Volatility of and cross-correlation between major international stock indices before and during the COVID-19 pandemic

JEAN MARC SENGABO
JUST ANDREAS ØVERBY

SUPERVISOR
Jochen Jungeilges

University of Agder, 2021
School of Business and Law
Department of Economics and Finance

Acknowledgements

This Master's thesis was written as a part of the Master's degree in Business Administration with a specialization in Financial Economics at the University of Agder. The work has been carried out at the Department of Economics and Finance during the spring semester 2021. First and foremost we would like to thank our supervisor, Professor Jochen Jungeilges, for his patience and expertise. During the past year, he has guided us in the field of financial econometrics and provided us with critical, useful and, when necessary, greatly appreciated constructive feedback. We also express our deepest gratitude to our families and friends for all the support we have received throughout the years.

Abstract

Following the arrival of the year 2020, the extraordinary outbreak of the novel coronavirus (COVID-19), which was initially seen as an epidemic, evolved into an all-out pandemic. Consequently, its effects have shaken the global economies and affected countries across the globe. This thesis investigates the relationship between market disturbances across countries and models the recent COVID-19 pandemic's influence on the volatility and cross-market correlation in six major stock indices: S&P 500, S&P/TSX, DAX, FTSE 100, Nikkei 225 and SSE. We estimated the pandemic effect on market volatility with a univariate GJR-GARCH model, and employed a multivariate DCC-GARCH to examine the conditional correlations between six of the largest economies in the world. We also visualized the regime switching between low and high correlation regimes with a two-regime Markov switching model. Our discoveries suggest that the six indices behaved almost identically under the COVID-19 period, with the Nikkei 225 being the only one that did not show evidence of a higher sensitivity towards COVID-19 news. Furthermore, the filtered and smoothed transition-probability charts showed evidence of stronger cross-correlation during periods of distress and uncertainty, and suggestions of one common market in situations like this are valid. Overall, our findings contribute to previous literature seeking to understand the recent pandemic's influence on capital markets and the negative consequences associated with markets being highly integrated.

Keywords: COVID-19, volatility, contagion, capital markets
JEL Classification: C12, C15, C32, C58

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Chapter 1

Introduction

The year of 2020 was for many people one of the most exhaustive, demanding and changing calendar years in recent memory. First discovered in the Chinese province of Wuhan in December 2019, the SARS-CoV-2 (coronavirus disease 2019 i.e., COVID-19) virus fairly quickly escalated from a small issue in a country far away from the Western world, into a global pandemic which is still causing havoc in the world. The World Health Organization (WHO) first issued an alert on January 30, 2020 declaring the coronavirus a public health emergency of international concern (PHEIC), and as of March 11 later the same year, WHO declared the virus a pandemic (WHO, 2020) indicating that the virus had crossed international borders and was now a serious global threat (Qiu, Rutherford, Mao, & Chu, 2017). The virus had caught us by surprise. The world had not seen a disease spread across the world to such a large scale since the 1918-20 influenza pandemic (CDC, 2019), and we are still living under and experiencing the effect of the COVID-19 pandemic, and (arguably) these effects are not changing in the near future. Global COVID-19 cases are getting close to a total of 170 million and the fatalities have crossed the three million mark (Worldometer, 2021), making the recent pandemic one of the deadliest in modern history (TST, 2020). For instance, great powers such as the United States (U.S.) saw the COVID-19 virus contributing to making 2020 the deadliest year in American history (NBC, 2020). In an attempt to reduce the spread of the virus and number of cases and deaths, governments across the world implemented strict domestic restrictions in the form of lockdowns, travel bans and social distancing. Such a sudden disruption to a country's supply chain did not go unnoticed, and many were predicting that we were approaching an economical recession more devastating than the previously experienced recessions of the past decades (Ahya, 2020; Bui, Button, & Picciotti, 2020; ILO, 2020; Passy, 2021). Many researchers had also argued in favor of these predictions. First out, Gopinath (2019) argued that we were approaching a weaker global growth as a result of multiple trade barriers (such as the China - U.S. trade war) and geopolitical tensions (for instance, the Brexit) contributing to ongoing uncertainty. Secondly, this uncertainty was solidified by the same problem that contributed to the Global Financial Crisis of 2007-08 (GFC), namely debt. IMF (2019) identified key vulnerabilities in the global economy, where some of them being a clear tendency of financial institutions in issuing riskier securities and a severe increase in corporate debt in major economies reminiscent of the downfall in 2007-08.

All these incidents and government restrictions contributed to the 2020 COVID-19 stock market crash. Starting in February 2020, global financial markets experienced months of high volatile movements and several record-low drops. The market entered a correction in late February, capping off a week recognized as the worst week on Wall Street since the GFC across several main indices (Imbert & Huang, 2020; Peltz, 2020). The following months saw a development recognized by more and more uncertainty, and an ongoing price war between the two heavyweights in the oil industry, Russia and Saudi-Arabia, inspired to a chain of historical drops in what is now known as "Black Monday I", "Black Thursday" and "Black Monday II", March 9, March 12 and March 16, respectively. The Dow Jones Industrial Average (DJIA) fell more than 2,000 points for the first time in history on Black Monday I (Partington & Wearden, 2020), the Financial Times Stock Exchange 100 Index (FTSE 100) in the United Kingdom (U.K.) experienced a £125 billion razor shave of its value marking the biggest drop since the GFC (Marris, 2020), while over in Asia, indices in Japan, The Philippines, Indonesia and Singapore entered bear-market territory (Vishnoi & Mookerje, 2020) meaning that the shares had on average fallen 20% from its 52-week closing high (Gonzalez, Powell, Shi, & Wilson, 2005). The DJIA continued to set new all-time records, and eclipsed its Monday performance with a 2,352 points drop on Black Thursday (Burch, 2020), which also saw bloodbaths, figuratively speaking, many places in Europe including the Italian Financial Times Stock Exchange Milano Indice di Borsa (FTSE MIB) which closed in a -16.92% all-time loss (Statista, 2021). The final day of this chain of events, Black Monday II, saw the Chicago Board Options Exchange's Volatility Index (VIX) surpassing levels of the GFC and closing at a historically high 82.69 points (Li, 2020). The VIX measures the expected 30-day volatility in the U.S. derived from put and call options of the Standard & Poor's (S&P) 500 Index (Cboe, 2021). Its value of 82.69 points indicates that the uncertainty in the market was now on an all-time high, this being only a couple of months into a global pandemic nobody had any ideas of when would end. Although the bear-market was short-lived, and the market slowly but steadily managed to crawl back to previous levels (in some parts of the world), the U.S. benchmark Western Texas Intermediate (WTI) oil price fell to a negative barrel value for the first time in history on April 20 (Nawaz, 2020), which in theory meant that buyers now were being paid to take the oil off the hands of the producers.

The psychology behind financial markets' behavior during crisis circumstances have been a widely researched topic for several decades. Mynhardt, Plastun, and Makarenko (2014) examined the efficiency of markets under the GFC, while Sandoval and Franca (2012) showed a direct link between high volatility and correlations of markets during the 1987 Black Monday fall, the 1998 Russian crisis, the 2001 Dot-Com bubble burst and 2008 GFC. Common to both articles is the fact that the crises being examined were caused by economic factors. With the COVID-19 being a virus pandemic, research on crises that are predominantly health driven is needed. Using historical data from the 1918-20 Influenza pandemic, James and Sargent (2006) argued that if we were to experience a modern day pandemic, the losses of human life and suffering would be superior to the economic concerns, while Hanna and Huang (2004) strongly recommended to improve the Asian public health system and the governance structure as a response to the economical implications that the 2002-2004 SARS outbreak brought to many Asian economies. With the COVID-19 being a relatively unexpected pandemic, and that we have not experienced a global crisis to such a large scale in modern history, the extensive publication of articles trying to answer questions regarding the pandemic occurrence and the aftermath effect have circulated in the landscape of financial researchers almost daily the past year. A wide range of the published articles has been centered around the uncertainty aspect that has been brought upon us by the pandemic. Altig et al. (2020) examined the economic uncertainty prior and during the COVID-19 pandemic, while Lyócsa and Molnár (2020), by using nonlinear models governed by abnormal COVID-19 Google searches and realized volatility, found that fear had a great impact on negative returns in financial markets. Often as a result when investors are experiencing high uncertainty, is the occurence of high volatile movement, and modelling this is often a quite interesting research topic for scholars to digest. Yousef and Shehadeh (2020) investigated the impact of the recent pandemic on gold spot prices using the generalized autoregressive conditional heteroskedasticity (GARCH) model by Bollerslev (1986) and the richer GJR-GARCH by Glosten, Jagannathan, and Runkle (1993), while Aslam, Ferreira, Mughal, and Bashir (2021) showed evidence for more stable volatility spillovers in the period after the WHO declaration date. Many articles concerning financial contagion, especially as a response to the GFC, have been published throughout the years. See, for example, Aloui, Aïssa, and Nguyen (2011); Guo, Chen, and Huang (2011); Dimitriou, Kenourgios, and Simos (2013). Apparently, there is a lack of literature considering the transmission of shocks in international financial markets as an effect of a global health crisis, and more specifically the recent pandemic.

On this basis, the goal of this thesis is to first examine the magnitude of the COVID-19 pandemic on the volatility in major stock indices across the globe using non-linear time-series techniques, and then perform a contagion analysis across these international borders to check if the cross-correlation was significantly impacted by the COVID-19 pandemic, i.e. if market shocks travel across international borders. Furthermore, the two hypotheses that we wish to test are:

1.

H_0: The global financial markets acted indifferently towards COVID-19 news, contrary to years before
H_1: Markets were more sensitive to new information

2.

H_0: The cross-correlation between global financial markets has been stable during the pandemic year of 2020
H_1: The correlation has changed significantly

The thesis is structured as follows: in chapter 2 we give an analytical account of the existing literature concerning both the econometric technique used and existing COVID-19 literature. Our data is described in chapter 3. In chapter 4 we describe the methodology employed and all underlying assumptions, while in chapter 5 we exhibit our findings by means of tables and graphs and an interpretation behind it all. In chapter 6 we discuss our findings in contrast to earlier findings by others, and finally in chapter 7, we provide a concise summary of our approach and findings including an outlook on future research efforts based on this thesis.

Chapter 2

Literature review

2.1 Autoregressive models

For the past year, many of the papers that were focusing on the pandemic's effect on market behavior have been conducted using famous extensions in the generalized autoregressive conditional heteroskedasticity (GARCH) family model. Yousef and Shehadeh (2020) used both the original GARCH by Bollerslev (1986) and the modified Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) by Glosten et al. (1993) to investigate the pandemic impact on gold spot prices. They gathered daily prices from 2012 to 2020, and both global new and the cumulative number of the COVID-19 pandemic cases from January to May, 2020 were used. Their findings were encouraging and they found a positive correlation between gold prices and the increasing number of cases. The pandemic had a significant impact on the conditional variance equation of the GARCH models, meaning that (to a degree) the volatility could be explained by uncertainty caused by the pandemic.

Another paper by Omari, Maina, and Ngina (2020) used the autoregressive models in a forecasting context. Investors being able to forecast the future volatility to the finest degree of accuracy is one of many reasons why the technological progress has made it easier for investors today to gather all the necessary information they need on a stock, and the GARCH family models are heavily utilized when it comes to this. Omari et al. (2020) modelled the tail behavior of stock market indices across the globe, both before and during the COVID-19 pandemic, using the traditional autoregressive models GARCH, GJR-GARCH, the exponential GARCH (EGARCH) by Nelson (1991), the component standard GARCH (CS-GARCH) by Lee and Engle (1993) and the asymmetric power ARCH (APARCH) by Ding, Granger, and Engle (1993). These models were then used to measure the Value-at-Risk (VaR) forecast ability compared to a GARCH model based on Extreme Value Theory (EVT), the GARCH-EVT, proposed by McNeil and Frey (2000). Indices from the U.S., U.K., Germany, France, Switzerland, EU, Canada, Japan, South Korea, Hong Kong, China and India were used. The sample period spanning from 2006 to 2020 more then confirms this notion, observing here that they are covering the 2008, 2011 and 2020 crisis, so we here have an article that compares crises, but the crises they are comparing are not 100% compatible since they are financial crises versus a health crisis, i.e. they are in some sense comparing apples to oranges. But, nevertheless, the findings were quite interesting. The EVT based model proved to have better one-day ahead VaR performance compared to the conventional GARCH models, giving evidence towards implementing conditional EVT based models being more sufficient than models that only capture the volatility clustering when you wish to assess the risk in periods of distress and uncertainty.

Understanding the pandemic impact across multiple financial assets seemed to be a heavily researched topic. Ali, Alam, and Rizvi (2020) used exponential GARCH models to understand the volatility of the financial markets during the pandemic. They ran bivariate regressions between returns and volatility for several financial securities including the S&P 500 index, U.S. Treasury bonds, Bitcoin, WTI oil spot price and gold. The sample period ran from January to March 2020 and the findings showed that for all financial instruments and commodities, except U.S. Treasury bonds, negative returns and high volatility were realized. Reboredo (2013)'s notion that gold is a "safe-haven asset" was justified as Ali et al. (2020) found that during the pandemic period, gold remained reasonably less volatile than the other assets. However, it also showed a decrease in returns as the other assets, but was less affected.

Shehzad, Xiaoxing, and Kazouz (2020) also used a sample period combining both the GFC and the COVID-19 pandemic period. With a goal of examining the position of China and the U.S. trade war in financial market returns and variances, they sought to answer several questions. First of all they asked whether the COVID-19 pandemic led markets to fall more considerably than in the GFC. Their remaining questions focused on the uncertainty impact on stock returns, size of leverage effect in the markets and the stature of the economies in the long-run. The results showed that major capital markets in the U.S., Europe and Asia had negative mean returns. They all indicated that the chances of market failure was significant through a negative skewness and elevated kurtosis value. In particular, the Asian markets were less affected than the other markets. Also in this article, the existence of ARCH effects was highly significant, and the proposed APARCH was concluded to suit the analysis perfectly.

Furthermore, Mirza, Naqvi, Rahat, and Rizvi (2020), using a GARCH-in-mean model, found that most European investment funds during the pandemic exhibited stressed performance, but social entrepreneurship funds endured resilience highlighting the importance of investors to have a safe-haven option in periods of high uncertainty. In continuation to approaches like this, Yousaf and Ali (2020) investigate return and volatility transfer between the cryptocurrencies Bitcoin, Ethereum and Litecoin using the vector autoregressive dynamic conditional correlation GARCH (VAR-DCC-GARCH) model to calculate hedge ratios and optimal weights. The authors found that return spillovers differ in both the before and the COVID-19 pandemic phase in all pairs of cryptocurrency, and during the COVID-19 phase the time-varying hedge ratios were higher, suggesting that hedging expense in the crisis period was higher than before. A final article also utilizing a dynamic conditional correlation framework, the asymmetric dynamic conditional correlation GARCH (ADCC-GARCH) model, is the one by Karkowska and Urjasz (2021) who wanted to identify connectivity across Central and Eastern European (CEE) post-communist countries and global sovereign bonds. Interestingly, they found that the CEE financial markets were more correlated to each other than global markets.

2.2 Regime switching models

Since the Markovian regime switching model by Hamilton (1989) only admits for occasions and exogenous changes, it is a very fitting model for describing cross-market correlations (Kuan, 2002). In earlier studies, Engel (1994) found some evidence of superior forecasting ability with the Markov switching model for many exchange rates. Fong and See (2002) showed clear presence of regime switching volatility in returns on crude oil futures prices. Alvarez-Plata and Schrooten (2006) found that shifts in financial agents' beliefs played a pivotal role in the 2002 Argentinean currency crisis, while Gallo and Otranto (2008) gave evidence in the long run of a spillover effect from markets in Hong Kong to Korea and Thailand, interdependence with Malaysia and co-movement with Singapore. Chevallier (2012) showed that increasing uncertainty and the development in U.S. housing markets not only contributed to various global imbalances and shocks, but that there also existed a strong cross-market linkage with commodity markets. Song, Ryu, and Webb (2018) also presented results of a persistence in global shocks while modelling inter-relatedness of volatility in both the U.S. and Korean financial markets.

However, only a few research projects seem to have utilized the Markov-switching models in the context of the COVID-19 pandemic. In more recent articles, Just and Echaust (2020) examined the relationship between the S&P 500 and implied - uncertainty, - correlation, and - liquidity during the pandemic period. Using a modified two-regime Markov switching model, they found that the day before the systemic split in the predicted volatility-returns relationship, the distortion of the expected correlation-return relationship emerged. Mishra, Rath, and Dash (2020) showed that the COVID-19 pandemic had a more severe impact on stock returns in the Indian financial market compared to the 2016 demonetization of the Indian rupee and implementation of Goods and Services Tax. Caferra and Vidal-Tomás (2021), by using a Markov switching autoregressive (MSAR) model, observed that during the pandemic period cryptocurrencies only experienced a short-term bear market compared to benchmark market indices (S&P 500), hence there were hedging opportunities for investors here. Konstantakis, Melissaropoulos, Daglis, and Michaelides (2021) noted that the high volatility regime during the COVID-19 pandemic had a significant higher range of volatility compared to the phase before. Baek, Mohanty, and Glambosky (2020) identified low and high volatility regimes and found that the volatility was affected by specific economic indicators and was sensitive to COVID-19 news. In continuation with previous literature on gold's hedging value during crisis periods, Burdekin and Tao (2021) compared the hedging performance of gold in both the GFC and the COVID-19 pandemic crisis periods. The results showed that in the GFC, gold had a highly significant hedging option for investors but since the financial markets where quicker to recover in the COVID-19 crisis, the 2020 results differed. Finally, Maheu, McCurdy, and Song (2020) captured regime changes and identified bull market corrections and bear market rallies during the COVID-19 pandemic in U.S. stock markets.

2.3 Comparisons across crises

In recent literature we have seen an extensive number of articles seeking to compare the COVID-19 pandemic to previous global crises. Some of these, for instance Omari et al. (2020) and Shehzad, Xiaoxing, and Kazouz (2020), have already been discussed in previous sections. But, as we also mentioned then, there exists some limitations in these articles when they compare global economic crises with a health crisis in the COVID-19 pandemic. Although the number of publications are not extremely high, articles putting the COVID-19 pandemic up against previously experienced health crises are necessary to address.

Bissoondoyal-Bheenick, Do, Hu, and Zhong (2020) examined the recent pandemic's impact on market return and volatility connectedness, and assessed whether countries who had already experience with the 2002-2004 SARS epidemic differed in results. They showed that in all phases of the COVID-19 pandemic, both the return and volatility connectedness increased in group 20 (G20) countries, and perhaps even more interesting was that countries with SARS experience had a lower degree of connectedness during the COVID-19 pandemic period. Barro, Ursúa, and Weng (2020) wrote a preliminary working paper back in March seeking to find plausible worst-case scenario upper bound values by comparing the mortality and economic activity during the 1918-1920 Influenza to potential effects that the COVID-19 pandemic could cause. Using estimates for the 1918-20 Influenza and adjusting for the current world population, Barro et al. (2020) found that the two-year long influenza would have killed over 150 million people if the fatality rate held for today. They also established evidence for a higher fatality rate having a decreasing effect on realized stock returns. This is in line with literature where it has been shown that different financial assets and commodities have been remarkably sensitive to the increasing uncertainty caused by the COVID-19 pandemic (Baek et al., 2020; Lyócsa & Molnár, 2020; Chikri et al., 2020; Ali et al., 2020). Bearing in mind that the differences in the world as we know it today, during each of these health crises are substantial, a direct comparison will not be sufficient enough to rely on in all situations.

2.4 Uncertainty, fear and volatility

Most likely, uncertainty is the underlying constant that drives the fear. Fear derives from uncertainty and this may then result in market volatility. On that account, we can define the volatility as the oscillations in financial securities returns. A more volatile security, i.e. higher movement, is recognized as a riskier asset which may generate returns to a larger dispersion than a safer asset, i.e. lower volatile movement. That is, the riskier asset has the possibility of generating returns that differ from the mean (both positive and negative) to a larger scale than the safer asset. Understanding the main driving factors behind the volatility is therefore a key interest not only for personal investors, but also policymakers, regulators and financial institutions. These three concepts have also been reflected in numerous publications the past year. Engelhardt, Krause, Neukirchen, and Posch (2021) used citizens' societal trust in the domestic government as a proxy, and found evidence that the market was more volatile in low-trust countries while, Chen, Liu, and Zhao (2020) examined the impact on Bitcoin price dynamics by individual's fear sentiment caused by the pandemic. The positive connection with the Chicago Board Options Exchange's Volatility

Index Volatility Index (VIX) and investors' fear sentiment, which was estimated from data gathered through Google Trends, showed evidence of fear generating a rise in uncertainty. The same fear evidence also had a highly significant effect on Bitcoin returns.

Aslam et al. (2021) utilized the Diebold Yilmaz-index (DY-index) framework by Diebold and Yilmaz (2012) and tested for the assumption that, during crises, the volatility in stock markets tends to change in one market as a response to a change in volatility in another market, i.e. volatility spillovers. Using 5-minute high frequency data, and the declaration date of WHO, they showed that 77.80% of the volatility forecast error variance could be explained by spillovers between 12 markets which represented all four regions of Europe. There also seemed to be more stable spillovers in the post declaration period.

Altig et al. (2020) showed that all investigated metrics displayed extensive jumps in instability related to the pandemic. They used autoregressive models to study the uncertainty impact which showed that uncertainty eventually stabilized and then plateaued, exposing disparities between Wall Street and Main Street's uncertainty measured through the employment losses mounted.

Sergi, Harjoto, Rossi, and Lee (2021) examined how capital markets and investors worldwide reacted to COVID-19 news. The results showed that, calculated by the Barro Misery Index (BMI), during the COVID-19 pandemic, the global stock markets in 76 countries responded adversely to misery. Shrinking real GDP growth and increasing unemployment, inflation and long-term interest rates have been seen to have adversely affected stock yields and raised uncertainty in financial markets. Results further indicated that rising COVID-19 cases and deaths also intensified the adverse effects of shifts in the misery index of the stock markets. In addition, all four elements of the BMI have been shown to have adverse effects on emerging stock markets. Another very similar article by the same authors, Harjoto, Rossi, Lee, and Sergi (2020), examined the effect of the COVID-19 pandemic during the growing infection period and the stabilizing infection period of the pandemic, and its impact on stock market returns, volatility, and trading volume. With this article they expanded the literature by conducting a larger analysis of the effects of the pandemic on returns, uncertainty, and trading volumes of stock markets across 76 different countries. They found that all 76 countries' global equity markets reacted negatively to the COVID-19 spreads, measured by the percentage of new cases every day and the COVID-19 mortality rate. Results also showed that investors withdrew their stock portfolios when they experienced increasing COVID-19 transmission (cases) and COVID-19 casualties, resulting in lower yields, higher uncertainty, and greater volume of trading.

Using a wavelet coherence technique to extract the multiscale interdependence between the panic index (PI) and currencies, Umar and Gubareva (2020) studied the causal relationships between panic level variations and exchange rates during the pandemic period. The results showed that in the respective heat maps, all the PI-currency pairs exhibit identical trends along the time and frequency scales, suggesting strong coherence and interdependence near the apogee in mid-March of the COVID-19 pandemic. However, relative to the euro, pound sterling, and Bloomberg's Galaxy Crypto Index, they noted some peculiarities in the Chinese Renminbi behavior. This suggests that, as demonstrated by the COVID-19 pandemic, the Chinese Renminbi could be eligible to design cross-currency hedge strategies that could operate through times of global crises.

While Lyócsa and Molnár (2020) showed that only in times of extreme volatility, the market volatility tend to drive autocorrelations of returns. Fear had a much more gradual impact, as the self-correlation of returns was also affected by medium levels of fear. In addition, the most appropriate model was that which included both fear and uncertainty as variables of transition. The greater the fear and uncertainty in the market, the more likely it is to be in a crisis regime with a negative autocorrelation of the returns.

2.5 Effects of government approaches

The COVID-19 virus did not hit all countries at the same time, nor did every country feel the same effects of it. One reason for this is the way each individual countries' governments chose to approach the virus. Countries such as New Zealand had a strict approach and implemented strict travel bans from inhabitants entering the country from China as early as February 3 (Jones, 2020). Meanwhile on the other hand, the Brazilian President Jair Bolsonaro not only put his countries economy at extreme risk, but also peoples health, with his conservative and naive approach to diminish the virus' importance in the early phase of the pandemic (Cowie, 2020). In other words, New Zealand and Brazil have been two good examples of *dos* and *don'ts* the past year, and several articles looking at the economical effect of government responses to the pandemic have been conducted.

Ashraf (2020) examined the economical effect in 77 different countries' government approach to the pandemic. On the one hand, the results showed that social distancing measures affected the market negatively because of a reduction in economic activity, which on the other hand had an indirect positive effect through the reduction in COVID-19 confirmed cases. But, the announcements of testing, quarantine policies, stimulus packages and so on had a positive effect on market returns. In another article, Shehzad, Xiaoxing, Arif, Rehman, and Ilyas (2020) showed that a lack of government investments in the health sector imperatively damaged the financial market structures. The deficiency in health systems was largely exposed, and they were not financially prepared for a pandemic to a scale so large. Therefore, in the future, the authors recommend that the government should allocate more of their budget towards crisis and pandemic preparations. The final article we mention here is the one by Zaremba, Kizys, Aharon, and Demir (2020) who assessed the degree to which the socioeconomic pressures placed by different governments around the world impacted the volatility in financial markets. A total of 67 countries were examined. The authors' findings support the notion that government interventions increased the volatility in international stock markets significantly and robustly. The impact was driven in particular by the role of information campaigns and public event cancellations. Results had explicit implications for policy. Governments around the world should be aware that coronavirus-related restrictions, in addition to having a substantial economic impact, have a significant impact on the trading environment in the financial markets. Episodes of mass purchases of volatile assets may have been caused by increased uncertainty in capital markets. Elevated uncertainty can also result in higher capital costs and equity portfolio managers can experience inferior details from the stringency of applied steps towards understanding potential stock market fluctuations.

2.6 Contagion effects

Contagion effect is a relatively broad term that does not hold any universally accepted definition. However, the definition of Forbes and Rigobon (2002) is heavily utilized. Since *contagion* in this context can be closely related to *interdependence*, that is, shared dependence between some things, it is important to separate the two of them. Forbes and Rigobon (2002) carefully discriminate between them, and explain that the difference is that contagion is only a valid conclusion if the *increase* in cross-market linkage is deemed to be significant, and if the markets of interest did not exhibit such strong correlated behavior before the shock as they did after. Furthermore, assuming that the difference should be a significant *increase* can be limiting. Wälti (2003) showed that shocks could be interpreted as country-specific so that a shock to one country could weaken these linkages, which also should be considered a contagion effect.

The literature concerning contagion effects related to the COVID-19 pandemic is however very limited. Akhtaruzzaman, Boubaker, and Sensoy (2021) examined the occurrence of contagion effects on both financial and non-financial firms between group 7 (G7) countries and China during the pandemic period. Some highlighted results were obtained on this. First off, by utilizing a dynamic conditional correlation (DCC) framework, all the firms that were investigated experienced a significant increase in the conditional correlations. Secondly, the financial firms transmitted contagion to a higher magnitude than the non-financial firms. Furthermore, the two Asian countries China and Japan received more spillovers than they spread during the pandemic period. Additionally, it is important to note here that one benefit of understanding contagion effects is that it heavily contributes to the ability of hedging portfolios. With portfolio hedging you are looking to balance your risk in order to be prepared for unexpected situations, so by recognizing the shock transmissions between different markets you are able to further diversify your assets. With that being said, Akhtaruzzaman et al. (2021) also showed that both the foreign exchange and international stock markets had high volatile days during the pandemic period, and that the hedging ratios have had a significant increase as a response to this, i.e. the likelihood of portfolio mismatching has risen and such has the risk for international investors.

Corbet, Larkin, and Lucey (2020) showed that typical flight-to-safety behavior occurred during the COVID-19 pandemic period. In financial terminology, so-called "flight-to-safety" behavior often occur during times of higher uncertainty. The phenomenon centers around the tendency to sell the assets that are deemed risky, and buy safer investments instead. Furthermore, they showed that crypotcurrencies (represented by Bitcoin) acted more as an intensifier for contagion rather than a hedging option, or safe-haven, given by the high volatile relationship it had with the Chinese stock markets. Corbet, Hou, Hu, Lucey, and Oxley (2021) took a new direction and implemented a reputational-based contagion analysis. They examined how companies that shared the brand name *corona*, or sold products named the same, were impacted by the coronavirus. They determined that some firms, even though they had no significant contribution to the spread of the virus, experienced negative effects of the pandemic because of their brand name. This result adds to previous research that suggests that companies are constrained when it comes to name and brand salience, and need to be cautious on potential drawbacks with almost any decision they make. Gunay (2020) showed that the volatilty between six different stock markets experienced structural breaks in four different time intervals, while Chevallier (2020), by combining both health and stock market data, showed that the stability in financial markets is only as strong as its weakest link.

These articles show clear evidence, and it appears to be common practice that GARCH models will perform a sufficient volatility modelling process. Although the extensions of GARCH family models used are multitude, we will follow in the line of Ali et al. (2020); Omari et al. (2020); Yousef and Shehadeh (2020); Mirza et al. (2020) and implement a modified asymmetric model taking the COVID-19 pandemic into consideration. Following in the line of Yousaf and Ali (2020); Karkowska and Urjasz (2021), we will in the contagion analysis use a dynamic conditional correlation (DCC) framework in order to examine variance - covariance transmissions among the markets. Chiang, Jeon, and Li (2007) proposed this when they examined contagion effects in Asian markets in their late 1990s financial crisis, and this has also been utilized in one sort of extension by previous presented literature (Akhtaruzzaman et al., 2021; Corbet et al., 2020, 2021; Chevallier, 2020). To conclude, this thesis will contribute to the established research on modelling volatility and cross-correlation between global financial markets in periods of distress. However, we will deviate from others, as to our knowledge, there is no substantial amount of literature concerning the correlation between key global economies during this new pandemic period. Additionally, we wish to identify the movement between finite correlation regimes, and evaluate how the introduction of a global pandemic changed the cross-market stability.

Chapter 3

Data

3.1 Description of data

This study examines the daily logarithmic returns of selected stock market indices. The raw data set used for this study was gathered from Yahoo Finance and consists of the following major stock indices: S&P 500 (U.S.), S&P/TSX (CAN), DAX (GER), FTSE 100 (U.K.), Nikkei 225 (JAP) and SSE (CHI). The returns were determined using the following formula on the daily adjusted closing prices:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

where r is the single period return, t is the time variable, P_t is the adjusted closing price at time t and P_{t-1} the previous day's adjusted closing price. The aim of selecting these stock indices is to analyze the volatility and correlation impact in times of uncertainty and turbulence for the major world stock indices. The U.S., Canada, Germany, U.K., Japan and China make up more than 56% of the world's GDP (WorldBank, 2019), as such we have chosen their respective benchmark indices as a proxy for the global financial market. The data set covers two sample periods; a pre-COVID-19 period (January 1, 2012 to December 31, 2019) and a one-time-for-all COVID-19 period (January 1 to December 31, 2020) with a sample size of 2,343 observations. Although the pandemic did not hit all countries at the same time, we have assumed a common sample period hence the name "one-time-for-all". Dates with lacking information and little relevance for estimation have been cleaned prior to the data gathering. This reflects the dates where no trading was done, such as holidays, weekends, etc.

3.2 Descriptive statistics

The descriptive statistics and well-recognized time-series assumptions tests have been sorted in to their recognized sample period, and then summarized in table 3.1.

Table 3.1: Descriptive statistics

Index	obs.	min	max	μ	σ	σ^2	Skewness	Kurtosis	JB	ADF	PP	LB	ARCH-LM
Panel A: pre-COVID-19 period													
S&P 500	2,082	-.0418425	.0382913	.0004058	.0077704	.0000604	-.5823608	6.269795	267.27*	-45.582*	-45.611*	10.4610***	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0632)	
S&P/TSX	2,082	-.0317446	.0289635	.0001009	.0064791	.000042	-.4891526	5.463568	199.99*	-42.686*	-42.579*	9.2592*	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0023)	
DAX	2,082	-.0706727	.0485206	.0003709	.0105613	.0001115	-.3112519	5.434251	155.55*	-45.262*	-45.412*	18.7296*	0.0112**
									(0.0000)	(0.0000)	(0.0000)	(0.0022)	
FTSE 100	2,082	-.0477976	.0351542	.0001719	.0080907	.0000655	-.178852	5.524492	138.92*	-45.168*	-45.201*	15.6381*	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0035)	
Nikkei 225	2,082	-.0825293	.0742617	.0005143	.0119063	.0001418	-.3582804	8.705557	302.70*	-47.954*	-48.065*	5.2270**	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0222)	
SSE	2,082	-.0887317	.0560356	.0001402	.0130003	.0130003	-1.054179	11.33728	604.89*	-43.557*	-43.548*	4.3565**	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Panel B: one-time-for-all COVID-19 period													
S&P 500	261	-.1276522	.0896832	.0005957	.0213872	.0004574	-.8875711	12.13667	82.65*	-23.053*	-22.151*	31.3964*	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0000)	
S&P/TSX	261	-.131758	.1129453	.0000252	.0206185	.0004251	-1.407649	18.8172	127.73*	-21.256*	-20.635*	19.4322*	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0000)	
DAX	261	-.1305486	.1041429	-.00000939	.0203369	.0004136	-.9068508	12.49701	84.88*	-16.137*	-16.230*	7.2415**	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0286)	
FTSE 100	261	-.1151171	.0866642	-.0006493	.0182429	.0003328	-1.019547	11.36305	86.39*	-16.702*	-16.695*	16.0489**	0.0742***
									(0.0000)	(0.0000)	(0.0000)	(0.0135)	
Nikkei 225	261	-.0627357	.0773138	.0003511	.0152585	.0002328	.2811161	8.539062	42.95*	-15.044*	-15.143*	4.6642***	0.0000*
									(0.0000)	(0.0000)	(0.0000)	(0.0971)	
SSE	261	-.0460272	.0555421	.000663	.0115404	.0001332	-.1178604	6.502673	27.77*	-15.628*	-15.738*	18.8031***	0.0376**
									(0.0000)	(0.0000)	(0.0000)	(0.0934)	

Table 3.1 reports the descriptive statistics and some general assumptions tests in both COVID-19 sample periods (1 January 2012 - 31 December 2019 and 1 January 2020 - 31 December 2020). *P*-values are reported below each estimation. * indicates significance at 1% level, ** at 5% level and *** at 10% level.

Looking at the pre-COVID-19 sample period first, we first observe that each index has 2,082 observations. All the indices exhibit negative minimum values and positive maximum values. Using these minimum and maximum realizations, we may further calculate their ranges which would render a first estimate of volatility. Starting at the top with the S&P 500, these estimates are equal to .0801338, .0607081, .1191933, .0829518, .156791 and .1447673. The negative skewness coefficient for all indices indicates that we are dealing with longer, or fatter, left-skewed distributions. Furthermore, we can see that the kurtosis values are all larger than the kurtosis of a normal Gaussian distribution which is 3. There is here evidence of extreme realizations in the returns. These are two common characteristics when we are dealing with financial asset returns. Each assumption test is also statistically different from zero, which gives us enough evidence to reject the null for each assumption. All the tests are scrutinized later, both in this chapter and the methodology.

The observations in the one-time-for-all COVID-19 period are all equal to 261. Calculating the ranges gives us the volatility estimates .2173354, .2447033, .2346915, .2017813, .1400495 and .1015693. Comparing these values with the previous sample period, we can see that all have increased except the Nikkei 225 and SSE which decreased, which could suggest the two Asian indices was less volatile in the pandemic period. The skewness coefficients have all decreased except for the Nikkei 225, which exhibits a right-skewed positive estimate in the pandemic period, and the SSE which still is negative skewed. A positive skewed coefficient in the Nikkei 225 could be an indicator of more small losses and less bigger gains in the returns. The kurtosis coefficients have also increased in all indices except for the Nikkei 225 and SSE, so the evidence of more extreme events occurring holds for the rest of the indices. The realizations in each test statistics have all decreased, but they all differ from zero, as seen in the *p*-values. The evidence to reject the null for each assumption holds in this sample period too.

3.3 Daily returns

Since returns are generally characterized by time-invariant distributions, we often say that a return time-series is deemed a stationary process. Stationarity implies that we are dealing with a constant mean and variance throughout time. We will further justify the thought behind this process in the methodology chapter. In order to emphasize the importance of market volatility within the context of stationary processes, we have plotted a time-series plot of our daily log-returns for the full sample-period in figure 3.1.

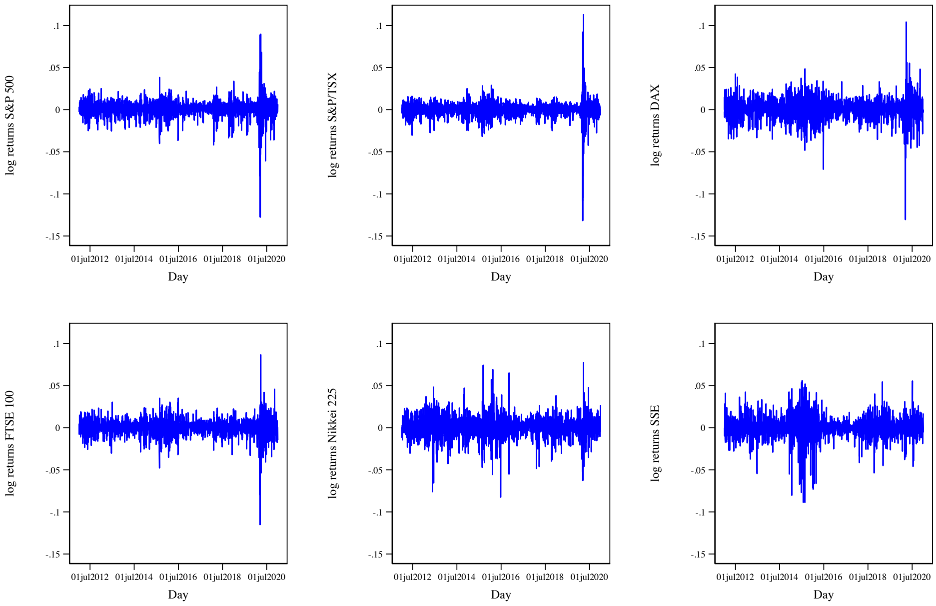

Figure 3.1: Daily logarithmic returns of selected indices

We can first observe that the returns are moving around the zero mean, and clear evidence of market disturbances that cause the returns to deviate from the mean. This is also evidence of the presence of volatile movements. Also, we can clearly see an indication of periods where high volatility is followed by high changes (on either sign) and low periods of volatility that acts in the same manner, or volatility clustering in other words. We observe that there are certain periods that have higher volatility than others meaning that large changes in the log returns seem to be followed by other large changes and vice versa. For the European and North-American capital markets, we clearly observe a notable large spike in the end of the time-series, marking the beginning of the 2020 COVID-19 pandemic. This spike is not as notable for the Asian countries, the last two respectively. However, for these countries there seems to be clearer periods of higher volatility clustering in the period moving up to 2020, and perhaps most notably in the time-period between 2013 and 2016.

In table 3.2 we have presented the correlation between each given index returns in a matrix. Both sample periods have been taken into account. So, panel A represents the pre-COVID-19 period while panel B is the one-time-for-all COVID-19 period.

Table 3.2: Contemporaneous correlations

	S&P 500	S&P/TSX	DAX	FTSE 100	Nikkei 225	SSE
			Panel A: pre-COVID-19 period			
S&P 500	1	0.7214*	0.5483*	0.5200*	0.1626*	0.1410*
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
S&P/TSX	0.7214*	1	0.5115*	0.5309*	0.1809*	0.1660*
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DAX	0.5483*	0.5115*	1	0.7818*	0.2673*	0.1483*
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
FTSE 100	0.5200*	0.5309*	0.7818*	1	0.2799*	0.1836*
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Nikkei 225	0.1626*	0.1809*	0.2673*	0.2799*	1	0.2431*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
SSE	0.1410*	0.1660*	0.1483*	0.1836*	0.2431*	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Table 3.2 continued from previous page

	S&P 500	S&P/TSX	DAX	FTSE 100	Nikkei 225	SSE
	Panel B: one-time-for-all COVID-19 period					
S&P 500	1	0.8891*	0.6818*	0.6992*	0.3034*	0.2798*
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
S&P/TSX	0.8891*	1	0.7479*	0.7857*	0.3813*	0.3117*
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DAX	0.6818*	0.7479*	1	0.9112*	0.4981*	0.3205*
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
FTSE 100	0.6992*	0.7857*	0.9112*	1	0.4764*	0.3196*
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Nikkei 225	0.3034*	0.3813*	0.4981*	0.4764*	1	0.4042*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
SSE	0.2798*	0.3117*	0.3205*	0.3196*	0.4042*	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Table 3.2 reports the correlation matrix in daily-log returns in both the pre-COVID-19 period (1 January 2012 - 31 December 2019) and one-time-for-all sample period (1 January 2020 - 31 December 2020). *P*-values are reported below each estimation. * indicates significance at 1% level.

At first glance we can clearly see that there exists a positive correlation across the global indices. As globalization and more advanced technological progress has intensified over the years, financial markets seem to behave more cohesive today. Additionally, the COVID-19 period actually experiences even stronger relationships across markets, and especially for the indices pertaining to the same continent. The occurrence of increasing linkages between countries after a shock to another country is what Forbes and Rigobon (2002) defined as contagion effects.

3.3.1 Gaussianity in returns

We have visualized the density distributions in the histogram in figure 3.2.

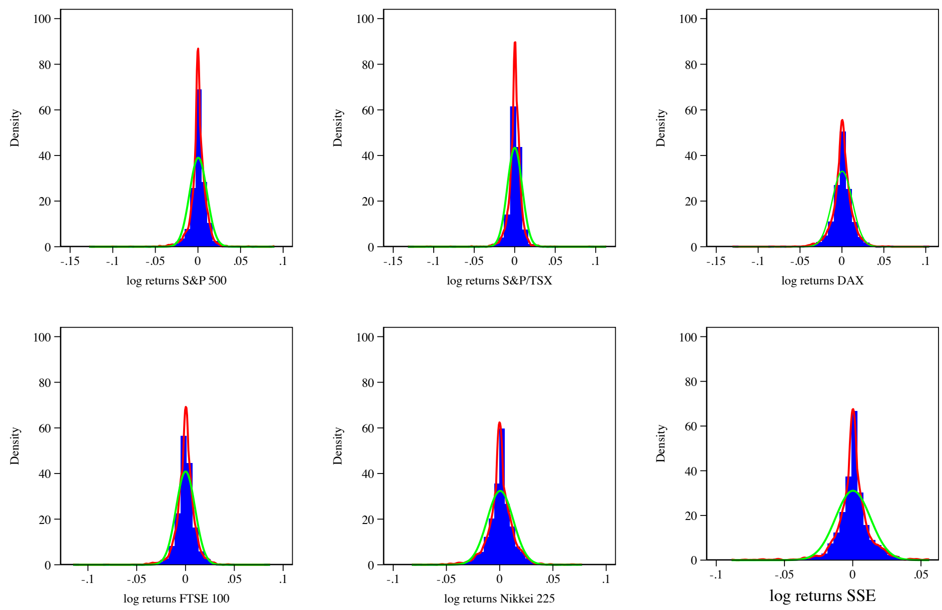

Figure 3.2: Histogram of daily returns

We clearly have indication that we are dealing with leptokurtic tails, meaning that compared to a Gaussian distribution, our tails are fatter. It has a high peak and hence is clearly not following the

Gaussian. In order to contrast the two estimated densities, we have plotted both a kernel density estimator in red, and the densities of the Gaussian in green, based on the mean and variance of the underlying data. If the returns were deemed to follow the Gaussian, the red and green line would behave similarly. Clearly from figure 3.2 this is not the case. The first indication of non-Gaussianity is therefore met. To further confirm this notion, we will also assess the Gaussianity with a Quantile-Quantile (Q-Q) plot in figures 3.3 and 3.4 below.

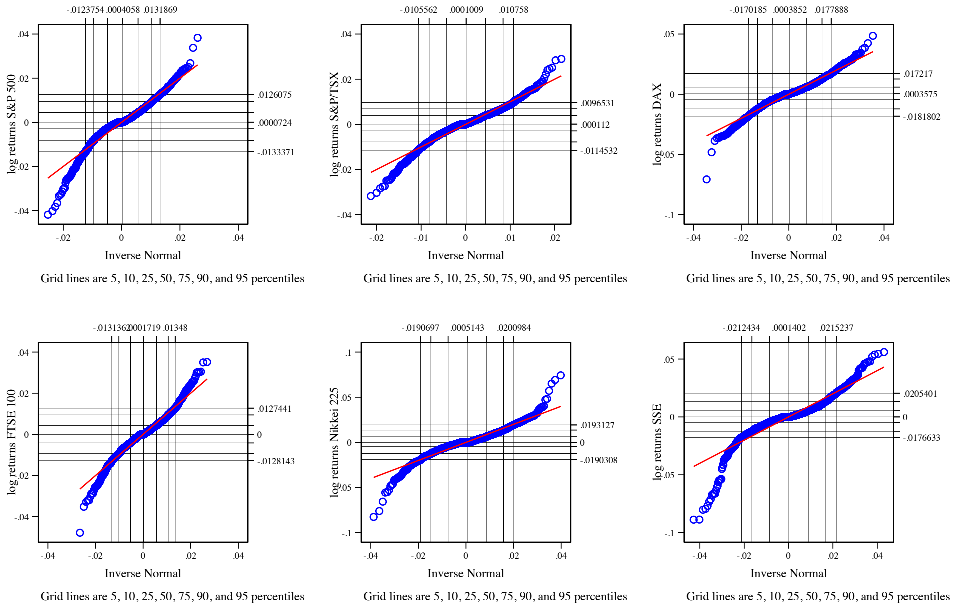

Figure 3.3: Q-Q plot of daily returns in the pre-COVID-19 period

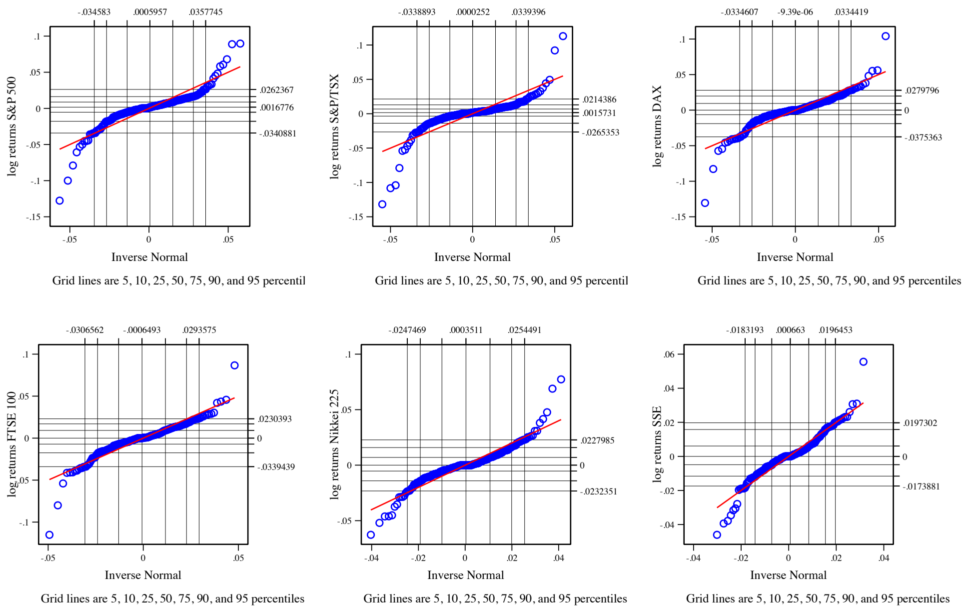

Figure 3.4: Q-Q plot of daily returns in the one-time-for-all COVID-19 period

We see here evidence of a significant difference of the blue plots and the red 45-degree inverse normal line. This evidence is especially pronounced over the tail regions. Perhaps even more so in the COVID-19 period, as we see many points in the Q-Q plots are differentiating to a larger degree than in their pre-COVID-19 sample period counterpart. Thus on the basis of the Q-Q plot one would suggest that the return data are not normally distributed. To ensure a more formal and precise testing procedure, we perform the unadjusted Jarque and Bera (1980) test as suggested by D'agostino, Belanger, and D'agostino (1990) previous work on Gaussianity testing. The test statistics are summarized in table 3.1 and we see that for both sample periods we can strongly reject the null hypothesis of Gaussianity for all return distributions.

3.3.2 Stationarity and autocorrelation in returns

The returns are also required to follow a stationary process in order for us to perform an adequate inference. We therefore also carry out multiple test statistics here. Both the parametric Augmented Dickey-Fuller test (ADF) by Dickey and Fuller (1979) and the non-parametric Phillips-Perron test (PP) by Phillips and Perron (1988) as an alternative of judgement, are unit root tests that allow us the possibility to test if our data contains a unit root, i.e. violating the condition of weak stationarity. The justification behind using both a parametric and non-parametric is that it gives us a more robust result, since a non-parametric test does not hold any underlying assumptions of a specific distribution. The PP test is specifically robust to unspecified autocorrelation and heteroskedastic behavior in the disturbance process. Realizations and p-values of the respective test statistics are given in table 3.1, and we can see that we first reject the null in the ADF for the more statistical evidence that our returns are stationary. The PP test also rejects the null and conclude that our returns follow a stationary process.

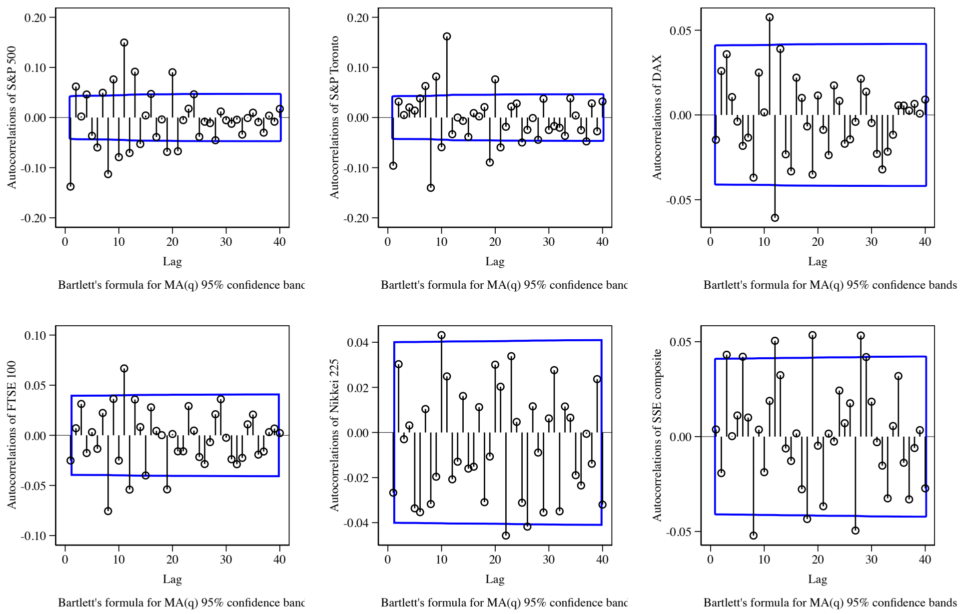

Figure 3.5: Correlogram of daily returns

In the correlogram in figure 3.5 we clearly observe some significant peaks in our returns indicating we may be dealing with autocorrelation in our data. If the spikes are lying inside the 95% confidence interval, the blue squared Bartlett's band, we fail to reject the null hypothesis of autocorrelation. To further comprehend this, the Ljung and Box (1978) test for autocorrelation has also been conducted. Realizations and p-values of the test statistic is given in 3.1. All the indices show a respective significant value in both sample periods, and the null of no autocorrelation is therefore rejected in both sample periods. ARCH effects tests have been conducted with a standard ARCH Lagrange Multiplier (ARCH-LM) test as suggested by Engle (1982) in table 3.1, and it has confirmed clear periods of high persistence in our residuals. We can therefore state that the data is adequate enough to handle an inference on our two hypotheses, and we may now model the financial markets volatility and cross-correlation.

Chapter 4

Methodology

4.1 Central moments

Some of the most frequently used techniques of descriptive statistics are the central moments. There are four central moments in descriptive statistics that are widely used as tools (Pébay, Terriberry, Kolla, & Bennett, 2016). The first and second moments of a distribution are the mean and variance, respectively, while the (standardised) third and fourth moments are known as skewness and kurtosis. Skewness describes the form of a distribution and indicates how asymmetric it is around its mean value. Kurtosis is a measure used to determine how fat the tails of a distribution are and how peaked the series are close to the mean (Brooks, 2014, p. 66). We will elaborate more on the descriptive central moments in the following sub sections.

4.1.1 Mean

When people hear mean they usually think of the word *average* (Acock, 2014, p. 92). Mean is the value that each case would have if they all had the same value. It is a fulcrum point that takes into account the number of instances above and below it, as well as the distance between them (Acock, 2014, p. 93). The arithmetic mean of n values of Y is given by,

$$\bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} = \frac{y_1 + y_2 + y_3 + ... + y_n}{n} \tag{4.1}$$

(Hill, Griffiths, & Lim, 2011, p. 25). Since sample averages converge to population means, which for true parameter values are zero, an estimator chosen to render these sample moments as close to zero as possible would converge to the true value and thus be consistent (Verbeek, 2004, p. 151). Now let's suppose that a random variable Y has k possible values, $y_1, \ldots\ y_k$, where y_1 denotes the first value, the second being y_2, and so on. The probability that Y is y_1 is given by p_1, and the probability of Y being y_2 is p_2, and so on. This gives us the expected value of Y, denoted as $E(Y)$

$$E(Y) = y_1p_1 + y_2p_2 + ... + y_kp_k = \sum_{i=1}^{k} y_ip_i \tag{4.2}$$

The estimated value of Y is denoted μ_y and is also known as the expectation of Y (Stock & Watson, 2015, p. 66). The population mean μ is determined using the sample mean $\bar{Y}$. As it is the predicted value of Y to the first power, the population mean is known as the "first moment". As mentioned previously, higher moments are obtained by taking the predicted values of higher powers of the random variable, so $E(Y^2)$ is the second moment of Y, $E(Y^3)$ is the third, and so on (Hill et al., 2011, p. 701). The random variable is said to be centered when the population mean is subtracted. Central moments are thus the expected values of powers of centered random variables, and they are often denoted as μ_r, this makes it so that the r_{th} central moment of Y equals:

$$\mu_r = E\left[(Y - \mu)^r\right] \tag{4.3}$$

The value of the first central moment is zero as

$$\mu_1 = E\left[(Y - \mu)^1\right] = E(Y) - \mu = 0 \tag{4.4}$$

This in turn makes the higher moments of Y more interesting to look at, given the following computations from the mean equation

$$\mu_2 = E\left[(Y-\mu)^2\right] = \sigma^2 \tag{4.5}$$

$$\mu_3 = E\left[(Y-\mu)^3\right] \tag{4.6}$$

$$\mu_4 = E\left[(Y-\mu)^4\right] \tag{4.7}$$

4.1.2 Variance

A probability distribution's dispersion, or "spread", is determined by its variance and standard deviation. The predicted value of the square of the deviation of Y from its mean is the variance of a random variable Y, denoted $\text{Var}(Y)$ (Stock & Watson, 2015, p. 67). The predicted or expected value can further be explained as

$$\text{Var}(Y) = E[(Y-\mu_y)^2] \tag{4.8}$$

The population variance is another term for this. Since an estimated value is a sort of "average," and assuming that we knew μ, we could approximate the variance using the sample analog $\sigma^2 = \sum_{i=1}^{N}(Y_i-\mu)^2/N$ (Hill et al., 2011, p. 701). In the cases we don't know μ, we can use its estimator Y instead, yielding:

$$\sigma^2 = \sum_{i=1}^{N} \frac{(Y_i-\bar{Y})^2}{N} \tag{4.9}$$

This estimator is decent. It has a rational appeal, and the sample size when $N \to \infty$ can be seen to converge to the true value of σ^2, but it is biased. In order to reduce this biasedness, we must divide by $N-1$. Since the population mean, μ, must be estimated before the variance can be estimated, this correction is required. This difference is not significant in samples with at least 30 observations, but it is significant in smaller samples. If the population variance σ^2 is an unbiased estimator, it can be formulated as

$$\sigma^2 = \sum_{i=1}^{N} \frac{(Y_i-\bar{Y})^2}{(N-1)} \tag{4.10}$$

This estimate is also known as the sample variance (Wooldridge, 2001). With this in mind we can further compute the estimated variance of $\bar{Y}$ as

$$\widehat{\text{Var}(\bar{Y})} = \frac{\sigma^2}{N} \tag{4.11}$$

Since variance includes the square of Y, the variance's units are also the square of Y's units, rendering the variance difficult to understand. Consequently, the standard deviation, which is the square root of the variance and is denoted as σ_y is generally used to calculate the distribution. The units of the standard deviation are the same as those of Y (Stock & Watson, 2015, p. 67). The discrete random variable Y, referred as Y, has a variance of

$$\sigma_Y^2 = Var(Y) = E[(Y-\mu_Y)^2] = \sum_{i=1}^{k}(y_i-\mu_Y)^2 p_i \tag{4.12}$$

Here the second moment is defined by $E[Y^2]$ and the variance of Y is determined if it has a discrete distribution. With discrete distribution we can define the variance as

$$V[Y] = \sum_{j=1}^{N}(y_j-\mu)^2 f(y_j) \tag{4.13}$$

where j denotes the number of possible outcomes. Furthermore, with a continuous distribution, the variance can be formulated as

$$V[Y] = \int_{-\infty}^{\infty} (y - \mu)^2 f(y) dy \tag{4.14}$$

In most cases, a random variable's distribution is not fully defined by its mean and variance, so we will use equation 4.6 and 4.7 to further define the k'th moment (Verbeek, 2004, pp. 399-400).

4.1.3 Skewness

With equation 4.6 in mind, we move on to define and discuss the third central moment in this section. This being the sample skewness, which measures the lack of symmetry of a distribution (Stock & Watson, 2015, p. 69). The skewness of a Gaussian distribution is zero, with the distribution being positively skewed if the skewness is greater than zero and negatively skewed if the skewness is less than zero (Acock, 2014, p. 277). Remembering that central moments are expected values,

$$\mu_r = E\left[(Y - \mu)^r\right] \tag{4.15}$$

As the sample size $N \to \infty$, the Law of Large Numbers states that sample means converge to population averages. By locating the sample analog and replacing the population mean μ with its approximation $\bar{Y}$, we can estimate the higher moments (Hill et al., 2011, p. 702). With this in mind we get the following representations:

$$\bar{\mu}^2 = \sum_{i=1}^{N} \frac{(Y_i - \bar{Y})^2}{N} = \bar{\sigma}^2 \tag{4.16}$$

$$\bar{\mu}^3 = \sum_{i=1}^{N} \frac{(Y_i - \bar{Y})^3}{N} \tag{4.17}$$

$$\bar{\mu}^4 = \sum_{i=1}^{N} \frac{(Y_i - \bar{Y})^4}{N} \tag{4.18}$$

Notice that we divide by N rather than $(N - 1)$ in these equations since we're using the rule of large numbers (i.e. large samples) as reasoning, and the correction has little to no effect in large samples. The skewness of a random variable Y's distribution can be formulated as

$$\text{Skewness} = \frac{E(Y - \mu_y)^3}{\sigma_y^3} \tag{4.19}$$

where σ_y is the standard deviation of Y. This is also referred to as the population skewness. Note that a value of Y that is a certain amount above its mean is just as probable as a value of Y that is the same amount below its mean in a symmetric distribution. If this is the case, positive $E(Y - \mu_y)^3$ values will be replaced by similarly likely negative values on average (H.-Y. Kim, 2013). As a result, $E(Y - \mu_y)^3 = 0$ for a symmetric distribution; the skewness of a symmetric distribution is zero (Stock & Watson, 2015, p. 70). A positive value of $E(Y - \mu_y)^3$ is not replaced on average by an equally possible negative value if a distribution is not symmetric, so the skewness for a non-symmetric distribution is nonzero (Verbeek, 2004, p. 185). In equation 4.19, dividing by σ_y^3 in the denominator cancels the units of Y^3 in the numerator, resulting in skewness that is unit free; in other words, changing the units of Y has little effect on its skewness (Stock & Watson, 2015, p. 71).

Now with μ_y being the first moment and σ_y being the second central moment of Y. The sample counterpart of $S(Y)$ is given as

$$\widehat{S}(Y) = \frac{1}{(T-1)\widehat{\sigma}_Y^3} \sum_{i=1}^{T} (Y_t - \widehat{\mu}_Y)^3 \tag{4.20}$$

where $\widehat{\mu}_Y$ and $\widehat{\sigma}_Y$ being the estimated first and second moment of Y. In a statistical context the skewness of modeled returns will indicate if there exists a trend of higher/lower distribution towards any given side (Boffelli & Urga, 2016, p. 5). In the next section we will define and explain the last of the central moments, kurtosis.

4.1.4 Kurtosis

A higher kurtosis distribution has a significantly bigger peak value than a Gaussian distribution. A low kurtosis, on the other hand, corresponds to a distribution that is too flat to be a Gaussian distribution (Acock, 2014, p. 97). Building on the estimations from equation 4.17 and the methodology to find the estimated coefficient of skewness, we can similarly get the estimated coefficient of kurtosis (K) (Hill et al., 2011, p. 702). Kurtosis is a measure of how dense, or "heavy", the tails of a distribution are. As a result, kurtosis is a measure of how much mass is in the tails, and therefore how much of Y's variance comes from extreme values. Outliers are Y values that are extremely low or high. Outliers are more probable the higher the kurtosis of a distribution (Stock & Watson, 2015, p. 71). It should be noted that negative outliers are often identified by the existence of a long-left tail, and distributions with negative excess kurtosis are referred to as platykurtic distributions, which means flat-topped curve (H.-Y. Kim, 2013). Y's distribution has a kurtosis given by:

$$\text{Kurtosis} = \frac{E(Y - \mu_Y)^4}{\sigma_Y^4} \tag{4.21}$$

If a distribution has a great volume in its tails, there will probably be some extreme Y deviations from the mean, and these deviations will lead to high $(Y - \mu_Y)^4$ values on average (in expectation). The kurtosis cannot be negative because $(Y - \mu_Y)^4$ cannot be negative. A Gaussian distributed random variable has a kurtosis of 3, so a random variable with a kurtosis greater than 3 has more mass in its tails than a Gaussian distributed random variable (Verbeek, 2004, p. 400). Thus, a high kurtosis, often called leptokurtic if it is larger than 3 (Longin, 2005), will be recognized with an asset that is generating more extreme returns, both positive and negative, more frequently. We can therefore say a risky asset will have more negative skewness and higher positive kurtosis (Boffelli & Urga, 2016, p. 6). Consequently, looking at the skewness and kurtosis of a sample of data; if the skewness and kurtosis are not equal or close to zero and three, we deny the notion of population Gaussianity (Hill et al., 2011, pp. 718-719). The kurtosis, like skewness, is unit free, meaning changing the units of Y has little effect on its kurtosis (Stock & Watson, 2015, p. 71). The frequency of the realization in the tails relative to a central realization is measured through the kurtosis. That is given by:

$$\widehat{K}(Y) = \frac{1}{(T-1)\sigma_Y^4} \sum_{t=1}^{T} (Y_t - \widehat{\mu}_Y)^4 \tag{4.22}$$

4.2 Time series assumptions

A financial time-series is characterized as an order of financial instruments gathered or measured over a sequence of time, and the goal of analysing these observations are done through an analysis that covers the method needed to understand it (Dodge, 2008, p. 536). As we saw in the data section, for an analysis on financial asset returns to succeed, more specifically to be able to model heteroskedasticity, there are four main assumptions that need to be digested and fulfilled. These are Gaussianity, stationarity, autocorrelation and heteroskedasticity.

4.2.1 Gaussianity

The Gaussianity assumption is asserted around the notion of the tail distribution. Recall figure 3.2. We demonstrated that our return distributions clearly did not follow the Gaussian distribution. In fact, we defined them to be characterized as leptokurtic. Leptokurtic distributions are recognized with longer and fatter tails indicating that they have a higher chance in experiencing a much greater variation in positive (and negative) returns, than distributions that are determined to be Gaussian. This is also a trait that has become almost synonymously recognized with financial asset returns, and the occurrence of asset returns actually following a Gaussian distribution is very unlikely (Ivanovski, Stojanovski, & Narasanov, 2015). Being Gaussian distributed indicates that both sides of the distribution "bell-curve" are alike, i.e. they are symmetrical, so the data that is measured around the mean in a Gaussian distribution are more likely to take place than the data that is far from the mean (Stock & Watson, 2015, pp. 82-84).

The Jarque and Bera (1980) (JB) test-statistic is a function of both, the skewness and the kurtosis, in order to check if it matches the Gaussian distribution. Recall that the skewness and kurtosis determines to what degree our curve distorts from the Gaussian distribution and the frequency of the realization in the tails relative to a central realization, respectively. So, the null hypothesis that will be tested in the JB-test is that both the skewness and excess kurtosis is equal to zero versus an alternative hypothesis that they are not.

$H_0 : S \text{ and } K = 0$
$H_1 : S \text{ and } K \neq 0$

The JB test is given by:

$$JB = \frac{n}{6}\left(\widehat{S}^2 + \frac{1}{4}\left(\widehat{K} - 3\right)^2\right) \sim \chi^2_2 \tag{4.23}$$

where n are sample observations, $\widehat{S}$ and $\widehat{K}$ are the estimated sample skewness and kurtosis, respectively, and asymptotically following a chi-squared distribution with two-degrees of freedom if the null hypothesis is true. Note here that the JB test is always non-negative, so we see from equation 4.23 that if the skewness and kurtosis don't equal to zero, the test statistic will increase and the null will be rejected.

Unfortunately, there does not exist any test statistic that will provide us with an immaculate result. For that reason, the JB-test has its own drawbacks and limitations. In their paper, Thadewald and Büning (2007) conducted a power comparison between well-known Gaussianity test statistics such as the JB-test, the tests of Shapiro and Wilk (1965), Kuiper (1960), the non-parametric Kolmogorov-Smirnov test proposed by Kolmogorov (1933) and an alternative in the Cramér–von Mises criterion which was generalized by Anderson (1962). The results that were obtained indicated that compared to its peers, the power of the JB-test was poor when dealing with short-tailed distributions, and even showed signs of biasedness, especially if the distributions were deemed to be bimodal. Furthermore, the adjusted version of the JB-test out-performed the standard test in this comparison. This adjusted JB-test was proposed by Urzúa (1996) who also experienced the same problems connected to the JB-test performance when dealing with small sample sizes.

4.2.2 Stationarity

Following this is the assumption of stationarity. Stationarity in a time-series context implies that the mean, variance and autocovariances are constant over time (Brooks, 2014, p. 353). For our main interest we always want to deal with stationary data. Why? Firstly, combining data that are both stationary and non-stationary can in some incidents lead to spurious regression. If we for example regressed a stationary variable on a non-stationary one over time, the output that we would gain could indicate a high R^2 (that is, that the regression is looking "good") even though the variables are not related to each other at all. Meaning that we would obtain results that look good on paper, but in real life are completely unrealistic. The problem with using the R^2 as a measurement of the goodness of fit is further detailed later in the methodology. Secondly, it may also be proven that if our variables are non-stationary, then the standard assumptions allying in an asymptotic analysis can not be valid, i.e. the distributions, say t-ratio or F-statistic, are not following a t- or F-distribution, so hypothesis testing the parameters in a regressed model containing non-stationary data will not be possible. Thirdly, when dealing with shocks in a time-series, we are often interested in analysing the behaviour and aftermath when a shock in the market occurs. For stationary data, shocks at time t, for instance, are likely to have decreasing effects in time $t+1$, then $t+2$ etc., while in a non-stationary context the shocks are infinite meaning that there are no smaller effect situations happening (Brooks, 2014, pp. 353-354). Since returns are generally characterized by time-invariant distributions, we can say that a return time-series, r_t, is deemed a stationary process, e.g. a white-noise process, if it satisfies the three conditions

$$1.\ E(r_t) = 0 \tag{4.24}$$

$$2.\, E(r_t^2) = \sigma^2 < \infty \tag{4.25}$$

$$3.\, E(r_t, r_{t-j}) = 0 \quad \forall_j \neq 0 \tag{4.26}$$

For testing for stationarity, we will make use of two highly utilized test statistics. The first one being the ADF proposed by Dickey and Fuller (1979) and the PP by Phillips and Perron (1988).

The model in the standard Dickey-Fuller test can be expressed as

$$X_t = \rho X_{t-1} + \varepsilon_t \tag{4.27}$$

where ε_t is independent and identically distributed (i.i.d.) with $\mathbb{E}[\varepsilon_t] = 0$ and $\mathbb{V}[\varepsilon_t] = \sigma^2 < \infty$. The model can from here be written in the equivalent model below, taking the lag, $\mathbb{L}$, in to consideration. We here remember that X_{t-1} is the lag, i.e. the difference in time between an observation and a previous observation. This gives

$$\underbrace{(1 - \mathbb{L})\, X_t}_{\Leftrightarrow} = \underbrace{\Delta X_t}_{\Leftrightarrow} = \underbrace{(\rho - 1)\, X_{t-1} + \varepsilon_t}_{\Leftrightarrow} \tag{4.28}$$

We also recognize here that the far right equation is a re-written version of the model given in equation 4.27. Remembering also that ρ is the correlation coefficient gives the following two hypotheses that will be the base of our test:

$H_0 : (\rho - 1) = 0$
$H_1 : (\rho - 1) < 0$

where the null hypothesis that is distributed is that the time series is not stationary versus an alternative of stationarity being present. If we solve H_0 with respect to ρ, we obtain that $\rho = 1$. This is an interesting notion that needs to be digested. If this situation takes place, we say that there exists a *unit root*. A unit root can be looked at as a stochastic trend, e.g. a random walk, which may cause problems when dealing with a statistical inference. Meaning, if we have a unit root in our data, the proposed stationary data at our hand will deviate from that assumption and show an unpredictable pattern instead (Glen, 2016). On that account, we clearly do not want to deal with unit roots in our data and if we experience a unit root situation, we need to differentiate the process until it becomes stationary. With that being said, unit roots processes are also often recognized as difference stationary. Furthermore, from H_A, we see that if $\rho < 1$, we have stationarity. Contrary, the situation where $\rho > 1$ is termed as an explosive process. The explosive process, using the previous example of shock transmissions in a stationary as opposed to non-stationary process, is recognized as a process where the shocks are increasing in each time-period. That is, if a shock occurs at time t, it will increase in $t+1$, $t+2$ and so on. Additionally, if we use the unconditional variance in the standard GARCH(1,1) model,

$$\sigma^2 = \frac{\omega}{1 - (\alpha_1 + \beta)} \tag{4.29}$$

we can easily see why the existence of a unit root is not beneficial, nor is a situation with non-stationarity. The unconditional variance is constant, i.e. stationary as long as $\alpha + \beta < 1$, by linearity not defined for $\alpha + \beta = 1$ and explosive for $\alpha + \beta > 1$. However, for more complex and longer time series, it is recommended to apply the augmented (ADF) version of the test. The ADF is based on the regression

$$\Delta y_t = \alpha + \beta_t + \theta y_{t-1} + \delta_1 \Delta y_{t-1} + ... + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{4.30}$$

with a constant equal to α, time trend t and p indicating the order of the AR process. Also here, the null hypothesis that is distributed is that the time series is not stationary, corresponding to $\theta = 0$, versus the alternative of θ being negative, $\theta < 0$, indicating stationarity (Boffelli & Urga, 2016, pp. 17 - 18).

The PP-test by Phillips and Perron (1988) is also a unit-root test that is built on the same decomposition as in equation 4.28. However, the PP-test differs from the ADF in that it is a more robust alternative that uses Newey and West (1987) standard errors in order to take autocorrelation into account.

One of the criticisms that has been recognised with unit root testing is concerning the power of the tests. It has been shown that the power of these tests are low if we are dealing with a stationary process and the root is located close to the non-stationary boundary. This can be proved. Consider, from equation 4.38, we are dealing with an AR(1) process and a coefficient, ϕ , equal to 0.95. That is,

$$\gamma_t = \mu + 0.95\gamma_{t-1} + \varepsilon_t \tag{4.31}$$

we will therefore reject a null of a unit root being existent if this was shown to be the true data generating process. However, if the ϕ coefficient was equal to 1 instead, we would not have enough evidence to reject the null. This problem with the power of these tests are especially common in small sample size situations. One technique to get away from a problem situation like this would be to both conduct stationarity and unit root tests (Brooks, 2014, p. 364).

4.2.3 Autocorrelation

Autocorrelation in our dataset means that the data is correlating with itself, i.e. there exists a systematic relationship between our returns which results in that our returns at time $t + \tau$ contain information of returns at time t. The autocorrelation of lag τ can be defined as

$$\rho_\tau = \frac{\mathbb{E}\left[(X_t - \mu_t)(X_{t+\tau} - \mu_t)\right]}{\sqrt{\mathbb{E}\left[(X_t - \mu_t)^2 (X_{t+\tau} - \mu_t)^2\right]}} \tag{4.32}$$

and if it follows a stationary process with $\mathbb{E}[X_t] = \mu$ and $\mathbb{V}[X_t] = \sigma^2$, equation 4.32 reduces to

$$\rho_\tau = \frac{\mathbb{E}\left[(X_t - \mu_t)(X_{t+\tau} - \mu_t)\right]}{\mathbb{V}(X_t)} = \frac{\mathbb{C}(X_t, X_{t+\tau})}{\sigma^2} \tag{4.33}$$

Ljung and Box (1978) proposed an estimator where the null hypotheses states that all L autocorrelations are simultaneously equal to zero versus an alternative of the autocorrelation in *at least* one lag differed from zero.

$H_0 : \rho_1 = \rho_2 = \rho_3 = ... = \rho_L = 0$
$H_1 :$ at least one $\neq 0$

The Ljung and Box (1978) test estimator can be formulated as,

$$\tilde{Q} = T(T+2)\sum_{\tau=1}^{L} \frac{\hat{\rho}_\tau^2}{T-\tau} \sim \chi^2_L \tag{4.34}$$

where T is the sample size, τ is the number of lags and $\hat{\rho_\tau}$ is the estimated correlation coefficient. Asymptotically, that is when $T \to \infty$, the $\tilde{Q}$ statistic is chi-squared distributed with L degrees of freedom, given H_0 is true. (Jungeilges, 2020a).

4.2.4 Heteroskedasticity

We may also perform a test statistic on the possible presence of ARCH effects in the residuals which will fulfill the assumption of heteroskedasticity. Heteroskedasticity is a term that explains the variability in the observed data, and the presence of heteroskedasticity is recognized with data that is not equal through the span of values of another variable that predicts it. A time-dependent relationship like this is quite common to find when we are dealing with stock returns and, especially, squared returns for that instance (Boffelli & Urga, 2016, pp. 26-29). The test statistic that is used to formally check for the presence of ARCH effects is a Lagrange multiplier test based on the null hypothesis of no heteroskedasticity.

$H_0 : \alpha_1 = \alpha_2 = ... = \alpha_p = 0$
$H_1 : \alpha_1 \neq \alpha_2 = ... \neq \alpha_p \neq 0$

The test statistic can be formulated as

$$TR^2 \rightarrow \chi^2_p \tag{4.35}$$

where T denotes the length in the time series of the residual and R^2 is the coefficient of determination in the auxiliary regression

$$\hat{\varepsilon}^2_t = \alpha_0 + \alpha_1 \hat{\varepsilon}^2_{t-1} + ... + \alpha_p \hat{\varepsilon}^2_{t-p} + u_t. \tag{4.36}$$

Given H_0 is true, the TR^2 statistic has chi-squared density with p lags.

4.3 Model selection

We will below present our three models of choice. The first one being the model that helps us answer the first hypothesis and determine the impact of the COVID-19 pandemic on financial market behavior. The second and third models makes it possible for us to analyze the dynamics across the key global economies during the crisis period and helps us determine whether the cross-correlation between the indices has been stable throughout the pandemic. All models will be scrutinized, and all assumptions and known weaknesses are discussed.

4.3.1 GJR-GARCH

The implementation of univariate time-series models when modelling financial variables based on previous knowledge and information, is a practice that has been done both in linear and non-linear situations in finance. For instance, it has been shown that the simpler autoregressive integrated moving average (ARIMA) model is convenient in the context of modelling commodity prices in the short term (Chu, 1978). The ARIMA model is basically an integrated autoregressive (AR) process version of the more familiar ARMA model. Following Brooks (2014, pp. 256-268), we can first model the ARMA(p, q) as

$$\gamma_t = \mu + \phi_1 \gamma_{t-1} + \phi_2 \gamma_{t-2} + ... + \phi_p \gamma_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{4.37}$$

where it states that the value of our time series at time t is linearly dependent on the previous values combined with an ε_t white noise error term. We also observe that the model is constructed from the characteristics in the AR of order p, which can be expressed as,

$$\gamma_t = \mu + \sum_{i=1}^{p} \phi_i \gamma_{t-i} + \varepsilon_t \tag{4.38}$$

and the moving average (MA) to the q'th order which can be expressed as,

$$\gamma_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{4.39}$$

This is an example of models that are linear in nature, meaning we can only apply them in a linear context. However, the relationship between variables from a financial point of view appears to be non-linear (Campbell, Lo, & MacKinlay, 1997, p. 467). Simplistic models such as equation 4.37 will therefore not be adequate to explicate the relationships that is needed in this thesis. Modelling stock return volatility require that we need a model that is non-linear in variance. Engle (1982) presented such a model in his autoregressive conditional heteroskedasticity (ARCH) model when he modelled the volatility in inflation rate in the U.K. Taking equation 4.38 into consideration, we can first assume that the return on an asset can be modelled as an AR(1) model,

$$\gamma_t = \mu + \phi_1 \gamma_{t-1} + \varepsilon_t \tag{4.40}$$

where ε_t is i.i.d with mean zero and variance σ^2. Assuming that the variance in error is constant in time is another way of concluding for homoskedasticity in the errors. However, Engle (1982) argued for the opposite with respect to financial markets. Financial volatility is characterized with random periods where the variation is high and then followed by random periods where it is low. Thus, taking heteroskedastic behavior into consideration. Assuming that the conditional variances of a random error term, ε_t, is equal to the conditional expected value of the squared error, that is,

$$\sigma_t^2 = \mathrm{Var}(\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2}, ...) = E[(\varepsilon_t - E(\varepsilon_t))^2|\varepsilon_{t-1}, \varepsilon_{t-2}, ...]. \tag{4.41}$$

In addition, if we assume that $E(\varepsilon_t) = 0$, we can write equation 4.41 as,

$$\sigma_t^2 = \mathrm{Var}(\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2}, ...) = E[\varepsilon_t^2|\varepsilon_{t-1}, \varepsilon_{t-2}, ...]. \tag{4.42}$$

We can now model the Engle (1982) ARCH by allowing our σ_t^2 to be contingent on the squared error value of the previous period. Also note here that in the original derivation by Engle (1982), the conditional variance of the error term is denoted as $h(t)$ instead of the use of the sigma notation σ_t^2 which we utilize in the remainder of the thesis.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{4.43}$$

That is, taking only the conditional variance into account, the ARCH(1) model which is characterized by only allowing the conditional variance to be contingent on one lagged square error $(t-1)$. Including the conditional mean, noting that the mean is a description of the dependent variable's, γ_t, variation in time, we can also model for q lags of squared errors which gives us the more general ARCH(q). An example of a full ARCH(q) model will look like this,

$$\gamma_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_t^2) \tag{4.44}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + ... + \alpha_q \varepsilon_{t-q}^2 \tag{4.45}$$

(Brooks, 2014, p. 424). The ARCH model has though come under some scrutiny. First of all, it is assumed that shocks, no matter if they are positive or negative, have the same effect on volatility. However, this is not the same in practice as it is well known that an asset price responds different to positive and negative shocks (Alessi & Kerssenfischer, 2019). Another limitation of the ARCH was that it was too constrained and therefore became a highly inadequate model to use in higher orders. As a response to this, both Bollerslev (1986) and Taylor (1986) developed the more flexible GARCH model.

Allowing for lagged conditional variances, the GARCH(1,1) model can be modelled in the simple form of,

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4.46}$$

$$y_t = \mu + \varepsilon_t \tag{4.47}$$

where the conditional variance σ_t^2 is composed of an offset term ω, and measurements of ARCH effects (α) and GARCH effects (β). The α-effects estimates the impact of previous periods volatile shocks in the present period, while the β-effects measures the time it takes for the ARCH effects to die out. Therefore, a higher α implies a greater sensitivity to contemporary information and a higher β indicates a longer amount of time for the ARCH effects to disappear. The sum of these two therefore provide us with an idea of the persistence, and a higher $\alpha + \beta$ value would indicate greater volatility persistence. The corresponding conditional mean, y_t, is also presented. It can be shown that this short and simple, model is equal to the ARCH model of infinite order, i.e. ARCH(∞). In light of this fact, one might refer to the GARCH(1,1) as a parsimonious model.

Proof. From equation 4.46 we have

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4.48}$$

Subtract 1 from each t

$$\sigma_{t-1}^2 = \omega + \alpha_1 \varepsilon_{t-2}^2 + \beta\sigma_{t-2}^2 \tag{4.49}$$

Subtract 1 from each t again

$$\sigma_{t-2}^2 = \omega + \alpha_1 \varepsilon_{t-3}^2 + \beta\sigma_{t-3}^2 \tag{4.50}$$

Insert equation 4.49 in to 4.48.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta\left(\omega + \alpha_1 \varepsilon_{t-2}^2 + \beta\sigma_{t-2}^2\right) \tag{4.51}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \omega\beta + \alpha_1\beta\varepsilon_{t-2}^2 + \beta^2\sigma_{t-2}^2 \tag{4.52}$$

Insert 4.50 in 4.52

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \omega\beta + \alpha_1\beta\varepsilon_{t-2}^2 + \beta^2\left(\omega + \alpha_1 \varepsilon_{t-3}^2 + \beta\sigma_{t-3}^2\right) \tag{4.53}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \omega\beta + \alpha_1\beta\varepsilon_{t-2}^2 + \omega\beta^2 + \alpha_1\beta^2\varepsilon_{t-3}^2 + \beta^3\sigma_{t-3}^2 \tag{4.54}$$

$$\sigma_t^2 = \omega\left(1 + \beta + \beta^2\right) + \alpha_1\varepsilon_{t-1}^2\left(1 + \beta\mathbb{L} + \beta^2\mathbb{L}^2\right) + \beta^3\sigma_{t-3}^2 \tag{4.55}$$

Reinserting the lag of σ_t^2 an infinite amount of times, we obtain:

$$\sigma_t^2 = \omega(1 + \beta + \beta^2 + \ldots) + \alpha_1\sum_{i=1}^{\infty}(\beta^{i-1}\varepsilon_{t-i}) \tag{4.56}$$

□

which gives proof to the proposition that a GARCH(1,1) model has a long memory and is sufficient enough to capture the necessary volatility clustering in the data, hence there are not many scenarios where the GARCH is entertained in higher orders (Brooks, 2014, p. 430). It is important to note here that although a strong model, the GARCH model has its own drawbacks too. For stationarity to exist in the conditional variance of our ε_t, there has to be a corresponding finite unconditional mean. Assuming that the unconditional mean of σ_t^2 is equal to the unconditional variance, our ε_t will have a finite unconditional variance which will suggest weak stationarity. The unconditional variance in a GARCH(1,1) can be modelled as,

$$\sigma^2 = \frac{\omega}{1 - (\alpha_1 + \beta)} \tag{4.57}$$

So, we can see that the unconditional variance is not changing over time when $\alpha_1 + \beta < 1$, i.e. there is stationarity in the variance, hence the logical intuition for $\alpha_1 + \beta > 1$ will be non-stationarity. It is though important to distinguish the possibility of $\alpha_1 + \beta = 1$ from the non-stationarity option. This scenario means that the existence of unit-roots is present, i.e. patterns in a time-series that are unpredictable (e.g. a random walk with drift).

As with most models, there are situations where the model at hand is not sufficient for capturing all salient features of the process to be modeled. This marked the extension of different models in the GARCH-family tree. The differentiated models are all derived from the original GARCH principles, the root of the tree, but then take a new direction by adjusting the model in order to account for different scenarios that the standard "vanilla" GARCH does not account for. One of the limitations with the vanilla GARCH model is based on the relationship between good and bad news. Black (1976) showed evidence for a negative correlation between stock returns and the volatility in return. Meaning that unlike previous beliefs, the volatility appears to rise more heavily in events of "bad news" than they would sink when "good news" occurred. When dealing with financial equity returns, this negative correlation can be ascribed by leverage effects. This assumption will however not be captured by the standard GARCH since it only assumes that the magnitude of the excess returns, not positive nor negative signs, has an effect on the conditional volatility. Therefore, in order to address asymmetries in periods of bad news, Glosten et al. (1993) introduced the GJR-GARCH model which is an extension of the standard GARCH but with an additional term to account for leverage effect. The general GJR-GARCH is defined as

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \tag{4.58}$$

where γ is the leverage effect of positive news parameter meaning that in the output reported by Stata, a negative and significant sign will be interpreted as further evidence of Black (1976) notion of bad news being more influential than good news. Furthermore in the GJR-GARCH conditional variance equation, we have an indicator variable I_{t-1} which equals to 1 if the previous shocks are negative. That is,

$$I_{t-1} = \begin{cases} 1 & \text{if} \quad \varepsilon_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.59}$$

We see that if the past innovations are deemed not negative, that is if $\varepsilon_{t-1} \geq 0$, the GJR-GARCH is equivalent to the vanilla GARCH(1,1). In addition:

if $\gamma > 0$ bad news are more decisive on the volatility than positive news.
and
if $\gamma < 0$ positive news are more decisive on the volatility than negative news.

Note here that the phenomena of leverage effect is written to be present when $\gamma > 0$, but however, as we stated above, Stata will report this notion to us if the γ is estimated to be negative (and significantly different from zero). Although it is a highly technical model, the GJR-GARCH also comes with its own drawbacks. The model imposes bounds to make sure that the estimated volatility is positive, and setting these bounds can from a computational point of view be difficult. This can therefore be seen as a limitation when we want to adapt the model.

In order to measure the impact of the COVID-19 pandemic on financial market volatility, we include a new dummy variable to the GJR-GARCH model. For our new conditional variance equation, based on equation 4.58, we get

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \delta\text{COVID}_t \tag{4.60}$$

where COVID is our dummy variable that takes a value 0 for the pre-COVID-19 period and 1 in the one-time-for-all COVID-19 period. The pandemic impact will therefore be dependent on the existence of a parameter δ. That is,

$$\text{COVID} = \begin{cases} 1 & \text{if the date is 1 January 2020 - 31 December 2020} \\ 0 & \text{otherwise} \end{cases} \tag{4.61}$$

On that account, our first hypothesis will not only just be evaluated based on the δ COVID-19 coefficient, but also the α parameter in the GJR-GARCH. First, if the COVID-19 coefficient in the conditional variance equation is estimated to be negative (and significant), we would have evidence of a correlating relationship between the pandemic period and lower volatility in the financial markets. This also means that a positive statistical significant COVID-19 coefficient would indicate an increasing relationship, i.e. higher volatility. Additionally, if the estimated ARCH effects have increased significantly in the one-time-for-all COVID-19 period, contrary to the period before, we would have evidence to reject the null and argue that the indices were more sensitive towards new information in the COVID-19 phase than before.

4.3.2 Dynamic conditional correlation (DCC) model

The univariate GARCH models presented above are not adequate to use when we want to analyze the dynamics across multiple assets. When assessing a pandemic effect on global financial indices, we need to take the correlation of these selected indices into account. Therefore, extending the univariate GARCH models to multivariate GARCH models (MGARCH) is the most logical thing to do. The application of these MGARCH models have been a widely utilized framework in financial literature. Bollerslev (1990) proposed a constant conditional correlation GARCH (CCC-GARCH) model where the conditional variance-covariance matrix H_t is based on the product of two diagonal matrices D_t of univariate GARCH processes and a constant conditional correlation matrix R of ε_t innovations. Following Boffelli and Urga (2016, pp. 149-174), we can formulate the CCC-GARCH and then its corresponding dynamic versions below. Starting with the CCC-GARCH, we have

$$H_t = D_t R D_t = \left(\rho_{ij}\sqrt{\sigma^2_{ii,t}\sigma^2_{jj,t}}\right) \tag{4.62}$$

$$D_t = \begin{pmatrix} (\sigma^2)^{1/2}_{11,t} & 0 & \dots & 0 \\ 0 & (\sigma^2)^{1/2}_{22,t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & (\sigma^2)^{1/2}_{mm,t} \end{pmatrix}$$

$$R = \begin{pmatrix} 1 & \rho_{12} & \dots & \rho_{1m} \\ \rho_{21} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \rho_{2m} \\ \rho_{m1} & \rho_{m2} & \dots & 1 \end{pmatrix}$$

The problem with the CCC model is the assumption that the conditional correlations are deemed to be *constant*. After estimating the CCC model, for example on the two assets gold and silver, you would obtain a set of values that exhibits the correlating relationship between them. The value that is observed indicates therefore that the correlation is constant over time, and if we visualized it, the chart would show a straight line. This, however, is quite unusual in practice. In reality, correlations appear to behave in a dynamic way, and both Engle (2002) and Tse and Tsui (2002) proposed a more dynamic approach to the CCC model, coining the dynamic conditional correlation Engle (DCCE) model and dynamic conditional correlation Tse and Tsui (DCCT) model, respectively. Although both models were published almost simultaneously, the two of them differ in the formulation of the conditional correlation matrix. Engle (2002) believed that the correlations were time dependent instead of constant. More specifically, taking equation 4.62 in to account, Engle (2002) formulated it as

$$H_t = D_t R_t D_t \tag{4.63}$$

where R_t is a correlation matrix which takes the product of two diagonal matrices:

$$R_t = \text{diag}\left(q^{-1/2}_{11,t}, q^{-1/2}_{22,t}, ..., q^{-1/2}_{mm,t}\right) \mathrm{Q}_t \text{diag}\left(q^{-1/2}_{11,t}, q^{-1/2}_{22,t}, ..., q^{-1/2}_{mm,t}\right) \tag{4.64}$$

and the elements of Q_t are assumed by Engle (2002) to follow a GARCH(1,1) process:

$$Q_t = V_{ij} + \lambda_1 \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}}\left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}}\right)' + \lambda_2 Q_{t-1} \tag{4.65}$$

where V_{ij} is an unconditional correlation matrix, the two time-invariant parameters, λ_1 and λ_2 are scalars which takes the same values for every considered time-series meaning they all follow the same dynamic, and the error innovations are vectors. We also note here that the matrix is positive semidefinite as long as the time-invariant parameters sum is less than 1, i.e. stationarity. That is, $\lambda_1 + \lambda_2 < 1$. In the DCCT model, contrarily to the DCCE's idea of time dependent conditional correlations, Tse and Tsui (2002) believed them to be a weighted sum of past observations. Relying on the same decomposition as in equation 4.63, Tse and Tsui (2002) assumed R_t to follow an ARMA process instead:

$$R_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \Psi_{t-1} + \lambda_2 R_{t-1} \tag{4.66}$$

where they consist of the same stationarity conditioned time-invariant parameters, λ_1 and λ_2, and the R correlation matrix as in the DCCE model, but now also the standardized residuals correlation matrix Ψ which takes the form

$$\Psi_{ij,t-1} = \frac{\sum_{l=1}^{L} \frac{\varepsilon_{i,t-l}}{\sqrt{\sigma^2_{ii,t-l}}} \frac{\varepsilon_{j,t-l}}{\sqrt{\sigma^2_{jj,t-l}}}}{\sqrt{\sum_{l=1}^{L} \left(\frac{\varepsilon_{i,t-l}}{\sqrt{\sigma^2_{ii,t-l}}} \right)^2 \sum_{l=1}^{L} \left(\frac{\varepsilon_{j,t-l}}{\sqrt{\sigma^2_{jj,t-1}}} \right)^2}} \tag{4.67}$$

where $L \geq m$ warrant that the matrix is positive semidefinite. For correlation testing, we first need to fit both models on the same parameters in our data set. The model of our choice will then be the one that yields the most sufficient results in the goodness of fit tests. Based on this, we will then obtain the conditional correlations across all indices from our specific model. These conditional correlations will then be the base of a two-regime Markov switching dynamic regression model.

4.3.3 Markov switching model

The Markov switching model by Hamilton (1989), often called the regime switching model, is an often used and popular alternative to more traditional non-linear models. The Markov switching model allows us to analyze time series that shift over a collection of finite states (regimes). Assuming that they follow a Markov chain process, the model lets us estimate more complex dynamic patterns between these regimes. Assuming the regimes are defined by an unobserved random variable s_t, the probability, $\mathbf{P}$, of a shift from regime i to regime j is given by

$$\mathbf{P}(s_t = j, s_{t-1} = i) = p_{ij}$$

which can be stored in the transition matrix,

$$\mathbf{P} = \begin{pmatrix} p_{ii} & p_{ij} \\ p_{ji} & p_{jj} \end{pmatrix}, \quad \sum_j p_{ij} = 1$$

Allowing for a faster adjustment after the process changes regimes, the Markov switching dynamic regression (MSDR) can be formulated as,

$$y_t = \mu_s + \mathbf{x_t}\alpha + \mathbf{z_t}\beta_s + \varepsilon_s, \quad \varepsilon_s \sim \mathcal{N}(0, \sigma_s^2) \tag{4.68}$$

where the dependent variable y_t is computed by a regime dependent intercept μ_s, a vector $\mathbf{x_t}$ of exogenous variables with regime invariant coefficients α, which may contain lags of the dependent variable y_t, and a vector $\mathbf{z_t}$ of exogenous variables with regime-dependent coefficients β_s, which also may contain lags of y_t, and ε_s is i.i.d. (Boffelli & Urga, 2016, pp. 244-250). For our thesis, we will fit the correlations between two given countries on the two-regime model

$$\rho_t = \mu_s + \varepsilon_t \tag{4.69}$$

where μ_s is a regime-dependent constant. To estimate the transition matrix corresponding to the correlation movement between each regime and the average duration in each period, we follow the formula by Hamilton (1989). Assuming that the transition between two regimes are governed by a first-order Markov process,

$$Prob\,[S_t = 1 | S_{t-1} = 1] = p \tag{4.70}$$

$$Prob\,[S_t = 0 | S_{t-1} = 1] = 1 - p \tag{4.71}$$

$$Prob\,[S_t = 0 | S_{t-1} = 0] = q \tag{4.72}$$

$$Prob\,[S_t = 1 | S_{t-1} = 0] = 1 - q \tag{4.73}$$

where S_t is a random variable taking the values 0 or 1 indicating the unobserved state (regime) of the system. Using the maximum likelihood parameter, we can then estimate the expected average duration for each regime. Conditioned that we are at regime 0, we can compute the expected average duration it takes to get to regime 1 as

$$\sum_{k=1}^{\infty} kq^{k-1}(1-q) = (1-q)^{-1} \tag{4.74}$$

which we also can see is the inverse of of equation 4.73. In order to visualise the patterns of regime-switches in the conditional correlation, that is we want to see when they move towards a turmoil period (and how long this lasts) and then the movement towards the tranquil period, we need to conduct a forecasting process on the unobserved regimes. Hamilton (1989) proposed both a nonlinear filter and smoothed approach to this, where the basic nonlinear filter only allows for previous (and today's) data in the sample to be used in the estimation, while the smoothing algorithm utilizes all information in the sample, i.e. both past and future data. The latter one gives us more fluid and hence, "smoother", regime patterns.

Contrary to previous work by Sclove (1983), the algorithm by Hamilton (1989) is a series of conditional probabilities, as opposed to a maximization of an imputed historical sequence of the unobserved state s. Furthermore, Hamilton (1989) constrained the test for two regimes and allowed for autocorrelation to exist. Following Mamula (2016), the inference of the nonlinear filter can be formulated as the following. If we first let

$$\boldsymbol{\xi}_{jt} = Pr\left(s_t = j|\Omega_t; \theta\right) \tag{4.75}$$

note here that j indexes the given regimes 1 or 2 and $\Omega = (y_t, y_{t-1}, ..., y_1; y_0)$ is the information that we have available at the time t and parameter vector θ. From this, using the steps of the Hamilton (1989) filter, at time 1, we first initialize an expectation of the probabilities in each regime. That is,

$$\boldsymbol{\xi}_{1|0} \tag{4.76}$$

then, we take the information available at time 1 to update this previous expectation. That is,

$$\boldsymbol{\xi}_{1|1} = \frac{1}{\boldsymbol{\xi'}_{1|0} f_t} \boldsymbol{\xi}_{1|0} \odot f_t \tag{4.77}$$

where $\odot$ indicates an element-wise multiplication. Moving on from here, we take the transition probabilities and perform step 1, but with respect to time 2, i.e. $\boldsymbol{\xi}_{2|1} = P\boldsymbol{\xi}_{1|1}$, and continue these steps until $t = T$.

For the smoothing probabilities, we can follow an algorithm by C.-J. Kim (1991):

$$\boldsymbol{\xi}_{t|T} = \boldsymbol{\xi}_{t|t} \odot \{\mathbf{P}'(\boldsymbol{\xi}_{t+1|T}(\div)\boldsymbol{\xi}_{t+1|t})\} \tag{4.78}$$

where $\boldsymbol{\xi}_{t|T}$ is a k x 1 vector that consists of conditional probabilities estimated from the probability equation $Pr(s_t = i|y_T; \boldsymbol{\theta})$, which expresses that the probability of being in the $i'th$ regime, $s_t = i$, is given by observations through time T. $(\div)$ indicates that there is an element-by-element division and, by backward iteration, the smoothed probabilities are obtained from $t = T-1, T-2, ..., 1$ (StataCorp, 2013, p. 461).

The DCC models have however come under some scrutiny. The assumption that the two time-invariant parameters, λ_1 and λ_2, are scalars that take the same values for every considered time-series, for the DCCE model in equation 4.65 and equation 4.66 for the DCCT, is quite infeasible, especially when we are dealing with a multiple amount of assets. In order to moderate this assumption, Cappiello, Engle, and Sheppard (2006) presented a richer and more flexible asymmetric generalized dynamic conditional correlation (AGDCC) model. The λ parameters are here substituted with two matrices A and B that consist of coefficients for each specific element of Q. In addition, Colacito, Engle, and Ghysels (2011) adressed the DCC assumption of a constant covariance matrix regardless of the time-period. They argued that this notion was quite unrealistic, and they do have a point when the data time-period is stretching over multiple decades, and introduced a mixed data sampling (DCC-MIDAS) model based on previous work by Ghysels, Santa-Clara, and Valkanov (2004) and Ghysels, Sinko, and Valkanov (2007). This model gave researchers the opportunity to combine data samples from different periods of time, e.g. using both yearly and quarterly frequency in the data set.

Nevertheless, in terms of our second hypothesis, by utilizing these DCC models for our data we will be presented with a graphical chart of our estimated conditional correlations. The estimated filtered and smoothed regime probabilities, based on a Markov switching model, gives us clear observable periods of correlation regime switches. Which of the periods that denotes the high and low correlation regime will also be estimated. This is highly useful since it lets us clearly observe if the dynamic correlations are stable, or if they have significantly differed during the pandemic year of 2020. If the latter proves to hold, we would reject the null of the second hypothesis.

4.4 Model estimation

For determining the goodness of fit of our statistical models, we need to validate that the parameters are sufficient enough to use. The goodness of fit of a statistical model indicates how well the data that has been predicted by our model can be compared to the actual observations that we would expect to see, so, logically, in order to be able to draw any form of beneficial conclusions of our research, the parameters that we estimate should hold a certain level of credibility.

4.4.1 Maximum likelihood

For statistical measurements, the concept of the likelihood is often visited, and the likelihood function plays an important role when we are dealing with estimating unknown parameters. From Dendukuri (2020), we can define the likelihood function as

$$L(\theta) = L(\theta|x_1, x_2, ..., x_n) = f(x_1, x_2, ..., x_n|\theta) \tag{4.79}$$

where $X_1, X_2, ..., X_n$ have a joint density function $f(X_1, X_2, ..., X_n|\theta)$ given $X_1 = x_1, X_2 = x_2, ..., X_n = x_n$ is observed. Also note here that θ indicates a parameter vector existing in the parameter space Θ. Given that the two terms *likelihood* and *probability* are often used synonymously in everyday language, we need to carefully distinguish between the two of them in statistical theory. The likelihood function is not a probability distribution function, but it is more of a measurement of a statistical model's goodness of fit. Given by Rossi (2018), the Law of Likelihood below highlight the significance of the likelihood function:

> Let $X_1, ..., X_n$ be a sample of i.i.d. random variables with common probability density function $f(x; \overrightarrow{\theta})$ and parameter space Θ. For $\overrightarrow{\theta} \in \Theta$, the larger the value of $L(\overrightarrow{\theta})$ is, the more $\overrightarrow{\theta}$ agrees with the observed data. Thus, the degree to which the information in the sample supports a parameter value $\overrightarrow{\theta_0} \in \Theta$, in comparison to another value $\overrightarrow{\theta_1} \in \Theta$, is equal to the ratio of their likelihoods $\Lambda(\overrightarrow{\theta_0}, \overrightarrow{\theta_1}) = \frac{L(\overrightarrow{\theta_0})}{L(\overrightarrow{\theta_1})}$. In particular, the information in the sample is in better agreement with $\overrightarrow{\theta_1}$ than $\overrightarrow{\theta_0}$ when $\Lambda < 1$ and vice versa for $\Lambda > 1$. (p. 223)

So, we now get an idea of how the likelihood function operates as an indicator of a statistical model's ability to deal with a set of data. As was the case with the daily returns, for convenience, we also here want to deal with the logarithmic form of the likelihood. There are several reasons for this. Firstly, it can be argued that it is more painless to deal with logarithmic asymptotic properties of sums instead of density products since you have the opportunity to use Central Limit Theorem and Laws of Large Numbers for an analysis, and secondly, density products coincide frequently meaning they are not numerically stable. A logarithmic transformation here can on that account be beneficial since sums are from a numerical point of view more stable (Taboga, 2017). Hence, the log-likelihood is taken. With that being said, we can state that the purpose of maximum likelihood estimation, we denote it as $\mathcal{L}(\theta)$, is to estimate the optimal way to fit a distribution to a set of data by maximizing a log-likelihood function, denoted $L(\theta)$. From Rossi (2018), the maximum likelihood principle below highlight this:

> Given a random sample $X_1, ..., X_n$ and a parametric model $f(x_1, ..., x_n; \theta)$, choose as the estimator of θ, say $\hat{\theta}(\overrightarrow{X})$, the value of $\theta \in \Theta$ that maximizes the likelihood function. (p. 226)

So, we can here see that by the Law of Likelihood, the value of this unknown parameter will be equal to a maximization of the log-likelihood function, i.e. solving

$$\mathcal{L}(\theta) = \max_{\theta \in \Theta} L(\theta) \tag{4.80}$$

Further, to give an example of how we conduct a maximum likelihood estimation, we first need to define a log-likelihood function of interest. Following Jakobsen (2019), we can formulate a log-likelihood function for our plain vanilla GARCH model

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4.81}$$

$$y_t = \mu + \varepsilon_t \tag{4.82}$$

which is the simplest conditional variance and corresponding conditional mean equation for a GARCH(1,1) process. Assuming that the errors are i.i.d.

$$\varepsilon_t \sim \mathcal{N}(0, \sigma_t^2) \tag{4.83}$$

presents us with the option to write the joint distribution as

$$f(\varepsilon_1, \varepsilon_2, ...\varepsilon_t; \theta) \tag{4.84}$$

Repeating the notion that this distribution is the multiple of the conditional and marginal density, we get the likelihood function

$$\begin{aligned} f(\varepsilon_0, ..., \varepsilon_T; \theta) &= f(\varepsilon_0; \theta) f(\varepsilon_1, ..., \varepsilon_T | \varepsilon_1; \theta) \\ &= f(\varepsilon_0; \theta) \prod_{t=1}^{T} f(\varepsilon_t | \varepsilon_{t-1}, ..., \varepsilon_0, ; \theta) \\ &= f(\varepsilon_0; \theta) \prod_{t=1}^{T} f(\varepsilon_t | \varepsilon_{t-1}, ; \theta) \\ &= f(\varepsilon_0; \theta) \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{\varepsilon_t^2}{2\sigma_t^2}\right) \end{aligned}$$

which can be transformed to the log-likelihood function

$$L(\theta) = \sum_{t=1}^{T} \frac{1}{2} \left[-\log 2\pi - \log(\sigma_t^2) - \frac{\varepsilon_t^2}{\sigma_t^2} \right] \tag{4.85}$$

which then can finally be estimated by maximization, i.e. maximum likelihood. For the GJR-GARCH model, the log-likelihood function is similar but not quite as exact because of the introduction of the leverage effect dummy variable in equation 4.58. By definition, the maximum likelihood estimates will take the exact same values for all situations where $\varepsilon_{t-1} \geq 0$ since the additional dummy variable will take the value zero. However, for situations where the previous shocks are negative, the log-likelihood function will differ to account for this change in the conditional variance, but the principle remains the same. Assuming that the innovations are following a Gaussian distribution for observation t, we can formulate the MGARCH DCC log-likelihood function, L, as

$$L_t = -\frac{1}{2} m \log(2\pi) - \frac{1}{2} \log\left\{\det(\mathbf{R}_t)\right\} - \log\left\{\det(\sqrt{\mathbf{D}}_t)\right\} - \frac{1}{2} \tilde{\boldsymbol{\varepsilon}}_t \frac{1}{\mathbf{R}_t} \tilde{\boldsymbol{\varepsilon}}'_t \tag{4.86}$$

$\tilde{\boldsymbol{\varepsilon}'}_t = \mathbf{D}_t^{-1/2}$ is here a column matrix of standardized residuals that takes the dimensions of m x 1, where m is the number of rows, $\boldsymbol{\varepsilon_t} = \mathbf{y}_t - \mathbf{C}\mathbf{x}_t$ is the corresponding standardized residuals function where $\mathbf{y}_t$ is a column matrix of the dependent variables and $\mathbf{C}\mathbf{x}_t$ is a product of an m x k parameters matrix and a column matrix of independent variables (StataCorp, 2013, pp. 329 - 339). For the Markov switching model, the conditional log-likelihood function for a given value θ can be formulated as

$$L(\theta) = \sum_{t=1}^{T} \log f(y_t|\Omega_{t-1};\theta) \tag{4.87}$$

where the conditional density function, $f(y_t|\Omega_{t-1};\theta)$, is constructed for $t = 1, ..., T$, then computed by following the Hamilton (1989) filters and, furthermore, numerical optimized to obtain the maximum likelihood estimates (Piger, 2011, p. 194).

It is also possible to carry out a likelihood-ratio (LR) test based on the likelihood function. The LR test can be used to compare two or more restricted and unrestricted models at hand, keeping in mind that the test statistic is only appropriate if the two models are nested (Boffelli & Urga, 2016, p. 32). If not, we have to implement information criteria for model comparison. These criteria are dignified in subsection 4.4.2. Nevertheless, two models being nested means that one model has the opportunity to explain the other one, and more. More specifically, the second model can be interpreted as a restricted version of the first model, where the first model contains all the terms (and more) as the first one. The LR test can be defined as

$$\text{LR} = -2\left\{\ln \text{L}\left(\Psi\right) - \ln \text{L}\left(\Omega\right)\right\} \sim \chi^2_m \tag{4.88}$$

where Ψ denotes the set of parameters in the limited model with its log-likelihood $\ln \text{L}(\Psi)$ and Ω where $\ln \text{L}(\Omega)$ corresponds to the same in the complete model. The test statistic is also chi-squared distributed with m-degrees of freedom, given the null hypothesis of an equivalence in goodness of fit between the two models is true (Boffelli & Urga, 2016, p. 31).

4.4.2 Information criteria

For statistical model evaluation, the selected statistical models can also be evaluated based on information criteria to determine the best fitted one. An information criterion can be seen as a measurement of a statistical model based on its ability to explain the data through its complexity and quality. Both the Akaike (1974) information criterion (AIC) and the Bayesian information criterion by Schwarz (1978) (SBIC) are commonly used information criteria by researchers. The AIC and SBIC can in general both be defined as

$$\text{AIC}(k) = -2\ln\left(likelihood\right) + 2k \tag{4.89}$$

$$\text{SBIC}(k) = -2\ln\left(likelihood\right) + k\ln n \tag{4.90}$$

where k equals the number of parameters in the estimated model and n denotes the amount of observations (Jungeilges, 2020b). From the two definitions, we can see that the AIC penalizes each added parameter with a value of 2, while the SBIC uses the value of $\ln n$ as the punishment for each added parameter k. Apart from that, the two criteria are both set up to answer different goals and assumptions. In general, the AIC has a goal of finding the most satisfactory unknown model with a high dimensional reality, i.e. it seeks to find the best predictor. The SBIC is tailored to identity, and deals with finding the true model out of a group of models (Kellen, 2019). On this notion, the SBIC has by some been preferred over the AIC since it is a more consistent measure (Dziak, Coffman, Lanza, Li, & Jermiin, 2020). However, Kuha (2004) also argued in-favor of combining both the AIC and SBIC information criteria in order to find the most favourable models. In order to further comprehend the differences in these two information criteria, consider a case of model comparison between two nested models. In this particular case, Lewis, Butler, and Gilbert (2011), for instance, have shown that the information criteria are equal to the likelihood ratio test that we previously presented. In terms of our hypotheses, we wish to use the two criteria in two different contexts, each suited to a different purpose. Since we gave a justifiable reasoning for why the first hypothesis will only be answered using a singular GARCH model, we will only interpret the estimated AIC and SBIC values out from how far they differ from zero in each given sample period. For the second hypothesis, we presented several MGARCH models and the information criteria therefore give us the possibility to judge which of the models that fits our data best. The procedure here will be based around which of the models that minimizes the respective measure.

Chapter 5

Results

5.1 Estimated results

In the following sections we present our results with respect to each given hypothesis. Firstly, how the COVID-19 pandemic has affected the market volatility on our selected indices. For the second hypothesis, we performed a contagion analysis to analyse how the COVID-19 pandemic influenced the cross-correlation between the given indices. We have also estimated the transition probabilities and visualized the dynamic correlation through low and high correlation regimes.

5.1.1 Pandemic effect on market volatility

Tables 5.1 and 5.2 presents the estimated results based on model 4.60, taking both sample periods into consideration. For simplicity, we have assumed the innovations to all follow a Gaussian distribution.

Table 5.1: Results of GJR-GARCH in the pre-COVID-19 period

	S&P 500	S&P/TSX	DAX	FTSE 100	Nikkei 225	SSE
	Panel A: conditional variance equation					
$\hat{\omega}$	.0000037*	.000000969*	.00000305*	.00000432*	.00000562*	.000000548*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\alpha}$	.2877734*	.1240445*	.1393728*	.2325269*	.1923085*	.0461708*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\beta}$	.8053272*	.9100203*	.8999857*	.8283912*	.8419919*	.9463729*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\gamma}$	-.3054011*	-.1301029*	-.1355744*	-.253637*	-.1374858*	.0112603**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0470)
	Panel B: model diagnostics					
AIC	-14828.439	-15517.818	-13353.938	-14528.37	-12990.789	-12997.25
SBIC	-14800.234	-15489.613	-13325.733	-14500.164	-12962.584	-12969.044
Log-likelihood	7419.22	7763.909	6681.969	7269.185	6500.395	6503.625

Table 5.1 reports the estimated results of the GJR-GARCH in the pre-COVID-19 sample period (1 January 2012 - 31 December 2019). *P*-values are reported below each estimation. * indicates significance at 1% level, ** is significance at 5% level. Goodness - of - fit and information criterion are also reported.

First off, ω, represents the intercept term in the equation, i.e. the expected mean value of the model if all other coefficients are equal to zero. We see that for all indices, this value is significant at 1% level, and they all take values close to zero. We have ensured for stability in the parameters through their given p-values, and all of them are either significant at a 1% or 5% level.

Secondly, we have the measurements of ARCH effects (α) and GARCH effects (β). The α-effects estimates the impact of previous periods volatile shocks in the present period, while the β-effects measures the time it takes for the ARCH effects to die out. We see that for all indices, the ARCH and GARCH effects are positive and significant at 1% level. We can therefore interpret this as the volatility is likely to have an increasing response to new information, and the magnitude is more recognized within the S&P 500 than it is in the SSE.

As mentioned in the methodology, the leverage effect of positive news parameter, γ, is introduced in order to address asymmetries in periods of bad news. We can observe that the parameter takes a negative (and significant) value for all indices apart from the SSE. For the SSE, this can be interpreted as a contradiction to the notion of Black (1976), and that good news have a greater impact on returns than bad news. While for the other indices, we have evidence in favor of this notion, i.e. bad news being more influential than good news.

For model diagnostics, all the values seem reasonable. The information criteria and goodness - of - fit measurements are far from zero, which supports the use of the GJR-GARCH model.

Table 5.2: Results of GJR-GARCH in the one-time-for-all COVID-19 period

	S&P 500	S&P/TSX	DAX†	FTSE 100 †	Nikkei 225 †	SSE ¤
			Panel A: conditional variance equation			
$\hat{\omega}$	.00000986**	.0000072*	.0000547*	.000023**	.00000549*	.0000293*
	(0.0200)	(0.0070)	(0.0000)	(0.0240)	(0.0020)	(0.0000)
$\hat{\alpha}$	.56684061*	.80109189*	.92124314*	.53490929*	.1797271*	.117806**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0310)
$\hat{\beta}$	.62151926*	.56872453*	.51899715*	.68911477*	.89333137*	.6049758*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{\gamma}$	-.2639505***	-.57089743*	-.89784173*	-.49093886*	-.19923414*	.1219652***
	(0.0560)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0610)
$\hat{\delta}$	1.356049*	.6834718*	1.159205*	1.1155*	.2567229**	.4110857**
	(0.0000)	(0.0010)	(0.0000)	(0.0000)	(0.0180)	(0.0240)
			Panel B: model diagnostics			
AIC	-1487.6827	-1621.8861	-1377.8972	-1432.2861	-1527.5216	-1626.7661
SBIC	-1469.8601	-1604.0635	-1360.0746	-1414.4635	-1509.699	-1608.9435
Log-likelihood	748.8413	815.943	693.9486	721.1431	768.7608	818.3831

Table 5.2 reports the estimated results of the GJR-GARCH model in the one-time-for-all COVID-19 sample period (1 January 2020 - 31 December 2020). P-values are reported below each estimation. * indicates significance at 1% level, ** is significance at 5% level, *** is significance at 10% level, † indicates that an additional ARCH, GARCH and threshold ARCH (TARCH) term has been injected to obtain significance, and ¤ denotes one extra GARCH term on there again.

We have here introduced the COVID-19 dummy parameter, δ. We can first see that for all, the parameter takes a positive and significant value. We therefore have evidence of a relationship between the pandemic period and increasing market volatility. Regarding the statistical stability of all the other parameters, we can see that all p-values are significant, but that they vary through 1% to 10% level.

Furthermore, we notice that the ARCH effects have increased for all indices except for the Nikkei 225, and that the GARCH effects have decreased for all except the Japanese benchmark index. From the methodology we know that a higher α implies a greater sensitivity to contemporary information and a higher β indicates a longer amount of time for the ARCH effects to disappear. The sum of these two therefore provide us with an idea of the persistence, and a higher $\alpha + \beta$ value would indicate greater volatility persistence. Therefore, we could interpret this as for the Nikkei 225, in this period of higher uncertainty, the index was not as sensitive to COVID-19 news as the other ones. However, the time it took for the change in ARCH effects to die out was longer for the respective counterparts. The opposite will logically hold for the other indices, i.e. the pandemic year seemed to be recognized with higher, but short-lived, sensitivity to new information.

Additionally, from the model diagnostics, we observe that all information criteria and goodness - of - fit measurements have decreased. However, this is not something that needs to worry us since the AIC, SBIC and the log-likelihood are dependent on the length of the given time series. Moreover, an estimation of a shorter period in time is likely to yield a lesser result.

Since the conditional variances are our main study of interest in this sub section, we have further examined them by first estimating and then plotting their entire time-series. Comparisons have been done continent - to - continent in figure 5.1 below. Because the differences between the largest and smallest value were for some indices quite high, we log scaled the Y-axis in order to visualize the conditional variances in a more compact and convenient way. The green vertical line represents the separation point between the two sample periods.

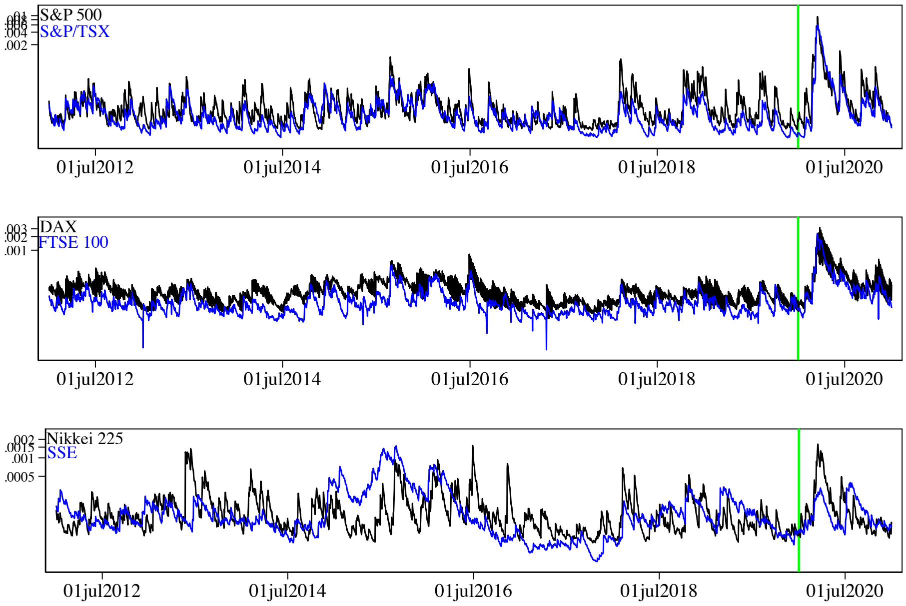

Figure 5.1: Estimated conditional variances

Quite evidently, we can observe that the conditional variances clearly behave in a dynamic manner and that there are periods of high volatile movements followed by low volatile movements. The North American and European markets almost move simultaneously, and the peaks in one market are often recognized with a peak to their continent counterpart index. Furthermore, what we will refer to as the "COVID-19 spike" from now, understandably distinguishes itself from the rest of the time-series plot in these two continents. However, we also notice that the behavior in the Asian markets is significantly different from the other indices. 2014 to early 2016 is recognized by severe turbulence in the Asian markets as a response to the Chinese stock market turbulence that began in 2015 and ended in 2016, and, logically, the Chinese based SSE felt the effects of this. Moreover, we notice a significant drop in the conditional variances after the market crash, and periods of sharp increases and drops leading up to the pandemic year of 2020. An interesting point here is that only, to an extent, the Nikkei 225 showed a similar COVID-19 burst in the conditional variances. Although China was the country where the coronavirus originated, and patient zero was discovered, the SSE actually had more volatile movement during the 2014 - 2016 crisis then they did during the whole of 2020.

5.1.2 Contagion analysis

As mentioned in the introduction, financial contagion, especially as a response to the GFC and other economically driven crises, have been a heavily researched topic over the years. We, however, deviate from that and want to test for contagion effects as a response to a health driven crisis such as the COVID-19 pandemic. In the literature review we distinguished contagion from simple interdependence, and showed that a modified definition of contagion by Wälti (2003) is useful for empirical work. Therefore, with that being said, we will follow the modification of Wälti (2003), and consider contagion as a significant *change* instead of only an increase specifically.

To decide which DCC model would yield the most appropriate results we have first conducted a likelihood-ratio test in order to discard the possibility of the non-dynamic model being possible to use, based on the methodology chapter. We have then compared each of the dynamic models up against each other.

Table 5.3: Likelihood-ratio test and conditional correlation model comparison

Model	Observations	LR test	Log-likelihood	df.	AIC	SBIC
CCC	1, 302	-	27629.37	39	-55180.73	-54979.04
DCCE	1, 302	0.0000	27643.91	41	-55205.81	-54993.77
DCCT	1, 302	0.0186	27633.35	41	-55184.7	-54972.66

Table 5.3 reports the likelihood-ratio test between each conditional correlation model presented in chapter 4, and information criterion estimation for each model. The sample period here is set from 1 January 2016 to 31 December 2020.

We see first that we most certainly can reject the null hypothesis of both the DCC and DCCT having an equivalence in goodness of fit with respect to the CCC model. Furthermore, we observe that the DCCE holds the highest log-likelihood and the lowest information criterion. Since the two models also hold the same number of parameters, we will choose the DCCE model as our model of interest for the rest of the analysis. We also note here that the sample period has been reduced by having the years prior to 2016 removed. The reasoning for this will become more clear at the end of this analysis when we present the filtered and smoothed regime probabilities figures. Since we want to clearly see the cross-market correlation in the year of 2020, the furthest part of the figure, it is reasonable to reduce the left-hand side of the figure.

In table 5.4 we present the estimated conditional correlation coefficients based on the DCCE model.

Table 5.4: DCCE correlation coefficients

	S&P 500	S&P/TSX	DAX	FTSE 100	Nikkei 225	SSE
S&P 500	1	.7248338*	.5954876*	.5219543*	.2177279*	.1473211*
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
S&P/TSX	.7248338*	1	.562348*	.5360581*	.2533668*	.1672369*
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DAX	.5954876*	.562348*	1	.7624373*	.3386639*	.2100764*
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
FTSE 100	.5219543*	.5360581	.7624373*	1	.328478*	.2221672*
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Nikkei 225	.2177279*	.2533668*	.3386639*	.328478*	1	.3610354*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
SSE	.1473211*	.1672369*	.2100764*	.2221672*	.3610354*	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Table 5.4 reports the estimated conditional correlation coefficients based on the DCCE model. *P*-values are reported below each estimation. * indicates that the coefficients are significant at 1% level.

First, we can see that all coefficients are positive and significant for all conventional levels. This can be interpreted as the indices tend to move similarly, and we see that the relationship between the DAX and FTSE 100 shows the highest estimated correlation of .76, followed by .72 for the two North American indices, that is, the S&P 500 and S&P/TSX, .60 and .56 for the S&P 500 and S&P/TSX versus the DAX, respectively. Compared to the FTSE 100, the cross-market linkage with the North American indices is estimated to be .52 for the S&P 500 and .54 for the S&P/TSX. We can also see that correlations are below the .5 threshold when we include the Asian market. The

Nikkei 225 have correlations in the range from .22 to .33 when evaluated with the other continents, while the SSE ranges from .15 to .22. The two Asian markets have a correlation corresponding to .36 between each other.

The estimated dynamic correlation patterns have been presented in figure 5.2. The green line also here defines the separation point between the two sample periods.

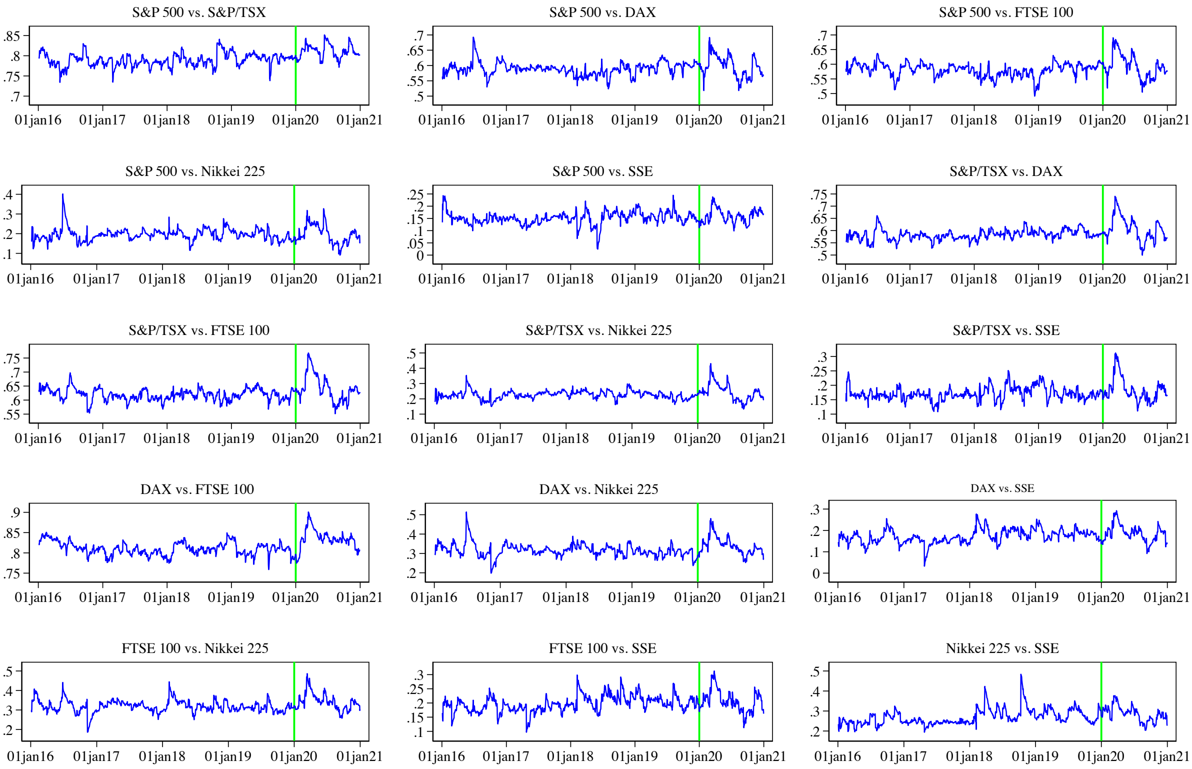

Figure 5.2: Estimated conditional correlations

The COVID-19 spike is clear and obvious for all comparisons and for some, the DAX evaluated with the FTSE 100 for example, the correlation even reaches an upper bound level of .9. The magnitude of each spike differs for all, and there is evidence towards that the COVID-19 stock market crash was more painful for the North American and European indices. However, the notion that markets tend to be more correlated in crisis situations as a result of shocks transmission is validated, to a degree, for all. All pairs except for the two Asian indices evaluated against each other have a COVID-19 spike equalling to a sample-period peak or closely related. The turbulence from the COVID-19 stock market crash seems to have been short-lived as we can observe a clear drop right after the initial spike.

Using the DCCE, we have in table 5.5 estimated the unobserved regime estimates.

Table 5.5: Regime coefficient estimates

	S&P 500	S&P/TSX	DAX	FTSE 100	Nikkei 225	SSE
			Panel A: regime 1 coefficients			
S&P 500	1	.7827981*	.5817107*	.5595172*	.174683*	.1371891*
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
S&P/TSX	.7827981*	1	.5796764*	.6107221*	.2099016*	.1658183*
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DAX	.5817107*	.5796764*	1	.8040503*	.3080782*	.1534438*
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
FTSE 100	.5595172*	.6107221*	.8040503*	1	.3051035*	.180922*
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)

Table 5.5 continued from previous page

	S&P 500	S&P/TSX	DAX	FTSE 100	Nikkei 225	SSE
Nikkei 225	.174683*	.2099016*	.3080782*	.3051035*	1	.2490761*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
SSE	.1371891*	.1658183*	.1534438*	.180922*	.2490761*	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
			Panel B: regime 2 coefficients			
S&P 500	1	.8118715*	.6218251*	.5988735*	.2234483*	.1743881*
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
S&P/TSX	.8118715*	1	.6462187*	.654364*	.2582777*	.2254587*
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)
DAX	.6218251*	.6462187*	1	.8370128*	.3714044*	.2059186*
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
FTSE 100	.5988735	.654364*	.8370128*	1	.357014*	.2277682*
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Nikkei 225	.2234483*	.2582777*	.3714044*	.357014*	1	.3135166*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
SSE	.1743881*	.2254587*	.2059186*	.2277682*	.3135166*	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Table 5.5 reports the conditioned regime 1, the steady more tranquil correlation, and the conditioned regime 2, the more aggressive and turmoil correlation period's coefficient estimates. *P*-values are reported below each estimation. * indicates that the coefficients are significant at 1% level.

Looking at the table, we first can observe that all coefficients are highly significant. Furthermore, we can see that for each coefficient in regime 1, the estimated corresponding regime 2 coefficient is increased, i.e. evidence in favor of higher correlation. On that account, we can therefore say that regime 1 is recognized as a lower more tranquil period of time where the cross-market correlation is low, while regime 2 is the more disturbed and turmoil time period, recognized with higher cross-market correlations. The regime probabilities have been visualized in figures A.1, A.2, A.3 and A.4 in the appendix.

In accordance with table 5.5, we have in table 5.6 presented the estimated transition probabilities and the duration in each given regime between the selected countries indices. The matrix is structured like this: the first estimated value, in the top left corner, is the estimated probability of being in regime 1 tomorrow given that we are in regime 1 today (P11). Then the estimated probability of being in regime 2 tomorrow given we are in 1 today (P12) and then the average duration in regime 1, i.e. X1 (given in amount of days). Hence, below there again, we have the probability of being in regime 1 tomorrow given that we are in regime 2 today (P21), the probability of being in regime 2 tomorrow given that we are in 2 today (P22) and the average duration in regime 2, i.e. X2. We can see from this that the sum of the two probabilities equals 1. For convenience, the country names are reported instead of the index names.

Table 5.6: Transition probabilities and average duration matrix

							U.S.							
	CAN			GER			U.K.			JAP			CHI	
.9817118	.0182882	54.68013	.9908019	.0091981	108.7181	.9723569	.0276431	36.17542	.9774756	.0225244	44.39631	.9724882	.0275118	36.34806
.0285378	.9714622	35.0412	.0313246	.9686754	31.9238	.0181184	.9818816	55.19238	.0312597	.9687403	31.99007	.0356666	.9643334	28.03745
							CAN							
	U.S.			GER			U.K.			JAP			CHI	
.9817118	.0182882	54.68013	.9945895	.0054105	184.8268	.9880359	.0119641	83.58367	.9801814	.0198186	50.45766	.9933525	.0066475	150.4326
.0285378	.9714622	35.0412	.0402874	.9597126	24.82163	.0261657	.9738343	38.21803	.0294768	.9705232	33.92497	.0461697	.9538303	21.65921
							GER							
	U.S.			CAN			U.K.			JAP			CHI	
.9908019	.0091981	108.7181	.9945895	.0054105	184.8268	.99191	.00809	123.6097	.9884733	.0115267	86.75485	.9809329	.0190671	52.4463
.0313246	.9686754	31.9238	.0402874	.9597126	24.82163	.0151282	.9848718	66.10182	.046676	.953324	21.4243	.0282958	.9717042	35.3409
							U.K.							
	U.S.			CAN			GER			JAP			CHI	
.9723534	.0276466	36.17076	.9880354	.0119646	83.58009	.9919097	.0080903	123.6044	.9862592	.0137408	72.77577	.9811904	.0188096	53.16446
.0181205	.9818795	55.1861	.0261661	.9738339	38.21736	.0151287	.9848713	66.09962	.0270108	.9729892	37.02221	.0303091	.9696909	32.99338
							JAP							
	U.S.			CAN			GER			U.K.			CHI	
.9774756	.0225244	44.39631	.9801803	.0198197	50.45488	.9884733	.0115267	86.75486	.9862592	.0137408	72.77577	.9859986	.0140014	71.42146
.0312597	.9687403	31.99007	.0294788	.9705212	33.92274	.0466779	.9533221	21.42342	.0270108	.9729892	37.02221	.0259991	.9740009	38.46288
							CHI							
	U.S.			CAN			GER			U.K.			JAP	
.9724882	.0275118	36.34806	.9933518	.0066482	150.4164	.9809313	.0190687	52.44199	.9811904	.0188096	53.16446	.9859986	.0140014	71.42146
.0356666	.9643334	28.03745	.0461713	.9538287	21.65849	.0282996	.9717004	35.33619	.0303091	.9696909	32.99338	.0259991	.9740009	38.46288

Table 5.6 reports the estimated transition probabilities and average duration matrix. The matrix is structured as the first estimated value, in the top left corner, is the estimated probability of being in regime 1 tomorrow given that we are in regime 1 today (P11), then the estimated probability of being in regime 2 tomorrow given we are in 1 today, i.e. P12 and then the average duration in regime 1, i.e. X1 (given in amount of days). Hence, below there again, we have the probability of being in regime 1 tomorrow given that we are in regime 2 today (P21), the probability of being in regime 2 tomorrow given that we are in 2 today (P22) and the average duration in regime 2, i.e. X2. The regime probabilities are also estimated through the predicted conditional correlation, from a DCCE model, between the given country in **bold**, and the respective countries below.

Starting with the S&P 500 (U.S.), we can first interpret the relationship with the S&P/TSX (CAN). We observe first that the probability of being in regime 1 tomorrow, given that we are there today, is approximately 98.17%. Furthermore, the probability of a regime change happening tomorrow, i.e. we move to regime 2 tomorrow given that we are in regime 1 today, is approximately 1.83%. Here we also have estimated that the average duration of regime 1 is computed to be around 55 days. Additionally, the S&P 500 vs. S&P/TSX matrix tells us that the probability of a regime change happening tomorrow if we are in the turmoil regime 2 today is roughly 2.85%, the probability of no regime change happening tomorrow, given that we are in regime 2 today, is more or less 97.15% and this regime is estimated to have an average duration just about 35 days. From this we can observe that the two indices correlation were, for the most part, tranquil. This is further evident when we estimated the regime probabilities with the DAX (GER). Here we could say that the two indices had a 99.08% chance of being in regime 1 tomorrow, given that they were there today. Additionally, a regime switch in this incident equalled to roughly 0.92%. This is further justified with the average duration in regime 1 being almost 109 days. Moreover, assuming we are in regime 2, the probabilities are approximately 3.13% and 96.87% of being in regime 1 and 2 tomorrow, respectively. In this condition, the average duration of regime 2 is estimated to be roughly 32 days. Interestingly, this relationship where regime 1 dominates regime 2 seems to change when we correlate the S&P 500 against it counterpart FTSE 100 (U.K.). First off, standing in regime 1 today, the probability of no change and regime switch tomorrow is given as 97.24% and 2.76%, respectively. From a regime 2 point of view, the results are estimated to be 1.81% and 98.19%. Notice here that the average durations are primarily in favor of the more turmoil regime, that is 55 vs. 36 in favor of regime 2. For the Asian countries, it appears that there are more in - and out movement between the regimes. Starting with the Nikkei 225 (JAP), the corresponding average durations are estimated to be very close to each other. That is, roughly 44 and 32 days in favor of the tranquil regime. Additionally, P11 is here 97.75%, P12 is more or less 2.25%, P21 3.13% and P22 96.87%. Meanwhile, with the SSE (CHI), the durations are even closer with only 8 days differentiating them in average. Here regime 1 is also more dominant, and P11 is estimated to be 97.25%, with a corresponding P12 equalling 2.75%. Finally, P21 has an estimated value of 3.57% and P22 is 96.43%.

Moving on to the S&P/TSX, we have already elaborated the correlating probabilities with respect to the S&P 500 above. Logically, the correlation between a country x vs. y is equal to the inverse of y vs. x. Therefore, looking at the relationship with the DAX, we also exhibit a similar relationship as we did with the other North American country vs. the DAX. P11 is here estimated to be over 99%, while P12 takes the value of 0.54%. The average duration for regime 1 and 2 is approximately 184 and 24 days, respectively, while P21 takes the estimate 4.03% and P22 95.97%. In our simulation, this average duration exhibited the largest differences in average days. There seems to be some evidence that the FTSE 100 contributes more to regime 2 than the other indices. We have already seen that, for the S&P 500, this regime was actually more dominant with respect to the FTSE 100. Although not the same result, we do have evidence of the FTSE 100 having more magnitude with respect to the S&P/TSX. P11, P12 and the average duration takes the corresponding estimates of 98.80%, 1.20% and 83 days. While on the other hand, with respect to regime 2, we obtained 2.62%, 97.38% and 38 days. If we foreshadow a little bit, we can see that, just as the S&P 500, both of these two indices have longer periods of disorder with the FTSE 100, than they do with the other. We can therefore briefly digest the remaining probabilities here. P11 with respect to Nikkei 225 has an estimated value of 98.02%, P12 1.98%, P21 2.95% and P22 97.05%. The average regime durations are 50 and 34 days, with respect to the first regime. SSE's estimates exhibited the second largest difference in average regime durations. 150 days in favor of regime 1, contrary to 22 for regime 2, is a staggering result. P11 took a value of 99.33%, while P12 estimated to be 0.67%, i.e. the probability of a turmoil period to exist tomorrow if today was calm, is not far from equal to zero. Furthermore, P21 is estimated to be 4.62% and P22 95.38%.

From the DAX's point of view, we can also observe a higher level of distress with the FTSE 100. The probability of being in a tranquil phase tomorrow, given that we are there today, is estimated to be 99.19%, while a regime switch equals 0.81%. Contrary, we see that P21 is equal to 1.51% while P22 is 98.49%. The average duration for each given phase is roughly 124 and 66 days for regime 1 and 2, respectively. If we take the Nikkei 225 in to consideration, we observe decreasing

P11, but increasing P21 estimates. They are equal to 98.85% and 4.67%, respectively. As of now, this is actually the highest probability of a regime switching from regime 2 to 1, and would indicate that the calm periods are more demanding than the distress periods. If we look at the average days for each regime, they have a significant difference from each other, being 87 days for regime 1 and 21 days for regime 2. Also note here that P12 and P22 takes the value of 1.15% and 95.33%. For the SSE, P11 is equal to 98.09%, P12 1.90%, P21 2.83% and P22 97.17%. Their average durations are 52 days for regime 1 and 35 days for regime 2, respectively.

The FTSE 100's magnitude seems to decrease a bit when we correlate it with the Asian markets. Starting with the Nikkei 225, we see that P11 is equal to 98.63%, while for the SSE it is roughly 98.12%. P12 equals 1.37% and 1.88%, for the Nikkei 225 and SSE, respectively. Average durations are approximately 73 and 53 days. Contrary, assuming we are in the turmoil phase regime 2, P21 is equal to 2.70% for the Nikkei 225 and 3.03% with respect to the SSE. P22 is estimated to be 97.30% and 96.96%. For these respective countries, regime 2 lasts on average 37 and 33 days.

Finally, looking at the Asian countries relationships with themselves, we see that the probability that the Nikkei 225's predicted correlation with the SSE moves towards a tranquil phase tomorrow, given that they are in the same regime today, is approximately 98.60%. Additionally, the probability of a regime switch to occur, and tomorrow being recognized as a distress period, is estimated to be around 1.40%. Contrary, if the two markets behave in a nervous way, we can say that the probability of this notion being changed tomorrow is roughly 2.60%. The expectation of a non-change from this state of behavior is approximately 97.40%. Furthermore, the two regimes last on average 71 and 38 days each.

We have shown estimated evidence that the stock markets do behave in two clear phases; one being a tranquil period where the correlations are low, and another being a more turmoil period where correlations are higher and they act more nervously. This pattern can also be visualized in order to emphasize these relationships. The figures below show both the filtered and smoothed regime probabilities between the selected countries. Referring to table 5.5, we showed that regime 1 could be interpreted as the low correlation regime, while regime 2 held the opposite. On the basis of this, the more stable regime 1 probabilities have been recognized with the black line in the figures below, while the distressed regime 2 is denoted by the red line. The blue line through the figure is the estimated correlations between the given country x and the respective country y. Finally, the green line here also corresponds to the split between the two sample periods, i.e. 2012 - 2019 and the year of 2020.

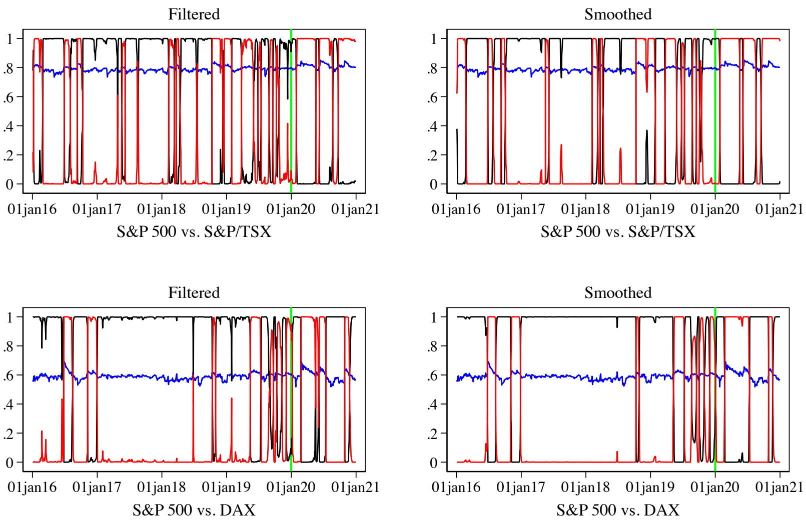

Figure 5.3: Filtered and smoothed regime probabilities I

From the figure above, if we focus on the two S&P's relationship, we can first clearly conclude that the correlation is moving in-between the two regimes. We see that the period leading up to the COVID-19 stock market crash of 2020 was characterized by longer periods of low correlation i.e., more stable market movement and short experienced periods of turbulence. The North American markets had at this point recovered from one of their worst decades in the 2000s, which we also know accumulated at the end with the GFC. As we mentioned in the introduction, the S&P 500 was also one of the indices that took the largest hits during the February - March stock market crashes of 2020, and we see in figure 5.3 that during this period, regime 2 prevails, and apart from a short period of regime switching roughly halfway through the year, regime 2 was clearly the dominant force for the year of 2020. We also observe that this relationship holds for both the filtered and smoothed probabilities. Considering that the correlation between both S&P indices were not recognized as being significantly turmoil for such a considerable amount of time, we can argue that it shows evidence in favor of contagion effects as a result of shocks brought on by the COVID-19 pandemic. The in-between each regime movement can also be explained. Referring to the transition probabilities and average duration table 5.6, we saw that the probabilities P11 and P22 were quite close, as was the average duration for each phase. Looking at figure 5.3, it is almost equivalent how many times the red regime 2 reaches the top (that is, 100% correlation) compared to the black regime 1. If we combined all the times each line reached the top, and counted them in days, the difference between them would be approximately 20 days, which also is the difference in average duration between regime 1 and regime 2 from table 5.6. If we keep table 5.6 in mind, and look at the average duration in regimes between the S&P 500 and the DAX, we clearly observe the dominant regime 1 in the S&P 500 vs. DAX chart. Apart from a couple of periods at the end of 2016 and end of 2018, the time-span 2016 to mid 2019 saw very little variation in the variance-covariance transmissions. However, we have clear evidence of a significant increase in linkage in the COVID-19 pandemic period, i.e. after the green line. Looking at the blue predicted correlation line first, we notice a sharp spike in around February - March. As before, this is corresponding to the market crash and we notice that the spike reaches levels that haven't been reached since mid 2016. Considering that this strong correlation lasted for around half a year, we could argue that this is evidence of financial contagion during the COVID-19 stock market crash. As we will see throughout the rest of the figures, the FTSE 100's linkage with the other indices is one of the most interesting points of the results. We clearly observed in table 5.6 that regime 2 dominated throughout the years, and looking at figure 5.4 from the S&P 500 vs. FTSE 100 point of view, we clearly observe this notion.

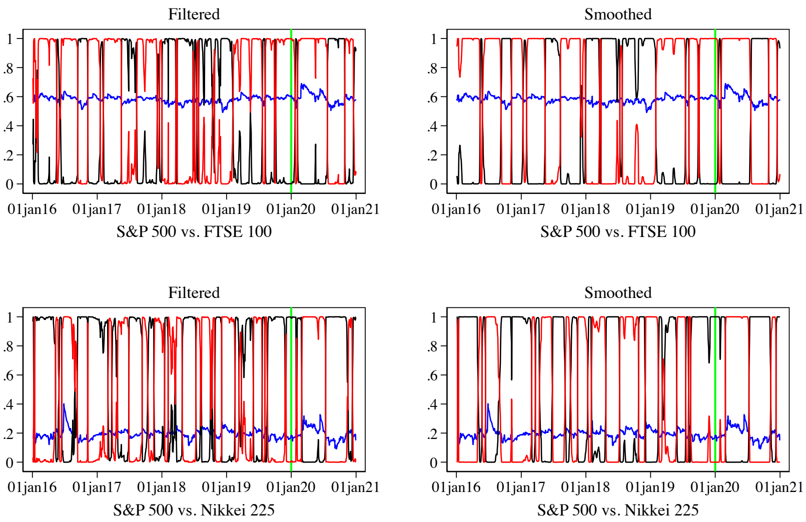

Figure 5.4: Filtered and smoothed regime probabilities II

The periods of market stability are not existing to such a magnitude as the distressed periods. Forbes and Rigobon (2002) noted that an important characteristic that distinguished contagion from simple interdependence, was the market behavior in the period before the shocks. If the high movement was realized before the shock, then we could not call the movement during the shock for a contagion effect. Davidson (2020) further confirmed this definition, but introduced also a term called "contagion through interdependence", which was a way of looking at the separation between contagion and interdependence from a more nuance point of view. They believed that even though the period before was recognized with the same pattern of high movement in linkage, it could still be recognized as contagion if the magnitude is significantly higher during the crisis. Looking at figure 5.4 we recognize that the spike in-around February - March is the clear maximum point in the chart. Taking that into consideration, we may say that we have evidence of contagion through interdependence in the linkage between the S&P 500 and the FTSE 100. Evidently from figure 5.4, we observe the notable COVID-19 spike in the S&P 500 vs. Nikkei 225 conditional correlations too. Contrary to previous years, the high correlating regime obtained a higher duration, but we also observe a clear correction around halfway through the year. Evidence for contagion effects in the beginning of the year is therefore valid, but not to the same extent as the North American and European markets. This last statement can be further amplified in figure 5.5 below.

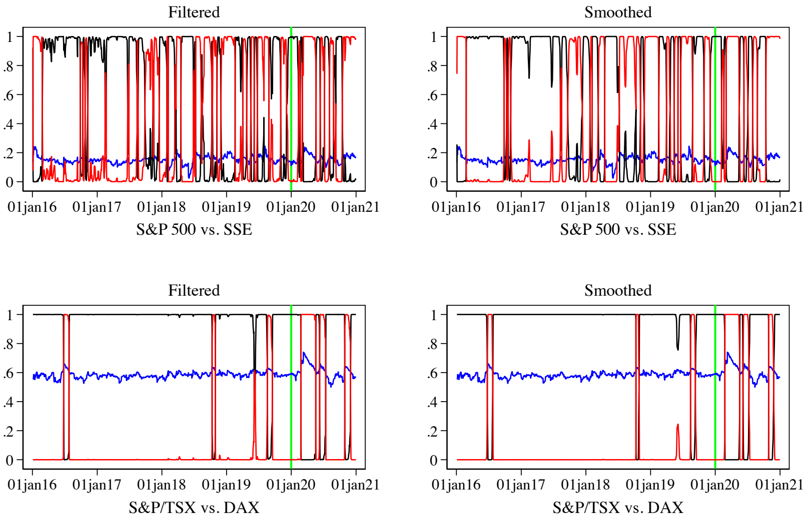

Figure 5.5: Filtered and smoothed regime probabilities III

So, we have several things to conclude from figure 5.4 and 5.5, respectively. Firstly, there seems to be more frequent movement when the two indices are from different continents, and especially if one of the countries is an Asian country. Secondly, there is some evidence of contagion effects around February - March for both the first half of 2020, while the second half is characterized with previous years dynamic behavior. It may therefore be evidence that the Asian markets were not as heavily influenced by the pandemic as the other markets. Comparisons with the Chinese benchmark index also appear to be less in-favor of contagion, since the patterns appear to behave like this in the period before - and during the pandemic. This particular incident will be further discussed later on. We may also look for contagion effects through a different perspective, and more specifically, from the dynamic behaviors between the S&P/TSX and the rest of the selected indices. Figure 5.5 presents the filtered and smoothed probabilities between the Canadian benchmark index and the DAX. Similarly to the previously presented S&P 500's relationship with the DAX in figure 5.3, we clearly observe the dominant low correlation regime and, apart from a couple of short periods with disturbance, the time-span 2016 to 2020 saw very little variation in the variance-covariance transmissions. Because of this, it is easier to say that the COVID spike is a clear change in cross-market correlation since the two markets did not behave like this at any point the last four years. We can therefore argue that there exists evidence towards contagion effects. Furthermore, we can observe that the effects slowly, but steadily, eased down and approximately halfway through the year, the lower correlation regime dominated. This may perhaps be a result as a response to the countries' attitude towards the pandemic, and different government approaches to limit the spread. Additionally, we compare the Canadian benchmark index to the British and Japanese indices in figure 5.6 below. As we mentioned before, the dynamics of the FTSE 100 seem to be more heavily influenced in the pandemic period than most of the other indices. The COVID spike in figure 5.6 is significantly larger than previous spikes the last four years. Furthermore, there is evidence in favor of regime switching correlation patterns, and that the cross-market correlation was predominantly restful. We therefore have evidence in favor of contagion effects here too.

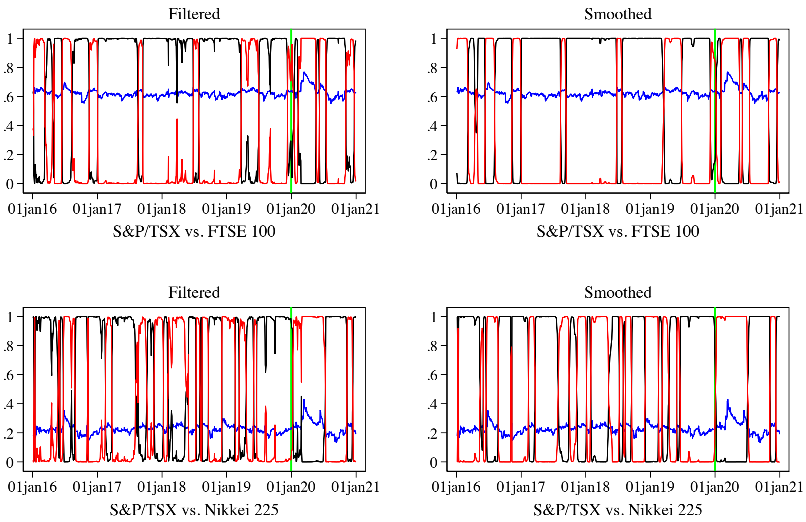

Figure 5.6: Filtered and smoothed regime probabilities IV

With respect to Nikkei 225, the COVID spike seems to be even more powerful. The conditional correlation intervals have previously seemed to be quite low, more specifically they appeared to be located between 0 to .3 for comparisons between the North American and Asian indices. We can observe here that in the February - March COVID-19 stock market crash, the cross-market correlation reached levels above .4. Also noticing the patterns before the stock market crash, we can argue that contagion effects did occur between the S&P/TSX and Nikkei 225. If we further look at it with respect to the SSE instead, we can observe that there is a regime switching correlation pattern, although at a lesser magnitude than before. The more tranquil regime 1 is clearly dominating the entire sample period, which is also evident from table 5.6 where regime 1 was estimated to last on average 150 days compared to 22 for regime 2.

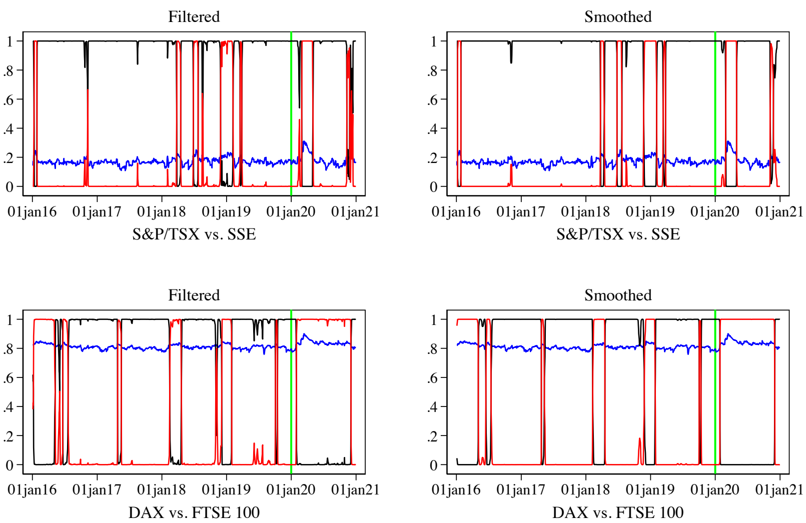

Figure 5.7: Filtered and smoothed regime probabilities V

The COVID-19 spike, however, is clearly notable as an abnormal change in the pattern. Not once in the previous four years had there been a spike as large as this, and although it appear to only have been short-lived, it does fulfill the criterion of our contagion definition, i.e. the change in cross-market linkage is significant. We can therefore argue that there is some contagion between the Canadian benchmark index and the SSE.

Clearly, this also holds for the dynamic conditional correlation between the DAX and FTSE 100. We also observe, for the first time, a full year almost completely recognized with high and distressed correlation. Not only can we perceive the clear COVID-19 spike, but we also observe that the cross-market correlation continues to behave like this throughout the year. The evidence of contagion is here clear, and the previous mentioned pandemic impact on the FTSE 100 is still relevant here.

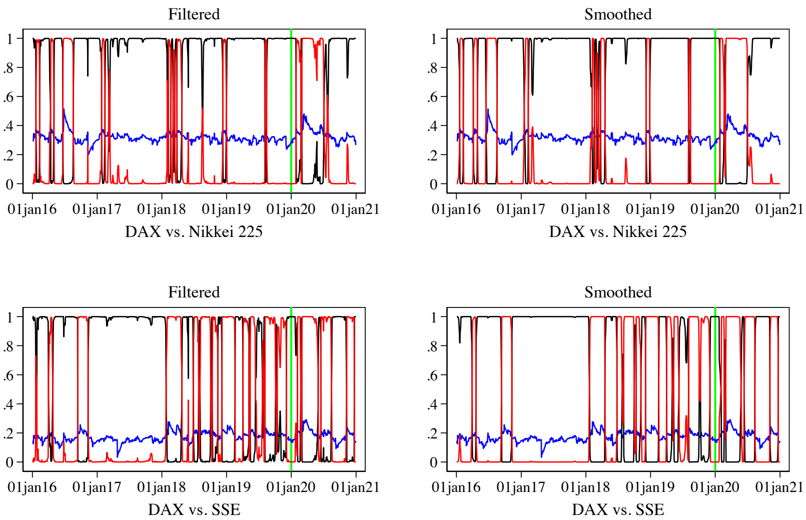

Figure 5.8: Filtered and smoothed regime probabilities VI

There also exists a COVID spike, to a degree, if we compare the DAX to the SSE, but it can be argued that the spike is corresponding to the previous years' pattern, i.e. there are more regime switches with several corresponding correlation spikes. We can therefore not say that there exists a significant change in the cross-market linkage, i.e. the two indices are behaving in simple interdependence. However, this does not mean that we accept the null of no contagion whatsoever. It only means that we, at this point in time, do not have enough evidence in order to reject it. Moreover, compared to the years before, the magnitude of the spike does seem to be greater than the periods before. It could therefore be helpful to follow Davidson (2020) nuanced view of contagion through interdependence here.

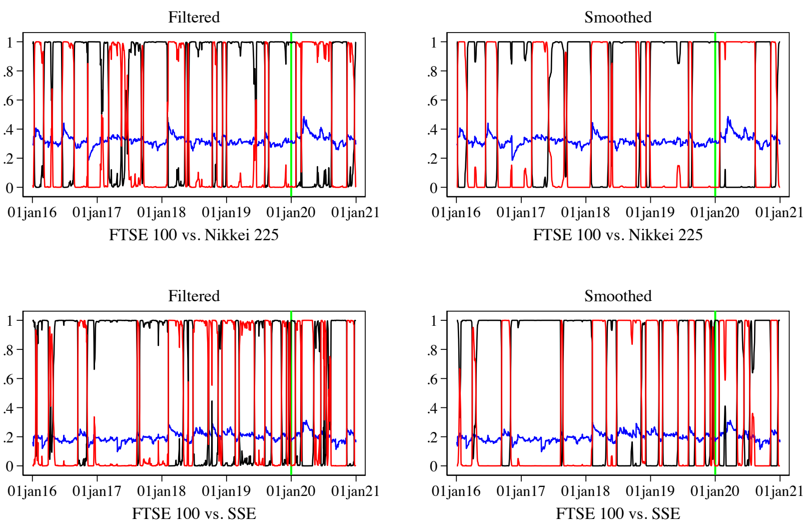

Figure 5.9: Filtered and smoothed regime probabilities VII

Furthermore in figure 5.9, we will first argue for evidence towards contagion effects between the FTSE 100 and Nikkei 225 based on the clear regime 2 dominated pandemic year, the COVID spike and the patterns leading up to the green line. We also here can not argue with sufficient evidence for contagion effects with the Chinese benchmark index, since the patterns are not differing to such a large scale that we can confidently say that the change in February - March 2020 is a result of solely contagion and not simple interdependence. But, we will also here argue that contagion through interdependence could still be a valid conclusion.

Finally, we can compare the two Asian indices to each other in figure 5.10

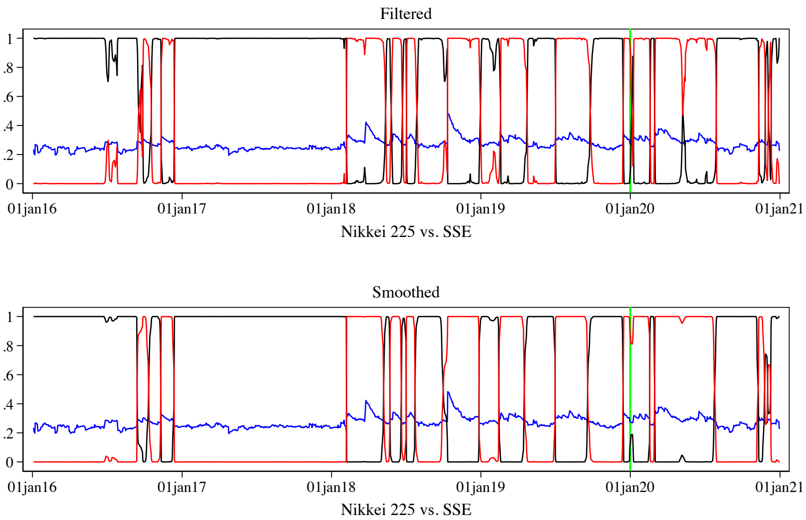

Figure 5.10: Filtered and smoothed regime probabilities VIII

First off, we clearly observe that the period leading up to 2018 was characterized as a more calm and restoring period. As mentioned previously, the years before 2016 saw the Asian markets experiencing their own stock market crash. Secondly, from 2018, we notice that the movements through different regimes are more clear, and that, compared to previous years, the higher correlation regime is becoming larger while the lower correlation regime is reducing in duration. Furthermore, the year of 2020 does not see a significant difference in the spikes contrary to the previous years. We actually see that the two spikes in 2018 are the largest ones during this time-span. However, the correlation patterns between the two regimes are different. The turmoil period is clearly dominating the year of 2020, and it is reasonable to argue in favor of contagion effects here also.

Chapter 6

Discussion

6.1 Elaboration of our findings

Our findings are encouraging, and in line with our expectations. The first hypothesis that we wanted to test was whether or not the COVID-19 pandemic had a significant impact on the market volatility. The introduction of the COVID dummy variable showed that for all indices, estimates on the coefficients of the variable took a positive and significant value indicating that we have evidence towards higher volatility in the COVID-19 era. The higher volatile COVID-19 period is also a result that is in line with previous results by Yousef and Shehadeh (2020) who found that the volatility in gold prices could, to a degree, be explained by the increasing uncertainty caused by the pandemic. The theoretical intuition that stock returns and market volatility appears to behave in a positive-negative asymmetrical relationship therefore holds true.

An interesting finding in figure 5.1 was that the European and North American markets almost moved simultaneously, giving evidence, to a degree, of volatility spillovers between these markets. A similar result has been reported by Aslam et al. (2021), who found that the volatility in stock markets tends to change in one market as a response to a change in volatility in another market. Aslam et al. (2021) however only tested for this with European indices, so we have further justified this notion with the inclusion of the North American markets, but have also contradicted it in the Asian markets since we saw that there were clear deviations in the patterns between the Nikkei 225 and SSE.

Additionally, we saw that in table 3.1 the DAX and FTSE 100 had negative mean returns during the COVID-19 sample period, and that both the North American and European markets had negative growth in their skewnesses and higher kurtoses. Shehzad, Xiaoxing, and Kazouz (2020) also found negative mean returns, negative skewness and increasing kurtoses for all their inspected indices. Given that they only assumed the COVID-19 period to last up to April 7, we believe that our results can be argued to be in line with theirs, so the conclusion that the chances of market failure was more likely to occur in the COVID-19 sample period than the previous one holds for our research too.

The increasing ARCH effects in table 5.2 confirmed that all indices, except for the Japanese benchmark Nikkei 225, were more sensitive to COVID-19 news. This is in line with findings reported by Sergi et al. (2021); Harjoto et al. (2020) and Baek et al. (2020). The Nikkei 225 exhibited decreasing ARCH effects in the COVID-19 phase, which was a clear contradiction to our other estimates. From news and factual data, we can see a clear distinction in the Japanese vs. European and North American incidence when it comes to government approaches under the pandemic. From figure 5.1, we can draw some educational comparisons. Looking past the sample separation line of the charts, we can see that around April 2020 Japan exhibits a drastically linear decline while the European and North American indices do similarly decline, but have great volatile upwards spikes also. Under this period, most of Europe and North America went into government restricted lockdowns, while Japan did not. Rather their governmental approach was a "soft lockdown". By law, the Japanese government does not hold the power to implement European-styled lockdowns where people were prevented to move where they wished (Osaki, 2020). Japan kept its local businesses running and did not close down, rather they believed that their people would act responsible and reduce the transmission of the virus on their own. In a way it is understandable that they would use this approach, as Japan is widely recognized as one of the cleanest countries in the world, and their inhabitants valuate hygiene highly (Powell & Cabello, 2019). The surgical face-masks that have become a symbol for the pandemic across the globe the past year, have been used by the Japanese people for decades before the coronavirus emerged. The discovery that Asian markets seemed to be less affected by the COVID-19 pandemic than American and European markets is also in accordance with previous literature by both Frezza, Bianchi, and Pianese (2021) and Shehzad, Xiaoxing, and Kazouz (2020), which begs questions of investors' abilities to diversify their portfolio investments during periods of uncertainty. This was also substantiated in our contagion analysis. We saw first in figure 5.2 that all the pairs exhibited clear dynamic patterns, where the COVID-19 spike distinguished itself after the green line in all indices comparisons except for the Nikkei 225 vs. SSE, which did have a spike but not to such a magnitude as the other comparisons that had spikes equalling to the sample period peak or close. It appears that during crisis circumstances, there exists a positive relationship between the volatility and cross-correlation. That markets tend to almost behave as one common market during crashes is in line with previous findings by Sandoval and Franca (2012). If they however exhibit this relationship, how will it affect the potential hedging ability for investors who seek to exploit arbitrage opportunities when one market is deemed inefficient? The likelihood of portfolio mismatching is obviously increasing in these situations, and literature seeking to answer questions like this not only argue in favor of typically used safe-haven assets such as gold or cryptocurrencies (Bouri, Shahzad, Roubaud, Kristoufek, & Lucey, 2020; Baur & McDermott, 2010), but some also found quite interesting evidence in-favour of some safe-haven properties in both the Chinese Renminbi (Fatum, Yamamoto, & Zhu, 2017) and Japanese Yen (Fatum & Yamamoto, 2016).

Furthermore, the notion of Black (1976) that bad news are more influential than good news was also contradicting and not evidential for China in our estimates. Although China was the country where the coronavirus originated, and patient zero was discovered, we saw in figure 5.1 that the SSE actually had more volatile movement during the 2014 - 2016 crisis then they did during the whole 2020. The sensitivity of Chinese stock markets in the COVID-19 era is an interesting discovery, and is in line with both Cristofaro, Gil-Alana, Chen, and Wanke (2020), who found that shocks in Chinese stock markets only had temporary effects in the COVID-19 era as a result of governmental responses as compared to the previous period, and Chikri et al. (2020) who found that all tested indices except for China showed significant values for their hypotheses of negative shocks contributing more to index prices than positive. China, in accordance with their research, differed in its reaction to new COVID-19 cases and deaths. Also in this case the governmental approach was mentioned as a reason why the Chinese economy was under control during the COVID-19 situation.

Lastly, the behavior of China, especially in correlation with the U.S., can also have been affected by the economical and political relationship between these countries. With his "America First" policy, former President Donald Trump began in 2018 to set tariffs and trade barriers on Chinese products with a goal of balancing the trade deficit between them (Swanson, 2018). That the two largest economies in the world (IMF, 2020) were involved, and arguably still are, in a trade war against each other most certainly did not go unnoticed in the rest of the world. So it can be argued that some of the correlation patterns with respect to China have been skewed as an aftershock to the U.S. - China trade war. We can see in figure 5.5 that the dynamic patterns between the U.S. and China are behaving in an extremely rapid fashion, and, quite interestingly, this pattern begins around the same time Trump launched the trade-war. The years before 2018 are not only more dominated by the lower correlation regime, but the average duration is longer too.

6.2 Limitations

It is important to elaborate on some of the limitations in our study. Firstly, these estimates have been conducted under the assumption that the returns were following a Gaussian distribution. We, however, have presented evidence that cast serious doubts on the validity of that assumption. The return distributions deviated from the standard Gaussian curve in both figure 3.2 and 3.3, while the Jarque and Bera (1980) test allowed us to reject the null of both the skewness and kurtosis being equal to zero, i.e. Gaussianity. From the descriptive statistics in table 3.1, there were some serious deviations from Gaussianity. For instance, the S&P/TSX in the COVID-19 era had a kurtosis of almost 18, suggesting that extreme events tend to occur significantly more often than for the case of the Gaussian distribution. Consequently, it is therefore logical to assume that testing our data using different members in the probability distribution family would yield different and perhaps more proper results. However, even though the return distributions seldom exhibit Gaussianity, it is looked at as a common practice to assume it. One reasoning behind this is the Central Limit Theorem argument, which states that even if the elements of observation are exhibiting abnormal tendencies, Gaussian distribution will result as the sum of these random processes (Smith, 2003). Furthermore, both Weiss (1986) and Bollerslev and Wooldridge (1992) showed that a maximum likelihood procedure under the assumption of Gaussianity result in quasi-maximum likelihood estimate (QMLE) which is compatible and asymptotically Gaussian distributed provided that the full GARCH is accurately specified (Boffelli & Urga, 2016, p. 86).

Secondly, we have also assumed the same COVID-19 period for all the given countries. Hence, the "one-time-for-all" COVID-19 sample period name. As we all know, the pandemic did not hit all countries at the same time, nor did it have the same effect on all, so the possibility of one country's estimated results being significantly different from other countries could be a consequence of treating all countries equal. The results could to an extent even be argued of being biased. In order to limit this biasedness and really digest the pandemic effect on each specific country, we could in one way treat each country's COVID-19 period as country-specific. This would give us the opportunity to compare the pandemic from a global point of view and a country-specific point of view, meaning that if we did not experience any significant form of changes from the one-time-for-all period and country-specific period, we would have evidence in favor of the pandemic being globally dominant. The problem here, however, would be determining what time-period fulfills the COVID-19 estimation window and if this sample size is largely differing across countries, some boundaries have to be set such that any comparison across unequal number of observations is adequate enough to conduct.

Lastly, one of our hypothesis was to investigate whether the global financial markets acted indifferent towards COVID-19 news, and we showed evidence towards it. It could however be flawed to conclude that this is a result of the markets (or indices, more specifically) that we investigated. Our selected markets were not only just six, but these countries were also six of the top 10 largest economies in the world (IMF, 2020). Even though we had a reasonable argument in favor of our *global market* proxy, it could still be argued that not including countries that do not represent the *1 percent* of the world would not give an accurate and efficient view of the COVID-19 effect on *global* financial markets. One of the things that the pandemic have actually shown us, is that the differences between the rich and poor are larger than we knew. In Norway we have seen that in the areas where the density is higher and inhabitants' net income is lower, the amount of cases and hospitalized persons are higher (Søegaard & Kan, 2021), whereas in the rest of the world, for instance, we have seen several cases where the amount of vaccines the poorer countries got was substantially less than, say, the U.S. (Steinhauser, Bariyo, & Emont, 2021). The countries we investigated almost all showed the same pattern in the results, whereas if we included countries that deviated in financial strength this would perhaps give us a more comprehensive view of how the pandemic actually affected the global markets. Obviously it is not possible to account for the entire market, but choosing some representative indices from all continents could be beneficial here. We limited ourselves to only North-America, Europe and Asia, and we saw that there did exist some continental similarities in both the results in the one-time-for-all COVID-19 period in table 5.2, the dynamic patterns in the conditional variances from figure 5.1, and the cross-correlation estimates in table 5.4 and figure 5.2. Taking indices from considerably poorer continents as South-America or Africa would therefore give us the opportunity of checking for any outliers in the obtained results, and a more reasonable conclusion for the global effect of the pandemic could then be drawn.

Chapter 7

Conclusion

Our main ambition with this master's thesis was to take previous literature concerning market disturbances across countries a step forward, and scientifically model the recent COVID-19 pandemic's influence on the volatility and cross-market correlation in six major stock indices: S&P 500, S&P/TSX, DAX, FTSE 100, Nikkei 225 and SSE Composite.

Following in the line of Ali et al. (2020); Omari et al. (2020); Yousef and Shehadeh (2020); Mirza et al. (2020), we estimated the pandemic effect on market volatility with an alternative GARCH model, and our choice of model was the GJR-GARCH by Glosten et al. (1993). We further modified this estimation model in order to take the COVID-19 sample period into consideration with an δCOVID_t dummy variable. To estimate the cross-correlation between the indices, we implemented a multivariate GARCH framework. More specifically, we first estimated dynamic conditional correlations through the Engle (2002) DCCE model, and to visualize the movement between low and high correlation regimes, we fitted the obtained dynamic correlations in a two-regime Markov switching model due to Hamilton (1989).

The results suggest that the six economies behaved almost identically, with the Nikkei 225 being the only index that did not show evidence of a higher sensitivity towards COVID-19 news. Most of the investigated indices showed evidence towards increasing leverage effects in the COVID-19 sample period, and they supported previous literature by Black (1976), for instance, where the negative correlation between financial returns and market volatility tells us that bad news has a stronger impact than good news. However, the SSE reacted differently to consensus, and was more affected by good news. Furthermore, the Markovian dynamic figures showed evidence of stronger correlation during periods of distress and uncertainty, and suggestions of one common market in situations like this are valid. The presence of contagion effects during the COVID-19 pandemic have therefore been validated based on the definition by Forbes and Rigobon (2002).

Based on this, we would reject both the hypotheses and conclude for a significant pandemic impact on both the market volatility and cross-correlation, but we are aware of the limitations of our research, so following classical hypothesis testing, we would not accept the alternative hypotheses on the basis of these results alone. Consequently, the results from this thesis could be used as a basis for future research that could be done in order to further validate these findings. One definitive refinement that could be done here is concerning the discussion about the Gaussian distribution in previous sections. Taking other distributions into consideration could be an alternative. Another option could be to take other macroeconomical relations into consideration. We have here only used the sample year of 2020 as the base of COVID-19, and introduced models that have taken into consideration and been adjusted to capture the qualitative aspects of past innovations, specifically whether it is positive or negative news. From this perspective, it could be interesting to include some specific variables that account for, for instance, infection trend and mortality rate. If we then re-estimated this procedure in certain time periods in the year of 2020 again, and found significant differences within a country at different periods of time, we could argue that the estimated results were affected by an increasing or decreasing infection rate, or if daily published deaths of the virus had an impact.

Appendix A

Regime probabilities

Figure A.1: Filtered regime 1 probabilities

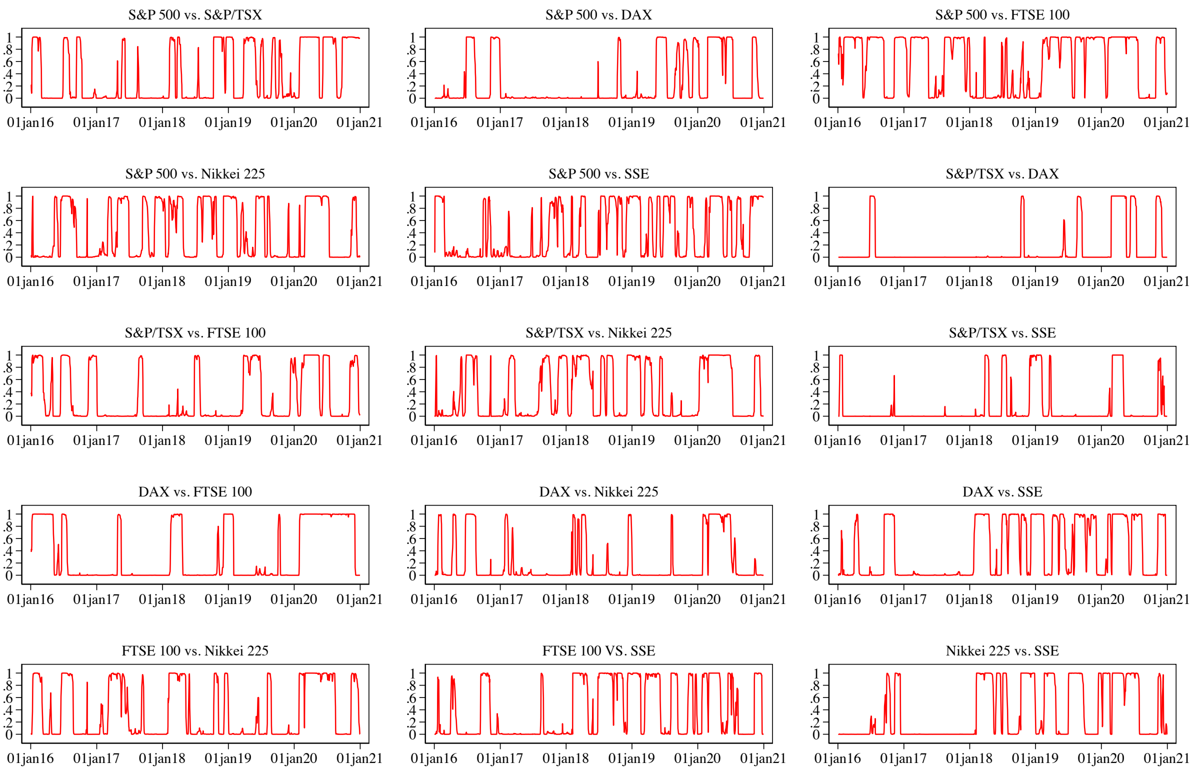

Figure A.2: Filtered regime 2 probabilities

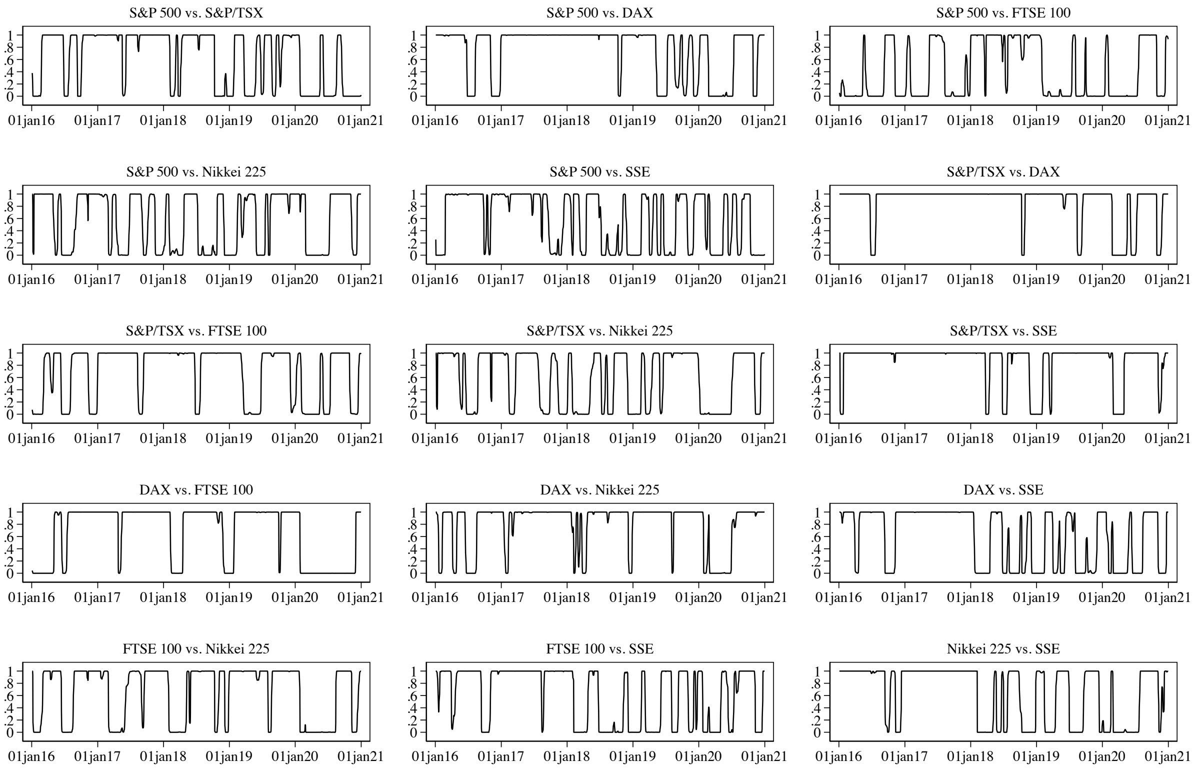

Figure A.3: Smoothed regime 1 probabilities

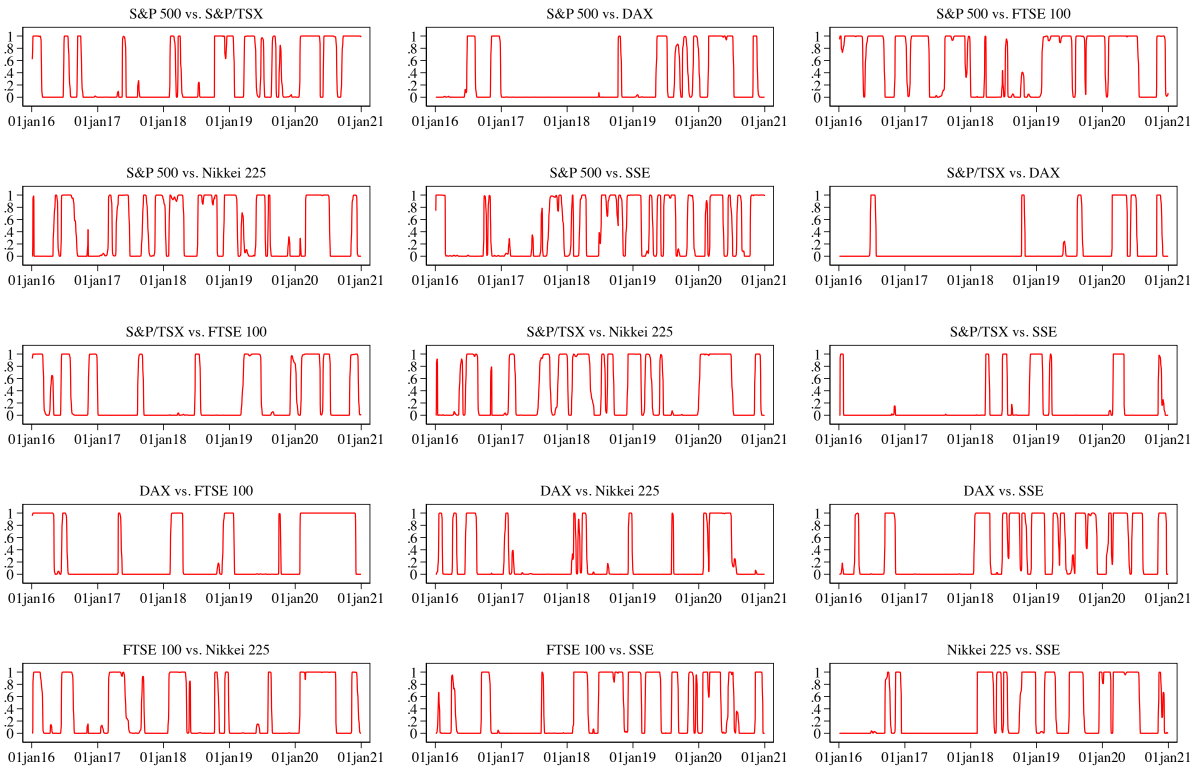

Figure A.4: Smoothed regime 2 probabilities

Appendix B

Stata do-file

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set more off
getsymbols ^GDAXI ^FTSE ^GSPC ^GSPTSE ^N225 000001.SS, fy(2012) ly(2020) ...
   clear yahoo

drop open__GDAXI high__GDAXI low__GDAXI close__GDAXI volume__GDAXI ...
   open__FTSE high__FTSE low__FTSE close__FTSE volume__FTSE open__GSPC ...
   high__GSPC low__GSPC close__GSPC volume__GSPC open__GSPTSE ...
   high__GSPTSE low__GSPTSE close__GSPTSE volume__GSPTSE open__N225 ...
   high__N225 low__N225 close__N225 volume__N225 open_000001_SS ...
   high_000001_SS low_000001_SS close_000001_SS volume_000001_SS

replace adjclose__GDAXI = 0 if missing(adjclose__GDAXI)
replace adjclose__FTSE = 0 if missing(adjclose__FTSE)
replace adjclose__GSPC = 0 if missing(adjclose__GSPC)
replace adjclose__GSPTSE = 0 if missing(adjclose__GSPTSE)
replace adjclose__N225 = 0 if missing(adjclose__N225)
replace adjclose_000001_SS = 0 if missing(adjclose_000001_SS)

gen trend = _n
tsset trend

gen returnDAX = log(adjclose__GDAXI[_n] / adjclose__GDAXI[_n-1])
gen returnFTSE = log(adjclose__FTSE[_n] / adjclose__FTSE[_n-1])
gen returnSP500 = log(adjclose__GSPC[_n] / adjclose__GSPC[_n-1])
gen returnSPTSE = log(adjclose__GSPTSE[_n] / adjclose__GSPTSE[_n-1])
gen returnNikkei = log(adjclose__N225[_n] / adjclose__N225[_n-1])
gen returnSSE = log(adjclose_000001_SS[_n] / adjclose_000001_SS[_n-1])

replace returnDAX = 0 if missing(returnDAX)
replace returnFTSE = 0 if missing(returnFTSE)
replace returnSP500 = 0 if missing(returnSP500)
replace returnSPTSE = 0 if missing(returnSPTSE)
replace returnNikkei = 0 if missing(returnNikkei)
replace returnSSE = 0 if missing(returnSSE)
drop trend
gen trend = _n
tsset trend
* Label
label variable adjclose__GDAXI "Adj. closing price Dax"
label variable adjclose__FTSE "Adj. closing price FTSE 100"
label variable adjclose__GSPC "Adj. closing price S&P 500"
label variable adjclose__GSPTSE "Adj. closing price S&P Toronto"
label variable adjclose__N225 "Adj. closing price Nikkei 225"
label variable adjclose_000001_SS "Adj. closing price SSE composite"
```

```
label variable returnDAX "log returns Dax"
label variable returnFTSE "log returns 100"
label variable returnSP500 "log returns S&P 500"
label variable returnSPTSE "log returns S&P Toronto"
label variable returnNikkei "log returns Nikkei 225"
label variable returnSSE "log returns SSE composite"

* Dummy
gen covid = 0
replace covid = 1 if date >= mdy(01,01,2020)

*----------------------------------------------------------------------------*
tsset period
tsline returnDAX, name(Dax)
tsline returnFTSE, name(FTSE)
tsline returnSP500, name(SP500)
tsline returnSPTSE, name(SPTSE)
tsline returnNikkei, name(Nikkei)
tsline returnSSE, name(SSE)
graph combine SP500 SPTSE Dax FTSE Nikkei SSE, ycommon


pwcorr returnSP500 returnSPTSE returnDAX returnFTSE returnNikkei returnSSE ...
   if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), sig
pwcorr returnSP500 returnSPTSE returnDAX returnFTSE returnNikkei returnSSE ...
   if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), sig


histogram returnDAX, normal normopts(lcolor(gs13)) kdensity ...
   kdenopts(lcolor(black)) name(dax2)
histogram returnFTSE, normal normopts(lcolor(gs13)) kdensity ...
   kdenopts(lcolor(black)) name(ftse2)
histogram returnSP500, normal normopts(lcolor(gs13)) kdensity ...
   kdenopts(lcolor(black)) name(sp2)
histogram returnSPTSE, normal normopts(lcolor(gs13)) kdensity ...
   kdenopts(lcolor(black)) name(sptse2)
histogram returnNikkei, normal normopts(lcolor(gs13)) kdensity ...
   kdenopts(lcolor(black)) name(nikkei2)
histogram returnSSE, normal normopts(lcolor(gs13)) kdensity ...
   kdenopts(lcolor(black)) name(sse2)
graph combine  sp2 sptse2 dax2 ftse2 nikkei2 sse2



qnorm returnDAX if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), ...
   grid name(daxpc)
qnorm returnFTSE if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), ...
   grid name(ftsepc)
qnorm returnSP500 if period >= mdy(01,01,2012) & period <= ...
   mdy(12,31,2019), grid name(sp500pc)
qnorm returnSPTSE if period >= mdy(01,01,2012) & period <= ...
   mdy(12,31,2019), grid name(sptsxpc)
qnorm returnNikkei if period >= mdy(01,01,2012) & period <= ...
   mdy(12,31,2019), grid name(nikkeipc)
qnorm returnSSE if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), ...
   grid name(ssepc)
graph combine sp500pc sptsxpc daxpc ftsepc nikkeipc ssepc

qnorm returnDAX if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), ...
   grid name(daxc)
```

```
qnorm returnFTSE if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), ...
    grid name(ftsec)
qnorm returnSP500 if period >= mdy(01,01,2020) & period <= ...
    mdy(12,31,2020), grid name(sp500c)
qnorm returnSPTSE if period >= mdy(01,01,2020) & period <= ...
    mdy(12,31,2020), grid name(sptsxc)
qnorm returnNikkei if period >= mdy(01,01,2020) & period <= ...
    mdy(12,31,2020), grid name(nikkeic)
qnorm returnSSE if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), ...
    grid name(ssec)
graph combine sp500c sptsxc daxc ftsec nikkeic ssec



*Ljung-Box pre covid
tsset period
lmalb returnSP500 if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), lags(5)
*osv ...

* covid

tsset period
lmalb returnSP500 if period >= mdy(01,01,2020) & period <= ...
    mdy(12,31,2020), lags(5)


// pre covid
summarize returnSSE returnSPTSE returnSP500 returnNikkei returnFTSE ...
    returnDAX if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), detail

*jbtest
sktest returnSP500 if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), noadjust
sktest returnSPTSE if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), noadjust
sktest returnDAX if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), ...
    noadjust
sktest returnFTSE if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), noadjust
sktest returnNikkei if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), noadjust
sktest returnSSE if period >= mdy(01,01,2012) & period <= mdy(12,31,2019), ...
    noadjust

*dfuller
dfuller returnSP500 if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), regress
dfuller returnSPTSE if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), regress
dfuller returnDAX if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), regress
dfuller returnFTSE if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), regress
dfuller returnNikkei if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), regress
dfuller returnSSE if period >= mdy(01,01,2012) & period <= ...
    mdy(12,31,2019), regress

*pp
pperron returnSP500 if period >= mdy(01,01,2012) & period <= mdy(12,31,2019)
```

```
pperron returnSPTSE if period >= mdy(01,01,2012) & period <= mdy(12,31,2019)
pperron returnDAX if period >= mdy(01,01,2012) & period <= mdy(12,31,2019)
pperron returnFTSE if period >= mdy(01,01,2012) & period <= mdy(12,31,2019)
pperron returnNikkei if period >= mdy(01,01,2012) & period <= mdy(12,31,2019)
pperron returnSSE if period >= mdy(01,01,2012) & period <= mdy(12,31,2019)

*arch
regress returnSP500
tsset trend
estat archlm, lags(1 5 10)
*osv ....

// COVID
summarize returnSP500 returnSPTSE returnDAX returnFTSE returnNikkei ...
   returnSSE if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), detail

sktest returnSP500 if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), noadjust
sktest returnSPTSE if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), noadjust
sktest returnDAX if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), ...
   noadjust
sktest returnFTSE if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), noadjust
sktest returnNikkei if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), noadjust
sktest returnSSE if period >= mdy(01,01,2020) & period <= mdy(12,31,2020), ...
   noadjust

dfuller returnSP500 if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), regress
dfuller returnSPTSE if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), regress
dfuller returnDAX if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), regress
dfuller returnFTSE if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), regress
dfuller returnNikkei if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), regress
dfuller returnSSE if period >= mdy(01,01,2020) & period <= ...
   mdy(12,31,2020), regress

pperron returnSP500 if period >= mdy(01,01,2020) & period <= mdy(12,31,2020)
pperron returnSPTSE if period >= mdy(01,01,2020) & period <= mdy(12,31,2020)
pperron returnDAX if period >= mdy(01,01,2020) & period <= mdy(12,31,2020)
pperron returnFTSE if period >= mdy(01,01,2020) & period <= mdy(12,31,2020)
pperron returnNikkei if period >= mdy(01,01,2020) & period <= mdy(12,31,2020)
pperron returnSSE if period >= mdy(01,01,2020) & period <= mdy(12,30,2020)

regress returnSP500 if period >= mdy(01,01,2020) & period <= mdy(12,31,2020)
tsset trend
estat archlm, lags(1 5 10)
*osv

*-----------------------------------------------------------------------------*

*USA
arch returnSP500, het(covid) arch(1) garch(1) tarch(1) nolog
*Canada
arch returnSPTSE, het(covid) arch(1) garch(1) tarch(1) nolog
*Tyskland
```

```
arch returnDAX, het(covid) arch(2) garch(2) tarch(2) nolog
*UK
arch returnFTSE, het(covid) arch(2) garch(2) tarch(2) nolog
*Japan
arch returnNikkei, het(covid) arch(2) garch(2) tarch(2) nolog
*China
arch returnSSE, het(covid) arch(2) garch(3) tarch(2) nolog

// GJR-GARCH pre-COVID //
*USA
arch returnSP500 if date >= mdy(01,01,2012) & date < = mdy(12,31,2019), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchusa
*Canada
arch returnSPTSE if date >= mdy(01,01,2012) & date < = mdy(12,31,2019), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchcanada
*Tyskland
arch returnDAX if date >= mdy(01,01,2012) & date < = mdy(12,31,2019), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchtyskland
*UK
arch returnFTSE if date >= mdy(01,01,2012) & date < = mdy(12,31,2019), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchengland
*Japan
arch returnNikkei if date >= mdy(01,01,2012) & date < = mdy(12,31,2019), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchjapan
*China
arch returnSSE if date >= mdy(01,01,2012) & date < = mdy(12,31,2019), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchkina

estimates table garchusa garchcanada garchtyskland garchengland garchjapan ...
   garchkina, stats(aic bic)

// GJR-GARCH one-for-all-time COVID //
*USA
arch returnSP500 if date >= mdy(01,01,2020) & date < = mdy(12,31,2020), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchusa2
*Canada
arch returnSPTSE if date >= mdy(01,01,2020) & date < = mdy(12,31,2020), ...
   arch(1) garch(1) tarch(1) nolog
estimates store garchcanada2
*Tyskland
arch returnDAX if date >= mdy(01,01,2020) & date < = mdy(12,31,2020), ...
   arch(2) garch(2) tarch(2) nolog
estimates store garchtyskland2
*UK
arch returnFTSE if date >= mdy(01,01,2020) & date < = mdy(12,31,2020), ...
   arch(2) garch(2) tarch(2) nolog
estimates store garchengland2
*Japan
arch returnNikkei if date >= mdy(01,01,2020) & date < = mdy(12,31,2020), ...
   arch(2) garch(2) tarch(2) nolog
estimates store garchjapan2
*China
arch returnSSE if date >= mdy(01,01,2020) & date < = mdy(12,31,2020), ...
   arch(2) garch(3) tarch(2) nolog
```

```
estimates store garchchina2

estimates table garchusa2 garchcanada2 garchtyskland2 garchengland2 ...
   garchjapan2 garchchina2, stats(aic bic)


*USA
tsset trend
arch returnSP500, arch(1) garch(1) tarch(1) nolog
predict var_GJR1_Forecast, variance dynamic(mdy(12,31,2020))
label variable var_GJR1_Forecast "S&P 500 conditional variance"


*Canada
tsset trend
arch returnSPTSE, arch(1) garch(1) tarch(1) nolog
predict var_GJR2_Forecast, variance dynamic(mdy(12,31,2020))
label variable var_GJR2_Forecast "S&P/TSX conditional variance"

*Tyskland
tsset trend
arch returnDAX, arch(2) garch(2) tarch(1) nolog
predict var_GJR3_Forecast, variance dynamic(mdy(12,31,2020))
label variable var_GJR3_Forecast "Dax conditional variance"

*UK
tsset trend
arch returnFTSE, arch(2) garch(1) tarch(1) nolog
predict var_GJR4_Forecast, variance dynamic(mdy(12,31,2020))
label variable var_GJR4_Forecast "FTSE 100 conditional variance"

*Japan
tsset trend
arch returnNikkei, arch(1) garch(1) tarch(1) nolog
predict var_GJR5_Forecast, variance dynamic(mdy(12,31,2020))
label variable var_GJR5_Forecast "Nikkei 225 conditional variance"

*China
tsset trend
arch returnSSE, arch(1) garch(1) tarch(1) nolog
predict var_GJR6_Forecast, variance dynamic(mdy(12,31,2020))
label variable var_GJR6_Forecast "SSE conditional variance"


tsset period
tsline var_GJR1_Forecast var_GJR2_Forecast, yscale(log) name(d1)
tsline var_GJR3_Forecast var_GJR4_Forecast, yscale(log) name(d2)
tsline var_GJR5_Forecast var_GJR6_Forecast, yscale(log) name(d3)
graph combine d1 d2 d3


tsset trend
/* Model comparison between DCCE og DCCT* Tar år 2016 - 2020*/
mgarch ccc returnDAX returnFTSE returnSP500 returnSPTSE returnNikkei ...
   returnSSE if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   arch(1) garch(1) nolog
estimates store ccc

mgarch dcc returnDAX returnFTSE returnSP500 returnSPTSE returnNikkei ...
   returnSSE if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   arch(1) garch(1) nolog
```

```
estimates store dcce

mgarch vcc returnDAX returnFTSE returnSP500 returnSPTSE returnNikkei ...
   returnSSE if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   arch(1) garch(1) nolog
estimates store dcct

lrtest ccc dcce
lrtest ccc dcct

estimates stats ccc dcce dcct

/* Transition matrix and average duration. */
drop _est_dcce _est_dcct _est_ccc
tsset trend
mgarch dcc returnDAX returnFTSE returnSP500 returnSPTSE returnNikkei ...
   returnSSE if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   arch(1) garch(1) nolog
predict corr*, correlation

/////////////////////////////
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration

*Canada
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
```

```
estat transition
estat duration

tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

*Germany
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

*UK
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
```

```
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration

*Japan
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration

*China
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
```

```
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration

tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration


/* Transition probabilities*/
*USA
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnSP500 state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usafilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnSP500 state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usasmooth)
graph combine usafilter usasmooth, ycommon
//////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
```

```
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usadaxfilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usadaxsmooth)
graph combine usadaxfilter usadaxsmooth, ycommon
///////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usaukfilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usauksmooth)
graph combine usaukfilter usauksmooth, ycommon
///////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
```

```
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(filter4)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(smooth4)
graph combine filter4 smooth4, ycommon
///////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(filter5)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(smooth5)
graph combine filter5 smooth5, ycommon

*Canada
```

```
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(xx)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(yy)
graph combine xx yy, ycommon
///////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(bra2)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(pra)
graph combine bra2 pra, ycommon
```

```
///////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(x11)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(x12)
graph combine x11 x12, ycommon
///////////////////////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(plm)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(blm)
```

```
graph combine plm blm, ycommon

*Germany
drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnFTSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(gq)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnFTSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(pq)
graph combine gq pq
///////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(nice)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
```

```
tsline corr_returnNikkei_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(mice)
graph combine nice mice,ycommon
/////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(bla)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(blabla)
graph combine bla blabla, ycommon

*UK
drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(qqq)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
```

```
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(q)
graph combine qqq q, ycommon

////////////////////////////////
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(pyy)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(uyy)
graph combine pyy uyy, ycommon

*Japan
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnNikkei state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(fin)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
```

```
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnNikkei state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(fin2)
graph combine fin fin2, ycommon


////// correlation comparison

tsline corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(uscancorr)
tsline corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(usgercorr)
tsline corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(usukcorr)
tsline corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(usjapcorr)
tsline corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(uskinacorr)
tsline corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(cangercorr)
tsline corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(canukcorr)
tsline corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(canjapcorr)
tsline corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(cankinacorr)
tsline corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(gerukcorr)
tsline corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(gerjapcorr)
tsline corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(gerkinacorr)
tsline corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(ukjapcorr)
tsline corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(ukkinacorr)
tsline corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020), name(japkinacorr)

graph combine uscancorr usgercorr usukcorr usjapcorr uskinacorr cangercorr ...
    canukcorr canjapcorr cankinacorr gerukcorr gerjapcorr gerkinacorr ...
    ukjapcorr ukkinacorr japkinacorr

/////////////////// 2 by 2 combination
clear all
set more off
getsymbols ^GDAXI ^FTSE ^GSPC ^GSPTSE ^N225 000001.SS, fy(2012) ly(2020) ...
    clear yahoo

drop open__GDAXI high__GDAXI low__GDAXI close__GDAXI volume__GDAXI ...
    open__FTSE high__FTSE low__FTSE close__FTSE volume__FTSE open__GSPC ...
    high__GSPC low__GSPC close__GSPC volume__GSPC open__GSPTSE ...
    high__GSPTSE low__GSPTSE close__GSPTSE volume__GSPTSE open__N225 ...
    high__N225 low__N225 close__N225 volume__N225 open_000001_SS ...
    high_000001_SS low_000001_SS close_000001_SS volume_000001_SS
```

```
replace adjclose__GDAXI = 0 if missing(adjclose__GDAXI)
replace adjclose__FTSE = 0 if missing(adjclose__FTSE)
replace adjclose__GSPC = 0 if missing(adjclose__GSPC)
replace adjclose__GSPTSE = 0 if missing(adjclose__GSPTSE)
replace adjclose__N225 = 0 if missing(adjclose__N225)
replace adjclose_000001_SS = 0 if missing(adjclose_000001_SS)

gen trend = _n
tsset trend

gen returnDAX = log(adjclose__GDAXI[_n] / adjclose__GDAXI[_n-1])
gen returnFTSE = log(adjclose__FTSE[_n] / adjclose__FTSE[_n-1])
gen returnSP500 = log(adjclose__GSPC[_n] / adjclose__GSPC[_n-1])
gen returnSPTSE = log(adjclose__GSPTSE[_n] / adjclose__GSPTSE[_n-1])
gen returnNikkei = log(adjclose__N225[_n] / adjclose__N225[_n-1])
gen returnSSE = log(adjclose_000001_SS[_n] / adjclose_000001_SS[_n-1])

replace returnDAX = 0 if missing(returnDAX)
replace returnFTSE = 0 if missing(returnFTSE)
replace returnSP500 = 0 if missing(returnSP500)
replace returnSPTSE = 0 if missing(returnSPTSE)
replace returnNikkei = 0 if missing(returnNikkei)
replace returnSSE = 0 if missing(returnSSE)
drop trend
gen trend = _n
tsset trend
* Label
label variable adjclose__GDAXI "Adj. closing price Dax"
label variable adjclose__FTSE "Adj. closing price FTSE 100"
label variable adjclose__GSPC "Adj. closing price S&P 500"
label variable adjclose__GSPTSE "Adj. closing price S&P Toronto"
label variable adjclose__N225 "Adj. closing price Nikkei 225"
label variable adjclose_000001_SS "Adj. closing price SSE composite"
label variable returnDAX "log returns Dax"
label variable returnFTSE "log returns 100"
label variable returnSP500 "log returns S&P 500"
label variable returnSPTSE "log returns S&P Toronto"
label variable returnNikkei "log returns Nikkei 225"
label variable returnSSE "log returns SSE composite"

* Dummy
gen covid = 0
replace covid = 1 if date >= mdy(01,01,2020)

tsset trend
mgarch dcc returnDAX returnFTSE returnSP500 returnSPTSE returnNikkei ...
    returnSSE if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    arch(1) garch(1) nolog
predict corr*, correlation



tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
```

```
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnSP500 state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(americafilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnSP500 state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(americasmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usadaxfilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(usadaxsmooth)

graph combine americafilter americasmooth usadaxfilter usadaxsmooth

////////////////////////
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
```

```
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnFTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(usaukfilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSP500_returnFTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(usauksmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(usajapanfilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(usajapansmooth)

graph combine usaukfilter usauksmooth usajapanfilter usajapansmooth
/////////////////////////
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
```

```
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(usakinafilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSP500 state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(usakinasmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadatysklandfilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadatysklandsmooth)

graph combine usakinafilter usakinasmooth canadatysklandfilter ...
    canadatysklandsmooth

//////////////////////////////////
drop state1prob state2prob
tsset trend
```

```
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnFTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadabritaniafilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSPTSE_returnFTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadabritaniasmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadajapanfilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadajapansmooth)

graph combine canadabritaniafilter canadabritaniasmooth canadajapanfilter ...
    canadajapansmooth
```

```
////////////////////////////////
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadakinafilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnSPTSE state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(canadakinasmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnFTSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(tysklandbritaniafilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnFTSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(tysklandbritaniasmooth)
```

```
graph combine canadakinafilter canadakinasmooth tysklandbritaniafilter ...
    tysklandbritaniasmooth

///////////////////////////////////////////
drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(tysklandjapanfilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(tysklandjapansmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnDAX state1prob state2prob if date >= ...
    mdy(01,01,2016) & date <= mdy(12,31,2020), name(tysklandkinafilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
```

```
tsline corr_returnSSE_returnDAX state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(tysklandkinasmooth)

graph combine tysklandjapanfilter tysklandjapansmooth tysklandkinafilter ...
   tysklandkinasmooth


////////////////////////////////////////
drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(britaniajapanfilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnNikkei_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(britaniajapansmooth)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(britaniakinafilter)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
```

```
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnFTSE state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(britaniakinasmooth)

graph combine britaniajapanfilter britaniajapansmooth britaniakinafilter ...
   britaniakinasmooth

/////////////////////////
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnNikkei state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(japankinafilter)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline corr_returnSSE_returnNikkei state1prob state2prob if date >= ...
   mdy(01,01,2016) & date <= mdy(12,31,2020), name(japankinasmooth)


graph combine japankinafilter japankinasmooth

///// bynnelse på filtered kombinert av alle
graph combine americafilter usadaxfilter usaukfilter usajapanfilter ...
   usakinafilter canadatysklandfilter canadabritaniafilter ...
   canadajapanfilter canadakinafilter tysklandbritaniafilter ...
   tysklandjapanfilter tysklandkinafilter britaniajapanfilter ...
   britaniakinafilter japankinafilter

///// regime 1 og regime 2 for appendix
* Filtered regime 1
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
```

```
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uscanr1f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usgerr1f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usukr1f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usjapr1f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
```

```
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uschir1f)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(cangerr1f)


drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canukr1f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canjapr1f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
```

```
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(canchir1f)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(gerukr1f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(gerjapr1f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(gerchir1f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
```

```
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(ukjapr1f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
   mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(ukchir1f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(japchir1f)

graph combine uscanr1f usgerr1f usukr1f usjapr1f uschir1f canukr1f ...
   cangerr1f canjapr1f canchir1f  gerukr1f gerjapr1f gerchir1f ukjapr1f ...
   ukchir1f japchir1f

*regime 2
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline state2prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(uscanr2f)
```

```
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usgerr2f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usukr2f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usjapr2f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uschir2f)
```

```
drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(cangerr2f)


drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canukr2f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canjapr2f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
```

```
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canchir2f)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerukr2f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerjapr2f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerchir2f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
```

```
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(ukjapr2f)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(ukchir2f)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(filter)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(japchir2f)


graph combine uscanr2f usgerr2f usukr2f usjapr2f uschir2f cangerr2f ...
    canukr2f canjapr2f canchir2f  gerukr2f gerjapr2f gerchir2f ukjapr2f ...
    ukchir2f japchir2f

* smoothed regime 1
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uscanr1s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
```

```
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usgerr1s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usukr1s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usjapr1s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uschir1s)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
```

```
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(cangerr1s)


drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canukr1s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canjapr1s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canchir1s)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
```

```
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerukr1s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerjapr1s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerchir1s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(ukjapr1s)


drop state2prob state1prob
tsset trend
```

```
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(ukchir1s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state1prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(japchir1s)

graph combine uscanr1s usgerr1s usukr1s usjapr1s uschir1s cangerr1s ...
    canukr1s canjapr1s canchir1s  gerukr1s gerjapr1s gerchir1s ukjapr1s ...
    ukchir1s japchir1s

*regime 2 smoothed
drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline state2prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uscanr2s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSP500_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
```

```
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usgerr2s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSP500_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usukr2s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSP500 if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(usjapr2s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSP500 if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(uschir2s)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnSPTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
```

```
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(cangerr2s)


drop state1prob state2prob
tsset trend
mswitch dr corr_returnSPTSE_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canukr2s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnNikkei_returnSPTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canjapr2s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnSPTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(canchir2s)

drop state2prob state1prob
tsset trend
mswitch dr corr_returnFTSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
```

```
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerukr2s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnDAX if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerjapr2s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnDAX if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(gerchir2s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnNikkei_returnFTSE if date >= mdy(01,01,2016) & date ...
    <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    name(ukjapr2s)


drop state2prob state1prob
tsset trend
mswitch dr corr_returnSSE_returnFTSE if date >= mdy(01,01,2016) & date <= ...
    mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
    pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
```

```
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(ukchir2s)

drop state1prob state2prob
tsset trend
mswitch dr corr_returnSSE_returnNikkei if date >= mdy(01,01,2016) & date ...
   <= mdy(12,31,2020)
estat transition
estat duration
predict state1prob if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   pr smethod(smooth)
generate state2prob = 1-state1prob
label var state1prob "regime 1"
label var state2prob "regime 2"
tsset period
tsline  state2prob  if date >= mdy(01,01,2016) & date <= mdy(12,31,2020), ...
   name(japchir2s)


graph combine uscanr2s usgerr2s usukr2s usjapr2s uschir2s cangerr2s ...
   canukr2s canjapr2s canchir2s  gerukr2s gerjapr2s gerchir2s ukjapr2s ...
   ukchir2s japchir2s
```

Appendix C

Discussion paper

C.1 Jean Marc Sengabo

This discussion paper is a written assessment of our thesis with respect to the concept "international". I will here discuss how our topic, hypotheses and findings are or could have been influenced by international trends and forces. Following the arrival of the year 2020, the extraordinary outbreak of the novel coronavirus, which was initially seen as an epidemic, evolved into an all-out pandemic. Consequently, its effects have shaken the global economies and affected countries across the globe. This thesis investigates the relationship between market disturbances across countries and models the recent COVID-19 pandemic's influence on the volatility and cross-market correlation in six major stock indices: S&P 500, S&P/TSX, DAX, FTSE 100, Nikkei 225 and SSE. We estimated the pandemic effect on market volatility with a univariate GJR-GARCH model by Glosten et al. (1993) and employed a multivariate DCC-GARCH by Engle (2002) to examine the conditional correlations between six of the largest economies in the world. We also visualized the regime switching between low and high correlation regimes with a two-regime Markov switching model. Our discoveries suggest that the six indices behaved almost identically under the COVID-19 period, with the Nikkei 225 being the only one that did not show evidence of a higher sensitivity towards COVID-19 news. Furthermore, the filtered and smoothed transition-probability charts showed evidence of stronger cross-correlation during periods of distress and uncertainty, and suggestions of one common market in situations like this are valid. Overall, our findings contribute to previous literature seeking to understand the recent pandemic's influence on capital markets and the negative consequences associated with markets being highly integrated. The thesis has been written by me and Just Andreas Øverby.

Based on our topic, I believe that the concept international is very relevant. Following the arrival of the year 2020, the extraordinary outbreak of the novel coronavirus, which was initially seen as an epidemic, evolved into an all-out pandemic. A pandemic indicates that the virus has crossed international borders and is now a serious global threat. So, in other words, our topic is heavily *newly* motivated. The world had not seen a disease spread across the world to such a large scale since the 1918-20 influenza pandemic (CDC, 2019), and we are still living under and experiencing the effect of the COVID-19 pandemic. Arguably, these effects are not changing in the nearby future. Global COVID-19 cases are getting close to a total of 170 million and the fatalities have crossed the three million mark (Worldometer, 2021), making the recent pandemic one of the deadliest in modern history (TST, 2020). For instance, great powers such as the United States saw the COVID-19 virus contributing to making 2020 the deadliest year in American history (NBC, 2020). In an attempt to reduce the spread of the virus and number of cases and deaths, governments across the world implemented strict domestic restrictions in the form of lockdowns, travel bans and social distancing. Such a sudden disruption to a country's supply chain did not go unnoticed, and many were predicting that we were approaching an economical recession more devastating than the previously experienced recessions of the past decades (Ahya, 2020; Bui et al., 2020; ILO, 2020; Passy, 2021). Our topic is also contributing to a very hot research topic in the fields of finance. With the COVID-19 being a relatively unexpected pandemic, and that we have not experienced a global crisis to such a large scale in modern history, the extensive publication of articles trying to answer questions regarding the pandemic occurrence and the aftermath effect have circulated in the landscape of financial researchers almost daily the past year.

The data we chose was also heavily influenced by international factors. We believe that in order to check how the global market have been influenced, we need to take the globe in to consideration. That is, we need to account for more countries. We examined the daily logarithmic returns of selected stock market indices. The raw data set used for this study was gathered from Yahoo Finance and consists of the following major stock indices: S&P 500 (U.S.), S&P/TSX (CAN), DAX (GER), FTSE 100 (U.K.), Nikkei 225 (JAP) and SSE (CHI). The U.S., Canada, Germany, U.K., Japan and China are six of the largest economies in the world, so we chose their respective benchmark indices as a proxy for the global financial market. The data set covered two sample periods; a pre-COVID-19 period (January 1, 2012 to December 31, 2019) and a one-time-for-all COVID-19 period (January 1 to December 31, 2020) with a sample size of 2,343 observations. Although the pandemic did not hit all countries at the same time, we have assumed a common sample period hence the name "one-time-for-all". Dates with lacking information and little relevance for estimation have been cleaned prior to the data gathering. This reflects the dates where no trading was done, such as holidays, weekends, etc. We are though aware of some limitations with this approach. Even though we had a reasonable argument in favor of our global market proxy, it could still be argued that not including countries that do not represent the 1 percent of the world would not give an accurate and efficient view of the COVID-19 effect on global financial markets. One of the things that the pandemic have actually shown us, is that the differences between the rich and poor are larger than we knew. In Norway we have seen that in the areas where the density is higher and inhabitants' net income is lower, the amount of cases and hospitalized persons are higher (Søegaard & Kan, 2021), whereas in the rest of the world, for instance, we have seen several cases where the amount of vaccines the poorer countries got was substantially less than, say, the U.S. (Steinhauser et al., 2021). The countries we investigated almost all showed the same pattern in the results, whereas if we included countries that deviated in financial strength this would perhaps give us a more comprehensive view of how the pandemic actually affected the global markets. Obviously it is not possible to account for the entire market, but choosing some representative indices from all continents could have been beneficial here. The two hypothesis we formulated made it possible for us to examine the magnitude of the COVID-19 pandemic on both the volatility and cross-correlation in major stock indices across the globe. The two hypotheses that we wished to test were in the end:

1.

H_0: The global financial markets acted indifferently towards COVID-19 news, contrary to years before
H_1: Markets were more sensitive to new information

2.

H_0: The cross-correlation between global financial markets has been stable during the pandemic year of 2020
H_1: The correlation has changed significantly

Where both hypotheses that are tested are directly influenced by international factors or trends.

The findings we found are also influenced by international factors. The introduction of the COVID dummy variable in the GJR-GARCH model showed that for all indices, estimates on the coefficients of the variable took a positive and significant value indicating that we have evidence towards higher volatility in the COVID-19 era. The higher volatile COVID-19 period is also a result that is in line with previous results by Yousef and Shehadeh (2020) who found that the volatility in gold prices could, to a degree, be explained by the increasing uncertainty caused by the pandemic. The theoretical intuition that stock returns and market volatility appears to behave in a positive-negative asymmetrical relationship therefore holds true. An interesting finding in our figure 5.1 was that the European and North American markets almost moved simultaneously, giving evidence, to a degree, of volatility spillovers between these markets. A similar result has been reported by Aslam et al. (2021) who found that the volatility in stock markets tends to change in one market as a response to a change in volatility in another market. Aslam et al. (2021) however only tested for this with European indices, so we have further justified this notion with the inclusion of the North American markets, but have also contradicted it in the Asian markets since we saw that there were clear deviations in the patterns between the Nikkei 225 and SSE.

If we adjust the international factors to also account for country-specific factors, we also found some interesting results that were very relevant to this. From news and factual data, we can see a clear distinction in the Japanese vs. European and North American incidence when it comes to government approaches under the pandemic. From figure 5.1, we can draw some educational comparisons. Looking past the sample separation line of the charts, we can see that around April 2020 Japan exhibits a drastically linear decline while the European and North American indices do similarly decline, but have great volatile upwards spikes also. Under this period, most of Europe and North America went into government restricted lockdowns, while Japan did not. Rather their governmental approach was a "soft lockdown". By law, the Japanese government does not hold the power to implement European-styled lockdowns where people were prevented to move where they wished (Osaki, 2020). Japan kept its local businesses running and did not close down, rather they believed that their people would act responsible and reduce the transmission of the virus on their own. In a way it is understandable that they would use this approach, as Japan is widely recognized as one of the most cleanest countries in the world, and their inhabitants valuate hygiene highly (Powell & Cabello, 2019). The surgical face-masks that have become a symbol for the pandemic across the globe the past year, have been used by the Japanese people for decades before the coronavirus emerged. The discovery that Asian markets seemed to be less affected by the COVID-19 pandemic than American and European markets is also in accordance with previous literature by both Frezza et al. (2021) and Shehzad, Xiaoxing, and Kazouz (2020), which begs questions of investors' abilities to diversify their portfolio investments during periods of uncertainty. This was also substantiated in our contagion analysis. We saw first in figure 5.2 that all the pairs exhibited clear dynamic patterns, where the COVID-19 spike distinguished itself after the green line in all indices comparisons except for the Nikkei 225 vs. SSE, which did have a spike but not to such a magnitude as the other comparisons that had spikes equalling to the sample period peak or close. It appears that during crisis circumstances, there exists a positive relationship between the volatility and cross-correlation. That markets tend to almost behave as one common market during crashes is in line with previous findings by Sandoval and Franca (2012). If they however exhibit this relationship, how will it affect the potential hedging ability for investors who seek to exploit arbitrage opportunities when one market is deemed inefficient? The likelihood of portfolio mismatching is obviously increasing in these situations, and literature seeking to answer questions like this not only argue in favor of typically used safe-haven assets such as gold or cryptocurrencies (Bouri et al., 2020; Baur & McDermott, 2010), but some also found quite interesting evidence in-favour of some safe-haven properties in both the Chinese Renminbi (Fatum et al., 2017) and Japanese Yen (Fatum & Yamamoto, 2016).

To conclude, I'm highly appreciative towards the entire faculty at UiA. This thesis gave me the opportunity to show what I was made of, and I will look back at my five years at UiA with great honour and pleasure.

C.2 Just Andreas Øverby

This discussion paper is a written reflection over what has been done in our thesis with respect to the concept "international", how we as a team have written, worked, and discussed. The process has been both challenging and demanding, but it has also been a very interesting project to work on and has given us lots of rich experience. First of all, our whole thesis is relevant for the topic "international", as its research is done on global indices. Secondly, the thesis in itself showcases international trends and how different forces have lead to movements during and prior to the pandemic of 2020. As such the thesis speaks for itself regarding the questioned topics of discussion.

The coronavirus quickly escalated from a small issue in a country far away into a global pandemic which is still causing problems in the world. From a financial point of view, the combination of increasing debt and government restrictions as a response to the virus accumulated into the 2020 COVID-19 stock market crash, starting in February 2020. Global financial markets experienced months of high volatile movements and several record-low drops.

Our thesis is about the relationship between market disturbances across countries, where we model the recent COVID-19 pandemic's influence on the volatility and cross-market correlation in six major stock indices: S&P 500, S&P/TSX, DAX, FTSE 100, Nikkei 225 and SSE. The aim of selecting these stock indices was to analyze the volatility and correlation impact in times of uncertainty and turbulence for the major world stock indices. The U.S., Canada, Germany, U.K., Japan and China make up more than 56% of the world's GDP (WorldBank, 2019), as such we chose these respective benchmark indices as a proxy for the global financial market. We further estimated the pandemic effect on market volatility with a univariate GJR-GARCH model by Glosten et al. (1993) and employed a multivariate DCC-GARCH by Engle (2002) to examine the conditional correlations between the different indices chosen. We also visualized the regime switching between low and high correlation regimes with a two-regime Markov switching model. The spread of market disturbances across countries has been a popular topic and there are many articles concerning it, especially as a response to the Financial crisis of 2007 - 2009, with many articles being published throughout the years. However, we felt there was a lack of literature considering the spread of disturbances as an effect of the recent pandemic.

With this thesis we wished to first examine the impact of the pandemic on the volatility in major stock indices across the globe, and then perform a contagion analysis across these international borders to check if the movement in one country could be explained by the movement in another. Thus, we would see how or what different international trends and or governmental approaches effected the regions differently. We further created two hypotheses to test for the different effects. Both hypotheses that were tested are directly influenced by international factors and or trends.

Our study examines the daily logarithmic returns of selected stock market indices. The raw data set used for this study was gathered from Yahoo Finance and consists of the following major stock indices: S&P 500 (U.S.), S&P/TSX (CAN), DAX (GER), FTSE 100 (U.K.), Nikkei 225 (JAP) and SSE (CHI). From the data gathered we created two sample periods: a Pre-COVID-19 period and a COVID-19 period, at a frequency of 2,343 observations. We also created visualizations of the log returns in the form of daily returns charts, where we firstly observed that the returns are moving around zero mean. We could also see that the different indices differ when it comes to their volatile movements and that there is clustering in the log returns. Furthermore, we clearly observe a notable large spike in the end of the time-series, marking the beginning of the 2020 COVID-19 pandemic. However, for the Asian countries there seems to be clearer periods of higher volatility clustering in the period moving up to 2020, and perhaps most notably in the time-period between 2013 and 2016. Regarding descriptive statistics, we created two panels of data, both representing a time period, pre-COVID-19 and the "one-time-for-all" COVID-19, respectively. This covered data from the 1st of January 2012 to the 31st of December 2019, and from the 1st of January 2020 to 31st of December 2020.

We first observed the pre-COVID-19 period. Here we are dealing with an expected positive mean that is close to zero for all indices. Typically, when we are analyzing financial returns, there seems to be an existence of a large difference between the maximum and minimum log-returns, negatively skewed left-tails and positive, large kurtosis. In short, the higher order moments, skewness and kurtosis, are typically used to test for the Gaussian distribution. The JB test (Jarque & Bera, 1980), uses both to drum up evidence against the normal. We see in our sample periods that the difference in minimum and maximum returns are quite large, all the indices' tails are negatively skewed with negative values and have positive kurtosis values that confirm that the distributional tails are often influenced by outliers. For the pandemic sample period (the one for all as we call it), we observe a steep drop in minimum log-returns compared to the previous period for most indices. Some of them also expect a negative mean for the entire sample year. The kurtosies have also increased, meaning that the tails are heavier influenced in this period than before. We also observe a small, positive skewness in Japan which can be interpreted as an indicator of smaller losses and less bigger gains in the returns. As the different indices operate inn different environments it is attractive for investors to understand that the Asian capital markets were more severely impacted during the period of 2016 than under the 2020 pandemic. This begs the question, why?

For a time-series analysis on asset returns to succeed, there are four main assumptions that need to be checked. These assumptions are normality, stationarity, serial correlation and heteroskedasticity. Being normal distributed means that the arithmetic mean is perfectly balanced between two symmetrical tails. Even though it is common to assume that returns follow a normal distribution, it is highly unlikely in reality. Testing for normality have been done with the Jarque Bera test (Jarque & Bera, 1980). Stationarity means that properties are not changing over time. We used an augmented version of the Dickey Fuller test (Dickey & Fuller, 1979) for this. Serial correlation means that there exists a systematic relationship between the returns, which results in that the returns today contain information of the returns yesterday. We used a standard Ljung and Box test (Ljung & Box, 1978) for this. Heteroskedasticity explains the variability in the observed data, and the presence of heteroskedasticity is recognized with data observations that are not equal through the span of values of another variable that predicts it. We used a Lagrange multiplier test proposed by Engle (Engle, 1982) for this. In our thesis we see from the test done that we can reject the null hypotheses of all test statistics.

Our findings are encouraging, and in-line with our expectations. However, it was interesting to learn that the Nikkei 225 exhibited decreasing ARCH effects in the COVID-19 phase, which was a clear contradiction to our other estimates. From news and factual data, we can see a clear distinction in the Japanese vs. European and North American indices when it comes to government approaches under the pandemic. From estimated figures we can draw some educational comparisons. We have also observed that around April 2020 Japan exhibits a drastically linear decline while the European and North American indices do similarly decline, however they also have greater volatile upwards spikes. During this time, a significant parts of Europe and North America were placed under government-sanctioned lockdowns, but Japan was not. Rather, their administration used a "soft lockdown" strategy. The Japanese government does not have the legal authority to impose European-style lockdowns that restrict individuals from going where they wish to go (Osaki, 2020). Japan maintained its local businesses open and did not shut them down, believing that its citizens would act responsibly and restrict the virus's spread on their own. In some ways, it's logical that they'd take this approach, given that Japan is often regarded as one of the cleanest countries in the world, and its citizens place a high value on hygiene (Powell & Cabello, 2019) . Surgical facemasks, which have become a global image for the pandemic in the last year, were used by the Japanese for decades before the coronavirus appeared. The finding that Asian markets were less affected by the COVID-19 pandemic than American and European markets is likewise consistent with earlier research by Frezza et al. (2021) and Shehzad, Xiaoxing, and Kazouz (2020). According to our research, there appears to be a positive association between volatility and cross-correlation during times of crisis. Sandoval and Franca (2012) had already observed that during collapses, markets tend to operate virtually like one single market. Then the question becomes, how will this affect the possible hedging capabilities of investors seeking to exploit arbitrage opportunities when one market is judged inefficient, if or when they display this relationship? In these circumstances, the possibility of portfolio mismatching is clearly growing, and literature attempting to answer concerns like this does not simply argue in favor of commonly used safe-haven assets like gold or cryptocurrencies (Bouri et al., 2020; Baur & McDermott, 2010). Nonetheless, some researchers discovered some intriguing evidence in favor of certain safe-haven features in both the Chinese Renminbi (Fatum et al., 2017) and the US dollar (Fatum & Yamamoto, 2016).

To summarize, in the case of future pandemics I believe our findings can contribute to making educational decisions regarding governmental approaches and international tendencies, and at the same time evaluate how actors in the different capital market of the world will act. Thus, making it possible to hedge risk and or exploit said predicament. Finally, I want to express my gratitude to the whole faculty at UiA. This thesis allowed me to demonstrate my capabilities and push myself. It has also been a pleasure working with my partner Jean Marc Sengabo, and I will look back on my five years at UiA with pride and joy.

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