INVESTOR BEHAVIOR AND STOCK MARKET RETURNS DURING COVID-19

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ABSTRACT

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Abstract

In recent years, the Covid-19 pandemic has had significant effects on stock markets worldwide as no sectors have been able to hide from it. This special time period has also highlighted the role of psychological phenomena that have been more visible now than before.

This thesis studies the behavior of two investor types and stock market returns during Covid-19 pandemic. The aim is to find long-term relationships between the variables and examine how coronavirus related information affected investor sentiment, VIX index, and stock market indices. Moreover, it examines whether different stock market indices reacted differently to covid-information.

The empirical research was conducted by using vector autoregressive (VAR) models. The data consists of weekly observations of the US market, ranging from January 2003 to January 2022. This large sample period enables to examine the long-term relationships and focusing on how coronavirus affected those. In addition to VAR models, two nonlinear models were used to further investigate the possible time-varying relationships.

Results from VAR models show that individual investors base their decisions on history and do not react heavily to crises, whereas for institutional investors the opposite is true. The empirics suggest that stock market indices react especially to covid-deaths, and Standard & Poor's 500 index and Standard & Poor's 500 Value index also react to covid restrictions. The linearity tests imply that there are strong nonlinearities in the covid-information.

This study allows an insight not only to investor behavior but also to the behavior of different stock market indices during a crisis. This information could be useful for policy makers, and institutional and individual investors.

Key words
Stock returns, Volatility, Covid-19, Sentiment, Behavioral finance, Investor behavior, Monetary policy

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Tiivistelmä

Covid-19 pandemia vaikutti merkittävästi maailmanlaajuisiin osakemarkkinoihin, sillä sen vaikutukset levisivät kaikille toimialoille. Tämä erityinen ajanjakso on nostanut myös psykologiset ilmiöt esille aiempaa voimakkaammin.

Tämä pro gradu -tutkielma käsittelee eri sijoittajaryhmien käyttäytymistä ja osakemarkkinatuottoja Covid-19 pandemian aikana. Tavoitteena on selvittää, kuinka koronavirukseen liittyvä informaatio vaikutti sijoittajasentimenttiin, VIX indeksiin ja osakemarkkinaindekseihin. Näiden lisäksi tarkoituksena on tutkia sitä, reagoivatko eri osakemarkkinaindeksit koronainformaatioon toisistaan poikkeavilla tavoilla.

Empiirisessä tutkimuksessa hyödynnetään vektoriautoregressiivisiä (VAR) malleja. Data sisältää havaintoja Yhdysvalloista ja aikavälinä on tammikuu 2003 – tammikuu 2022. Pitkä aikaväli mahdollistaa muuttujien välisten pitkäaikaisten suhteiden tutkimisen ja tarjoaa mahdollisuuden tarkastella, kuinka koronakriisi vaikutti niihin. Näiden lisäksi tutkimus hyödyntää kahta epälineaarista mallia, joiden tarkoituksena on tutkia koronainformaation mahdollisia ajassa vaihtelevia merkitsevyyssuhteita.

VAR mallien tulokset korostavat yksityissijoittajien ja instituutionaalisten sijoittajien välisiä eroja. Etenkin yksityissijoittajilla erilaiset harhat päätöksenteossa korostuvat, kun sijoituspäätökset perustuvat lähinnä historiaan. Osakemarkkinaindeksit reagoivat etenkin koronakuolemiin, jonka lisäksi Standard & Poor's 500 indeksi ja Standard & Poor's 500 Value indeksi reagoivat myös koronarajoituksiin. Empiria osoittaa, että koronainformaatiossa on vahvoja epälineaarisuuksia, ja näitä tulisi tarkastella tulevissa tutkimuksissa.

Asiasanat
Sentimentti, Osaketuotot, Volatiliteetti, Covid-19, Rahapolitiikka, Sijoittajakäyttäytyminen

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1 INTRODUCTION

1.1 Background

Covid-19 pandemic has affected almost every country and person in the world. The coronavirus, detected first in Wuhan, China in December 2019, started as a health crisis, but its influence spread to all areas of society, and it finally led to a financial crisis. The stock market collapse in March 2020 was nearly 35% in the US and Euro area (Qontigo, 2021), making investors all around the world suffer major losses quicker than ever before. The impacts of the pandemic have been significant.

Typically, there has been differences in performance based on firm size, industrial sector, and between value and growth stocks. It was also captured during the pandemic that some sectors and stocks could be considered as winners whereas others were hit extremely hard. It has been argued in previous research papers that technology and health care sector (Narayan, Gong & Ahmed, 2022; Mazur, Dang & Vega, 2020), and growth stocks (Rahman, Amin & Mamun, 2020) gained some abnormal returns and might have even benefited from the pandemic. Because of the different impacts that the pandemic had on different stocks and industries, it seems interesting to investigate these more deeply and find reasoning behind them.

One extremely notable characteristic of the pandemic is the behavior of risks and risk perceptions (investors' feeling about risk). There are many ways to describe what a risk is, but one applicable definition is by Kenton (2021): "risk is a deviation from an expected outcome". In other words, people have assumptions about different things or situations, and a risk can be either the positive or the negative change that occurs. Usually in finance risk is defined to be asymmetric, the possibility to make a significant loss. In the financial world risks typically consist of two parts: systematic and unsystematic risk. Unsystematic risk (or a risk that is relevant only in a specific company or industry) can be mitigated with efficient diversification. Systematic risk, however, has an impact on the overall market rather than just a specific asset, and it cannot be easily diversified or mitigated (except with hedging or using some allocation strategies which are mostly intended for institutional investors). When considering investments, risks are usually measured with volatility which indicates the price changes that an asset may have. When an asset is more volatile, price movements are bigger and less predictable, therefore, it is seen also as a riskier investment than another asset with lower volatility. One of the main expectations in financial markets is that risks (volatility) and expected returns should go somewhat hand in hand. However, risk is not only about measurable statistics but also about our perceptions, and the definition of a risk may be more complex than conventional finance theories imply. Afterall, riskiness is a concept which has been developed to capture the uncertainty or probabilities of different outcomes. We evaluate risks in our minds by our personal criteria and every person has their own perceptions of risks which then again affect their decision-making and everyday life. When looking at Covid-19 pandemic together with risks, it seems obvious that there was systematic risk which increased the risks (and volatility) of all assets. But to which extent was the risk evaluation rationally related to uncertainty of future cash flows? During the years 2020-2021, investors faced a huge amount of information regarding the pandemic and its impact on society and economy. This study focuses on testing whether this information was rationally reflected in investment decision-making and risk perception.

Risk measurement might be extremely hard as there are quite a few characteristics involved. To capture risks, I use investor sentiment and VIX index in this research. The sentiment indicator is a survey-based measurement which describes the ratio between bullish and bearish views of individual investors, whereas the VIX index captures the implied volatility of S&P500 index options, therefore capturing the views of institutional investors.

To get a better understanding of the actual impacts of the crisis, this paper studies the relationships between covid-related information, sentiment, investors' risk perceptions, and stock market returns during Covid-19. In earlier research Aggarwal, Nawn and Dugar (2021) investigated the relationship between investor panic and stock market meltdown during Covid-19, analysing data from twelve countries. This thesis, on the contrary, focuses specifically on the US market. This choice enables us to get a better understanding on the virus's impacts. To meet this goal, this paper focuses on presenting a thorough literature review about the topic, and testing empirically how Covid information impacted investor sentiment, risk perception and stock market returns. To investigate these aspects a little bit further, this thesis uses a vector autoregressive (VAR) model which was created to fit the needs of this research. The data sample ranges from 6^{th} of January 2003 until 24^{th} of January 2022, including weekly observations from the US market.

1.2 Research questions

The purpose of research questions is to help focusing on the steps that need to be taken later as they are an efficient way of finding and focusing on the right information.

The research questions could be specified as:

i. How did sentiment and VIX index react to covid-information?
ii. How did stock market returns react to covid-information? Can that reaction be explained by sentiment and VIX?
iii. What kind of relationship dynamics can be found between stock market returns, sentiment and VIX?

iv. Do returns on different indices (Standard & Poor's 500 Composite, Standard & Poor's 500 Value, Standard & Poor's 500 Growth, and Nasdaq) react differently to Covid information?

1.3 Structure

This master's thesis is structured into seven main chapters which all have subchapters. The first chapter focuses on the topic itself, its background, key terms, importance, and also introduces the research questions. This gets followed by the second chapter, presenting relevant literature and theories about behavioral patterns. The third chapter also includes literature and previous research papers related to the topic, but the focus is more on the empirical side. It offers crucial information and background, in addition to some important discoveries from earlier research. The fourth chapter focuses on data and methodologies. It has an overall view on the collection of data, reasons for limitations, and variables, offering a great discussion of these details. Fifth chapter includes interpretation of the results and analysis based on the research. Sixth chapter focuses on the nonlinearities of Covid-19. It includes background information and two models which were used to test the nonlinearities in the series. Lastly, the seventh chapter discusses conclusions of the main findings. It also offers recommendations on what kind of research could be useful in the future.

2 THEORETICAL FRAMEWORK: A BEHAVIORAL APPRPOACH

2.1 Behavioral Patterns

During the past 30 years our understanding of human behavior has changed drastically. Regarding finance, we would like to see us as purely rational decision makers. However, psychology and the behavioral approach to finance have shown that the human decision-making mechanism is often based on heuristics, rules of thumb and biases (Kahneman, 2011). Extreme conditions highlight the impact of these features.

One of the most important factors impacting our decision-making is sentiment, which is described in the Cambridge Dictionary (2021) as "a thought, opinion, or idea based on a feeling about a situation, or a way of thinking about something". There are many things affecting sentiment - media, rumours, and narratives, to name a few. In general, positive sentiment has been linked with positive stock market returns whereas negative sentiment is seen to cause declines in the returns. In addition, overly optimistic and pessimistic expectations might cause movements in stock market returns and thereby, even cause mispricing in the markets. For example, Smales (2017) argues that negative sentiment drives prices below fundamental value, providing below average returns.

To continue with biases in decision-making, representativeness is one heuristic which needs to be considered. Kahneman and Tversky (1972) define it as follows: "the subjective probability of an event, or a sample, is determined by the degree to which it: (i) is similar in essential characteristics to its parent population; and (ii) reflects the salient features of the process by which it is generated". In other words, people expect that an event which is more representative is more likely in the future if it also reflects uncertainty of the process (or "randomness"). This heuristic emphasizes the role of previous events.

Moreover, our decision-making is also affected by the negativity bias. The main idea behind this bias is that the response to a negative event is stronger than the response to a positive event of the same magnitude. With coronavirus this could mean for example reacting more heavily to new negative information (increased deaths) than to new positive information (such as cured cases).

In addition to these patterns, risk aversion should also be considered as it is one of the fundamentals of behavioral finance. Risk aversion is related with preferring certainty over uncertainty, for example keeping one's money in a normal savings account rather than investing it to stocks which have higher riskiness. There are different stages of risk aversion but normally we assume that investors are risk-averse: preferring risk-free investments or demanding rational compensation for their risk taking. Earlier research by Vasileiou (2021) found that with a feel that health is in danger, there is higher risk aversion which then could lead to a stock market decline. This behavioral aspect could have been one of the reasons affecting the stock market collapse in March 2020.

Furthermore, terror management theory (TMT) is something to be considered when investigating pandemics. Greenberg, Pyszczynski & Solomon came up with TMT in 1986, proposing that awareness of mortality could potentially generate paralyzing anxiety, and that managing this anxiety is essential for effective functioning. Based on the theory, people need to procure self-esteem and meaningful worldview to shield from the awareness of death and to cope with such anxiety. With coronavirus the overwhelming anxiety could be seen especially during the early stages of the pandemic, when the increasing number of covid-cases was causing fear of death all around the world. During a crisis, the first panic or shock reaction is typically the most significant in the beginning, but the reaction starts to weaken over time.

Another aspect is commonly held beliefs of which some are totally incorrect based purely on some popular narratives. With the coronavirus this could mean, for example, a text about curing Covid-19 with ginger as ginger has antiviral properties. This belief, however, does not have any evidence that it would actually work with coronavirus. (Banerjee & Rao, 2021). Some have suggested that stories are the main thing that distinguish people from animals (Shiller, 2019), and it seems to be that stories are easily adapted, understood, and, at the best, they are able to reflect our values and views. When looking at all of these factors, it seems only logical that these kind of stories or narratives spread rather quickly. Shiller (2019) argues that when the narrative creates a significant emotional connect, it might cause a powerful response. This explains some amount of the wide spreading of (fake) news and deepens our understanding of the behavioral patterns.

When it comes to stock markets, we are typically interested about the behavior of investors. There is evidence that the two types of investors, institutional and individual ones, act differently. Ben-David, Franzoni, and Moussawi (2011) show evidence that during the Subprime Crisis, hedge funds reduced their equity holdings significantly compared to other investors. According to their research, one reason for different behavior is that institutional investors' compensation and career depends on their selection of funds, therefore adding pressure to reacting quickly to bad news. Another argument in their paper is the selling pressure that especially hedge funds face by their investors and lenders, pressuring to deleverage. Individual investors do not face the same problematics. The empirics of Ben-David et al. (2011) show that the role of institutions (e.g., banks, pension funds, corporates, the government, and other institutions) is significant, and funds with higher institutional structure sold their assets more and experienced below average flows.

These characteristics will be beneficial in making a coherent conclusion of behaviour's impacts. In order to see how these characteristics actually affected decision-making during coronavirus, it is important to investigate the measurable statistics and channels a little bit further.

2.2 Media impacts

Media has a remarkable impact on human behavior as it acts as a channel to share our thoughts and emotions. According to Banarjee & Rao (2021), the impact can vary between faulty treatment, panic, and mass hysteria. They also note that media impacts can be positive as it improves preparedness towards diseases, helps in crisis communication, and mitigates loneliness. This might be the most severe problem, as media might be useful and harmful at the same time. Due to this, some have described media's role in pandemics as a double-edged sword.

Information seeking is a natural way of trying to process situations and reduce uncertainty (Skarpa & Garoufallou, 2021). When comparing COVID-19 pandemic to SARS, influenza, or Ebola, there has been significantly higher number of digitalized facts and statistics during the new pandemic. The amount of coronavirus-related news has also been phenomenal as there has been daily news about vaccinations, covid-cases, covid-deaths, new recommendations, governmental actions, etc. (Banarjee & Meeda, 2021).

As the use of social media increases with time, it becomes an extremely potential way of sharing knowledge and information rapidly. This enables the whole humankind to fight against a pandemic where time is actually our biggest opponent. There have been memes, videos, and messages shared every day in social media and, therefore, social media can be seen as both good and bad, as it makes possible to share facts and raise public awareness, but it is also used to share disinformation. (Banerjee & Meena, 2021). One wrong (senseless) message with a strong emotional connection is enough the set out a rumour which can then spread and create a snowball effect where the information is more easily adopted as it moves along (Banerjee & Rao, 2021). In fact, the biggest challenges that media brings are misinformation and recognizing fake news (Banerjee & Meena, 2021). Croucher, Nguyen, and Rahmani (2020) found out that participants have a habit of believing anything shared on social media and considering the shared information as facts.

Communication about health and understanding public health is really dependent on how the data is interpreted by the masses and, therefore, there is always a possibility for misunderstandings (Banerjee & Rao, 2021). During the pandemic, all investors were able to access the same new information equally – the biggest difference was that the information was interpreted very differently (Vasileiou, 2021). And because of the internet and social media, the issue of a wide amount of information that is available is now bigger than ever before. This causes problems when investors have to be selecting information which might then lead to either underreaction (not reacting to some key information or reacting late) or overreaction (paying attention to something that is irrelevant). (Smales, 2020). Barberis, Shleifer, and Vishny (1998) found that financial markets overreact to consistent pattern of news even when that kind of news should have only a little weight put on them. Vasileiou (2021) found that for longer periods in the USA, markets underestimate the health risk with Covid-19. It was also noted that it is in contrast to the Efficient Market Hypothesis, indicating that prices in the stock market do not reflect all the information that is available.

All health-related news and misinformation, especially, is crucial during pandemic periods, such as Covid-19. This kind of misinformation has been studied before by, for example, Jamuna Prasad (a social psychologist). Prasad was the first person to find the connection between anxiety and the spread of "fake" news. When people have anxious minds and fears about unknown infections, they tend to accept any solutions or theories that are easily and quickly available. It is important to note that the logic behind the solution or theory is irrelevant for people at that point. (Banerjee & Rao, 2021).

Media's role during Covid-pandemic has been highlighted many times as its role and impacts are bigger than ever before. Earlier research by Haroon and Rizvi (2020) argues that negative sentiment in news has been connected with increases in volatility in the US market. Hence, media seems to have significant effects not only on human behavior but also on volatility and stock market returns.

To conclude, media still seems to be a double-edged sword. It has some positives, but during a pandemic such as the coronavirus, the negatives seem to be more highlighted as media causes panic among people. This panic, created by the media and then fuelled by our behaviourist characteristics, affects our decision-making, and eventually causes panic-selling and stock prices decline.

3 A SURVEY OF EMPIRICAL RESEARCH

3.1 Stock market dynamics

The Covid-19 pandemic affected heavily stock market returns, making different impacts on different industries and firms. Research by Baek, Mohanty and Glambosky (2020) suggests that the pandemic increased risks for all industries in the US, but they also mention that there are some differences.

Firstly, there are industry level differences which could be seen during the pandemic. Some sectors (e.g., health care and information technology) were affected positively while others (e.g., energy and finance) were affected negatively (Narayan et al., 2022; Just & Echaust, 2020). In their research Narayan et al. (2022) note that there were investments in the vaccines and personal protection equipment, which benefited the health care sector. For the technology industry the positive impacts came from, for example, distance work policies.

What comes to the other characteristics of stock markets, Rahman et al. (2021) found that smallest, least profitable and value portfolios were hit the hardest by Covid. Firstly, let's take a closer look at value stocks (low P/B) and growth stocks (high P/B). As value stocks trade below their book value, they might be seen as less risky, beneficial, and stable investments. However, it will take time for the markets to change its perceptions for the stock to be priced correctly based on its book value. What comes to growth stocks, their issuers are usually smaller and not as stable, which can increase their riskiness. However, growth stocks might seem more appealing than value stocks, as they might be able to offer above average returns. The innovation opportunities among growth stocks seem appealing for investors. Rahman et al. (2021) argue that value firms are more burdened with unproductive capital, hence, it is more difficult to adjust their capital compared to growth firms. They suggest that value stocks are more exposed to disaster risk and more vulnerable to pandemic such as Covid, and this could be one of the reasons for preferring growth stocks. Their research also indicates that, due to the outbreak of Covid, value stocks suffered more than growth stocks.

These differences give implications that stock market returns could be studied through multiple different indices that, for example, have different industry weighting. It also indicates that investors should consider diversification when making investment decisions.

3.2 Volatility and Covid

Volatility is one main concept of financial market functions, and there are several research papers investigating its meaningfulness. Typically, high volatility is associated with a higher probability of a market decline and lower volatility is associated with a higher probability of a market increase. This section focuses on getting a good outlook on the research that has already been conducted about volatility and Covid-19.

One measurement for volatility is the CBOE Volatility (VIX) index which measures market's expectations based on the implied volatility of S&P500 index options. The VIX index is a real-time reflection of future volatility, and it increases when the price changes are more drastic as it means that volatility levels are also higher. Some papers refer to VIX also as a "fear" or "panic" index. Panic in stock markets has been researched before and the declines have often been temporary – indicating that the reason is more related to sentiment than rationality (Aggarwal et al., 2021).

By taking a closer look at the behavior of VIX index, it can be seen that Covid made severe impacts on the index. Baker (2021) found that VIX has typically been between 10 to 30, and any value over 20 is usually a sign of market stress. During Covid-19 crisis in March 2020, the VIX index had an all-time-high daily value of 82.69, whereas during the Great Financial Crisis (GFC) it had the second-highest value of 80.86 (Baker, 2021; Macrotrends, 2021). This indicates that the price changes were very volatile during Covid-19 pandemic, and that people were concerned about the future price changes. It also suggests that this health-crisis caused investors to panic even more than during the GFC. In addition, as VIX had the most dramatic changes at the same time with the stock market collapse in March, it can be reasoned that panic affects overall returns negatively. This kind of negative relationship between volatility and stock returns has been established also earlier by many research papers (for example, Aggarwal et al., 2021; Just & Echaust, 2020; Marfatia, 2019; Smales, 2017). In addition, Aggarwal et al (2021) found that when panic levels increase, investors become more risk-averse.

Research by Mazur et al. (2021) document extreme volatility for S&P1500 firms during Covid-period. The highest volatility is documented for crude petroleum sector which plunges the most. In addition, they found that stocks that faced extremely negative returns during the stock market meltdown in March 2020 faced also extreme volatility. This kind of asymmetric volatility, where stocks experience negative returns and high volatility at the same time, is against the theory of rational investors. Some reasons behind asymmetric volatility could origin from, for example, heterogenous beliefs or overreactions.

3.3 Nonlinearities

Nonlinearities refer to the case where a direct linear relationship between two variables cannot be found, hence, their relationship creates a curved line instead of a straight one. There are some nonlinear models, such as Markov Switching model, Threshold Autoregressive model, and the Smooth Transition Autoregressive model that can capture the nonlinearities in regards of stock returns.

The empirics of Humpe and Macmillan (2014) give evidence that there are non-linear relationships between stock market returns and some macroeconomic and financial variables. They argue that the relationships between these are dependent on the state of the market, meaning that, for example, investor risk tolerance differs between return regimes. Based on their research, Humpe and Macmillan (2014) suggest that the different regimes may be a result from changes that happen in investor's feelings, such as fear or hope.

Dahmene, Boughrara and Slim (2020) state that as investors (with different risk preferences) get information, they compare the information to a threshold level and then each investor makes their own decisions. They argue that this makes the stock market switch smoothly between regimes. This implies that nonlinear models could be appropriate when investigating stock market returns.

Stock market nonlinearities have also been investigated during Covid-19. Izzeldin, Muradoglu, Pappas and Sivaprasad (2021) present evidence that the impacts of Covid-19 might be nonlinear. Their paper suggests that there is a nonlinear transition to a crisis regime for all of the G7 economies (Canada, France, Germany, Italy, Japan, UK, and US).

Hsu and Chiang (2011) found evidence on nonlinearities, and they suggest that monetary policy has bigger impacts on excess returns when they are low. They reason this by financial constraints where the constraints are more binding during poor stock market performance. In other words, monetary policy is more effective when the stock returns are low. Dahmene et al. (2020) also captured the nonlinear effects of monetary policy. They investigated nonlinearity in stock returns and found an asymmetric relationship with monetary shocks and stock returns. For the US, the relationship was negative and nonlinear, and they suggest that the explanation lies, similarly to the work of Hsu and Chiang (2011), in the financial constraints.

A bit more recent work by Junttila and Martin (2021) found that controlling the joint nonlinear effects of near-term stock market risks and unconventional monetary policy actions is highly important in order to explain dividend yields' movements (by Gordon discount model) during exceptional risk conditions. They find that introducing nonlinear tail effects is especially relevant for US markets, and if it is not considered, the future real economic growth factor is no longer statistically significant. Their research suggests that if these nonlinearities are controlled, expectations of future real economic activity can actually be used in explaining stock market pricing in the US.

3.4 Effects of covid-information

Covid-related literature has been growing at a fast pace, thereby offering possibilities to rely also on earlier research. This chapter focuses on coronavirus-related information and its impacts. By having a more thorough look into Covid-related vaccinations, deaths, confirmed cases, and restrictions, it is possible to get valuable data on the spread of the virus. It also gives more knowledge on whether and how these factors have affected the stock market collapse in March 2020.

Firstly, focusing on the confirmed covid-cases as they have been quite used in earlier research. The connection between covid-cases and stock market returns has been established by many research papers (Liu, Manzoor A., Wang, Zang & Manzoor Z., 2020; Al-Awadhi A.M, Alsaifi, Al-Awadhi A. & Alhammadi., 2020; Shear, Ashraf & Sadaqat, 2021). This previous literature suggests that there is a significant and negative connection between confirmed cases and stock market returns, implying that new cases decrease stock market returns. In addition, Grima, Özdemir, Özen & Romanova (2021) found that confirmed covid-cases have a high correlation with VIX. They state that when there is a 1% increase in Covid-19 cases, it increases the VIX index by 32,5%. This implies that as the number of confirmed cases increases, also risk perceptions increase, hence increasing VIX. These confirmed covid-cases might not, however, be offering reliable information for two reasons 1) people are not always taking the tests, and 2) there might be measurement errors.

For tackling the problems there might be with covid-cases, another indicator was chosen to reflect the negative effects of the virus. Covid-related deaths are used since they offer a more reliable way to measure the real-life negative impacts. In earlier research Al-Awadhi et al. (2020) found that deaths have significant negative impacts to stock market returns. In addition, the statistics by Our world in data (2021) shows that the number of Covid-19 deaths starts to increase on March 12th, and the steep growth continues until April. When combining this data with VIX index, it seems that deaths and VIX index go somewhat hand in hand – as deaths increase, also the VIX index increases. This indicates that deaths add panic within investors and make them see the market even more volatile than before. This connection has been confirmed also by Baig, Butt, Haroon, and Rizvi (2021) as they found that confirmed Covid-19 deaths increase volatility considerably.

In addition to the negative impacts of the virus, it is important to take a look at preventing actions. In order to reduce the spread of the virus, there have been new vaccines developed, and their purpose is to reduce the risk of getting a serious Covid-19 infection. Intuitively thinking, increased vaccination levels should decrease implied volatility but there are not too many research papers that would have included vaccination levels in the analysis. However, after vaccination levels started to increase, the VIX index decreased a bit. This would imply that preventing actions (vaccinations) add the feeling of safety and, therefore, decreases uncertainty and fear. The connection between these two has not been studied enough and for this reason it cannot be yet stated whether vaccinations would play a huge role in volatility movements or the stock market returns.

Another measurement for prevention actions is the stringency index or, in other words, measure of lockdown policies. Stringency index describes the strictness of policy actions, and it includes information on school and workplace closures, restrictions on public gatherings, cancellation of public events, closures of public transport, stay-at-home requirements, public information campaigns, and restrictions on internal and international traveling (Roser, 2021). The index is between 0 and 100, where higher values imply a stricter response. First covid-restrictions in the US were implemented on 2nd of February 2020, where the stringency index got a value of 5.56. This value, however, started to grow, and more restrictions were implemented constantly. From the starting of covid-restrictions to 24th of January 2022, the average value for stringency index in the US is 59.38. Hence, it can be said that covid-restrictions have been heavily used in the US, and this has made it hard for companies to conduct business in the same way as before. Previous research paper by Aggarwal et al. (2021) found that stringency affects stock market returns both, negatively (via investors updating growth expectations) and positively (via investors demanding higher market risk premium).

Lastly, there have been some papers that compare the different impacts between negative and positive covid-information. For example, Shehzad, Zamann, Liu, Górecki & Pugnetti (2021) and Basouny, Bouadi, Ali & EmadEldeen (2021) found that negative information (deaths) affects more clearly to stock markets than positive information (recovered cases). This finding highlights the role of negativity bias.

3.5 Monetary policy

Monetary policy actions have been changing their form, as unconventional monetary policy actions have been stealing the spotlight from conventional monetary policy. Even though the ways of operating may have changed, the goals have stayed the same – promoting maximum employment, stabilizing prices, and moderating long-term interest rates (Federal Reserve, 2022). This section offers a more in-depth view of the monetary policy actions that were used during Covid-19.

One major monetary policy act during the Covid-crisis were purchase programs, where Federal Reserve and the European Central Bank (ECB) announced that they will do anything to save the enterprise sector and reduce the negative effects of Covid-19 (Junttila & Martin, 2021). As the markets' actions were unpredictable, this was the way to convince investors that everything will be fine as

FED and ECB are involved in the process and will do anything in their capabilities to help companies. These purchase programs decreased risks during Covid-19.

The effects of unconventional monetary policy have been studied earlier and, for example, Marfatia (2020) found that unconventional monetary policy actions increased confidence in the financial markets, therefore causing VIX to decrease after the Great Financial Crisis. This implies that unconventional monetary policy could work as a tool with Covid-19 challenges as well.

Wei & Han (2021) discuss that unconventional monetary policy is more effective than conventional monetary policy and, therefore, it could be used to reverse the economic downturns after Covid-19. They argue that the changes could have a positive impact on economic recovery, even if the effects may not be significant. This indicates that focusing on unconventional monetary policy could prohibit downfalls and support the real economy in the future.

One way of measuring unconventional monetary policy actions is central banks' balance sheet assets (Junttila & Martin, 2021). The empirical results of Junttila and Martin (2021) suggest that unconventional monetary policy actions are essential in pricing stocks especially during periods of uncertainty (such as Covid-19).

Another policy act during Covid-19 was that the Federal funds rate was lowered in March 2020 to stimulate economic growth. In addition, FED encouraged institutions to use their capital and liquidity buffers to lend and to co-operate with borrowers who were already affected by the coronavirus. FED also lowered the bank leverage ratio to 8%. (International Monetary Fund, 2021).

Lutz (2015) investigated the relationship between monetary policy and investor sentiment. The research suggests that shocks in conventional and unconventional monetary policies have economically significant impacts on sentiment. This gives implications that central banks are able to make significant effects on investor sentiment. It still stays unknown whether central banks can affect stock prices by using sentiment as a channel.

4 DATA AND METHODOLOGY

4.1 Data and variables

The empirical research focuses on exploring the relationships between stock market returns, sentiment, and VIX during Covid-19 pandemic. One of the key focus areas is on the covid-information and investigating how it affected investor behavior and stock market returns. The data is a collection of time series, and it is collected from Refinitiv Datastream and Our World In Data. The series begins on 6.1.2003 and runs until 24.1.2022, having weekly observations on the US market. The long time period enables us to get a better understanding of the long-term relationship dynamics of the dependent variables, and then see how covid-related information affected those.

I investigate investors' sentiment and risk perceptions by two different indicators. First of them is AAII index which is a survey-based measurement about investor sentiment. The survey is done for the members of AAII (American Association of Individual Investors), and it is done on a weekly basis. Its purpose is to indicate whether investors are being bullish, bearish, or neutral on the stock market for the next six months (American Association of Individual Investors, 2022). In other words, this indicator describes individual (or retail) investors' feelings about future views of the market. When the index rises above one, the greater is the bullish sentiment. If the ratio is less than one, the sentiment is more bearish, and more investors expect the market to decline. As it can be seen from figure 1, investors tend, in general terms, to be more optimistic and assume that bullish market will continue.

The second sentiment indicator is volatility index (VIX), also known as the "fear index". It is based on the implied volatility of SP500 Index options for the upcoming 30 days, and it captures the views of institutional investors. To put this another way, VIX was chosen to describe the volatility perceptions of institutional investors. If the index has low values, it indicates that the implied volatility is also low. If the index is high, implied volatility is also high. High volatility is usually an indicator of fear, and this can be seen in figure 2 for example, during the Great Financial Crisis (2008) and Covid-19 outbreak (2020). In the regressions I use variable "DVIX" which includes the logarithmic returns of VIX index.

A comparison between figure 1 and figure 2 supports theories of differences in the behavior of institutional and individual investors. Taking a glance at figures 1 and 2, it seems obvious that there have been major swings in the indices during Covid, which highlight the role of panic. The comparison, however, gives an implication that individual investors' reactions are more moderate and perhaps even more rational than those of institutional ones.

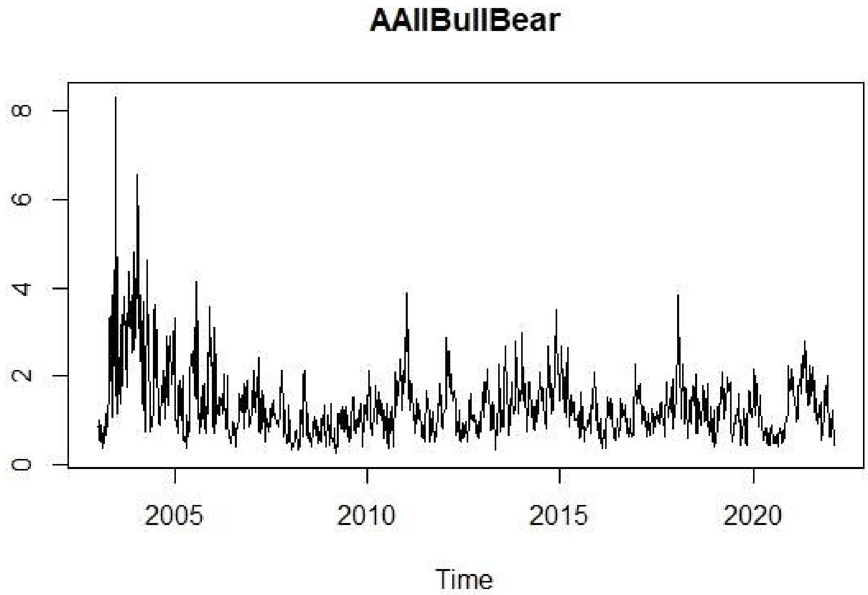


Figure 1. Weekly observations of AAII index, 2003-2022.

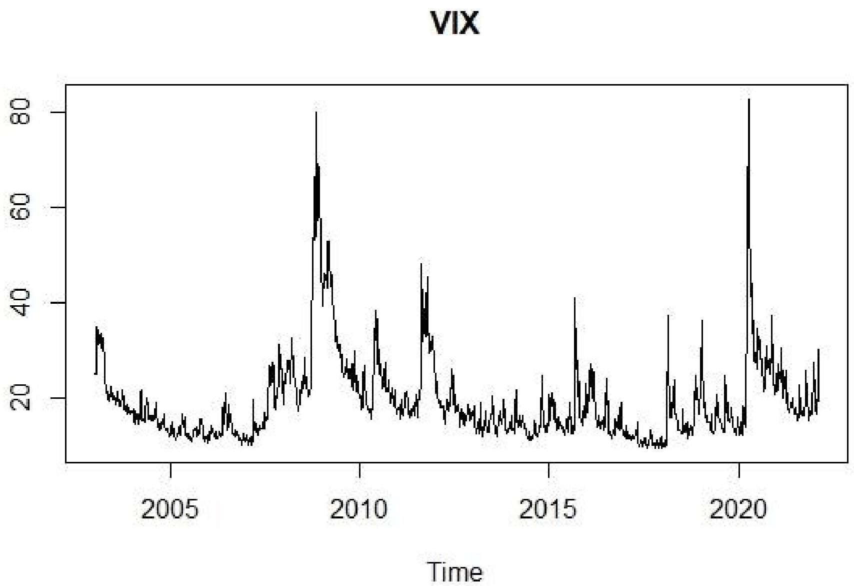


Figure 2. Weekly observations of VIX index, 2003-2022.

Let's continue with the different stock market return indicators – SP500, SP500Value, SP500Growth, and Nasdaq. First one, SP500, is highly used in the field of finance as it measures the value of the 500 largest listed companies, hence giving a thorough outlook on the markets. Second and third indices, SP500Value and SP500Growth, are based on the SP500 index. SP500Value measures stock values using ratios of book value, earnings, and sales to price, and SP500Growth measures stocks' growth with sales growth, ratio of earnings change to price, and momentum (S&P Global, 2022). Last return indicator is Nasdaq which differs a bit from the previous ones. Whereas SP500 index gives greatest weighting for such companies that have most shares available to trading, Nasdaq focuses on the market value of stocks that are traded in Nasdaq market. One key point is in the structure of the indices as, according to Nasdaq Global Indexes (2022), 50.3% of Nasdaq is on the technology industry.

All the return indicators behave similarly to each other, and volatility clustering is obvious (see figure 3). It can also be seen that there are few spikes in the indices, for example during GFC and outbreak of coronavirus. It seems that Nasdaq did not react to Covid-19 as heavily as the other indices, and one explanation could lay in the structure – Nasdaq is heavily focused on technology sector which did not suffer as major losses during the crisis as some other industries.

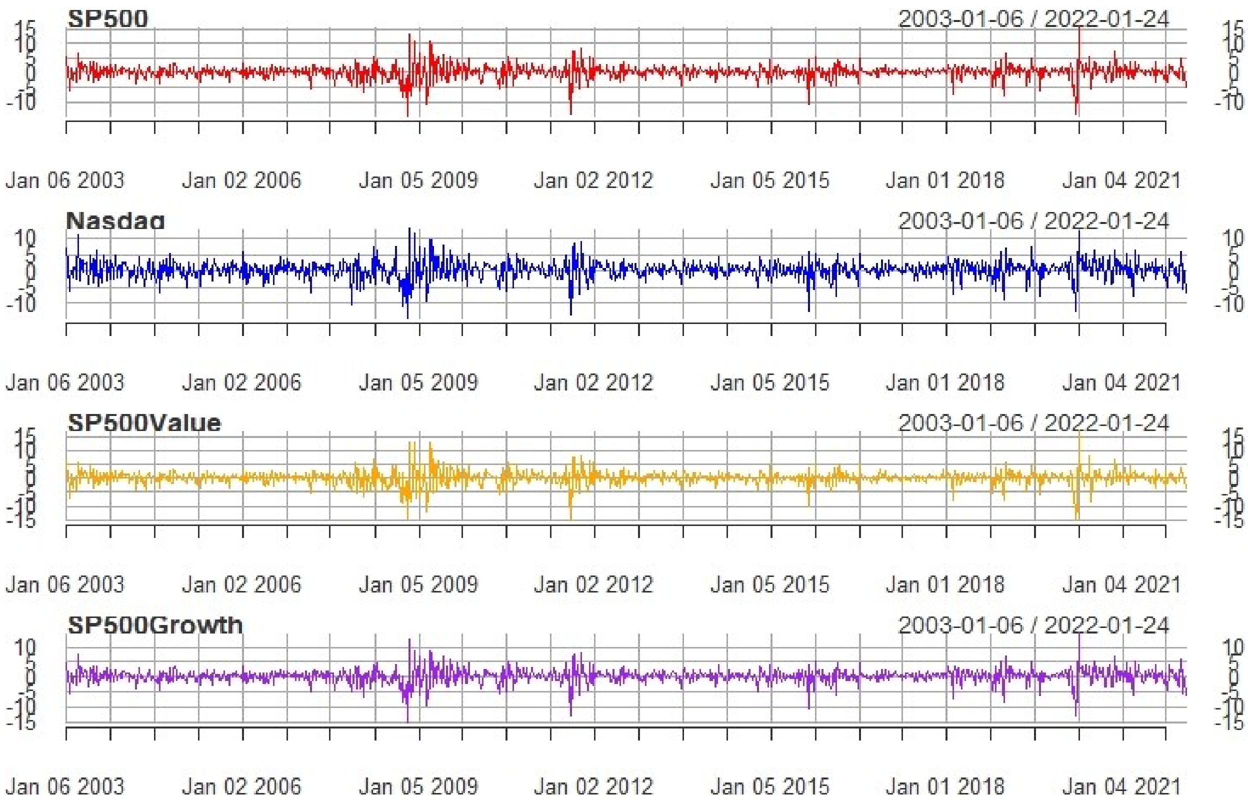


Figure 3. Logarithmic returns of stock market returns, 2003-2022.

Thirdly, focusing on the covid-related variables. Their purpose is to identify whether covid-related information made a difference in investors' sentiment, risk perceptions, or stock market returns. These variables include new confirmed Covid-cases (weekly), new Covid-deaths (weekly), the level of fully vaccinated people, and Covid-stringency index.

On top of the coronavirus indicators, there are a few variables to investigate the role of monetary policy – federal reserve assets (central bank's balance sheet at the end of the week) and federal funds rate. These were chosen to take a more thorough look on whether monetary policy has been effective or significant during the crisis.

Lastly, Covid and Subprime dummy variables were added to the estimations. The purpose of these is to take a closer look at crises and see how they affect the main variables. The intuitive idea would be that a crisis period adds negative sentiment (for example, uncertainty and fear), increases implied volatility, and decreases stock market returns. With the dummy variables, it is possible to get empirical evidence either for or against this intuition.

4.2 Methodology

Vector autoregressive models are the conventional method when investigating the impacts of exogenous shocks and dynamic of economic systems. I will estimate the following model:

$$Y_t = \beta_0 + \sum_{i=1}^{N} \beta_i Y_{t-i} + \sum_{i=0}^{n} \alpha_i X_{t-i} + \varphi D_t + \varepsilon_t \qquad (1)$$

in which Y_t is a vector of endogenous variables, and X_t is a vector of exogenous variables. In the first model the endogenous variables are sentiment index or AAII Bull/Bear ratio (AAII), Standard & Poor's 500 index (SP500), and logarithmic returns of VIX index (DVIX). In the second model the endogenous variables are sentiment index (AAII), Value index (SP500Value), Growth index (SP500Growth), and logarithmic returns of VIX index (DVIX). In the third model the endogenous variables are sentiment index (AAII), Nasdaq index (Nasdaq), and logarithmic returns of VIX index (DVIX).

In all models the exogenous variables include new confirmed coronavirus cases (Covidnew), new Covid-deaths (Deaths), amount of fully vaccinated people (VaccinatedFully), stringency index (Stringency), changes in Federal Reserve assets at the end of week (DFedAssets), and changes in Federal funds rate (DFedFunds). The purpose of these variables is to see how coronavirus related information or monetary policy (and their first lags) impacts the endogenous variables.

In addition, there are two dummy variables in all of the models – Covid-19 and Subprime. the purpose of these is to see how crises affect stock market returns, sentiment, or implied volatility.

The optimal lag length for the regressions was chosen by Schwartz-Bayes (SC) criteria. For endogenous variables, the optimal lag length was two (weeks), and for the exogenous variables, the optimal lag length was one.

5 EMPIRICAL RESULTS AND ANALYSIS

This section focuses on presenting and interpreting the obtained results. Firstly, I will cover the descriptive statistics and unit root test results. The rest of this section focuses on analysing results in relations to the endogenous variables based on different VAR models, Granger-causality tests, impulse responses, and variance decompositions. The standardized results of VAR models are presented in tables 2, 3, and 4.

5.1 Descriptive statistics

I constructed a descriptive statistics table which can be used as a summary of used variables (see Table 1), excluding dummy variables. The table includes means, medians, skewness, kurtosis, and results from two different unit root tests.

There are some big differences between the mean and median values which can be explained, in the case of covid-related information, by the lack of observations in the first years. One explanation for differences in mean and median of sentiment (AAII) and implied volatility (DVIX) could be that higher values during positive sentiment in AAII or greater "fear" in DVIX increases the mean values of the variables significantly.

The skewness values imply that AAII, DVIX, covid-related information, monetary policy, and the dummy variables have a highly skewed distribution. For the four return indices the distribution is approximately symmetric. Kurtosis values imply that the values are too peaked with all the variables. The kurtosis also suggests that the whole data series has more tails than a normal distribution.

For unit root testing I used the Augmented Dickey-Fuller (ADF) test, and Phillips-Perron (PP) test. Optimal lag length was chosen with Bayesian information criteria (BIC). As the null hypothesis is that there is a unit root in the series, the optimal results would be rejecting the null, implying stationarity in the series. After running the estimations, both tests reflect high significance and the null hypothesis (or existence of unit roots) can be rejected at 1% level for all of the endogenous variables – the sentiment indicator AAII Bull/Bear ratio (AAII), logarithmic returns on VIX (DVIX), Standard & Poor's 50 index (SP500), Value index (SP500Value), Growth index (SP500Growth), and return on Nasdaq index (Nasdaq). The ADF test also indicates stationarity for fully vaccinated people, whereas the PP test did not.

There are quite a few variables for which the tests implied non-stationarity. Firstly, looking at fully vaccinated people – ADF test indicates stationarity, but the PP test does not. This could indicate problems with heteroscedasticity or autocorrelation. Other variables reflecting non-stationarity (as the null hypothesis cannot be rejected, hence, it is assumed that there are unit roots in the series) focus on the exogenous variables, including new confirmed coronavirus cases, coronavirus related deaths, vaccinated people, federal reserve assets, and federal funds rate. For the monetary policy variables, I used the differences and ran the tests again. Now both series reflect stationarity as the null hypothesis can be rejected at 1% level with both (ADF and PP) tests. The four covid-variables (new cases, deaths, stringency, and fully vaccinated) still remain nonstationary for the regressions.

Table 1. Descriptive statistics.

	Mean	Median	Skewness	Kurtosis	ADF	PP
AAIIBullBear	1.3432	1.1815	2.411702e+00	14.472310	-10.3163***	-14.2675***
DVIX	0.00095	-0.90738	1.174735e+00	9.595193	-26.1923***	-38.3968***
SP500	0.1621	0.3020	-4.471849e-01	10.090610	-23.1661***	-34.4661***
SP500Value	0.1264	0.2630	-3.668814e-01	10.440218	-22.8977***	-34.3353***
SP500Growth	0.1904	0.3201	-4.899956e-01	9.103657	-23.382***	-34.3935***
Nasdaq	0.2698	0.4534	-4.181028e-01	6.270072	-23.9353***	-34.2307***
Covidnew	58561	0	1.031634e+01	136.916111	8.0992	9.7884
Deaths	4390	0	4.237083e+00	22.361561	-2.7305*	-1.9743
VaccinatedFully	7642653	0	4.688376e+00	23.657864	-3.525***	9.9414
Stringency	6.213	0	2.770121e+00	8.874500	-1.1053	-0.4826
DFedAssets	8178	2202	6.613100e+00	74.531844	-12.7269***	-15.2037***
DFedFunds	-0.001146	0	-2.409504e+00	44.920543	-26.8558***	-39.2292***

Interpretation of table 1: Significance levels of unit root tests: 1%: '***', 5%: '**', and 10%: '*'.

5.2 Results for the sentiment index (AAII)

First glance at tables 2, 3, and 4 imply that the AAII sentiment indicator is mostly affected by history. Significant explanatory factors for AAII are history of itself, SP500, Nasdaq, and the logarithmic return of VIX (DVIX). Looking at this more thoroughly, the estimated VAR models show that the lags of AAII, SP500, and Nasdaq have positive coefficient estimates. This positive relationship implies that whenever the return indices grow, the positive investor sentiment grows as well. In addition, the Granger-causality tests implied that all of the stock market return indices Granger-cause the sentiment indicator, hence, the changes in stock market returns causes changes in sentiment. This kind of relationship suggests that if investors base their views on the movements of stock returns, they focus on representing the current state rather than the upcoming future. This is in line with Hoffmann, Post & Pennings (2013) as they suggest that individual investors adjust their future expectations based on return experiences.

On the contrary, the first lag of DVIX has a negative and statistically significant coefficient on AAII. This can be explained intuitively: as the perceived risks increase, also the fear, uncertainty, and negative sentiment increases, hence decreasing the positive investor sentiment. The estimations give empirical support to the intuitive idea of volatility affecting negatively to sentiment. Also, the Granger-causality tests suggest that changes in VIX cause changes in sentiment. The relationship between market sentiment and risk has been established also in earlier research (for example, Smales, 2017).

What comes to unconventional monetary policy (measured by changes in Federal Reserve assets), it seems that the results are a bit mixed. The variable itself has positive coefficient estimate but its first lag has a negative one. However, these estimates are mainly insignificant as there are only two situations where unconventional monetary policy is statistically significant at 5% level. More specifically, the variable itself has a statistically significant coefficient estimate only in model 3 (table 4), and its first lag has a statistically significant coefficient estimate only in model 2 (table 3). This suggests that sentiment is mildly affected by unconventional monetary policy. Based on model 3, it seems that sentiment increases together with Federal Reserve assets, and the response is immediate. In model 2, on the contrary, sentiment decreases when Federal Reserve assets increase, and the response comes with one period lag (one week).

Next, let's focus on the covid-information. All of the results show statistical significance for the level of fully vaccinated people and its first lag. The coefficient estimate is positive, suggesting that vaccinations increase the feeling of safety and, therefore, positive sentiment. The effect, however, changes as the variable's first lag has a negative coefficient estimate. These negative coefficient estimates are perhaps against intuition, as they suggest that increased level of fully vaccinated people decrease the AAII sentiment index. When focusing on the size of the coefficients, it can be seen that the two estimates are close to each other. In other words, the effects (that an increase in the level of fully vaccinated people causes to AAII) are almost perfectly diminished by the lagged effects.

Surprisingly, other variables, such as covid-cases, covid-deaths, restrictions and even the dummy variables seem to be insignificant for explaining AAII in all the models. Thereby, the three VAR models suggest that sentiment did not react heavily to covid-information.

If looking at the sizes of coefficient estimates, we can see that the sentiment index is actually most heavily affected by its own lags, implying that the index represents only the current state. The results indicate that individual investors forecast recent events and assume that the same sentiment will continue to the future. This gives empirical support to previous literature (e.g., Kahneman & Tversky, 1972; Hoffman et al., 2012; Barberis, 2013) of biases in decision making, rule of thumb and especially representativeness.

Variance decompositions indicate that only one standard deviation shock to AAII is significant for the sentiment whereas the effects of shocks in other dependent variables only transfer to the sentiment index, at maximum, 0.6%. This is an interesting finding as stock market returns and DVIX are significant in explaining sentiment, but their shocks do not seem to transfer to AAII.

Lastly, the adjusted R^2 values for AAII are 0.5139 in model 1, 0.5131 in model 2, and 0.5201 in model 3. These suggest that the model which includes Nasdaq is the best one in explaining sentiment.

5.3 Results for implied volatility (VIX)

Continuing the analysis in relations to logarithmic changes of VIX (DVIX), the results seem to be very different compared to sentiment (AAII). Hence, we can assume that there are different factors affecting sentiment and volatility. Whereas AAII had most statistical significance from the history of endogenous variables, the significance of those has dropped. Even though the significance of three return indices (SP500, SP500Growth, and Nasdaq) has dropped compared to AAII, they are still significant at 1% level. They all have positive coefficient estimates which implies that in case the returns grow, also grows the implied volatility. The relationship between risks and returns is one fundamental of financial theories and, hence, it has been applied in many economic theories (e.g., CAPM by Sharpe, 1964; Efficient market hypothesis by Samuelson, 1965 and Fama, 1963& 1965). However, Granger-causality tests suggest that changes in stock market returns do not cause changes in DVIX. This is supported by the variance decompositions, as it seems that effects of a shock in stock return index transfers, at maximum, 0.1% to DVIX. It seems that stock market returns and implied volatility do have a relationship but at this stage shocks in stock market returns do not seem to cause major effects to DVIX.

One interesting finding is that the first lag of DVIX has a significant negative coefficient, whereas the second lag is not statistically significant. It implies that institutional investors do not rely heavily on historical data nor project that the same market state continues in the future. The impulse responses and variance decompositions support this argument as the effects of a one standard deviation shock in DVIX stays only about 43-48.8% in DVIX.

In addition to these, the two dummy variables, Covid and Subprime, have positive and statistically significant coefficient estimates. This gives empirical support to previous literature (Lyócsa, Baumöhl, Výrost & Molnár, 2020; Zhang, Hu & Ji, 2020) that crisis periods add volatility, and fear, in the markets. What should be noted here is that the effects of coronavirus on DVIX seem to be, on average, about three times the impacts of Subprime crisis. This suggests that Covid-crisis increased volatility considerably compared to Subprime. The greatest impact for DVIX actually comes from Covid-dummy, which is fascinating as the Covid-dummy did not seem to be significant at all in relations to AAII. The estimated results for the two different investor-based indicators give empirical support to previous theory that the two different investor groups, individual and institutional ones, behave differently during crises.

None of the other covid-variables are statistically significant. The results suggest that new covid-cases, covid-deaths, amount of fully vaccinated people, and covid-restrictions cannot be used in explaining VIX. It might be that the significance of covid-information changes its role and after a certain period it becomes insignificant.

In addition, monetary policy does not have statistical significance over DVIX either. Based on these, it seems that volatility is affected by something that the model omits or that there might be time-variation. The adjusted R^2 values for DVIX are 0.08697 in model 1, 0.08988 in model 2, and 0.0876 in model 3. If comparing these R^2 values to those of sentiment, there is a huge difference. To put it roughly, the models were able to explain over 50% of sentiment but only 9% of DVIX.

Next, let's focus on the relationship between sentiment and DVIX. Even if the sentiment indicator, AAII, does not seem to have statistically significance over DVIX, the impulse responses and variance decompositions suggest that there might be a relationship. Based on these, the effects of one standard deviation shock in AAII transfers approximately 2.5% to DVIX. This implies that changes in sentiment of individual investors transfer, at least some amount of it, to implied volatility.

These results do not support the same biases as the results related to sentiment, hence, giving empirical support that the two sentiment indices measure the behavior of two types of investors: individuals and institutional ones. The results with AAII index (together with research by Smales, 2017) indicate that it is individual investors affecting on the sentiment index whereas institutional investors have impact on the behavior of DVIX. Based on the results it seems that institutional investors have different justifications on making decisions compared to individual investors.

5.4 Results for stock market returns

Next, investigating the returns a little bit further. For S&P500 and Nasdaq, their own lags have significant negative coefficient estimates. For SP500 the impact decreases with lags (lag 1 making greater negative impact than lag 2) whereas for Nasdaq the coefficient gets even more negative values (lag 2 making greater impact than lag 1). What comes to value and growth stocks, their own first lags are statistically significant and have negative coefficient estimates. One interesting finding is that the second lag of S&P500 Growth index is significant for itself but also for the value index. In addition, the impacts of one standard deviation shock in any of the return indices stay about 99% in the particular stock market index. These results indicate that the stock market returns do not assume that the same state continues to the future (compared to AAII and its assumptions).

What comes to monetary policy, the two indicators seem to be significant in all models. To begin with, the role of changes in Federal Reserve Assets (DFedAssets) is, at first, a bit extraordinary. The variable and its first lag are significant in models 1 and 2 (and the lag is significant also in model 3), however, the effect changes. The variable itself has a positive effect whereas its first lag has a negative one. In other words, the immediate effect to stock returns is that the returns increase together with increased Fed assets, however, the returns decrease after one period (one week). As Fed's assets increase, it increases money supply and also lowers interest rates, hence, stock markets may decline. These results could also be an indicator that a non-linear model would be a better fit.

The second indicator, changes in Federal Funds Rate (DFedFunds), has a statistically significant and negative coefficient estimate, implying that its increase makes the stock market returns decline. This relationship can be explained intuitively: increased federal funds rate increase costs for financial institutions, therefore charging more from customers that are borrowing money and making it less attractive to spend. As consumers are decreasing consumption, companies' profits decrease, hence also causing the stock market returns to decline.

Let's continue the analysis with Covid-related information. First looking at the significant factors, it seems that the death variable is significant for all of the return indicators. It has a positive coefficient estimate but its first lag has a negative one. The positive coefficient estimate is against intuition as it suggests that as covid-deaths increase, stock markets increase as well. However, the results with a one lag give empirical support to previous literature (Al-Awadhi et al., 2020), implying that deaths have significant negative impacts to stock market returns. History of Covid-related deaths matters but the effects are not transmitted instantly as markets react slowly to news.

The second significant covid-variable is the stringency index or, in other words, the strictness of governmental policies. Stringency is statistically significant only for S&P500 and S&P500 Value, and it has a negative coefficient estimate. This suggests that these two indices suffered from tightened policies and restrictions. On the contrary, the first lag of stringency has a positive coefficient estimate, indicating that the lagged effects increased stock returns. The findings with negative effects are in accordance with Aggarwal et al (2021), indicating that stringency (or difficulty of conducting business) affects growth expectations negatively, hence, making stock returns to decline. Another explanation could origin from the industry weighting as these two indices, S&P500 and S&P500 Value, consist of many traditional sectors which were hit the hardest by the pandemic. The results give empirical support to Narayan et al. (2022) where they found that some sectors (e.g., communications, energy, finance, and consumer discretion) suffered from the pandemic more than, for example, technology sector. However, as stringency's effect changes, the results are a bit mixed.

Intuitively thinking, also the dummy variables, covid and subprime, should have a negative impact on stock market returns. Empirical evidence from this research suggests that the intuitive idea is correct, and both of the dummy variables are significant and have negative coefficient estimates on stock market returns. Covid-dummy has a slightly bigger coefficient estimate, therefore indicating that the negative impacts of Covid were bigger than those of Subprime. However, it can be concluded that returns tend to decrease during crises periods.

The relationship between Covid-19 outbreak and its negative effects on stock market returns has been established also in earlier work by Liu et al (2020).

One interesting result in the models is the insignificance of changes that happen in confirmed Covid-related cases and vaccination levels. The empirical estimations suggest that when the level of fully vaccinated people increase, also the stock market returns increase. However, this relationship is not statistically significant. Earlier research has not focused on vaccination levels and, thereby, there is little to no empirical settings to which these results could be compared to. On the contrary, the connection between confirmed cases and stock market returns has been established by many research papers (Shear et al., 2021; Al-Awadhi et al., 2020; Liu et al., 2020). This previous literature suggests that there is a significant and negative connection between confirmed cases and stock market returns, implying that new cases decrease stock market returns. On the contrary to previous literature, this paper failed in finding empirical evidence on this relationship as it suggests that, even if the coefficient seems to be negative, confirmed cases do not have statistically significance over stock returns. The results differ from previous papers because of different modelling and data, as this paper included more covid-data than many earlier research papers. It could also be that the significance of covid-cases or vaccinations varies over time. The situation we are in now is very different compared to the start of the pandemic and, hence, it is possible that covid-information has been significant at the early stages of the pandemic, but it might have lost its significance over time. This observation implies that a nonlinear model could be appropriate when investigating these matters.

Then to one of the main questions – how does sentiment and VIX affect stock market returns? Based on the VAR estimations, sentiment (AAII index) does not have statistical significance and, thereby, it cannot be used in explaining stock market returns. On the contrary, the variance decompositions suggest that the effects of a shock in sentiment transfer about 11-13% to stock market indices. In other words, it seems that the sentiment of individual investors is not a significant factor in explaining returns. However, if there is a positive (negative) shock in sentiment, it might increase (decrease) stock market returns.

In contrast, effects from a shock in DVIX transfers about 50-55% to stock market indices. The variance decompositions imply that the majority of a shock's effects in VIX transfers to stock market indices, suggesting that the role of institutional investors is significant in explaining stock market returns. Also, the VAR models show that the second lag of DVIX is highly significant and negative in all of the cases, implying that the history of this indicator is meaningful. In other words, an increase (decrease) in implied volatility decreases (increases) stock returns over time. The results of the relationship between DVIX and stock market returns are in line with previous literature (Marfatia, 2019; Smales, 2017) giving empirical evidence that investors risk perceptions, and fear, make statistically significant impacts on the stock market returns.

These results suggest that stock returns do not reflect the sentiment of individual investors but the risk perceptions of institutional investors. This can, to some extent, be also explained by the size of institutional investors compared to individual ones.

Lastly, the adjusted R^2 values are 0.1412 for S&P500, 0.1324 for S&P500 Growth, 0.1444 for S&P500 Value, and 0.09418 for Nasdaq. It seems that the dependent variables are best at explaining S&P500 (Composite, Growth & Value) indices whereas Nasdaq has significantly lower R^2 value. However, the chosen variables are explaining only a minor part of all the stock market return indices.

Table 2. Results for VAR 1 Model.

Model 1			
	AIIBullBear	SP500	DVIX
AAIIBullBear.l1	0.4097085***	-0.027529	0.0460614
SP500.l1	0.1307091***	-0.207836***	0.1054085 *
DVIX.l1	-0.1784285***	-0.038760	-0.1812521 ***
AAIIBullBear.l2	0.2979069***	0.010175	0.0373653
SP500.l2	0.0679607*	-0.151794***	0.0629743
DVIX.l2	-0.0406652	-0.159535***	-0.0495585
Const	-0.0007287	-0.001995	0.0003267
Covidnew	0.0157068	-0.047764	0.0152394
L1Covidnew	-0.0313567	-0.096240	0.1100924
VaccinatedFully	1.5449214.	-0.215143	-0.5138168
L1VaccinatedFully	-1.5259828.	0.199578	0.5189757
Stringency	0.4126109	-0.819126.	-0.3519322
L1Stringency	-0.4676004	0.934394.	0.3044469
DFedAssets	0.0481019	0.102694**	-0.0616939
L1DFedAssets	-0.0482620	-0.103375**	0.0424212
DFedFunds	0.0080186	-0.095763**	0.0001117
L1DFedFunds	-0.0081160	0.044238	-0.0048636
CovidDummy	0.0171386	-0.265405***	0.2386064***
SubprimeDummy	-0.0349522	-0.198244***	0.0738818*
Deaths	-0.0721128	0.435082*	-0.1709074
L1Deaths	0.0818192	-0.388150*	0.1105022

Interpretation of table: Columns represent the endogenous variables and rows the exogenous and dummy variables included in the model. There are coefficients of each variable, followed with a significance mark. Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'.

Table 3. Results for VAR 2 Model.

Model 2				
	AIIBullBear	SP500Growth	SP500Value	DVIX
AAIIBullBear.l1	0.4097318***	-0.024454	-0.026955	4.772e-02
SP500Growth.l1	0.0604421	-0.151886*	-0.075206	1.679e-01*
SP500Value.l1	0.0736945	-0.044995	-0.137464.	-5.680e-02
DVIX.l1	-0.1781545***	-0.024364	-0.044996	-1.759e-01***
AAIIBullBear.l2	0.2976751***	0.008064	0.007123	3.642e-02
SP500Growth.l2	-0.0011812	-0.235334**	-0.166725*	1.689e-01*
SP500Value.l2	0.0679003	0.065873	0.015965	-9.586e-02
DVIX.l2	-0.0442667	-0.175165***	-0.156622***	-3.781e-02
Const	-0.0006645	-0.001507	-0.001915	-6.688e-05
Covidnew	0.0155520	-0.153446	0.060696	6.850e-03
L1Covidnew	-0.0362647	-0.065456	-0.153557	1.461e-01
VaccinatedFully	1.5053764.	-0.984094	0.506416	-2.780e-01
L1VaccinatedFully	-1.4856223.	0.987948	-0.530851	2.777e-01
Stringency	0.4207691	-0.545018	-0.981918*	-3.573e-01
L1Stringency	-0.4709274	0.723474	1.042725*	2.866e-01
DFedAssets	0.0467890	0.093877*	0.098895*	-5.429e-02
L1DFedAssets	-0.0487247.	-0.099684*	-0.105961**	4.212e-02
DFedFunds	0.0084618	-0.076685*	-0.107539***	-1.576e-03
L1DFedFunds	-0.0078785	0.042747	0.045753	-7.179e-03
CovidDummy	0.0171066	-0.257987***	-0.263622***	2.367e-01***
SubprimeDummy	-0.0339061	-0.170711***	-0.208649***	6.733e-02*
Deaths	-0.0605517	0.491741*	0.459468*	-2.182e-01
L1Deaths	0.0703933	-0.458311*	-0.394574*	1.567e-01

Interpretation of table: Columns represent the endogenous variables and rows the exogenous and dummy variables included in the model. There are coefficients of each variable, followed with a significance mark. Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'.

Table 4. Results for VAR 3 Model.

Model 3			
	AIIBullBear	Nasdaq	DVIX
AAIIBullBear.l1	0.4074909***	-0.023037	0.0417922
Nasdaq.l1	0.1666679***	-0.147138***	0.0918678*
DVIX.l1	-0.1558168***	-0.005991	-0.1937760***
AAIIBullBear.l2	0.2983673***	0.009960	0.0404316
Nasdaq.l2	0.0704544*	-0.160524***	0.0803372.
DVIX.l2	-0.0376616	-0.149905***	-0.0405624
Const	-0.0007313	-0.002839	0.0002563
Covidnew	0.0109918	-0.153202	0.0135932
L1Covidnew	-0.0166058	-0.023545	0.1179621
VaccinatedFully	1.7744145*	-1.344723	-0.3587404
L1VaccinatedFully	-1.7530086*	1.324453	0.3657227
Stringency	0.4380080	-0.410128	-0.3622147
L1Stringency	-0.5071096	0.575431	0.3045635
DFedAssets	0.0509106.	0.054487	-0.0609851
L1DFedAssets	-0.0437965	-0.075252.	0.0464635
DFedFunds	0.0145445	-0.101512**	0.0025666
L1DFedFunds	0.0018916	0.048841	-0.0020730
CovidDummy	0.0139347	-0.192981***	0.2348937***
SubprimeDummy	-0.0342435	-0.159584***	0.0705781*
Deaths	-0.0876530	0.419896*	-0.1774828
L1Deaths	0.0988872	-0.397167*	0.1194345

Interpretation of table: Columns represent the endogenous variables and rows the exogenous and dummy variables included in the model. There are coefficients of each variable, followed with a significance mark. Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'.

6 NONLINEAR EFFECTS OF COVID

6.1 Background

Based on the empirics of this and previous research papers, it seems that the impacts of Covid-19 might be nonlinear. There are a few papers that analyse the nonlinearities around Covid-19, but the literature still remains very limited. Izzeldin et al. (2021) focused on the G7 economies' (Canada, France, Germany, Italy, Japan, UK, and US) stock market volatility, and they present evidence of the appropriateness of a nonlinear estimation. Another paper by Basuony, Bouaddi, Ali & EmadEldeen (2021) focuses on stock markets of countries that have the largest number of confirmed Covid-19 cases (at the time being US, Italy, Spain, UK, Germany, China, Brazil, Russia, and India). The findings of Basuony et al. (2021) show that excessive increase in conditional volatility is not persistent during the coronavirus as it exhibits a significant decrease after the shock has been absorbed.

One significant note from previous papers and literature is the data sample as most of the sample periods end in 2020. On the contrary, this paper includes data about the more recent covid-information with having observations of the early 2022 as well. The larger data set might offer more insights about the time varying impacts of coronavirus.

6.2 Methodology

To investigate the nonlinear effects of Covid-19 a bit further, I consider a smooth transition vector autoregressive (STVAR) model. This choice enables us to get a better understanding of nonlinearities in multivariate context. Covid's nonlinear effects have not been studied thoroughly and, thereby, the aim is to get new insights of the relationships between covid-variables, sentiment, volatility, and stock market returns.

The main idea behind STVAR is to allow the possibility of two or more different economic regimes and to model behavior of the time series as a nonlinear in time changing combination of these regimes. Compared to some other nonlinear models, smooth transition (STR) models allow the change from one regime to another to be a smooth process (Van Dijk, Teräsvirta, Franses, 2002). One example of this could be the change between bullish and bearish markets: investors react to news differently and at different times and, hence, the transition becomes a smooth process.

STR models include a transition function ($G(s_t: \gamma, c)$) that is bounded between 0 and 1. This function includes a transition variable (s_t), a threshold value (c), and γ, which controls the smoothness of the transition process. (Van Dijk et al., 2002).

For investigating nonlinearities during coronavirus, I will estimate the following model:

$$Y_t = \left(\Phi_{1,0} + \Phi_{1,1}Y_{t-1} + \cdots + \Phi_{1,p}Y_{t-p} + \alpha_{1,0}X_t + \alpha_{1,1}X_{t-1} + \varphi D_t\right) + \left(\Phi_{2,0} + \Phi_{2,1}Y_{t-1} + \cdots + \Phi_{2,p}Y_{t-p} + \alpha_{2,0}X_t + \alpha_{2,1}X_{t-1} + \varphi D_t\right)G(s_t; \gamma, c) + \varepsilon_t \quad (2)$$

in which Y_t is a vector of endogenous variables, X_t is a vector of exogenous variables, D_t is a vector of dummy variables, G is the logistic function (diagonal matrix of functions), $\Phi_{i,j}$, $\alpha_{h,l}$ are parameters matrices, and ε_t is the error term (assumed to be a white noise process).

The transition function ($G(s_t; \gamma, c)$) enables the model to detect the two extreme states 0 and 1, but also the states between them. The regime at time t is dependent on the transition variable, s_t, which can either be an endogenous or an exogenous variable. The appropriate transition variable can be determined by computing linearity tests and selecting the variable that gets the lowest p-value. The threshold parameter (c) indicates where the transition takes place. Moreover, if the parameter determining the smoothness of the process (γ) has large values, the transition between regimes happens more quickly, and when getting smaller values, the transition happens slower. (Van Dijk et al., 2002).

The models are constructed similarly to VAR models: in the first model, the endogenous variables are sentiment index or AAII Bull/Bear ratio (AAII), logarithmic returns of Standard & Poor's 500 index (SP500), and logarithmic returns of VIX index (DVIX). The endogenous variables in the second model are sentiment (AAII), logarithmic returns of Value index (SP500Value), logarithmic returns of Growth index (SP500Growth), and logarithmic returns of VIX index (DVIX). The endogenous variables in the third model are sentiment (AAII), logarithmic returns of Nasdaq index (Nasdaq), and logarithmic returns of VIX index (DVIX).

In all models, the exogenous variables include new confirmed coronavirus cases (Covidnew), new Covid-deaths (Deaths), amount of fully vaccinated people (VaccinatedFully), stringency index (Stringency), changes in Federal Reserve assets (DFedAssets), and changes in Federal funds rate (DFedFunds). The dummy variables, Covid and Subprime, are included in D_t.

To find out the appropriate transition variable (s_t) for each equation, I used joint linearity test (Taylor series approximation). The null hypothesis is H_0: $\Phi_1 = \Phi_2$ and if not rejected, it would indicate that the series are linear (Luukkonen, Saikkonen & Teräsvirta, 1988a, 1998b; Teräsvirta 1994). For testing this hypothesis, I used time, cumulative percentage of confirmed cases and its three lags, and cumulative percentage of deaths and its three lags. These indicators were chosen as they reflect the initial shock and panic reactions that occur when the confirmed cases or deaths increase. However, the initial panic reaction may decrease over time. The possible fading (or nonlinear) effects of covid give ground for previous literature about terror management theory (Greenberg, Pyszczynski & Solomon, 1986).

6.3 Results

The results of joint linearity tests are presented in table 5. Based on them, all the variables strongly reject the null hypothesis, thereby implying that the time series are strongly nonlinear. Interestingly, time got the smallest p-values in all models. Apart from that, the second smallest p-values were the first lag of cumulative percentage of confirmed cases (L1Covid-%) for y_1 and y_3, and cumulative percentage of covid-deaths (Deaths-%) for y_2. These two variables were used as transition variables in the STVAR models.

Table 5. Joint linearity test results (Third-order Taylor expansion)

Indicator	**y_1**	**y_2**	**y_3**
Covid-%	2.56e-33	3.36e-58	1.04e-22
L1Covid-%	**2.02e-34**	8.61e-60	**9.04e-23**
L2Covid-%	1.06e-32	1.57e-60	2.63e-21
L3Covid-%	1.06e-32	1.57e-60	2.63e-21
Deaths-%	1.23e-28	**2.12e-62**	2.92e-18
L1Deaths-%	1.72e-31	3.68e-59	3.49e-19
L2Deaths-%	1.33e-32	1.57e-55	2.63e-19
L3Deaths-%	2.55e-32	1.1e-50	1.6e-19
Time	**9.48e-57**	**2.06e-72**	**1.68e-41**

Y_1, y_2, and y_3 represent the grouped endogenous variables that include different stock market indices. The rows with "-%" present cumulative percentages with 0, 1, 2, or 3 lags. The bolded cells reflect two lowest p-values for each y_t.

After making the STVAR estimations, it could be seen that the models do not converge properly. Previous literature suggests that convergence might be a problem with this model and, unfortunately, the empirics support this argument. The results of nonlinearity analysis present evidence that there are nonlinearities in the timeseries, even though this model was not the best fit. This raises a suggestion for further research. It would be important to find an appropriate nonlinear model that enables examining the role of cumulative confirmed Covid-cases and Covid-deaths as it seems that these two factors are economically meaningful.

6.4 Markov Switching model

As the STVAR model was found to be non-suitable for the purpose of exploring the nonlinear effects of Covid-19, Markov Switching model was considered. The aim remains the same: getting new insights of covid's nonlinear effects on sentiment, volatility, and stock market returns. The time period is limited to coronavirus pandemic: January 2020 to January 2022.

There are four models for stock market indices: one for each. In addition, VIX and sentiment were tested against each stock market index and, thereby, the discussions of their results are a combination of four models. To keep the models fairly simple, a restricted number of variables were selected. Explanatory variables include the first lag of a stock return index, first lag of sentiment (L1AAIIBullBear), first lag of logarithmic returns of VIX (L1DVIX), changes in Federal funds rate (DFedFunds), first lag of changes in Federal funds rate (L1DFedFunds), and cumulative percentage of confirmed covid-cases. The chosen variables reflect the relationships between investor sentiment, VIX, and stock market returns, and give implications on the role of covid-information. In addition, these chosen variables gave the models the highest R^2 values. The models assume two regimes but none of the models were able to make a clear distinction between positive and negative return regimes. For demonstration, the regimes for each stock return index are presented in appendix 1.

The results for Standard & Poor's 500 index (SP500) are presented in table 6. The estimations show that the first lag of SP500 (L1SP500), first lag of AAII (L1AAIIBullBear), and changes in Federal funds rate (DFedFunds) are statistically significant in regime 1. In regime 2 the significant variables are the first lag of SP500, first lag of DVIX (L1DVIX), changes in Federal funds rate, first lag of changes in Federal funds rate (L1DFedFunds), and cumulative percentage of confirmed Covid-cases (COVIDPerCent). These findings suggest that the role of sentiment, DVIX, and coronavirus-information is dependent on the regime. For example, effects of the first lag of SP500 changes its role, having positive effect in regime 1 and a negative one in regime 2. The R^2 value increases from 0.623 to 0.919 when changing from regime 1 to regime 2. Hence, the model is better in explaining regime 2 where most of the variables have explanatory power over SP500.

Table 7. Markov Switching model for Standard & Poor's 500 index.

	Regime 1	Regime 2
(Intercept)(S)	-1.9098*	0.5623
L1SP500(S)	0.3410.	-0.3487*
L1AAIIBullBear(S)	1.9026**	-0.2276
L1DVIX(S)	0.0300	0.0431.
DFedFunds(S)	9.2422.	40.1063***
L1DFedFunds(S)	-8.3727	88.1072***
COVIDPerCent(S)	-0.0088	0.0958***

Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'.

For Standard & Poor's 500 Growth index (SP500Growth), there are more significant variables compared to SP500. The results for SP500Growth are presented in table 8. Now the significant factors in regime 1 are the first lag of AAII

(L1AAII), changes in Federal funds rate, and cumulative percentage of confirmed covid-cases (COVIDPerCent). In regime 2, however, all the variables are statistically significant. The effect changes for L1AAII (going from positive in regime 2 to negative in regime 2) and cumulative percentage of confirmed Covid-cases (negative in regime 1, positive in regime 2). The R^2 experiences similar but even more drastic change than SP500 as it increases from 0.4696 in regime 1 to 0.9727 in regime 2. The results indicate that confirmed coronavirus cases have been statistically significant for SP500Growth for the whole pandemic period even though the effect changes.

Table 8. Markov Switching model for Standard & Poor's 500 Growth index.

	Regime 1	Regime 2
(Intercept)(S)	-0.9302.	3.2174***
L1SP500Growth(S)	0.0824	-0.2703***
L1AAIIBullBear(S)	1.3730***	-2.6436***
L1DVIX(S)	0.0165	0.0820***
DFedFunds(S)	11.1464*	36.4581***
L1DFedFunds(S)	-8.5545	87.1287***
COVIDPerCent(S)	-0.0127**	0.0938***

Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'

Continuing with the results with Standard & Poor's 500 Value index (SP500V) for which the results are presented in table 9, it can be seen that the variables' roles are time-varying. By taking a look at any of the variables, it can be noted that either the effect or significance of each variable changes when switching between regimes. Similarly to the results of SP500Growth, the role of coronavirus-information has been significant also for SP500Value for the entire pandemic period.

Table 9. Markov Switching model for Standard & Poor's 500 Value index.

	Regime 1	Regime 2
(Intercept)(S)	-2.3196*	-0.1666
L1SP500V(S)	-0.4095.	0.5168***
L1AAIIBullBear(S)	2.2415**	0.1973
L1DVIX(S)	0.0119	0.0400**
DFedFunds(S)	86.3294***	-3.6426
L1DFedFunds(S)	-11.4082	15.2267***
COVIDPerCent(S)	0.0765***	-0.0070**

Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'.

For Nasdaq, the results are presented in table 10. Now the significant factors in regime 1 include the first lag of AAII (L1AAII), changes in Federal funds rate (DFedFunds), and cumulative percentage of confirmed covid-cases (COVIDPerCent). In regime 2, there are some changes. L1AAII loses its significance, whereas the first lag of DVIX gains statistical significance, indicating that if VIX increases, it increases Nasdaq in regime 2. The effect of DFedFunds gets stronger as the estimate in regime 2 is about three times the size in regime 1. In addition, the effect of COVIDPerCent changes when changing to regime 2 as it goes from negative to positive, and its significance gets stronger. This implies that even when covid-information is significant in terms of Nasdaq in both regimes, the effect is time varying.

Table 10. Markov Switching model for Nasdaq index.

	Regime 1	Regime 2
(Intercept)(S)	-3.0929*	2.312.
L1Nasdaq(S)	0.1931	-0.2048
L1AAIIBullBear(S)	2.9075**	-1.3556
L1DVIX(S)	0.0208	0.0728*
DFedFunds(S)	10.6462**	32.3405***
L1DFedFunds(S)	-8.3519	66.9463***
COVIDPerCent(S)	-0.0087.	0.0750***

Significance levels: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, and 0.05 ‘.’.

All in all, the results for the four stock market indices highlight regime-dependence. When conventional monetary policy or DVIX are statistically significant, they have a positive effect on the indices, thereby implying that the increase of Federal funds rate or implied volatility also increases stock market returns. In addition, increase in positive investor sentiment mainly causes increases on stock market returns (except for SP500Growth for which the effect changes between regimes). What comes to coronavirus information, it seems to have both, negative and positive associations with the return indices. It has statistical significance over the indices even though its effect changes between regimes. This finding is somewhat in accordance with previous literature (Liu et al., 2020; Al-Awadhi et al., 2020; Shear et al., 2021), suggesting that there is a statistically significant relationship between stock returns and confirmed coronavirus cases. Earlier literature suggests only for a negative relationship and, thereby, there are some contradictions.

Let’s then change the focus on DVIX, which was investigated with four different models. The results can be found in appendix 2. The model including SP500 had the lowest (0.2777 in regime 1) but also the highest (0.8947 in regime 2) R^2 values. Other models had R^2 values between 0.536 and 0.629, respectively. What could be summed up by the models is that SP500Growth and Nasdaq were the only stock market indices that had statistical significance over DVIX. Their coefficient estimates were positive, implying that increased stock market returns also increase DVIX. Another key point from the models was the role of sentiment which had negative effect on DVIX, implying that positive sentiment decreases implied volatility. Sentiment does not, however, seem to be statistically significant throughout the regimes. On the contrary to previous VAR modelling, the

Markov switching model suggests statistical significance for confirmed coronavirus cases, having a positive coefficient estimate. This finding is in accordance with previous literature (Grima et al., 2021), suggesting that as the number of confirmed covid-cases increase, it increases volatility in the markets. It seems that, even though the size of the coefficient estimates changes between regimes and models, the amount of confirmed coronavirus cases has a significant role in explaining implied volatility.

Investor sentiment was also studied with four models that included different stock market indices. The results tables can be found in appendix 2. For sentiment, the results are fairly similar to previous VAR models. Throughout the models, sentiment is mostly affected by its first lag, the first lag of DVIX, and the intercept term. According to the Markov switching model, stock market returns do not have explanatory power over investor sentiment. The models were better in explaining sentiment than DVIX as the models for sentiment got R^2 values between 0.8244 and 0.836. The results support the previous argument of two types of investors and the differences in their decision-making.

To conclude, it seems that Covid-19 has changed the behavior of VIX index and stock market returns whereas sentiment was impacted only mildly. The pandemic period suggests nonlinearities in the series for most of the variables.

7 CONCLUSIONS

Covid-19 crisis made large impacts to stock market returns, investor sentiment, and risk perceptions. Covid-related research papers have been growing at a fast pace, offering great insights of the crisis. My aim was to take a closer look at the stock market returns and the different behavioral characteristics that might have affected the returns during the pandemic.

Empirical results of this paper show that outbreak of a crisis is highly significant and affects negatively stock market returns. Crises also affect institutional investors (measured by implied volatility, making spikes to VIX index). Hence, this paper gives empirical support to previous theories about the relationship between returns and implied volatility during coronavirus.

One interesting finding, in line with previous literature, is that individual and institutional investors behave differently during crises. For instance, the dummy variables (Covid and Subprime) in VAR modelling do not make significant impacts on the AAII index, implying that crises periods do not affect the sentiment of individual investors. On the contrary, the dummy variables were significant in explaining implied volatility. The insignificance of the dummy variables, together with other empirical results in regards of AAII, suggest that sentiment is best at representing the current state. Moreover, the empirics support theories of biases in decision-making.

In addition, the results imply that unconventional monetary policy is a significant factor in explaining stock market returns. Thereby, FED can affect stock market returns directly, at least to at some extent. In regards of conventional monetary policy, the nonlinear models suggests that Federal funds rate has a statistically significant and a positive effect on stock market returns and the VIX index.

In accordance with previous literature, my research found that changes in covid-related deaths are significant in explaining stock market returns. However, the linear models failed in establishing relationships between 1) new confirmed coronavirus cases and the stock market returns, and 2) covid-information and VIX. The results may differ because of different modelling and a longer time period. The nonlinear tests suggest that confirmed coronavirus cases are significant in explaining both, stock market returns and volatility. It strongly seems that the role of covid-information is time varying.

Finally, there are some implications for further research. The surface level empirics on Covid's nonlinear effects suggests that the series contain strong nonlinearities. Thereby, the role of covid-information is most probably time-varying and should be covered in further research. Especially examining the role of confirmed covid-cases and deaths would seem appropriate.

REFERENCES

Aggarwal, S., Nawn, S. & Dugar, A. 2021. What caused global stock market meltdown during the COVID pandemic – Lockdown stringency or investor panic? Finance Research Letters 38 (2021). https://doi.org/10.1016/j.frl.2020.101827.

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A. & Alhammadi, S. 2020. Death and contagious infectious diseases: Impact of the COVDI-19 virus on stock market returns. Journal of Behavioral and Experimental Finance, 27. https://doi.org/10.1016/j.jbef.2020.100326.

American Association of Individual Investors. 2022. AAII Investor Sentiment Survey. https://www.aaii.com/sentimentsurvey. [Read: 17.3.2022].

Baek, S., Mohanty, S. & Galmbosky, M. 2020. COVID-19 and stock market volatility: An industry level analysis. Finance Research Letters, Vol. 37. https://doi-org.ezproxy.jyu.fi/10.1016/j.frl.2020.101748.

Baig, A., Butt, H., Haroon, O & Rizvi, S. 2021. Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. Finance Research Letters. Volume 38. https://doi.org/10.1016/j.frl.2020.101701.

Baker, B. 2021. Cboe Volatility Index (VIX): What is it and how is it measured? Bankrate. https://www.bankrate.com/investing/vix-volatility-index/. Read: 29.11.2021.

Banerjee, D. & Meena, K. S. 2021. COVID-19 as an ”Infodemic” in Public Health: Critical Role of the Social Media. Frontiers in Public Health, March 2021 Volume 9.

Banerjee, T. & Rao, S. 2021. Psychology of Misinformation and the Media: Insights from the COVID-19 Pandemic. Indian Journal of Social Psychiatry.

Barberis, N., Shleifer, A. & Vishny, R. 1998. A model of investor sentiment. Journal of Financial Economics. Volume 49, Issue 3, Pages 307-343. https://doi.org/10.1016/S0304-405X(98)00027-0.

Barberis, N. 2013. Psychology and the Financial Crisis of 2007-2008. M. Haliassos (Ed.), Financial Innovation: Too Much or Too Little?, MIT Press, Cambridge (2013), pp 15-28. Google Scholar. https://books.google.fi/books?hl=en&lr=&id=V93xCwAAQBAJ&oi=fnd&pg=PA15&dq=Psychology+and+the+financial+crisis+of+20072008&ots=xGb9FdlYPz&sig=O5T7D9X9aruX1qUeTUtMLwtDo5Y&redir_esc=y#v=onepage&q=Psychology%20and%20the%20financial%20crisis%20of%2020072008&f=false.

Basuony, M., Bouaddi, M., Ali, H. & EmadEldeen, R. 2021. The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics. Journal of Public Affairs. https://doi.org/10.1002/pa.2761.

Ben-David, I., Franzoni, F. & Moussai, R. 2011. Hedge Fund Stock Trading in the Financial Crisis of 2007-2009. The Review of Financial Studies, Volume 25, Issue 1, pp 1-54. https://doi.org/10.1093/rfs/hhr114.

Cambridge Dictionary. Sentiment. https://dictionary.cambridge.org/dictionary/english/sentiment. Read: 5.1.2022.

Cboe. 2022. VIX Volatility Suite. https://www.cboe.com/tradable_products/vix/. [Read: 17.3.2022].

Croucher S., Nguyen T. & Rahmani, D. 2020. Prejudice toward Asian Americans in the COVID-19 pandemic: the effects of social media use in the United States. Fron Commun.

Dahmene, M., Boughrara, A. & Slim, S. 2020. Nonlinearity in stock returns: Do risk aversion, investor sentiment and, monetary policy shocks matter? International Review of Economics and Finance, Volume 71, pp. 676-699. https://doi.org/10.1016/j.iref.2020.10.002.

Federal Reserve. 2022. Monetary Policy Principles and Practice. https://www.federalreserve.gov/monetarypolicy/monetary-policy-what-are-its-goals-how-does-it-work.htm. [Read: 8.11.2021].

Grima, S., Özdemir, L., Özen, E & Romanova, I. 2021. The Interactions between COVID-19 Cases in the USA, the VIX Index and Major Stock Markets. International Journal of Financial Studies 9(2). https://doi.org/10.3390/ijfs9020026.

Haroon, O & Rizvi, S. 2020. COVID-19: Media coverage and financial markets behavior – A sectoral inquiry. Journal of Behavioral and Experimental Finance 27. https://doi.org/10.1016/j.jbef.2020.100343.

Hoffman, A. O. O., Post, T. & Pennings, J. M. E. 2013. Individual investor perceptions and behavior during the financial crisis. Journal of Banking & Finance, Volume 37, pp. 60-74. http://dx.doi.org/10.1016/j.jbankfin.2012.08.007.

Hsu, K. & Chiang, H. 2011. Nonlinear effects of monetary policy on stock returns in a smooth transition autoregressive model. The Quarterly Review of Economics and Finance, Volume 51, pp. 339-349. https://doi-org.ezproxy.jyu.fi/10.1016/j.qref.2011.08.003.

Humpe, A., & Macmillan, P. 2014. Non-linear predictability of stock market returns: comparative evidence from Japan and the US. Investment Management and Financial Innovations, Volume 11, Issue 4, 2014.

International Monetary Fund. Policy Responses to Covid-19. https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19. [Read: 8.11.2021].

Izzeldin, M., Muradoglu, Y., Pappas, V. & Sivaprasad, S. 2021. The impact of Covid-19 on G7 stock markets volatility: Evidence from a ST-HAR model. International Review of Financial Analysis, Volume 74. https://doi.org/10.1016/j.irfa.2021.101671.

Junttila, J. & Martin V. 2021. COVID-19 and the Discounting of Real Economic Activity in the U.S. and European Stock Markets.

Just, M. & Echaust, K. 2020. Stock market returns, volatility, correlation and liquidity during the COVID-19 crisis: Evidence from the Markov Switching approach. Finance Letters, Vol. 37. https://doi.org/10.1016/j.frl.2020.101775.

Kahneman, D. 2011. Thinking, fast and slow. New York: Farrar, Straus and Giroux.

Kahneman, D. & Tversky, A. 1972. Subjective Probability: A Judgment of Representativeness. Cognitive Psychology, Volume 3, Issue 3, pp. 430-454. https://doi-org.ezproxy.jyu.fi/10.1016/0010-0285(72)90016-3.

Kenton, W. 2021. Risk Management in Finance. Investopedia. https://www.investopedia.com/terms/r/riskmanagement.asp. Read: 5.1.2022.

Liu, H., Manzoor, A., Wang, C., Zang, L. & Manzoor, Z. 2020. The COVID-19 Outbreak and Affected Countries Stok Markets Response. International Journal of Environmental Research and Public Health 2020. https://doi.org/10.3390/ijerph17082800.

Lutz, C. 2015. The impact of conventional and unconventional monetary policy on investor sentiment. Journal of Banking and Finance, Volume 61, pp.89-105. https://doi.org/10.1016/j.jbankfin.2015.08.019.

Luukkonen, R., Saikkonen, P. & Teräsvirta, T. 1988a. Testing Linearity Against Smooth Transition Autoregressive Models. Biometrika, Vol. 75, No. 3, pp. 491–499. http://www.jstor.com/stable/2336599.

Luukkonen, R., Saikkonen, P. & Teräsvirta, T. 1988b. Testing Linearity in Univariate Time Series Models. Scandinavian Journal of Statistics, Vol 15, No 3, pp. 161-175. https://www.jstor.org/stable/4616098.

Lyócsa, S., Baumöhl, E. Výrost, T. & Molnár, P. 2020. Fear of the coronavirus and the stok markets. Finance Research Letters, Volume 36. https://doi.org/10.1016/j.frl.2020.101735.

Macrotrends. VIX Volatility Index – Historical Chart. https://www.macrotrends.net/2603/vix-volatility-index-historical-chart. [Read: 29.11.2021].

Manconi, A., Massa, M. & Yasuda, A. 2010. The role of institutional investors in propagating the crisis of 2007-2008. Journal of Financial Economics 104 (491-518), 2012. doi:10.1016/j.jfineco.2011.05.011.

Marfatia, H. A. 2019. Investors' risk perceptions in the US and global stock market integration. Research in International Business and Finance 52. https://doi.org/10.1016/j.ribaf.2019.101169.

Mazur, M., Dang, M. & Vega, M. 2021. COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. Finance Research Letters, Vol 38. https://doi.org/10.1016/j.frl.2020.101690.

Narayan, P., Gong, Q. & Ahmed, J. 2022. Is there a pattern in how COVID-19 has affected Australia's stock returns? Applied Economics Letters, 2022, Volume 29, NO 3, pp. 179-182. https://doi.org/10.1080/13504851.2020.1861190.

Nasdaq Global Indexes. 2022. NASDAQ Composite COMP. Industry Breakdown. https://indexes.nasdaqomx.com/Index/Breakdown/COMP. [Read: 13.4.2022].

Our world in data. Worldometer. Coronavirus, United States. https://www.worldometers.info/coronavirus/country/us/#graph-cases-daily. [Read: 23.12.2021].

Qontigo. STOCC North America 600. https://www.stoxx.com/index-details?symbol=SXA1E. Read: 5.1.2022.

Rahman, M., Amin, A., Mamun, M. 2021. The COVID-19 outbreak and stock market reactions: Evidence from Australia. Finance Research Letters, Vol 38. https://doi.org/10.1016/j.frl.2020.101832.

Roser, M. 2021. What is the COVID-19 Stringency Index? Our world in data. https://ourworldindata.org/metrics-explained-covid19-stringency-index. Read: 5.1.2022.

Shear, F., Ashraf, B. N. & Sadaqat, M. 2021. Are Investors' Attention and Uncertainty Aversion the Risk Factors for Stock Markets? International Evidence from the COVID-19 Crisis. Risks 9: 2. https://doi.org/10.3390/risks9010002.

Shehzad, K., Zaman, U., Liu, X., Górecki, J. & Pugnetti, C. 2021. Examining the Asymmetric Impact of COVID-19 Pandemic and Global Financial Crisis on Dow Jones and Oil Price Shock. Sustainability 021, Volume 13. https://doi.org/10.3390/su13094688.

Shiller, R. J. 2019. Narrative Economics: How Stories Go Viral & Drive Major Economic Events.

Skarpa, P. & Garoufallou, E. 2021. Information seeking behavior and COVID-19 pandemic: A snapshot of young, middle aged and senior individuals in Greece. International Journal of Medical Informatics. Volume 150. https://doi-org.ezproxy.jyu.fi/10.1016/j.ijmedinf.2021.104465.

Smales, L. A. 2017. The importance of fear: investor sentiment and stock market returns. Applied Economics. 49:34, 3395-3421. https://doi.org/10.1080/00036846.2016.1259754.

Smales, L. 2020. Investor attention and the response of US stock market sectors to the COVID-19 crisis. Review of Behavioral Finance, 13 (1), 20-39. https://doi.org/10.1108/RBF-06-2020-0138.

S&P Global. 2022. S&P500 Value. S&P Dow Jones Indices. A Division of S&P Global. https://www.spglobal.com/spdji/en/indices/equity/sp-500-value/#overview. [Read: 13.3.2022].

S&P Global. 2022. S&P Growth. S&P Dow Jones Indices. A Division of S&P Global. https://www.spglobal.com/spdji/en/indices/equity/sp-500-growth/#overview. [Read: 13.3.2022].

Teräsvirta, T. 1994. Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models. Journal of the American Statistical Association, Vol. 89, No. 425, pp. 208-218. https://www.jstor.org/stable/2291217.

Van Dijk, D., Teräsvirta, T. & Franses, P. 2002. Smooth Transition Autoregressive Models – A Survey of Recent Developments. Econometric Reviews, 21:1, pp. 1-47. https://doi.org/10.1081/ETC-120008723.

Vasileiou, E. 2021. Behavioral finance and market efficiency in the time of the COVID-10 pandemic: does fear drive the market? International Review of Applied Economics, 35 (2), 224-241.

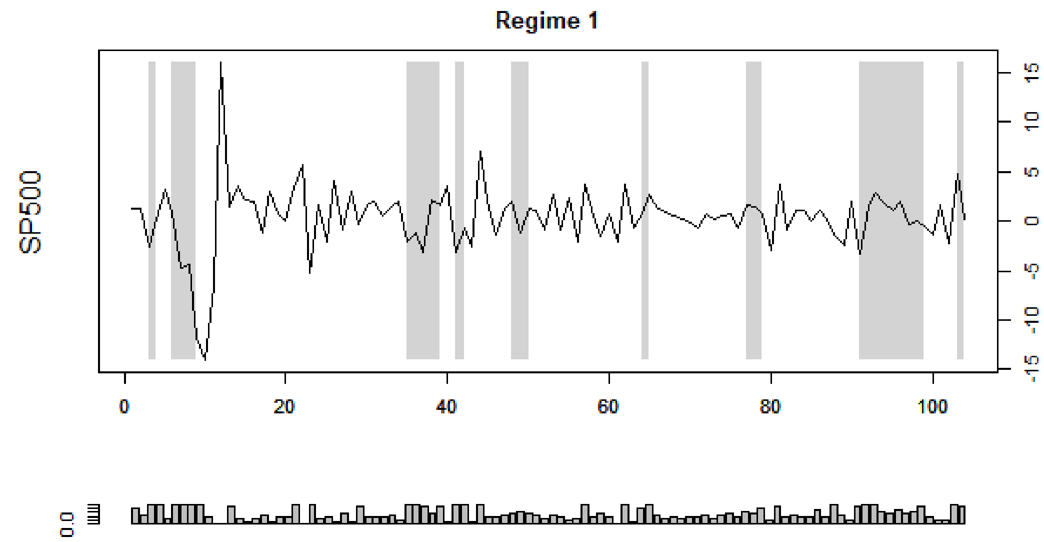
Wei, X. & Han, L. 2021. The impact of COVID-19 pandemic on transmission of monetary policy to financial markets. International Review of Financial Analysis, 74. https://doi.org/10.1016/j.irfa.2021.101705.

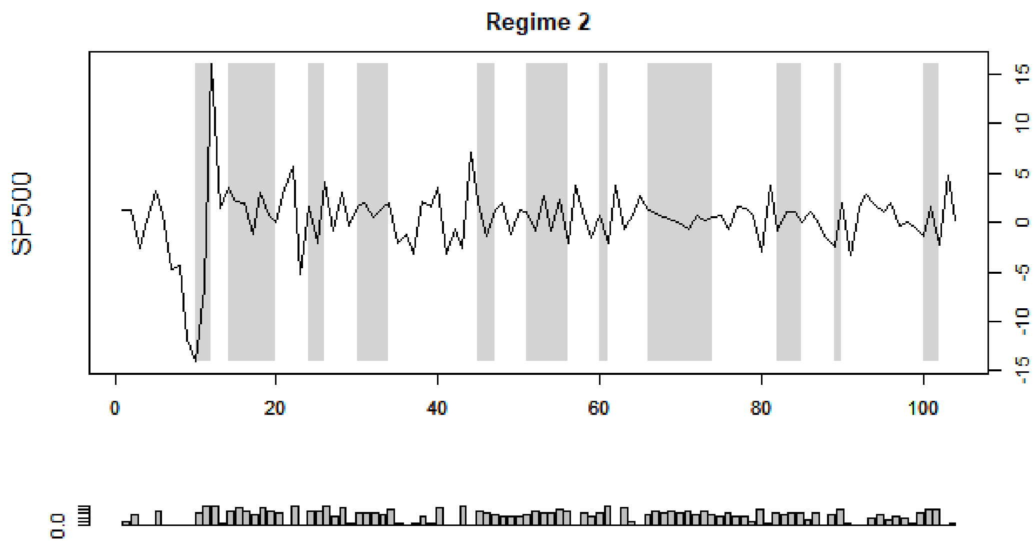
Zhang, D, Hu, M. & Ji, Q. 2020. Financial markets under the global pandemic of COVID-19. Finance Research Letters, 36. https://doi.org/10.1016/j.frl.2020.101528.

APPENDIX 1 – MARKOV SWITCHING MODEL REGIMES

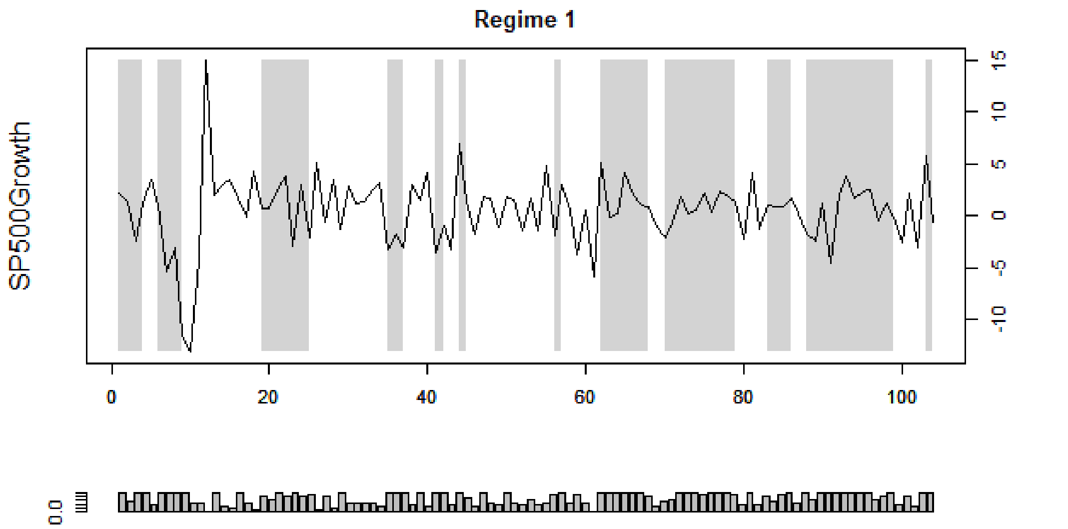
Markov switching models were not able to make a clear distinction between positive and negative mean return regimes. The behavior of stock market indices and activity of the regimes are presented below (1a-1d).

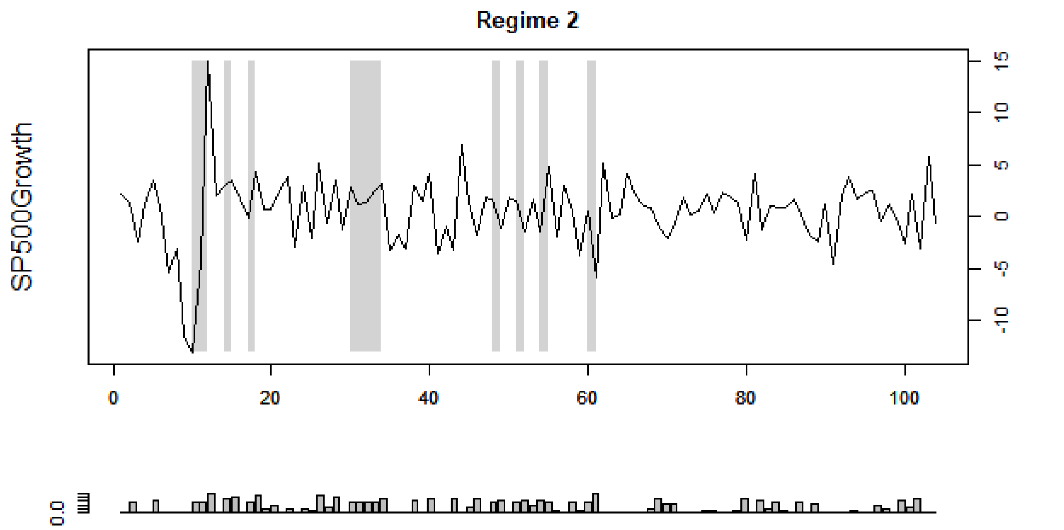
1a. Behavior of Standard & Poor's 500 index during 2020-2022, regimes.



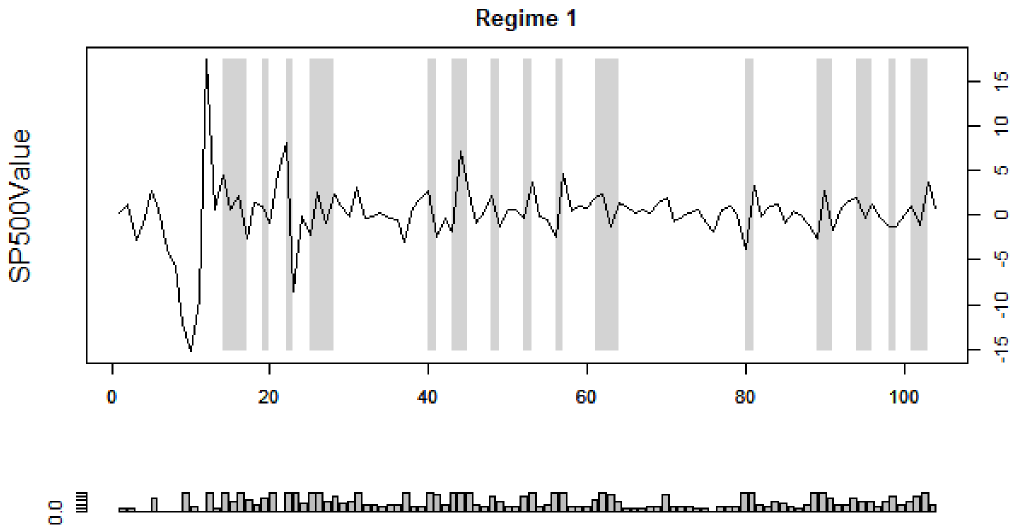


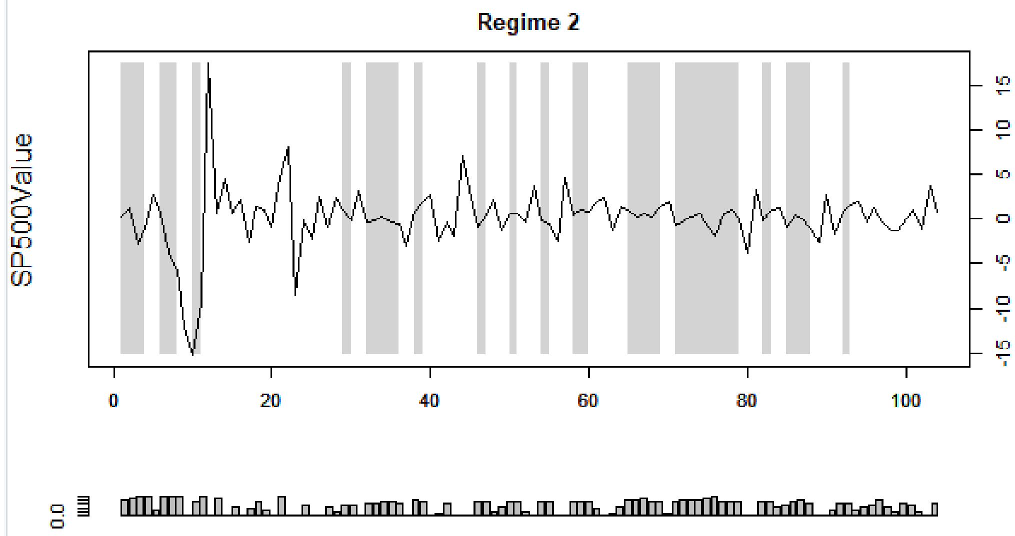
1b. Behavior of Standard & Poor's 500 Growth index during 2020-2022, regimes.



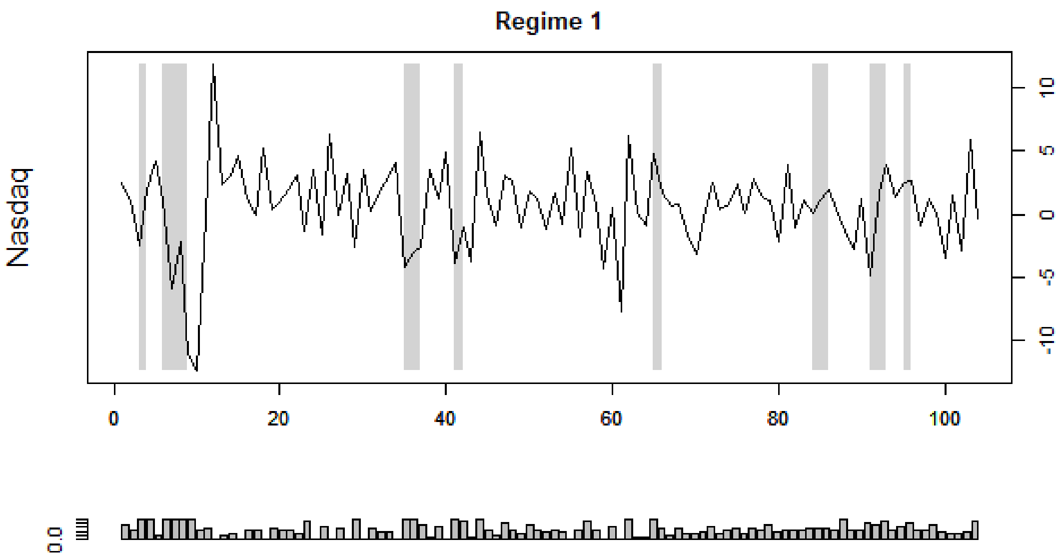


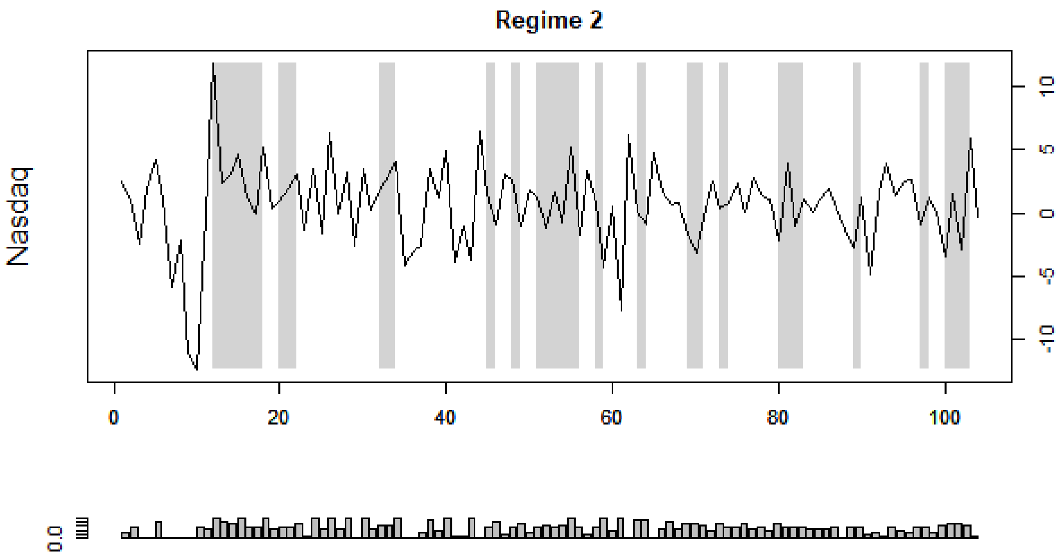
1c. Behavior of Standard & Poor's 500 Value index during 2020-2022, regimes.





1d. Behavior of Nasdaq index during 2020-2022, regimes.





APPENDIX 2 – MARKOV SWITCHING MODEL RESULTS

The tables include results for logarithmic return of VIX (DVIX) and investor sentiment (AAII Bull/Bear ratio). Estimations are based on Markov switching model, assuming two regimes. Significance levels: 0 '***', 0.001 '**', 0.01 '*', and 0.05 '.'.

2a. Regression results for DVIX, using Standard & Poor's 500 index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	-1.7776	30.6539***
L1DVIX(S)	-0.3426	-0.3672***
L1AAIIBullBear(S)	-3.7776	-14.7530***
L1SP500(S)	0.9104	-1.0702
DFedFunds(S)	-89.8668*	36.6025*
L1DFedFunds(S)	-5.0027	107.7517***
COVIDPerCent(S)	-0.0673	0.1345***

2b. Regression results for DVIX, using Standard & Poor's 500 Growth index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	-17.3018**	12.5787***
L1DVIX(S)	0.5594**	-0.3364**
L1AAIIBullBear(S)	0.7479	-5.2301*
L1SP500Growth(S)	3.1068*	-1.0963
DFedFunds(S)	-127.0960	-4.4613
L1DFedFunds(S)	132.2306**	188.1152***
COVIDPerCent(S)	0.0590	0.16444***

2c. Regression results for DVIX, using Standard & Poor's 500 Value index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	-9.8003*	19.6214*
L1DVIX(S)	-0.7559***	-0.0706
L1AAIIBullBear(S)	14.7050	-14.5946*
L1SP500Value(S)	-0.0559	-0.0682
DFedFunds(S)	-70.9871	30.6988
L1DFedFunds(S)	-46.9524.	185.7495***
COVIDPerCent(S)	-0.910*	0.1547***

2d. Regression results for DVIX, using Nasdaq index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	-18.2589***	12.1991***
L1DVIX(S)	0.5689**	-0.2966**
L1AAIIBullBear(S)	0.4420	-5.2164*
L1Nasdaq(S)	3.3882**	-0.8110
DFedFunds(S)	-122.7015***	34.4463
L1DFedFunds(S)	131.5771**	197.3519***
COVIDPerCent(S)	0.0606.	0.1701***

2e. Regression results for AAII, using Standard & Poor's 500 index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	0.1464	0.1804*
L1AAIIBullBear(S)	1.1095***	0.6949***
L1DVIX(S)	0.0020	0.0077**
L1SP500(S)	-0.0349	0.0205
DFedFunds(S)	1.2314	-0.4807
L1DFedFunds(S)	0.1816	0.4154
COVIDPerCent(S)	0.0008	0.0001

2f. Regression results for AAII, using Standard & Poor's 500 Growth index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	0.1864*	0.1120
L1AAIIBullBear(S)	0.6947***	1.1238***
L1DVIX(S)	0.0073*	0.0042
L1SP500Growth(S)	0.0171	-0.0062
DFedFunds(S)	-0.3693	0.6429
L1DFedFunds(S)	0.2809	0.9468
COVIDPerCent(S)	0.0001	0.0010

2g. Regression results for AAII, using Standard & Poor's 500 Value index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	0.1690	0.1769*
L1AAIIBullBear(S)	1.0927***	0.6968***
L1DVIX(S)	0.0021	0.0068**
L1SP500(S)	-0.0410	0.0145
DFedFunds(S)	1.4163.	-0.4015
L1DFedFunds(S)	-0.2448	0.3309
COVIDPerCent(S)	0.0006	0.0002

2h. Regression results for AAII, using Nasdaq index as the stock market indicator.

	Regime 1	Regime 2
(Intercept)(S)	0.1105	0.1915*
L1AAIIBullBear(S)	1.1263***	0.6953***
L1DVIX(S)	0.0043	0.0062*
L1Nasdaq(S)	-0.0046	0.0088
DFedFunds(S)	0.6103	-0.1690
L1DFedFunds(S)	0.9946	0.0419
COVIDPerCent(S)	0.0010	0.0000