance level is at 5%.

Table 4.2.2 records the result of Phillips-Perron test applied on four of the variables. When the test was run on level, KLCI_return, GSVI_Covid_19 and Trading_volume is stationary, while GSVI_coronavirus is non-stationary. After running PP test at 1st difference, all four variables are then become stationary after rejecting the null hypothesis, proving there are no unit roots in all of the variables.

Hence, we are to conclude that GSVI_Coronavirus is not suitable to be used in our research, as in both Unit root test, it is proven to be non-stationary at level.

4.3 E-Garch (1,1) Model

Table 4.3: E-Garch (1,1) Model

Dependent variable – KLCI_Return		
Probability: 0.00740		
Variable	Representation	Coefficients
C(2)	Constant (Omega)	2.847364
C(3)	ARCH (alpha)	0.226764
C(4)	Leverage (gamma)	0.392056
C(5)	GARCH (beta)	-0.906059

Our research applies E-GARCH test to run on KLCI_Return to see the volatility of the data. Looking at the ARCH term, we observed a spill over effect. The positive coefficient indicates that a positive relationship exists between the past variance and the current variance at absolute level. This also shows that the volatility will be high if the magnitude of shock to variance is big. For the leverage coefficient, the positive sign indicates that positive shocks will exert more impact on the volatility compared to negative shocks at same size, this also implies that an asymmetric effect exist. GARCH term helps in determining the significance of the data, with a p-value smaller than 5% significance level, the data is said to be significant. Volatility persistence is supported by a significant GARCH term. After running the E-Garch, the data of KLCI_return will be adjusted into a garch variance series. The adjusted data will be renamed as KLCI_risk and a new model of KLCI_risk and GSVI_Covid_19 will be formed.

4.4 VAR Model – Lag Length Selection

Table 4.4(a):

KLCI_Return & GSVI_Covid_19						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-343.7566	NA*	6190.570*	14.40652*	14.48449*	14.43599*
1	-343.0211	1.379061	7094.801	14.54255	14.77645	14.63094
2	-342.7863	0.420687	8309.805	14.69943	15.08926	14.84675
3	-341.0431	2.977901	9153.562	14.79346	15.33923	14.99971
4	-340.7038	0.551424	10713.03	14.94599	15.64769	15.21116

In this combination of lag length selection, we will be choosing Lag 1. Since we will be choosing the second lowest lag, Lag 1 will be chosen despite all criterion suggests Lag 0.

Table 4.4(b):

Log_Trading_volume & GSVI_Covid_19						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-208.9271	NA	22.48590	8.788630	8.866597	8.818094
1	-199.7051	17.29130*	18.09468	8.571046	8.804946*	8.659437*
2	-195.6366	7.289386	18.06461*	8.568192*	8.958026	8.715511
3	-192.0878	6.062515	18.45670	8.586992	9.132759	8.793239
4	-189.1909	4.707502	19.41758	8.632954	9.334654	8.898128

For this combination, Lag 1 will be chosen as the previous combination. Three criterion chosen Lag 1, only 2 criterion suggested Lag 2.

Table 4.4(c):

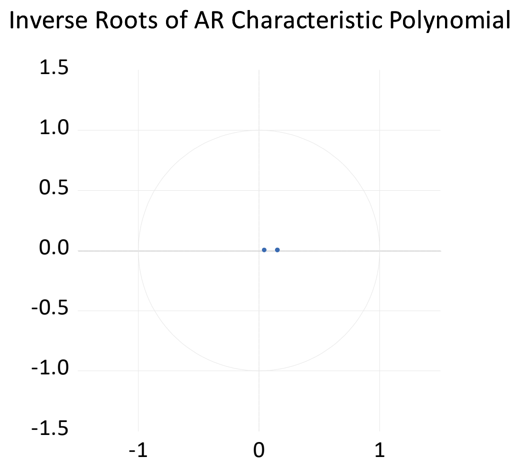
KLCI_Risk & GSVI_Covid_19						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-384.4995	NA	33806.38	16.10415	16.18211*	16.13361
1	-379.2208	9.897632	32062.37	16.05087	16.28477	16.13926
2	-373.3710	10.48092*	29719.34*	15.97379*	16.36362	16.12111*
3	-371.4556	3.272146	32502.87	16.06065	16.60642	16.26690
4	-370.6105	1.373310	37247.03	16.19210	16.89380	16.45728

In this combination, Lag 2 will be chosen. Among five criterions, only SC recommends Lag 0, while other 4 criterion suggest Lag 2.

4.5 Diagnosis Checking

4.5.1 Breusch-Godfrey LM Test

Model 1 : KLCI_Return & GSVI_Covid_19



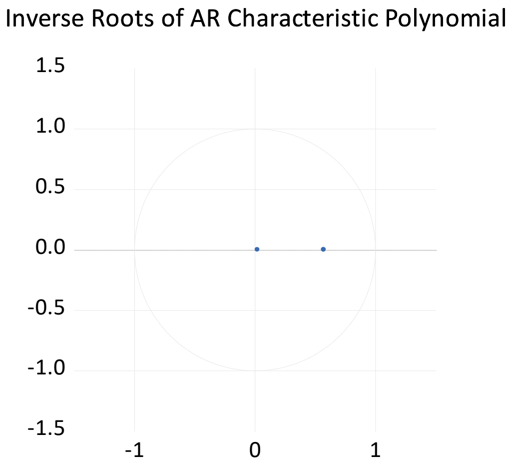
Graph 4.5.1(a)

Table 4.5.1(a): LM test result

Lags	Probability
1	0.9002
2	0.9714

Based on the figure, the inverse characteristics roots are touching the 0 line, showing this model of KLCI_return and GSVI_Covid_19 is dynamic stable. The table results shows the probability of 2 lags to be larger than significance level of 1%, 5% and 10%. For this model, the lag length suggested Lag 1 to be used, since the p-value of 0.9002 is larger than the significance level of 5%, the null hypothesis is not rejected. Hence, this model is not autocorrelated.

Model 2 : Trading Volume (Log) & GSVI_Covid_19



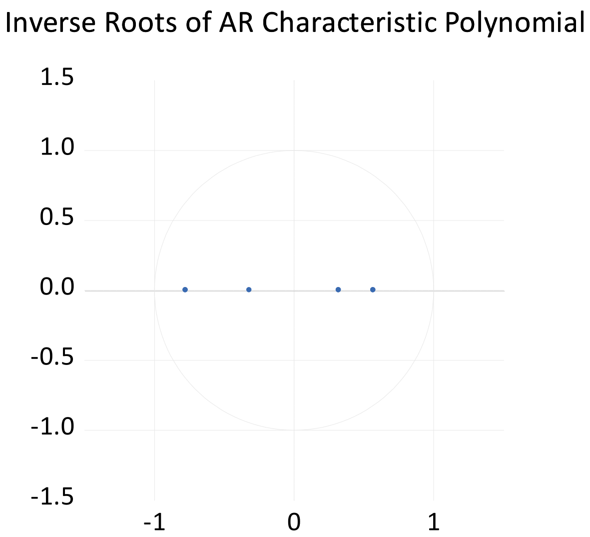
Graph 4.5.1(b)

Table 4.5.1(b): LM Test result

Lags	Probability
1	0.3098
2	0.0838

The graph shows the inverse characteristics roots lies on the zero line, showing this model of Trading_volume(Log) and GSVI_Covid_19 is dynamic stable. From the LM results, the probability of 2 lags are larger than significance level of 1%, 5% ; where Lag 2 has a probability that is smaller than 10% significant level. For this model, the lag length suggested Lag 1 to be used, since the p-value of 0.3098 is larger than the significance level of 5%, the null hypothesis is not rejected. Hence, this model is not autocorrelated.

Model 3 : KLCI_Risk & GSVI_Covid_19



Graph 4.5.1(c)

Table 4.5.1(c): LM Test result

Lags	Probability
1	0.4168
2	0.3404
3	0.3514

The inverse roots for this model of KLCI_Risk and GSVI_Covid_19 lies on the 0 line on the graph, indicating that this model is dynamic stable. From the autocorrelation LM tests, there are three lags for this model. All three lags have p-value larger than 1%,5% and 10% of significance level. The lag length criterion suggests Lag 2 for this model, p-value of Lag 2 is 0.3404. The null hypothesis is not rejected as p-value is larger than the 5% significance level. Hence, this model is proven to be not autocorrelated.

4.5.2 Normality Test

Table 4.5.2: Normality Test result

Model	Skewness	Kurtosis	JB - Prob.
KLCI_Return & GSVI_Covid_19	-0.676128	5.436612	0.0003
Trading_Volume (log) & GSVI_Covid_19	0.226197	3.039311	0.8032
KLCI_Risk & GSVI_Covid_19	2.644234	11.31714	0.0000

The normality test result was shown as in Table 4.5.2. For the first model, skewness is -0.6761, a negative figure skewing to the left and a figure close to 0 indicates the normality of residuals. The kurtosis of 5.4366 is more than 3, normality is proven. At last, the p-value of Jarque-Bera test is less than 5% significant level, thus the null hypothesis is not rejected. The normality in error term is proven. For model 2, the skewness is close to 0 and the kurtosis reading is more than 3, which shows normality. However, the p-value is larger than 5% significance level, null hypothesis is rejected, the residual is not normally distributed. For the last model, the skewness is far away from 0, not strong to prove normality however the kurtosis of 11.3171 and p-value did support normality in residual as the figure is more than 3 and p-value is smaller than 5% significance level.

4.5.3 White Heteroscedasticity Test

Table 4.5.3: White Test result

Model	Prob.
KLCI_Return & GSVI_Covid_19	0.4069
Trading_Volume (log) & GSVI_Covid_19	0.6556
KLCI_Risk & GSVI_Covid_19	0.4873

From Table 4.5.3, we realised the p-value for all three models is larger than 5% significance level. Thus, the null hypothesis for the models is not rejected, no heteroscedasticity problems in the residual is found.

4.6 Granger Causality Test

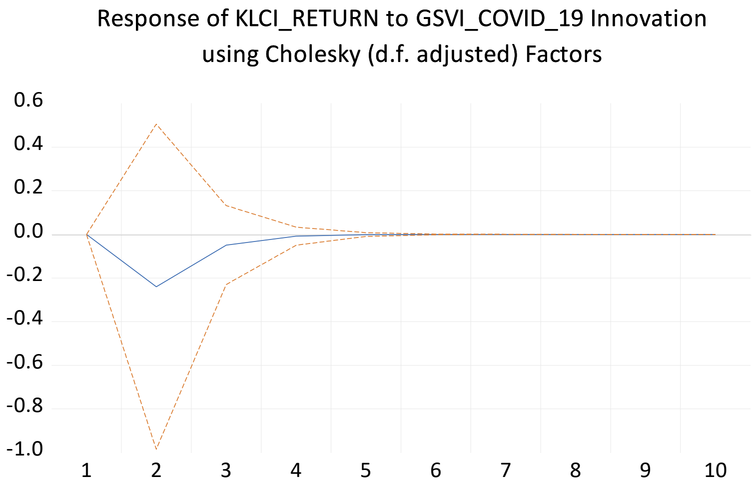
Table 4.6: Granger Causality Test

Independent / Dependent	KLCI_return	Trading_volume	KLCI_Risk	GSVI_covid_19
KLCI_return	-	-	-	0.5187
Trading_volume	-	-	-	0.6601
KLCI_Risk	-	-	-	0.3919
GSVI_covid_19	0.8771	0.0643	0.8558	-

** denotes rejection of the hypothesis at significance level of 5%

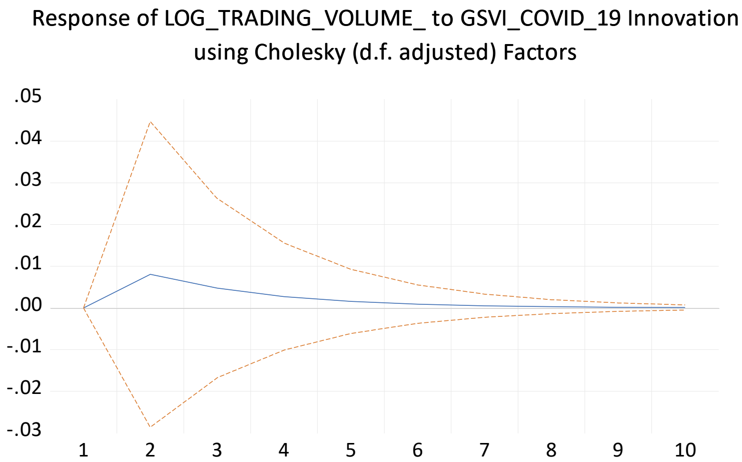
Based on Table 4.6, we found no granger causality relationship between GSVI_Covid_19 with KLCI_Return ; GSVI_Covid_19 with Trading_Volume ; and GSVI_Covid_19 with KLCI_Risk. There is no unidirectional nor bidirectional relationship between the dependent and independent variable. No null hypothesis is able to be rejected, as the p-value of 0.5187 for KLCI_Return ; 0.6601 for Trading_Volume ; and 0.3919 for KLCI_Risk are all more than 5% significance level. Thus, we concluded that no granger causality exists for all 3 models.

4.7 Impulse Response Function



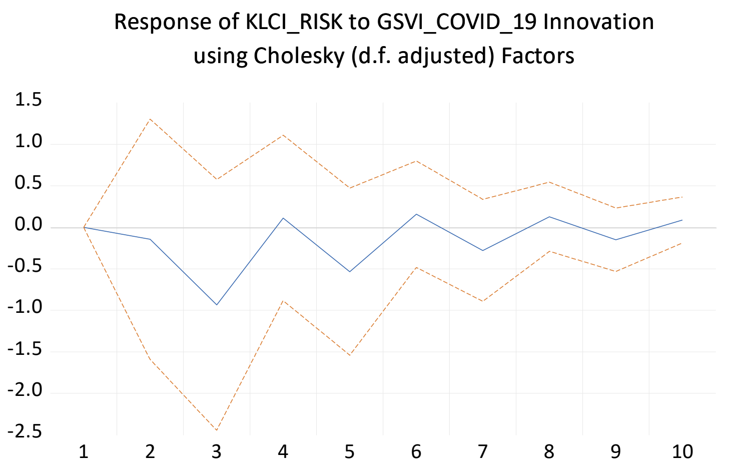
Graph 4.7.1

When a standard deviation of stock is given to GSVI_Covid_19, KLCI_return response hits the negative region, it hits the lowest in second period, and climbs slowly then remains constant throughout the time period. The results suggest that this model is insignificant.



Graph 4.7.2

Trading volume(Log) reacts positively when a standard deviation of stock is given to GSVI_Covid_19. It rises to a peak during the 2nd period and subdue slowly throughout the periods and remains in the positive region. The significance of the model is not proven.



Graph 4.7.3

The impulse function graph shows fluctuations of KLCI_risk when shocks is applied to GSVI_Covid_19. The reaction is very unstable as it fluctuates up and down throughout the entire period. It rushes into the negative region and hit the lowest during the 3rd period, then rises and slightly enter into positive region during the 4th period and shifting back and forth between positive and negative region throughout the period. The model is said to be insignificant referring to the graph.

4.8 Variance Decomposition

Table 4.8.1: Variance Decomposition of KLCI_Return

Period	S.E.	KLCI_ Return	GSVI_Covid_19
1	2.587878	100.0000	0.000000
2	2.613280	99.15773	0.842272
3	2.613999	99.12258	0.877416
4	2.614018	99.12158	0.878415
5	2.614019	99.12156	0.878441
6	2.614019	99.12156	0.878442
7	2.614019	99.12156	0.878442
8	2.614019	99.12156	0.878442
9	2.614019	99.12156	0.878442
10	2.614019	99.12156	0.878442

Variance decomposition helps us to better predict the future movements by looking at how the past trends bring effects to the future. We will separate into short run and long run, taking 3rd period as the short run and 10th period as the long run.

For variance decomposition of KLCI_Return, in the short run, we are seeing a 99.123% variation of fluctuation on KLCI_return when there are shock or impulse to its own term. A shock to GSVI_covid_19 will influence 0.8774% fluctuation to KLCI_Return. Moreover, in the 10th period which we consider as the long run, when there is an impulse or shock on KLCI_Return, the variation percentage to its own term remains at 99.122%. A shock on GSVI_covid_19 affect KLCI_return for 0.8784% variation.

Table 4.8.2: Variance Decomposition of Trading_Volume

Period	S.E.	Trading_Volume	GSVI_Covid_19
1	0.131455	100.0000	0.000000
2	0.149585	99.71042	0.289584
3	0.155008	99.63621	0.363788
4	0.156731	99.61416	0.385844
5	0.157287	99.60719	0.392810
6	0.157467	99.60495	0.395055
7	0.157526	99.60422	0.395782
8	0.157545	99.60398	0.396019
9	0.157551	99.60390	0.396096
10	0.157553	99.60388	0.396121

Likewise, in the short run, we are observing shock to trading volume will bring 99.6362% of variation to its own terms. For shock to GSVI_covid-19 in the short run contributes to 0.3638% to the variation of trading volume. Moving onto the long run, 99.6039% of trading volume can be explained by its own impulse absorbed. GSVI_covid-19 reports a 0.3912% variation to trading volume upon shock absorption. The percentage increase of GSVI_Covid_19 impact is minimal, for less than 0.03% from the short run to the long run.

Table 4.8.3: Variance Decomposition of KLCI_Risk

Period	S.E.	KLCI_ Risk	GSVI_Covid_19
1	4.861020	100.0000	0.000000
2	5.012968	99.91724	0.082758
3	5.640573	97.19110	2.808903
4	5.739809	97.24972	2.750280
5	5.906172	96.58153	3.418469
6	5.953743	96.56595	3.434051
7	6.003573	96.40636	3.593643
8	6.023539	96.38571	3.614293
9	6.039749	96.34284	3.657165
10	6.047576	96.33152	3.668483

In the 3rd period, we sees that KLCI_risk is affected by itself when shock is absorbed for 97.1911%. Where it is affected for 2.8089% by GSVI_Covid_19 when shock is applied on the independent variable. However in the long run, the percentage variation for KLCI_Risk dropped to 96.3315%, showing it to be slightly less affect by own shock absorption in the long run compared to short run. On the other hand, risk absorbed GSVI_Covid_19 exerts a percentage variation of 3.6685% to KLCI_risk. The percentages increased, showing KLCI_risk is affected more in the long run by GSVI_Covid_19. In overall, GSVI_covid_19 exerts only a small impact on KLCI_risk, for a percentage that is less than 5%.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.1 Discussion on Major Findings

This study investigates the impact of COVID-19 attention on the stock market performances in Malaysia. In this study, it is found that the GSVI on the keyword "Coronavirus" has unit root in the study. Hence, the GSVI on the keyword "Coronavirus" is not suitable to be used in this study. This might be due to the announcement of the official name of the coronavirus disease 2019 with the abbreviation of COVID-19 at February 2020. The keyword "Coronavirus" becomes less searched on the Google search engine and hence, it is an insignificant variable in this study. Instead, the GSVI on keyword "COVID-19" plays a significant part in this study when investigating the relationship between the investor attention and the stock market performances in Malaysia.

Utilising the Google search volume index (GSVI), our results contribute to the growing literature of investor attention during the COVID-19 pandemic. This study found out that there is insignificant relationship between the investor attention and the stock market performances in Malaysia in both short run and long run. The empirical results support efficient market hypothesis (EMH) which stated that the Malaysian stock market is efficient and hence, there is no arbitrage opportunities for investors since stock prices fully reflect all information.

Although this study shown insignificant results, the study have implications for investors, policy makers and researchers. The investors and policy makers have deeper insight into the efficiency and vulnerabilities of the Malaysian stock market and hence, it is helpful for them in making investment decisions and responses to crisis. Also, the researchers can use this study as reference and have to rectify the limitations of this study for comparison and completeness in order to have the whole picture of the impact of COVID-19 attention on the stock market performances.

Table 5.1 Comparison between Previous Studies and Empirical Results

Dependent and Independent Variables	**Previous Studies**	**Results**	**Supported by**
Investor Attention and Stock Market Return	Negative and significant	Insignificant	Kim, et al. (2018)
Investor Attention and Stock Market Volatility	Positive and significant	Insignificant	Xiao & Wang (2021)

The results obtained showed there is insignificant relationship between Google Search Volume Index on keywords "COVID-19" and "Coronavirus" to the stock market performance, the empirical results supported by Kim, et al. (2018) and Xiao & Wang (2021).

5.1.1 Investor Attention and Stock Market Return

Insignificant relationship is found between investor attention and stock market return in this study. Based on results from Chapter 4, the granger causality test has been carried out and found that there is no granger causal relationship between investor attention and stock market returns. Therefore, it proved that the investor attention and stock market returns are insignificant related. The results from variance decomposition revealed no effects in both short run and long run towards the relationship between investor attention and stock market return.

The insignificant results between the investor attention and stock market return in our study are similar with the result from Kim et al. (2018). Study from Kim et al. stated that they cannot find either contemporary relationship or predictive potential of investor attention proxied by google searches on Norway stock market return. However, this finding is different from previous studies (Smales, 2020; Zhang et al., 2020; Papadamou, 2020) which reveal significant relationship between stock market return and investor attention towards Covid-19, the previous research indicated negative relationship towards investor attention and stock return as the Covid-19 pandemic has created financial panic to the global stock market return. This study proven that the Covid-19 pandemic have no insignificant impacts between investor attention towards Malaysia stock market.

The Efficient Market Hypothesis (EMH) also explained that the price of security is completely affected by the available information and the changes in prices of security is random; therefore, according to random walk theory, the security price is unpredictable and no one can monitor and cover up the information on financial market (Naseer & Tariq, 2015). Our results in Chapter 4 reveal an insignificant relationship between the investor attention and stock market return that can be indicated and supported by the EMH and changes of the stock prices are therefore expected to be random and independent. It means that investor attention on the Covid-19 pandemic will not affects the KLCI returns, therefore; GSVI is unable to be used to forecast the return on KLCI. As the random walk theory stated that, the market prices movement that changes the future prices are unpredictable and the market prices will experience the same probability of falling as of rising.

5.1.2 Investor Attention and Stock Market Volatility

In this research, results shows that there is insignificant relationship between investor attention, as proxy by Google Search Volume Index (GSVI) on "COVID-19" and "Coronavirus" between Trading Volume. It means that investors search keywords of "COVID-19" and "Coronavirus" on Google Trends are no impacts on trading volume in FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLCI). Hence, the trading volume related to stock market volatility is performing insignificant relationship between the investor attention.

To support the results obtained in this research, Xiao & Wang (2021) proved that there is insignificant result between the GSVI and volatility in the oil market. In the study, the authors examined on the impact of GSVI on the good and bad volatilities. Good volatility refers the volatility that is related to the upward movements of oil prices, while bad volatility refers the volatility that is related to the downward movements of oil prices. The authors found that the impact of increasing and decreasing investor attention is significant for the bad volatility but it is insignificant for the good volatility.

The insignificant results obtained in our research could be explained by the EMH. In EMH, stock prices reflect all available information, while in our study showed the available COVID-19 related news on Google Trends is no impact on the stock price. It indicates that the COVID-19 related news is not much useful to predict the future prices as COVID-19 pandemic is an unpresented event. Besides, there is lack of studies and information on the effect of pandemic to the stock market performance, hence; it considered a problem of sources limitation to support investors' decision making. From results, GSVI with keywords "COVID-19" and "Coronavirus" are insignificant to the trading volume. Namely, it is insignificant to the stock market volatility.

5.2 Implications of Study

The empirical results are helpful to investors when making investment decisions. This study shows that the stock market in Malaysia is efficient and hence, there is almost no arbitrage opportunities from the perspective of investor attention. Since the impact of investor attention on the stock market performances in Malaysia is very little, investors can ignore this factor when tailoring their investment strategy and making investments in Malaysia stock market.

Policy makers could take the results of this study as a reference to improve the stock market vulnerability and efficiency. Since the results found that the impact of investor attention on the stock market performances is insignificant which proves that the Malaysian stock market is efficient, the policy makers can ignore this factor when trying to monitor the stock market from the impact of crisis.

The empirical results in this study varies with the previous studies (Iyke and Ho, 2021; Smales, 2020; Zhang et al., 2020; Papadamou, 2020) who found that the investor attention does impact the stock market performances. Hence this study gives researchers more insight to investigate the role of investor attention on the stock market performances under different macroeconomic environments. This study also proves that the Malaysian stock market is efficient which is tally with the efficient market hypothesis (EMH) and hence, it can be used as a reference for researchers in studying this theory.

5.3 Limitation of study

There are few limitations found in this study. Firstly, the part of the results is incomplete. In this study, the data collected to investigate the investor attention on the stock market performance during COVID-19 pandemic involve only data from year 2020. However, the COVID-19 pandemic is still ongoing in year 2021. It is still unpredictable that when the COVID-19 pandemic will come to an end and hence, it is hard to include all the data. This might affect the accuracy of results since we cannot have a whole picture on the impact of COVID-19 attention on the stock market which involve the data from the beginning of the COVID-19 pandemic till the end of the COVID-19 pandemic.

Second, the capacity of Google search volume index as an indicator of investor attention is limited. Although the Google owns a large search engine market share in Malaysia (98.57%), it still does not represent the whole search engine markets. There might be loss of data since other search engines such as bing, Yahoo and Baidu are not included in the study. Also, Google search volume index is not the direct and unambiguous indicator of investor attention. Investor attention can also be reflected on the media coverage (Fang & Peress, 2009), marketing expenses (Grullon et al., 2004) and consumer confidence (Schmeling, 2009). Consequently, it might affect the accuracy when investigating the relationship between the stock market performance and investor attention from the lens of Google search volume index.

Third, Malaysia is chosen in this study as Malaysia has experienced extreme volatilities in the stock market. However, this study which is only focused in Malaysia is not enough. Using of the sole main index which is FTSE Bursa Malaysia KLCI might not show the accuracy of the results. Although the FTSE Bursa Malaysia KLCI is one of the largest exchanges in the Association of Southeast Asian Nations (ASEAN), it only represents the top 30 companies listed in Malaysia (Bursa Malaysia, 2020). Other markets such as bond markets, derivatives market and sector indices are not taken into consideration in this study. Besides, other major stock indices such as S&P 500, Nasdaq, Shanghai Composite Index, Nikkei are not included in this study for comparison and completeness in order to have the whole picture of the impact of COVID-19 attention on the stock market performances.

5.4 Recommendations for Future Research

It is recommended to extend the data collection of the study. The data throughout whole COVID-19 pandemic should be included in the study starting from 2019 at which the first COVID-19 case was discovered in China. Although the date of the end of this pandemic is still unknown, the panel data should be included in this study. Therefore, the COVID-19 attention on the stock market performance can be investigate from the whole picture. The pre-crisis and post-crisis data can also be included in the research in order to make the comparison of investor attention during different phases of the crisis.

Second, it is recommended to include more perspectives as the indicator of the investor attention. Not only Google, other search engine indices including Yahoo, Baidu and bing should be included as the indicator of investor attention. Apart from the internet searches, other ways of expressing investor attention such as consumer confidence and media coverage should also be taken into consideration. This is to increase the accuracy of the results when investigating the relationship between the investor attention and the stock market performances.

Third, indices of other markets such as bond markets, derivatives market and sector indices should be included in the study. This is to increase the accuracy of the results and to have a deeper understanding on the impact of investor attention on different markets. Besides, major indices in other market should be included in the study. For example, data of 24 emerging stock markets have been included in the study to investigate the impact of COVID-19 pandemic on the emerging stock markets for completeness and comparison (Salisu et al., 2020). Therefore, it is recommended to include data from other markets such as major indices like Nikkei 225 and Hang Seng index to compare the impact of COVID-19 attention on the stock market performances.

5.5 Conclusion

This study found that the impact of COVID-19 attention on the stock market performances in terms of stock volatility and stock return in Malaysia is insignificant. The results bring implications to investors, policy makers and researchers. The limitations and recommendations of this study are discussed as well to act as an insight for future research direction.

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APPENDICES

Descriptive statistics

Appendix 4.1

Date: 02/21/21 Time: 20:30
Sample: 1/06/2020 12/28/2020

	LOG_TRADING_VOLUME_	GSVI_COVID_19	KLCI_RETURN	GSVI_CORONAVIRUS
Mean	8.854311	22.82692	0.050802	26.78846
Median	8.840777	0.000000	-0.503363	21.50000
Maximum	9.241744	100.0000	5.639230	100.0000
Minimum	8.607922	0.000000	-9.328432	0.000000
Std. Dev.	0.156850	29.99067	2.542474	23.86427
Skewness	0.448641	0.897396	-0.503738	1.557542
Kurtosis	2.361740	2.719557	5.195612	5.138132
Jarque-Bera	2.627067	7.149844	12.64406	30.92993
Probability	0.268868	0.028018	0.001796	0.000000
Sum	460.4242	1187.000	2.641716	1393.000
Sum Sq. Dev.	1.254702	45871.44	329.6728	29044.67
Observations	52	52	52	52

Unit Root Test

Appendix 4.2.1

ADF test

Null Hypothesis: GSVI_CORONAVIRUS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.538632	0.1126
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GSVI_COVID_19 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.529575	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: KLCI_RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.298250	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LOG_TRADING_VOLUME_ has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.824622	0.0049
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LOG_TRADING_VOLUME_) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.116408	0.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(KLCI_RETURN) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.29297	0.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GSVI_COVID_19) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.196903	0.0000
Test critical values:	1% level	-3.571310	
	5% level	-2.922449	
	10% level	-2.599224	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GSVI_CORONAVIRUS) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.678207	0.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Appendix 4.2.2

PP test

Null Hypothesis: GSVI_CORONAVIRUS has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.507291	0.1197
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	216.0204
HAC corrected variance (Bartlett kernel)	208.8629

Null Hypothesis: GSVI_COVID_19 has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.617980	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	884.7339
HAC corrected variance (Bartlett kernel)	1073.969

Null Hypothesis: KLCI_RETURN has a unit root

Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.298326	0.0000
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	6.357844
HAC corrected variance (Bartlett kernel)	6.359063

Null Hypothesis: LOG_TRADING_VOLUME_ has a unit root
Exogenous: Constant
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.824622	0.0049
Test critical values:	1% level	-3.565430	
	5% level	-2.919952	
	10% level	-2.597905	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.016330
HAC corrected variance (Bartlett kernel)	0.016330

Null Hypothesis: D(GSVI_CORONAVIRUS) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.861423	0.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	237.0897
HAC corrected variance (Bartlett kernel)	200.0037

Null Hypothesis: D(GSVI_COVID_19) has a unit root
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-19.08153	0.0001
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	1223.102
HAC corrected variance (Bartlett kernel)	339.7562

Null Hypothesis: D(KLCI_RETURN) has a unit root
Exogenous: Constant
Bandwidth: 35 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-32.78647	0.0001
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	9.300540
HAC corrected variance (Bartlett kernel)	0.603170

Null Hypothesis: D(LOG_TRADING_VOLUME_) has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.288448	0.0000
Test critical values:	1% level	-3.568308	
	5% level	-2.921175	
	10% level	-2.598551	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.021006
HAC corrected variance (Bartlett kernel)	0.016918

E-Garch Model

Appendix 4.3

Dependent Variable: KLCI_RETURN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 02/27/21 Time: 14:55
Sample: 1/06/2020 12/28/2020
Included observations: 52
Convergence achieved after 40 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(1) + C(2)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(3)
*RESID(-1)/@SQRT(GARCH(-1)) + C(4)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C(1)	2.847364	0.345577	8.239459	0.0000
C(2)	0.226764	0.191982	1.181173	0.2375
C(3)	0.392056	0.172975	2.266549	0.0234
C(4)	-0.906059	0.056320	-16.08778	0.0000

R-squared	-0.000407	Mean dependent var	0.050802
Adjusted R-squared	0.018832	S.D. dependent var	2.542474
S.E. of regression	2.518420	Akaike info criterion	4.696570
Sum squared resid	329.8070	Schwarz criterion	4.846666
Log likelihood	-118.1108	Hannan-Quinn criter.	4.754113
Durbin-Watson stat	1.779070		

Lag Length Selection

Appendix 4.4(a)

VAR Lag Order Selection Criteria
Endogenous variables: KLCI_RETURN GSVI_COVID_19
Exogenous variables: C
Date: 02/14/21 Time: 20:47
Sample: 1/06/2020 12/28/2020
Included observations: 48

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-343.7566	NA*	6190.570*	14.40652*	14.48449*	14.43599*
1	-343.0211	1.379061	7094.801	14.54255	14.77645	14.63094
2	-342.7863	0.420687	8309.805	14.69943	15.08926	14.84675
3	-341.0431	2.977901	9153.562	14.79346	15.33923	14.99971
4	-340.7038	0.551424	10713.03	14.94599	15.64769	15.21116

Appendix 4.4(b)

VAR Lag Order Selection Criteria
Endogenous variables: LOG_TRADING_VOLUME_
GSVI_COVID_19
Exogenous variables: C
Date: 02/21/21 Time: 20:18
Sample: 1/06/2020 12/28/2020
Included observations: 48

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-208.9271	NA	22.48590	8.788630	8.866597	8.818094
1	-199.7051	17.29130*	18.09468	8.571046	8.804946*	8.659437*
2	-195.6366	7.289386	18.06461*	8.568192*	8.958026	8.715511
3	-192.0878	6.062515	18.45670	8.586992	9.132759	8.793239
4	-189.1909	4.707502	19.41758	8.632954	9.334654	8.898128

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 4.4(c)

VAR Lag Order Selection Criteria
Endogenous variables: KLCI_RISK GSVI_COVID_19
Exogenous variables: C
Date: 02/27/21 Time: 15:00
Sample: 1/06/2020 12/28/2020
Included observations: 48

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-384.4995	NA	33806.38	16.10415	16.18211*	16.13361
1	-379.2208	9.897632	32062.37	16.05087	16.28477	16.13926
2	-373.3710	10.48092*	29719.34*	15.97379*	16.36362	16.12111*
3	-371.4556	3.272146	32502.87	16.06065	16.60642	16.26690
4	-370.6105	1.373310	37247.03	16.19210	16.89380	16.45728

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Breusch-Godfrey LM Test

Appendix 4.5.1(a)

VAR Residual Serial Correlation LM Tests
Date: 02/27/21 Time: 15:46
Sample: 1/06/2020 12/28/2020
Included observations: 51

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.062397	4	0.9002	0.264220	(4, 90.0)	0.9002
2	0.521630	4	0.9714	0.129345	(4, 90.0)	0.9714

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	1.062397	4	0.9002	0.264220	(4, 90.0)	0.9002
2	4.334724	8	0.8257	0.536536	(8, 86.0)	0.8259

*Edgeworth expansion corrected likelihood ratio statistic.

Appendix 4.5.1(b)

VAR Residual Serial Correlation LM Tests
Date: 02/27/21 Time: 15:41
Sample: 1/06/2020 12/28/2020
Included observations: 51

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.787602	4	0.3098	1.215440	(4, 90.0)	0.3098
2	8.221221	4	0.0838	2.127369	(4, 90.0)	0.0838

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.787602	4	0.3098	1.215440	(4, 90.0)	0.3098
2	9.328632	8	0.3153	1.187943	(8, 86.0)	0.3158

*Edgeworth expansion corrected likelihood ratio statistic.

Appendix 4.5.1(c)

VAR Residual Serial Correlation LM Tests
Date: 02/27/21 Time: 15:47
Sample: 1/06/2020 12/28/2020
Included observations: 50

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	3.921669	4	0.4167	0.991581	(4, 84.0)	0.4168
2	4.518283	4	0.3404	1.146483	(4, 84.0)	0.3404
3	4.426451	4	0.3514	1.122570	(4, 84.0)	0.3514

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	3.921669	4	0.4167	0.991581	(4, 84.0)	0.4168
2	5.659768	8	0.6853	0.705687	(8, 80.0)	0.6856
3	7.951534	12	0.7889	0.653265	(12, 76.0)	0.7898

*Edgeworth expansion corrected likelihood ratio statistic.

Normality Jarque-Bera Test

Appendix 4.5.2

KLCI Return & GSVI_Covid_19

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 02/27/21 Time: 15:58
Sample: 1/06/2020 12/28/2020
Included observations: 51

Component	Skewness	Chi-sq	df	Prob.*
1	-0.676128	3.885769	1	0.0487
2	0.648174	3.571096	1	0.0588
Joint		7.456865	2	0.0240

Component	Kurtosis	Chi-sq	df	Prob.
1	5.436612	12.61629	1	0.0004
2	2.391674	0.786379	1	0.3752
Joint		13.40267	2	0.0012

Component	Jarque-Bera	df	Prob.

1	16.50206	2	0.0003
2	4.357475	2	0.1132
Joint	20.85953	4	0.0003

*Approximate p-values do not account for coefficient estimation

Trading_Volume & GSVI_Covid_19

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 02/27/21 Time: 16:00
Sample: 1/06/2020 12/28/2020
Included observations: 51

Component	Skewness	Chi-sq	df	Prob.*
1	0.226197	0.434904	1	0.5096
2	0.939268	7.498904	1	0.0062
Joint		7.933807	2	0.0189

Component	Kurtosis	Chi-sq	df	Prob.
1	3.039311	0.003284	1	0.9543
2	3.137554	0.040207	1	0.8411
Joint		0.043491	2	0.9785

Component	Jarque-Bera	df	Prob.
1	0.438187	2	0.8032
2	7.539111	2	0.0231
Joint	7.977298	4	0.0924

*Approximate p-values do not account for coefficient estimation

KLCI_Risk & GSVI_Covid_19

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 02/27/21 Time: 15:53
Sample: 1/06/2020 12/28/2020
Included observations: 50

Component	Skewness	Chi-sq	df	Prob.*
1	2.644234	58.26642	1	0.0000
2	0.886089	6.542948	1	0.0105
Joint		64.80937	2	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	11.31714	144.1143	1	0.0000
2	2.923926	0.012057	1	0.9126
Joint		144.1263	2	0.0000

Component	Jarque-Bera	df	Prob.
1	202.3807	2	0.0000
2	6.555005	2	0.0377
Joint	208.9357	4	0.0000

*Approximate p-values do not account for coefficient estimation

<u>White Heteroscedasticity Test</u>

Appendix 4.5.3

<u>Trading_Volume (log) & GSVI_Covid_19</u>

VAR Residual Heteroskedasticity Tests (Levels and Squares)
Date: 02/27/21 Time: 16:31
Sample: 1/06/2020 12/28/2020
Included observations: 51

Joint test:

Chi-sq	df	Prob.
9.546917	12	0.6556

Individual components:

Dependent	R-squared	F(4,46)	Prob.	Chi-sq(4)	Prob.
res1*res1	0.114144	1.481799	0.2232	5.821362	0.2129
res2*res2	0.031279	0.371325	0.8278	1.595237	0.8096
res2*res1	0.027113	0.320488	0.8628	1.382760	0.8472

KLCI_Risk & GSVI_Covid_19

VAR Residual Heteroskedasticity Tests (Levels and Squares)
Date: 02/27/21 Time: 16:34
Sample: 1/06/2020 12/28/2020
Included observations: 50

Joint test:

Chi-sq	df	Prob.
23.55478	24	0.4873

Individual components:

Dependent	R-squared	F(8,41)	Prob.	Chi-sq(8)	Prob.
res1*res1	0.215812	1.410420	0.2212	10.79058	0.2138
res2*res2	0.033139	0.175659	0.9930	1.656955	0.9898
res2*res1	0.099800	0.568177	0.7976	4.989980	0.7586

KLCI_Return & GSVI_Covid_19

VAR Residual Heteroskedasticity Tests (Levels and Squares)
Date: 02/27/21 Time: 16:35
Sample: 1/06/2020 12/28/2020
Included observations: 51

Joint test:

Chi-sq	df	Prob.
12.49291	12	0.4069

Individual components:

Dependent	R-squared	F(4,46)	Prob.	Chi-sq(4)	Prob.
res1*res1	0.036894	0.440532	0.7786	1.881587	0.7575
res2*res2	0.083796	1.051789	0.3911	4.273593	0.3702
res2*res1	0.049796	0.602660	0.6626	2.539580	0.6376

Granger Causality Test

Appendix 4.6

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 02/14/21 Time: 20:58
Sample: 1/06/2020 12/28/2020
Included observations: 51

Dependent variable: KLCI_RETURN

Excluded	Chi-sq	df	Prob.
GSVI_COVID_19	0.416384	1	0.5187
All	0.416384	1	0.5187

Dependent variable: GSVI_COVID_19

Excluded	Chi-sq	df	Prob.
KLCI_RETURN	0.023928	1	0.8771
All	0.023928	1	0.8771

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 02/21/21 Time: 20:26
Sample: 1/06/2020 12/28/2020
Included observations: 51

Dependent variable: LOG_TRADING_VOLUME_

Excluded	Chi-sq	df	Prob.
GSVI_COVID_19	0.193397	1	0.6601
All	0.193397	1	0.6601

Dependent variable: GSVI_COVID_19

Excluded	Chi-sq	df	Prob.
LOG_TRADING_VOLUME_	3.421901	1	0.0643
All	3.421901	1	0.0643

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 02/27/21 Time: 15:07
Sample: 1/06/2020 12/28/2020
Included observations: 50

Dependent variable: KLCI_RISK

Excluded	Chi-sq	df	Prob.
GSVI_COVID_19	1.873474	2	0.3919
All	1.873474	2	0.3919

Dependent variable: GSVI_COVID_19

Excluded	Chi-sq	df	Prob.
KLCI_RISK	0.311387	2	0.8558
All	0.311387	2	0.8558

<u>Variance Decomposition</u>

Appendix 4.8.1

Variance decomposition of KLCI_Return

Period	S.E.	KLCI_RETURN	GSVI_COVID_19
1	2.587878	100.0000	0.000000
2	2.613280	99.15773	0.842272
3	2.613999	99.12258	0.877416
4	2.614018	99.12158	0.878415
5	2.614019	99.12156	0.878441
6	2.614019	99.12156	0.878442
7	2.614019	99.12156	0.878442
8	2.614019	99.12156	0.878442
9	2.614019	99.12156	0.878442
10	2.614019	99.12156	0.878442

Cholesky Ordering: KLCI_RETURN GSVI_COVID_19

Appendix 4.8.2

Variance decomposition of Log_trading_volume

Period	S.E.	LOG_TRADING_ VOLUME_	GSVI_COVID_19
1	0.131455	100.0000	0.000000
2	0.149585	99.71042	0.289584
3	0.155008	99.63621	0.363788
4	0.156731	99.61416	0.385844
5	0.157287	99.60719	0.392810
6	0.157467	99.60495	0.395055
7	0.157526	99.60422	0.395782
8	0.157545	99.60398	0.396019
9	0.157551	99.60390	0.396096
10	0.157553	99.60388	0.396121

Cholesky Ordering: LOG_TRADING_VOLUME_ GSVI_COVID_19

Appendix 4.8.3

Variance decomposition of KLCI_risk

Period	S.E.	KLCI_RISK	GSVI_COVID_19
1	4.861020	100.0000	0.000000
2	5.012968	99.91724	0.082758
3	5.640573	97.19110	2.808903
4	5.739809	97.24972	2.750280
5	5.906172	96.58153	3.418469
6	5.953743	96.56595	3.434051
7	6.003573	96.40636	3.593643
8	6.023539	96.38571	3.614293
9	6.039749	96.34284	3.657165
10	6.047576	96.33152	3.668483

Cholesky Ordering: KLCI_RISK GSVI_COVID_19