A Directed Research Work Project, comprising Joint Work and two Individual Contributions,

and presented as part of the requirements for the Award of a

Master Degree in Finance from the NOVA School of Business and Economics.

The Covid-19 Timeline: Returns and Volatility Movements in Different Sectors

Catrin Hassdenteufel 44820

This paper details the first Individual Contribution of the Directed Research Project carried out for the Master in Finance Program, under the supervision of Luís Brites Pereira

December 17, 2021

Abstract

As described in the joint work of Adams and Hassdenteufel (2021), to capture stock market volatility amid the Covid-19 pandemic, a GARCH model is appropriate. Here, this is applied by studying the stand-alone Covid-19 impact on volatility of the S&P500 and its sectors. Controlling for additional factors IR, CPI, BAA10Y, EPU and OIL, a positive and significant Covid-19 effect on volatility of returns is detected in all sectors, except for Information Technology. This impact seems stronger in some sectors such as Energy, Materials and Financials. Preceding this, we thoroughly describe the Covid-19 timeline with regards to monetary and fiscal interventions.

Keywords: US Stock Market, Covid-19, GARCH Model, Volatility, Pandemic Timeline

A Directed Research Work Project, comprising Joint Work and two Individual Contributions, and presented as part of the requirements for the Award of a Master Degree in Finance from the NOVA School of Business and Economics.

Measuring the effect of Covid-19 on volatility in the US Stock Market:

Theoretical Approach, Literature Review and Model Selection

Frederike Adams 44091

Catrin Hassdenteufel 44820

This paper details the Joint Work of the Directed Research Project carried out for the Master in Finance Program, under the supervision of Luis Brites Pereira

December 17, 2021

1 Introduction

When the first Covid-19 case was reported on 31 December 2019 in Wuhan, China (World Health Organization 2020), only few suspected the tremendous impact the deadly virus would have on global economies and financial markets alike. Namely, the economic superpower United States (US) experienced a fall in Gross Domestic Product of 31.2% in the second quarter of 2020 (*Trading Economics*). While it was not until 11 March 2020 that the World Health Organization WHO officially declared Covid-19 a pandemic (World Health Organization 2020), the Trump administration imposed several measures prior to the announcement. The first of such measures was an entry restriction for foreign nationals traveling from China (Taylor 2021) announced on 31 January 2020. Financial markets in the US started to react to the pandemic in mid-February with a sharp "freefall" (Bradley and Stumpner 2021) in share prices. Climaxing on 19 February 2020 with a record high, the S&P500 (SPX) severely declined within the next month as investors moved into safe-haven assets (Smith and Badkar 2020). This was also visible in returns of the underlying 11 Global Industry Classification Standard (GICS) sectors, which consist of Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate and Utilities (MSCI 2021). The slumping on financial markets was followed by a two month recession (NBER 2021), stay-at-home orders, governmental relief packages, interest rate adjustments by the Federal Reserve System (Fed), circuit breakers on stock markets, new variants of the virus, four infection waves and, lastly, vaccination campaigns. Governmental interventions and the general development of the pandemic are explained in more detail in Hassdenteufel (2021). The uncertainty that arose from the rapid spread of the virus and its economic consequences led to increased volatility in stock markets (Bachman 2020; Curto and Serrasqueiro 2021) as implied by the sharp increase of the Chicago Board Options Exchange CBOE Volatility Index (VIX) to 82.69 points in March 2020, its highest level since the Financial Crisis of 2007-2008. To measure the uncertainty caused by rising Covid-19 cases, this thesis measures market volatility via the GARCH(1,1) model to capture variance in stock returns amid the Covid-19 pandemic. So far, extensive research has been conducted on the S&P500 (see Literature Review) and its performance during the pandemic. These results are challenging to interpret as the index is comprised of several sectors which we assume to have reacted differently to the pandemic and to have, at least partly, offset each other. While Information Technology probably benefited from increased demand in video conferencing due to home-office orders, we assume sectors that rely on production, i.e., Industrials, to have been hit harder by the pandemic due to disrupted supply chains and factory closings. Motivated by the lack of empirical research on sector level, this paper seeks to contribute to existing literature by splitting the analysis into the 11 GICS sectors. The structure is as follows: Section two reviews existing literature on the impact of Covid-19 on returns and volatility of the US stock market and presents the few available papers analysing different sectors. The section identifies the papers which were used as benchmarks for this analysis and demonstrates gaps in academic literature that we attempt to fill. Section three defines and describes the underlying data and presents dependent and independent variables. In section four, the methodology, namely the GARCH(1,1) model, is introduced. The section will critically inspect this methodology and propose possible alterations. Section five summarizes the findings. The actual application of this thesis, namely of the GARCH model, is conducted in *The Covid-19 Timeline: Returns and Volatility Movements in Different Sectors* (Hassdenteufel 2021) and *Assessing volatility drivers during the Covid-19 pandemic: A Sectoral Approach using the GARCH Model* (Adams 2021). The former thesis stipulates a thorough timeline of the pandemic development and uses the GARCH model to analyse the standalone effect of Covid-19 on the 11 GICS sectors. The latter thesis provides context about what characterized each sector during the pandemic and then applies the GARCH model to a combination of possible volatility drivers for each of the 11 GICS sectors.

2 Literature Review

No preceding pandemic has had such a severe impact on the US stock market like the one of Covid-19 (Baker et al. 2020; Goodell 2020). Initial literature on the pandemic in relation to financial markets focused on total Covid-19 cases and their impact on stock returns (Al-Awadhi et al. 2020; Ashraf 2020; Bretscher et al. 2020) as well as stock market reactions to media news about Covid-19 (Croce, Farroni, and Wolfskeil 2020; Ramelli and Wagner 2020). With the second infection wave, research interest shifted to the influence of Covid-19 cases on market uncertainty and the associated market fluctuations, often accounted for via the CBOE Volatility Index VIX (Albulescu 2021; Okorie and Lin 2021; Onali 2020; Mazur, Dang, and Vega 2021; Zhang, Hu, and Ji 2020). Analyzing 64 countries during the period of 22 January to 17 April 2020, Ashraf (2020) demonstrates that stock market returns declined with an increase in confirmed Covid-19 cases via a panel data analysis. He finds that equity markets respond more strongly to the increase in confirmed cases than to the increase in reported deaths. His research, along with others (He et al. 2020; Xu 2021), indicates that market reactions are particularly strong in the wake of first confirmed cases. Due to local asymmetries in the spread of Covid-19, He et al. (2020) use conventional t-tests and non-parametric Mann-Whitney tests on daily returns to explain the effects of Covid-19 on stock markets. To test for spill-over effects on stock markets, they review eight different countries, namely the People's Republic of China, Italy, South Korea, France, Spain, Germany, Japan, and the US, and include a domestic as well as a foreign timeline. They find a negative, yet short-term, impact on the stock markets of the eight countries under consideration and a bidirectional spill-over effect between these markets. Similarly, Ramelli and Wagner (2020) conduct an event study which examines three distinct phases - incubation, outbreak, and fever - between January and March 2020. They find that US enterprises which trade heavily with China receive negative abnormal returns during the incubation period and significantly negative returns during the outbreak phase. Harjoto et al.(2021) analyze two event studies, one on the shock from the WHO announcement on 11 March 2020 in which Covid-19 was declared a pandemic, and another one on the Fed announcement of the $ 2.3 trillion heavy stimulus package on 9 April 2020. They derive that emerging stock markets are more negatively affected by Covid-19 than markets of developed countries. In addition, they show that small firms experience stronger negative shocks from Covid-19 compared to large firms. They further provide evidence that the Fed stimulus package had a significant positive impact on the US equity market. The majority of these studies focus on the period January to March/April 2020 and examine the impact of Covid-19 on returns at both, global and national, level. All of these studies consider the broader US market. As the pandemic is still prevalent and to this day influences stock markets, our study covers a much longer time period from January 2020 to June 2021 to investigate the presence of the Covid 19 effect. Moving away from returns and more towards the variance therein, Zhang et al. (2020) focus on market volatility in February and March 2020 and point out that out of the ten most affected countries, the United States showed the biggest increase in volatility with the standard deviation of daily returns quadrupling in the two-month period. Baker et al. (2020) explain the stock market swings in late February and early March 2020 as a reaction to news about the progress of the pandemic in the United States. They associate the jumps in March and up to the end of April 2020 with political reactions to the pandemic and the accompanying news about actual and expected monetary policy measures. Following their paper, we consider it relevant to elaborate on policy decisions in a follow-up paper (Hassdenteufel 2021) and to understand the measures and restrictions against the pandemic. Okorie and Lin (2021), using a detrended moving cross-correlation analysis and detrended cross-correlation analysis techniques, report significant yet short-lived fractal contagion effects on stock market returns and volatility as a result of the Covid-19 pandemic. Mazur et al. (2021) investigate the stocks of the S&P 1500 in March 2020 and filter for the best and worst performer. They believe that loser stocks experience more asymmetric movement and exhibit extreme volatility that is negatively correlated with stock returns. With their sector approach, they further show that healthcare, food, natural gas, and software outperform the market and generate higher returns, while equity values in the oil, real estate, entertainment, and hospitality sectors fell significantly, losing more than 70% of their market capitalization. Their paper reflects the different movement at industry as well as at sector level. A sector approach seems necessary to determine whether and how Covid-19 has affected US markets and is hence applied in this thesis. Albulescu (2021) examines the impact of official Covid-19 announcements of new Covid-19 infections and the mortality rate on financial volatility by means of an Ordinary Least Squares regression. From mid-March to mid-May 2020, he finds evidence that new infections increase volatility at both, global and US level, with the former impact being stronger than the latter. Zaremba et al. (2020) run a panel data regression with seven explanatory variables (school closing, workplace closing, cancelled public events, closed public transport, public information campaigns, restrictions on internal movement, and international travel controls) on daily volatility and discover a link between the stringency of government policies and rising stock market volatility in their analysis of 67 countries. Haroon and Rivizi (2020) use an EGARCH model to examine the relationship between news coverage and financial market volatility from January to April 2020. They find that media-induced panic is associated with increased volatility in global financial markets, especially for hard-hit industries such as transportation, automobiles and components, energy, travel, and leisure. Sharif et al. (2020) consider the relationship between daily Covid-19 cases and oil price volatility shocks, the stock market, geopolitical risks, and economic policy uncertainty in the US by the wavelet method. Their paper shows that Covid-19 has a stronger impact on geopolitical risk and economic uncertainty than on the stock market.

Secondly, they conclude that the US stock market reacted more to oil price fluctuations than to news from Wuhan. Their study clarifies that the pandemic was accompanied by a high level of uncertainty, as captured by the Economic Policy Uncertainty Index (EPU), and that the oil price might have had an even bigger impact on the stock market than Covid-19 or the EPU. Motivated by their results we find it necessary to consider EPU and OIL as a control variable in our analysis. Using the Markov switching approach, Just and Echaust (2020) examine volatility, correlation, and liquidity to explicate the impact of the coronavirus pandemic on the US equity market and conclude that illiquidity does not affect stock market returns and is independent of Covid-19 data. Baek et al. (2020) apply a Markov switching AR model to highlight the regime change from lower to higher volatility as a response of the stock market to daily Covid-19 cases from January to April 2020. They show a significant increase in total risk and idiosyncratic risk for all 30 industries under consideration. They also reveal that volatility is more strongly influenced by Covid-19 news than by economic indicators such as the CBOE Volatility Index VIX, Economic Policy Uncertainty Index EPU, Term Spread, TED spread, ICE Bofa High Yield Index Effective Yield, Moody's AAA Corporate Bond Yield, WTI Crude Oil Price, Federal Fund Target Range, Overnight Libor, and Effective Federal Fund Rate. Finally, they indicate that there is a negative bias on volatility, with negative death toll news having twice as large an effect as positive recovery news. In their paper, Yousfi et al. (2021) use a multivariate GARCH model to study the first two Covid-19 waves and show that even after easing quarantine restrictions following the first wave, correlations between Covid-19 infections and uncertainty on the US stock market as well as the overall economy remain to exist. This hints at the fact that market reactions were different in each distinct infection wave and motivated our follow-up paper Hassdenteufel (2021) to divide the pandemic into its four major infection waves. Xu (2021) uses a bivariate structural GARCH-in-mean VAR to examine stock returns and the growth rate of Covid-19 cases from 22 January to 2 July 2020. He finds that volatility, which he refers to as “uncertainty”, has a negative impact on returns. Furthermore, he discovers that the reactions of stock returns to the rise and fall of the Covid-19 cases are largely symmetric. Curto and Serrasqueiro (2021) test with an APARCH model whether stocks in different sectors are equally affected by Covid-19. In addition to the 11 GICS, they also place a focus on volatility of FATANG[1] stocks. They identify a consistently positive coefficient for the Covid-19 period, from which they derive an increase in volatility after February 2020. Their study also detects that, as suspected, US sectors and their stock prices are affected differently by Covid-19. They reveal that higher volatility favours sectors such as Information Technology, Consumer Discretionary, Communication Services, Consumer Staples, and Industrials, as well as FATANG stocks, while Energy is affected most negatively. However, they could not identify any impact of vaccination measures on volatility. As preceding literature on later stages of the pandemic predominately focus on market volatility (Albulescu 2021; Okorie and Lin 2021; Onali 2020; Mazur, Dang, and Vega 2021; Zhang, Hu, and Ji 2020), this is where we commence. In line with Haroon and Rivizi (2020), Yousfi et al. (2021) and Xu (2021), a sort of GARCH model may serve as a suitable way to estimate this. The aforementioned assumption that the 11 GICS sectors have reacted differently to the shock Covid-19 motivates us to examine the impact of the pandemic on stock volatility not only at the index level but at the sectoral level. An overview of the literature review can be found in *Appendix Table 1.*

3 Data

3.1 Dependent Variable (Sectors)

The analysis of the Covid-19 effect on the United States equity market suggests the use of an index proxy for United States stock returns. As such, we chose the frequently used Standard and Poor 500 Index, which is composed of 500 leading companies and covers approximately 80% of available market capitalization in the United States (S&P Dow Jones

[1] The FATANG stocks consists of the following 6 companies: Facebook, Amazon, Tesla, Apple, Netflix and Google.

Indices LLC 2020, 500). As economic intuition and previous literature predict different sectors to react differently to exogenous shocks (Nicola et al. 2020; Ramelli and Wagner 2020; Curto and Serrasqueiro 2021), a sector approach seems appropriate. The analysis is conducted for the 11 GICS sectors. Data for the S&P500 as well as for the 11 GICS sectors has been retrieved from *investing.com* from 1 July 2019 to 30 June 2021 on a trading day basis. This particular time frame was chosen to account for the four major Covid-19 waves in the United States, namely from January to May 2020, from June to October 2020, from November 2020 to March 2021 and from April to June 2021 and to include a brief pre-pandemic time horizon to better describe the conditional heteroskedasticity of financial returns. The latter will be described in more detail in the methodology section. Returns are expressed as daily percentage changes of closing prices. Summary statistics of the selected dependent variables for 501 observations can be found in *Appendix Table 2* with a description in *Appendix Comment 1* and a visualization in *Appendix Figure 2.*

3.2 Independent Variables

To effectively measure the Covid-19 effect on financial markets, this paper considers new confirmed Covid-19 cases in the United States. Data was retrieved from *Our World In Data* from 22 January 2020 (first confirmed Covid-19 case in the US) to 30 June 2021 on a daily basis for seven days a week, which amounts to 526 observations. Due to the availability of stock returns, our analysis can only account for trading days, namely Monday to Friday. However, simply omitting weekend Covid-19 cases may manipulate the dataset and subsequently the results. Hence, for each Monday, a three-day average of new cases from Saturday to Monday was formed. Together with the exclusion of bank holidays, this approach leaves 362 observations. Financial markets are certainly influenced by factors other than Covid-19 cases. Based on existing literature, we introduce a set of control variables which further affect the S&P 500. These factors have been retrieved from 1 July 2019 to 30 June 2021 on a trading day basis and are explained hereafter. Financial theory (Sharpe 1964; Fama and French 1993) suggests that the risk-free interest rate has explanatory power over expected returns of an asset, i.e., a stock. Various analyses of the stock market hence include the interest rate as an independent variable (Charles and Kim 2016; Hu, Hu, and Tsai 2018; Pilinkus 2010; Thorbecke 2020). As a modern proxy for the risk-free rate, it is common to use the interest rate on three-month treasury securities, which we retrieved from the *Federal Reserve Website*[2]. Another influence on stock returns derives from inflation (Charles and Kim 2016; Pilinkus 2010). Measuring changes in prices for a market basket of consumer goods and services (U.S. Bureau of Labor Statistics 2020), the Consumer Price Index CPI can serve as an proxy thereof (Bryan and Cecchetti 1993). To track the monthly reported CPI on a daily basis, we consider returns on the IQ Real Return ETF (CPI) as reported on *investing.com*. Expanding or contracting yield spreads reflect changes in the underlying economy or financial markets. In accordance with Smales (2020) and Thorbecke (2020), we hence include the spread between Moody's Seasoned Baa Corporate Bond Yield and Yield on 10-Year Treasury Constant Maturity (BAA10Y), retrieved from *Federal Reserve Economic Data St. Louis Fed*[3]. Prior research suggests that the Economic Policy Uncertainty Index for the United States (EPU), which measures uncertainty around government policy decisions, also affects stock returns (Antonakakis, Chatziantoniou, and Filis 2013; Pástor and Veronesi 2013) which motivated its inclusion in our analysis. The EPU Index for United States (USEPUINDXD) has been retrieved from *Federal Reserve Economic Data St. Louis Fed*[4] and has been transformed into percentage changes. As tested and proven by several studies (Hamilton 1983; Narayan and Gupta 2015; Narayan and Sharma 2011; Seong and Nam 2021; Zhu et al. 2016), the oil price heavily influences economies and subsequently stock returns. The Crude Oil Price has thus been considered for stock return

[2] www.federalreserve.gov
[3] https://fred.stlouisfed.org/series/BAA10Y
[4] https://fred.stlouisfed.org/series/USEPUINDXD

predictions in various literature (Ciner 2021; Thorbecke 2020). Returns on the price of Crude Oil West Texas Intermediate Futures (TZ1), a future contract on the following month, have been retrieved from *investing.com*. Since stock markets react almost immediately to current events, for the purpose of this thesis, daily data is required. This implicitly excludes variables that are reported on a monthly or quarterly basis for our purposes as any attempt to transform their time horizon (i.e., interpolation) could potentially manipulate the analysis. This eliminates, for example, the use of Purchasing Managers Index PMI, US Dollar Index, Unemployment Rate (Hu, Hu, and Tsai 2018), Gross Domestic Product, Industrial Production Index, or Money Supply Indices (Pilinkus 2010). Summary statistics of the independent variables can be found in *Appendix Table 3* with a description in *Appendix Comment 2* and graphs in *Appendix Figure 3* to *Appendix Figure 7*.

4 Methodology

4.1 Model Selection

While analysing a time series, it is crucial to find a model that optimally describes the underlying data and takes its properties into account. For financial data this usually incorporates non-linearity and heteroskedasticity, i.e., volatility clustering (Mandelbrot 1967), meaning the variance of their residuals is not constant over time. The Autoregressive Conditional Heteroskedasticity ARCH (Engle 1982) approach and, more specifically, the Generalized Autoregressive Conditional Heteroskedasticity GARCH model (Bollerslev 1986), account for conditional variance and are hence commonly used for financial time series analysis. The GARCH process is mean reverting, conditionally heteroskedastic and stationary but with a constant unconditional variance (Bollerslev 1986). The required stationarity and autocorrelative structures of the underlying data (Bollerslev 1986) are tested in the next section. Generally, the GARCH (1,1) model derives from two formulas. The mean equation:

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t \tag{1}$$

describes the stock returns r at time t as a function of a constant a_0, a coefficient a_1, the mean return from the previous period r_{t-1}, as well as the independent and identically distributed error term ε_t. The variance equation:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \tag{2}$$

describes the variance σ^2 at time t as a function of a constant β_0, the coefficients β_1 and β_2, the squared residuals of the previous period ε_{t-1}^2 and the GARCH effect, namely the variance of the previous period σ_{t-1}^2. Controlling for the factors specified in section 3, the GARCH models in the follow-up work Adams (2021) and Hassdenteufel (2021) follow the undermentioned mean formula:

$$r_{it} = a_0 + a_1 Covid_t + a_2 IR_t + a_3 CPI_t + a_4 BAA10Y_t + a_5 EPU_t + a_6 OIL_t + \varepsilon_i \tag{3}$$

where r_{it} denotes stock return r of index i at time t, $Covid_t$ denotes confirmed new Covid-19 cases in the US, IR symbolizes the interest rate on three-month Treasury securities, CPI measures inflation, $BAA10Y$ stands for the spread between BAA corporate bonds and 10-Year Treasury Constant Maturity, EPU acts for the USEPUINDXD, OIL represents the TZ1 and ε is the independent and identically distributed error term. While the lagged squared residuals in the variance function account for the regressors of the mean function, namely Covid-19, IR, CPI, BAA10Y, EPU and OIL, additionally including these regressors as contemporaneous exogenous variables in the variance equation allows to detect their effect on stock volatility in combination with the Covid-19 effect. The variance function then follows the general undermentioned formula:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 X_t \tag{4}$$

Where X_t denotes the additional independent variable at time t included as a variance regressor. This is applied and specified in Adams (2021) and Hassdenteufel (2021). Both papers generally test the null hypotheses, that the exogenous variable at time t has no significant influence on the variance, i.e. volatility, of that sector during the pandemic sample period:

$$H_0\colon \beta_3 = 0 \iff H_0\colon R^2 = 0 \tag{5}$$

H_0 is rejected if $p < 0.01$ (99% confidence interval) or if $p < 0.05$ (95% confidence interval). The econometric modelling and tests of this thesis and the two preceding papers have been conducted in *eViews*.

4.2 Stationarity and Unit Roots: Augmented Dickey and Fuller Test

For autoregressive models, the assumption of stationarity needs to hold. This means the underlying time-series needs to have a constant mean and variance. As can be seen in *Appendix Figure 1*, the trend in new daily Covid-19 cases does not seem to follow the same distribution over the time frame and is therefore probably non-stationary. A first step towards stationarity is to reduce heteroskedasticity by taking the natural logarithm of the data. In this case, the results presented in *Appendix Figure 8* still seem to imply non-stationarity due to the jump in March 2020. A common solution to this is to transform the data by taking first differences. Now, in *Appendix Figure 9*, the times series seems to assumably have a constant mean. However, a slight structural break in variance is observable which could pose as a threat to stationarity. To improve this, first differences is applied to the logged data points. Covid-19 cases have to be increased by one to allow prior values of zero to be logged. A visualization of the results can be seen in *Appendix Figure 10*. The first half of the data differs from the second part of the data, starting in March 2020, as no major Covid-19 outbreak has been reported prior. Despite this, the time-series now appears to be stationary. To test if the expected stationarity holds for our sample period from July 2019 to June 2021, we employ the commonly used Augmented Dickey and Fuller technique ADF (Dickey and Fuller 1979). The ADF tests the null hypothesis that a unit root is present in a time series which means the alternative hypothesis implies stationarity. As opposed to the simple DF test, the ADF allows for the underlying time series to have a more complicated dynamic structures than assumed in a simple autoregressive AR(1) model. The empirical results presented in *Appendix Table 4* confirm our assumption. With p-values of

0.3386 and 0.4466 for new Covid-19 cases and, respectively, logged new Covid-19 cases, the null hypothesis cannot be rejected at 5% significance level. In other words, unit-roots are present. However, when taking the first difference as well as the difference of the natural logarithm, the p-values of 0.0000 and 0.013 allow for a rejection of the null hypothesis at 5% significance and stationarity can be assumed. The same ADF test has been applied to variations of the remaining independent variables and to the S&P500 and its 11 sectors with the results presented in *Appendix Table 5* and *Appendix Table 6*. The results suggest that the null hypothesis for IR and BAA10Y can be rejected at a 1% significance level when taking the first difference of the variables. They further imply that percentage changes on the CPI Index, EPU Index, and Oil Price can be assumed to be stationary without taking their first difference and that natural logarithms of the control variables are not necessary for stationarity. The small p-values for the dependent variables suggest that the returns of the S&P500 and its 11 sectors are in fact stationary without taking first differences or natural logarithms.

4.3 ARCH effects: Lagrange Multiplier Test

To further determine if a GARCH model is, in fact, appropriate for the data at hand, the presence of heteroscedasticity needs to be confirmed. For this, it is sensible to use the Lagrange Multiplier LM test (Engle 1982) by means of regressing the squared residuals (Brooks and Wichmann 2019). It tests the null hypothesis that there are no ARCH effects present, namely that the residuals are homoscedastic. Results of the heteroskedasticity test for each sector over the full sample period are shown in *Appendix Table 7*. Except for Utilities, all p-values are well below the 5% and even the 1% threshold which indicates the anticipated presence of ARCH effects in stock returns. Justified by the strong results for 10 out of the 11 sectors as well for the S&P500, which includes Utilities, and by the p-value of 0.1263 we will hereinafter assume returns of Utilities to have ARCH effects as well. As this is a strong assumption given the statistical results, we will interpret the final results for Utilities with high prudence.

4.4 Multicollinearity: Variance Inflation Factors

In a next step, multicollinearity was tested by means of the Variance Inflation Factor VIF. The explanatory variables are required to be independent of each other. The Belsley-Kuh-Welsch collinearity diagnostic and VIF are portrayed in *Appendix Table 8* and *Appendix Table 9*. They show no evidence of excessive collinearity.

4.5 GARCH Model Estimation

After ensuring stationarity, ARCH effects and the absence of multicollinearity, the GARCH model can be estimated for the S&P500 and its 11 sectors. Initially, it was planned to conduct the analyses for the four major Covid-19 waves from January to May 2020, June to October 2020, November 2020 to March 2021 and April to June 2021, to see if the different phases yield different results, as well as for a pre Covid-19 period to use as a benchmark for the remaining independent variables. The GARCH model, being based on maximum likelihood (Bollerslev 1986), requires a certain number of observations in order to run sufficient iterations. This limited the analysis of the underlying data in that, after several trials, we only found results for all sectors when considering the full Covid-19 period of our dataset, namely January 2020, when the first Covid-19 case was reported in the US, to June 2021, when Covid-19 cases hit the lowest rate since the beginning of the pandemic. This time period includes 375 observations. In some cases, the estimation failed to improve likelihood (non-zero gradients) after a certain number of iterations. The corresponding table cells in these cases are generally left blank. The analysis further has to be limited to first differences of logged new cases, since the maximum likelihood function did not find results when considering first differences of simple new cases. We are aware that our estimation approach faces some limitations. For a start, hazards to the usability of the underlying data lie within the manipulation of weekend data for Covid-19 cases applied in this paper. We consider the computation of a Monday average to be legitimate as this captures the fact that less cases are reported on Saturdays and Sundays and, consequently more cases are reported on Mondays. However, one could also omit Saturday and Sunday data and implement a dummy variable for Mondays to account for the higher number of reported cases. It should further be mentioned that the GARCH(1,1) model treats volatility in a symmetric way. More specifically, upward and downward movements of the same magnitude are considered to be of equal volatility. In reality, especially with financial time series, downward trends usually impact volatility more severely than upward trends, which means that volatility is not necessarily symmetric per se. To account for asymmetry, future studies on the topic could extent the analyses to a Threshold-Asymmetric GARCH (Glosten, Jagannathan, and Runkle 1993) or Exponential-GARCH model (Nelson 1991).

5 Summary and Next Steps

From the thorough literature analysis of this paper, it is derived to now move forward with an analysis of volatility during the pandemic in the 11 GICS sectors. This will be done using the GARCH(1,1) model. The model fits the properties of financial time series and our data passed the necessary tests for stationarity, ARCH effects (with one exception), and multicollinearity. Hence, the GARCH serves as a suitable model to proceed with. This is applied in Adams (2021) and Hassdenteufel (2021). In these papers, the model is extended to estimate the standalone effect of Covid-19 on volatility in the 11 GICS sectors and to identify potential other volatility drivers. The papers further include an analysis of the Covid-19 timeline, a description of cumulative returns, and provide context about developments in each sector during the pandemic.

1 Introduction

This individual paper extends the theoretical work derived in the joint thesis *Measuring the effect of Covid-19 on volatility in the US Stock Market: Theoretical Approach, Literature Review and Model Selection* (Adams and Hassdenteufel 2021). The GARCH(1,1) model is now applied to the 11 Global Industry Classification Standard (GICS) sectors and the previously introduced independent variables from January 2020 to June 2021. Thereby, we analyze the effect of Covid-19 on volatility in stock returns. With the onset of the pandemic and the first case in the United States (US) on 20 January 2020 (Rabin 2020), US equity markets such as the S&P 500 went into turmoil in mid-February, which was reflected in a sharp drop in returns and high volatility (*Bloomberg*). While Covid-19 cases increased exponentially, peaking at 303007 cases on 8 January 2021 (*Our World in Data*), the US stock market, after its initial shock in February and March 2020, moved from one all-time high to the next (*Bloomberg*). To understand this, it is necessary to examine the Covid-19 timeline in more detail and consider the economic and financial consequences of fiscal and monetary packages introduced by the government or other institutions in these initial stages. The thesis is structured as follows: section two reviews the timeline of the Covid-19 virus. It mainly covers the first infection wave, including the most important events and the various stimulus packages introduced by the US government. Section three covers the four different infection waves and their implications for stock market returns. Section four analyzes these returns by diving into the mean and variance equations of the GARCH model as introduced and tested empirically in the joint work of Adams and Hassdenteufel (2021). Section five discusses the limitations of the model. Section six summarizes the main findings and explores potential areas for further research to complement this analysis.

2 A Covid-19 Timeline

Harjoto et al (2021) showed the positive impact of the Federal Reserve System (Fed) stimulus package on the US stock market, and Baker et al. (2020) found a correlation between the stock jumps and the fiscal and monetary policy in March and April 2020. Motivated by these two, the timeline of Covid-19 and the associated governmental reactions will be discussed in more detail below. The first official Covid-19 case, detected in Wuhan, was reported by the Chinese Government on 31 December 2019 (World Health Organization 2020). The US government responded exactly one month later by restricting entry to passengers arriving from China in the hope to avoid a spread of the virus to the US (Taylor 2021). Recognizing the risk the pandemic posed on economic activity, the Federal Reserve System (Fed) intervened on 3 March 2020 by lowering the target range for the federal funds rate to range between 1% and 1.25% (Federal Reserve System 2020a). Lower interest rates encourage spending and inject capital into the economy (Knueven 2020). This boosts household spending and demand, i.e., for consumer durables or residential investments. Likewise, lower rates help businesses borrow cheap which encourages investments in plant, equipment and production which will grow supply (Labonte 2020). Despite the Fed intervention, the markets remained unsettled and continued to fall (Huang 2020). To support the development of vaccines, humanitarian assistance and grant loans for affected small businesses, the first governmental relief package *Coronavirus Preparedness and Response Supplemental Appropriations Act 2020,* signed on 6 March 2020, provided USD 8.3 billion of emergency funding (116th Congress 2020a). On 11 March 2020 the World Health Organization officially declared Covid-19 a pandemic (World Health Organization 2020). The following week was met by four circuit breakers[5], which haltered all trading activities under extreme volatility on the New York Stock Exchange (Pisani 2021; Funakoshi and Hartman 2020). On 15 March 2020, the Centers for Disease Control and

[5] The circuit break is triggered when the S&P500 falls more than 7%.

Prevention (CDC) instructed US citizens to avoid gatherings of more than 50 people, which was followed the next day by Trump's advice to avoid gatherings of more than 10 people (Smith-Schoenwalder 2020). This marked the start of social distancing rules, stay at home orders (Romo 2020) and more severe travel restrictions. Evidently, these measures would limit spending and affect business and disposable incomes. The S&P500 reached a record low of - 11.98% on 16 March 2020 and its lowest price of 2237.4 on 23 March 2020 (*Figure 1*). Rising uncertainty among investors led to tremendous movement in stock markets which, on 16 March 2020, led to a peak of over 82 points of the CBOE Volatility Index (VIX), an index measuring the 30-day implied volatility of the S&P500. The VIX more than doubled solely in March 2020 (Li 2020).Motivated to counteract the possibly severe consequences this would have on the financial system and to support credit flows (Cheng et al. 2020), the Fed intervened once more on 15 and 16 March 2020 by engaging in Quantitative Easing (QE) and by lowering the target range for the federal funds rate by 100 basis points to range between 0% and 0.25% (Federal Reserve System 2020b). Around the same time, on 18 March 2020, the second relief package, the *Families First Coronavirus Response Act*, allocated funds to pay for sick leave, tax credits, free Covid-19 testing and nearly USD 1 billion to unemployment benefits (116th Congress 2020b). Regardless, business shut downs and condensed economic activity in the US induced a cross sectional reduction in workforce and a consequent unemployment rise, decreased demand, and supply shortages for commodities and manufactured products which was induced by panic-purchases and stock piling of food products (Nicola et al. 2020). The US and other nations alike were either heading towards a recession or already deep within one (NBER 2021; Taylor 2021). Thorbecke (2020) claims the Covid-19 pandemic announcement led to a drop in the overall US stock market of more than 40% in the period from 19 February to 23 March 2020. The third and largest relief package, the *Coronavirus Aid, Relief, and Economic Security (CARES) Act*, was ultimately introduced on 27 March 2020. It included another USD 2.3 trillion to aid individuals, businesses and industries, and to expand unemployment benefits and support hospitals (116th Congress 2020c). New Covid- 19 cases reached their first peak on 9 April 2020 (*Figure 1*). Notably, the stock market seemed to react positively to the Fed's actions, especially the CARES Act, as stock prices trended upwards between 23 March and 10 July. In particular, stocks related to home and renovation gained momentum, suggesting that economic stimulus has encouraged people to spend again (Thorbecke 2020). This was also reflected in the household savings rate, which peaked in April at 33.8 % compared to 13.1 % in the previous month and then dropped again (U.S. Bureau of Economic Analysis 2021). May 2020 marked the first month post-recession while Covid-19 cases touched their second high on 16 July 2020 (*Figure 1*). By the end of the year, on 29 December 2020, the new SARS-CoV-2 variant from the United Kingdom was confirmed in the US (Singh and Bekiempis 2020), which contributed to the third, and thus far highest, peak of new Covid-19 infections in the US on 8 January 2021 (*Our World in Data*). This was followed by the arrival of the new P.1. variant from Brazil on 25 January 2021 (Firestone 2021). Although new infections sharply declined after January 2021, they still reached a considerable high on 24 March 2021 (*Our World in Data*). On 16 April 2021, mass vaccinations started as all US citizens were eligible for a Covid-19 vaccine (Anthes, Ngo, and Sullivan 2021). By 30 July 2021, the US has reported over 35 million Covid-19 cases, and more than 0.6 million Covid- 19 related deaths (*Our World in Data*). The aforementioned description demonstrates that financial markets were influenced by Fed reactions and governmental relief packages. While these measures were especially present in early stages of the pandemic development, it is interesting to see how the S&P500 and its 11 GICS sectors behaved in the second, third and fourth infection wave. This is examined in the following section.

3. Cumulative Returns

The study of stock returns during the four major infection waves, namely from January to May 2020, from June to October 2020, from November 2020 to March 2021, and from April to June 2021, is conducted on a sector level. This is because, as mentioned in Adams and Hassdenteufel (2021), similar to Cutro and Serraqueiro (2021), we suspect that not all sectors reacted to the pandemic in the same manner. The S&P500 can be categorized into 11 GICS sectors, each contributing with different weights to the composition of the broader index (MSCI 2021). One should notice that the index is market-capitalization weighted. Whereas Information Technology dominates more than a quarter of the index with 28%, followed by Health Care with 13% and Consumer Discretionary with 12% respectively, Real Estate and Energy each account for merely 3% and Materials and Utilities merely for 2% each (*Appendix Figure 13*). While some industries were hit severely, others gained momentum via their business model or the prevailing dovish monetary policy. During the sample period, all sectors, except for Consumer Staples, suffered their biggest one-day loss on 16 March 2020, while index prices reached their respective lows on 23 March 2020 (*Figure 1*). In the first infection wave, Energy

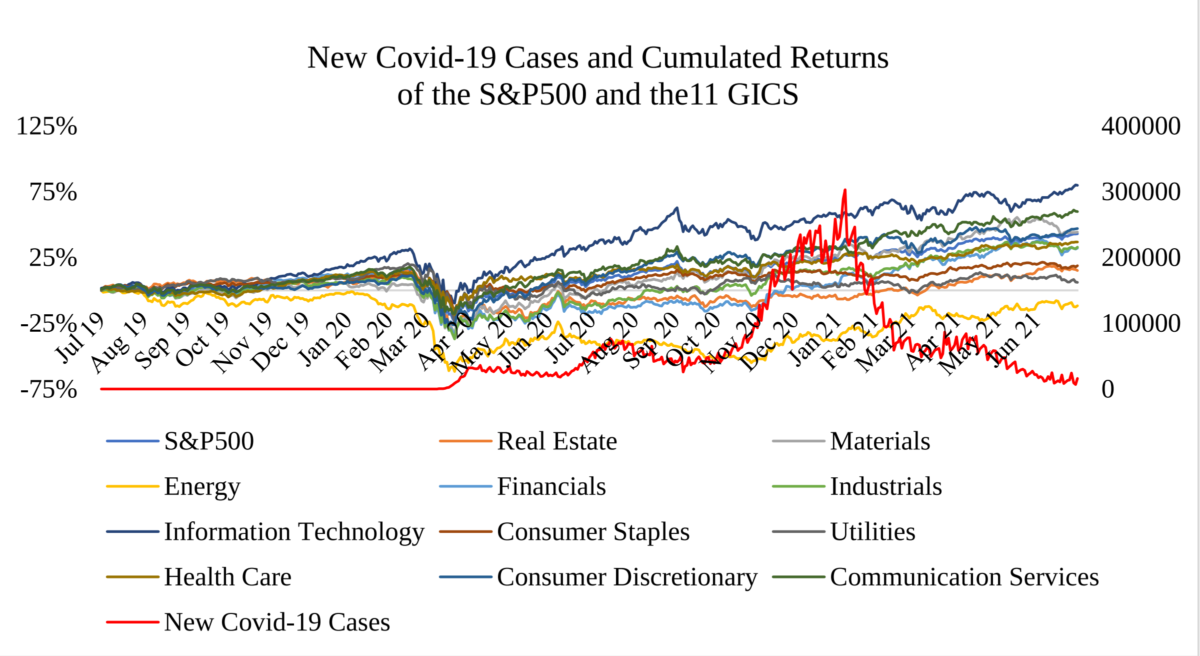


Figure 1 *New Covid-19 Cases and Cumulative Returns of the S&P500 and the 11 GICS sectors (Own illustration with data from Our World and Data and investing.com)*

was hit hardest with -35.45%, followed by Financials, Industrials and Real Estate with -23.98%, -16.97% and -16.81%, respectively. In general, no sector was able to return to their pre Covid- 19 level in these months (*Appendix Figure 14*). Amid the second wave, Energy still suffered the most with cumulative returns of -26.21%. Financials (0.81%) and Real Estate (- 0.47%) ended close to zero in this period. Materials (14.09%), Consumer Discretionary (13.64%), Industrials (11.49%) and Information Technology (10.11%) seemed to recover and outperformed the broader index (5.64%) (*Appendix Figure 15*). In the third wave, Energy gained momentum and ended as the best performer with cumulative returns of 72.65%, while Financials profited and ended with 43.26%. Only Utilities gained a mere 2.24% in this period while the S&P500 grew by 20.49% (*Appendix Figure 16*). The fourth infection wave showed a slight upward trend across all sectors (8.19%), particularly for Information Technology (11.22%) and Communication Services (10.41%) which grew the most and outperformed their peers (*Appendix Figure 17*). From the first Covid-19 case on 22 January 2020 to 30 June 2021, the end of our sample window, the S&P500 gained 26.26% with the strongest performance observed in Information Technology (44.59%), followed by Materials (38.42%), Communication Services (37.95%) and Consumer Discretionary (36.97%). Having analyzed the cumulative returns of the four major Covid-19 infection waves in the US is a testament to the fact that sectors performed differently during the pandemic. In a next step, this is detected empirically. The GARCH(1,1) model is applied in order to identify and compare the distinct effect of Covid-19 on stock volatility of different sectors. We hope to reveal to what extent changes in stock returns, and mainly in stock volatility, can actually be explained by increasing or decreasing Covid-19 cases.

4 Model

4.1 Mean and Variance Estimation

This paper derives from Adams and Hassdenteufel (2021) and their theoretical and empirical justification of the use of a GARCH(1,1) model. To quantify the impact of Covid-19 on stock returns and volatility, we build on the general mean and variance functions. For the sample period of January 2020 to June 2021, the two formulas are applied to returns of the S&P500 and the 11 GICS sectors while controlling for certain independent variables that capture the macroeconomic environment and its impact on returns. The independent variables are the Interest Rate, Consumer Price Index, the spread between Moody's Seasoned Baa Corporate Bond Yield and Yield on 10-Year Treasury Constant Maturity, Economic Policy Uncertainty index and the Crude Oil Price, denoted by IR, CPI, BAA10Y, EPU, and OIL, respectively. The mean function is denoted as

$$r_{it} = a_0 + a_1 Covid_t + a_2 IR_t + a_3 CPI_t + a_4 BAA10Y_t + a_5 EPU_t + a_6 OIL_t + \varepsilon_i \qquad (1)$$

which is explained in more detail in Adams and Hassdenteufel (2021). To measure the distinct influence of Covid-19 on volatility, the variable is included as an exogenous variance regressor in the variance function. The variance equation follows the undermentioned formula:

Model 1
$$\sigma_{it}^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 Covid_t \qquad (2)$$

Summarized results of the GARCH estimations are portrayed in *Table 1* and are analyzed thereafter.

4.2 Results

Table 1 presents the Covid-19 coefficients a_1 and β_3 for the mean and variance function as well as their respective p-values. None of the Covid-19 coefficients for the mean function show any significance, indicating that Covid-19 cases had no statistical effect on any of the sectors' actual returns. As shown in the Literature Review (Adams and Hassdenteufel 2021), there are models which are more appropriate when testing for abnormal returns. In *Appendix Table 10* a visualization of the sector specific mean coefficients is presented. Here, one can see

	Covid-19 Coefficient α_1 (mean function)	p-value	Covid-19 Coefficient β_3 (Model 1)	p-value
S&P500	-0.0001	0.9480	0.000043	0.0018**
Energy	0.0010	0.7867	0.000231	0.0003**
Materials	0.0028	0.2678	0.000113	0.0011**
Financials	0.0026	0.3167	0.000109	0.0007**
Industrials	0.0012	0.6201	0.000080	0.0011**
Utilities	0.0022	0.1597	0.000079	0.0000**
Health Care	0.0003	0.8066	0.000076	0.0010**
Communication Services	-0.0013	0.4430	0.000065	0.0023**
Consumer Discretionary	0.0006	0.6902	0.000062	0.0002**
Information Technology	-0.0029	0.1037	0.000056	0.0745
Real Estate	-0.0007	0.6959	0.000049	0.0440*
Consumer Staples	0.0013	0.2613	0.000045	0.0022**

**significant at 1% *significant at 5%

Table 1 *Summarized Model 1 Results Sorted by Size of Covid-19 Coefficient*

that CPI, BAA10Y and EPU seem significant for mean returns in most sectors. IR yields a significant positive effect for the overall S&P500 index. Notably, with the exception of Financials, none of the underlying sectors seem to be affected by IR. This seems somewhat unexpected considering that Financials only accounts for 11% of the S&P500. The OIL coefficient of the mean function only shows significance in the Energy sector. As described in the Literature Review section of Adams and Hassdenteufel (2021), the Covid-19 effect on financial markets may be captured most visibly by investigating volatility as opposed to stock returns. Analyzing the variance equation, with the exception of Information Technology, the low p-values for all Covid-19 coefficients show significance at 5% significance level and, with the exception of Real Estate, even at 1% significance level. This implies that, holding all other variables constant, we can mostly reject the null hypothesis[6] and can conclude that Covid-19 cases have a significant effect on stock variances, i.e., volatility, during the sample period. All significant coefficients in the Model are positive, indicating that an increase (decrease) in

[6] The null hypothesis states that the exogenous variable Covid-19 has no significant influence on the variance of stock returns at time t. The derivation for this can be found in the study of Adams and Hassdenteufel (2021).

Covid-19 cases increases (decreases) the variance of returns by that specific coefficient. This is in line with the study of Curto and Serrasqueiro (2021), who also find exclusively positive Covid-19 coefficients. However, their paper detects significant results for Information Technology, Consumer Discretionary, Communication Services, Industrials, Consumer Staples, and Energy, whereas our results lack significance for Information Technology but show significance for Materials, Financials, Utilities, Health Care and Real Estate. Our analysis shows that the pandemic had the largest effect on volatility in the Energy, Materials and Financials sectors, a relatively moderate effect on volatility of Industrial, Utilities, Health Care, Communication Services and Consumer Discretionary and the smallest effect on volatility in Real Estate and Consumer Staples. A more in-depth sectoral analysis as well as an extension to other exogenous factors in the GARCH Model can be found in the work *Assessing volatility drivers during the Covid-19 pandemic: A Sectoral Approach using the GARCH Model* by Frederike Adams (2021).

5 Discussion

Based on empirical analysis by means of the GARCH(1,1) model, our results suggest that volatility in almost all GICS sectors significantly increases (decreases) with rising (falling) Covid-19 cases. The only sector which yielded no significant result for the Covid-19 coefficient was the Information Technology sector. Criticism could derive from the sector approach taken in this thesis. Considering their corresponding weights in the S&P500 (*Appendix Figure 13*), not all sectors contribute equally to the US stock market. The Covid-19 effect in the Information Technology sector, the biggest contributor to the S&P500 (28%), shows no statistical significance. At the same time, the largest Covid-19 effects are observed in Energy, Materials and Real Estate (*Table 1*), sectors that cumulatively account for less than 10% of the broader S&P500 index. Furthermore, one should mention that each of the GICS sectors is comprised of various industries, each of which have presumably been impacted via different channels and to different extents by the pandemic. For some sectors it may be difficult to capture the Covid-19 effect on the sector as a whole. An analysis on industry level could lead to more definite conclusions. Although it is standard in academic literature to use the S&P500 as a proxy for the US stock market, it could be argued that, covering mainly large-caps, the index may not be a perfect reflection of the whole market. For a broader conclusion of the full stock market, it could be useful to repeat the study with the S&P1500 or Russell3000 to also capture movements of firms with smaller market capitalizations. Another aspect that could potentially lead to different results would be the inclusion of major events that affected the US and its economy in 2020/2021 that were unrelated to the pandemic such as the presidential election of 2020. Accounting for these occurrences in a statistical model may, for some sectors, reduce the explanatory power of Covid-19 on market volatility.

6 Conclusion

This paper analyzes the impact of the Covid-19 pandemic on returns and volatility via a GARCH(1,1) model in the S&P500 and the 11 GICS for a sample period from January 2020 to June 2021. While controlling for additional factors that are considered to be core drivers of financial markets during the sample period, i.e., IR, CPI, BAA10Y, EPU and OIL, this paper attempts to find the autonomous Covid-19 effect on stock volatility by including reported cases as an exogenous variance regressor. To put the empirical findings in economic context, a timeline of the pandemic development including government interventions and Fed announcements, and cumulative returns amid the four major infection waves are presented. In the GARCH variance equation, Model 1 Covid-19 coefficients are found to be positive and significant for all sectors, with the exception of Information Technology. The effect seems stronger for some sectors such as Energy, Materials and Financials and more moderate for others such as Real Estate and Consumer Staples, which confirms the joint work hypothesis that the Covid-19 influence on volatility differs across sectors. Possible reasons for a positive effect of Covid-19 on stock market volatility include, but are not limited to, the closing of production facilities, decreased demand for certain products and disruptions in supply chains (Adams 2021), most of which, directly or indirectly, stem from federal reactions to the pandemic such as stay at home orders, travel restrictions, stimulus packages or interest rate adjustments. The results of this analysis should illustrate the impact of fiscal and monetary interventions on the stock market and demonstrate the fact that market uncertainty is reflected in volatility as measured by the GARCH model. However, given the lack of significance for any of the Covid-19 coefficients in the GARCH mean equation, the model is not necessarily appropriate to capture the empirical Covid-19 effect on actual stock returns. Further research is necessary to identify an optimal model. With the discovery of the new Covid-19 variant *Omikron* in November 2021, financial markets started to drop once again (Rocco et al. 2021). It will hence be necessary to update research on this topic frequently. Justified by the abovementioned limitations of the sector approach, we also recommend to repeat the analyzes on an industry level to allow for a more accurate economic reasoning behind the empirical results.

References Joint Part

Adams, Frederike. 2021. "Assessing Volatility Drivers during the Covid-19 Pandemic: A Sectoral Approach Using the GARCH Model." Individual Contribution of the Directed Research Project carried out by Frederike Adams and Catrin Hassdenteufel: Nova School of Business and Economics.

Al-Awadhi, Abdullah M., Khaled Alsaifi, Ahmad Al-Awadhi, and Salah Alhammadi. 2020. "Death and Contagious Infectious Diseases: Impact of the COVID-19 Virus on Stock Market Returns." *Journal of Behavioral and Experimental Finance* 27 (September): 100326.

Albulescu, Claudiu Tiberiu. 2021. "COVID-19 and the United States Financial Markets' Volatility." *Finance Research Letters* 38 (January): 101699. https://doi.org/10.1016/j.frl.2020.101699.

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and George Filis. 2013. "Dynamic Co-Movements of Stock Market Returns, Implied Volatility and Policy Uncertainty." *Economics Letters* 120 (1): 87–92. https://doi.org/10.1016/j.econlet.2013.04.004.

Ashraf, Badar Nadeem. 2020. "Stock Markets' Reaction to COVID-19: Cases or Fatalities?" *Research in International Business and Finance* 54 (December): 101249. https://doi.org/10.1016/j.ribaf.2020.101249.

Bachman, Daniel. 2020. "The Economic Impact of COVID-19 (Novel Coronavirus)." Deloitte Insights. March 3, 2020. https://www2.deloitte.com/us/en/insights/economy/covid-19/economic-impact-covid-19.html.

Baek, Seungho, Sunil K. Mohanty, and Mina Glambosky. 2020. "COVID-19 and Stock Market Volatility: An Industry Level Analysis." *Finance Research Letters* 37 (November): 101748. https://doi.org/10.1016/j.frl.2020.101748.

Baker, Scott R, Nicholas Bloom, Steven J Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin. 2020. "The Unprecedented Stock Market Reaction to COVID-19." *The Review of Asset Pricing Studies* 10 (4): 742–58. https://doi.org/10.1093/rapstu/raaa008.

Bollerslev, Tim. 1986. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31 (3): 307–27. https://doi.org/10.1016/0304-4076(86)90063-1.

Bradley, Chris, and Peter Stumpner. 2021. "The Impact of COVID-19 on Capital Markets, One Year In." McKinsey & Company. March 10, 2021. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/the-impact-of-covid-19-on-capital-markets-one-year-in.

Bretscher, Lorenzo, Alex Hsu, Peter Simasek, and Andrea Tamoni. 2020. "COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission." *The Review of Asset Pricing Studies* 10 (4): 705–41. https://doi.org/10.1093/rapstu/raaa017.

Brooks, Chris, and Robert Wichmann. 2019. "EViews Guide to Accompany Introductory Econometrics for Finance." SSRN Scholarly Paper ID 3466908. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=3466908.

Bryan, Michael F., and Stephen G. Cecchetti. 1993. "The Consumer Price Index as a Measure of Inflation." Working Paper 4505. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w4505.

Charles, Ammlie, and Jae H. Kim. 2016. "Stock Return Predictability: Evaluation Based on Prediction Intervals." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2750185.

Ciner, Cetin. 2021. "Stock Return Predictability in the Time of COVID-19." *Finance Research Letters* 38 (January): 101705. https://doi.org/10.1016/j.frl.2020.101705.

Croce, Mariano Massimiliano, Paolo Farroni, and Isabella Wolfskeil. 2020. "When the Markets Get COVID: COntagion, Viruses, and Information Diffusion." *London, Centre for Economic Policy Research,* April, 55.

Curto, José Dias, and Pedro Serrasqueiro. 2021. "The Impact of COVID-19 on S&P500 Sector Indices and FATANG Stocks Volatility: An Expanded APARCH Model." *Finance Research Letters*, June, 102247. https://doi.org/10.1016/j.frl.2021.102247.

Dickey, D., and Wayne Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series With a Unit Root." *JASA. Journal of the American Statistical Association* 74 (June). https://doi.org/10.2307/2286348.

Engle, Robert F. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica* 50 (4): 987–1007. https://doi.org/10.2307/1912773.

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56. https://doi.org/10.1016/0304-405X(93)90023-5.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. 1993. "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks." *The Journal of Finance* 48 (5): 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x.

Goodell, John W. 2020. "COVID-19 and Finance: Agendas for Future Research." *Finance Research Letters* 35 (July): 101512. https://doi.org/10.1016/j.frl.2020.101512.

Hamilton, James D. 1983. "Oil and the Macroeconomy since World War II." *The Journal of Political Economy* 91 (2): 228–48.

Harjoto, Maretno Agus, Fabrizio Rossi, and John K. Paglia. 2021. "COVID-19: Stock Market Reactions to the Shock and the Stimulus." *Applied Economics Letters* 28 (10): 795–801. https://doi.org/10.1080/13504851.2020.1781767.

Haroon, Omair, and Syed Aun R. Rizvi. 2020. “COVID-19: Media Coverage and Financial Markets Behavior—A Sectoral Inquiry.” *Journal of Behavioral and Experimental Finance* 27 (September): 100343. https://doi.org/10.1016/j.jbef.2020.100343.

Hassdenteufel, Catrin. 2021. “The Covid-19 Timeline: Returns and Volatility Movements in Different Sectors.” Individual Contribution of the Directed Research Project carried out by Frederike Adams and Catrin Hassdenteufel: Nova School of Business and Economics.

He, Qing, Junyi Liu, Sizhu Wang, and Jishuang Yu. 2020. “The Impact of COVID-19 on Stock Markets.” *Economic and Political Studies* 8 (3): 275–88. https://doi.org/10.1080/20954816.2020.1757570.

Hu, John Wei-Shan, Yi-Chung Hu, and Amber Chia-Hua Tsai. 2018. “Multiple Criteria Decision Making and General Regression for Determining Influential Factors on S&P 500 Index Futures.” *Symmetry* 10 (1): 5. https://doi.org/10.3390/sym10010005.

Just, Małgorzata, and Krzysztof Echaust. 2020. “Stock Market Returns, Volatility, Correlation and Liquidity during the COVID-19 Crisis: Evidence from the Markov Switching Approach.” *Finance Research Letters* 37 (November): 101775. https://doi.org/10.1016/j.frl.2020.101775.

Lin, Zhe. 2018. “Modelling and Forecasting the Stock Market Volatility of SSE Composite Index Using GARCH Models.” *Future Generation Computer Systems* 79 (February): 960–72. https://doi.org/10.1016/j.future.2017.08.033.

Mandelbrot, Benoit. 1967. “The Variation of Some Other Speculative Prices.” *The Journal of Business* 40 (4): 393–413.

Mazur, Mieszko, Man Dang, and Miguel Vega. 2021. “COVID-19 and the March 2020 Stock Market Crash. Evidence from S&P1500.” *Finance Research Letters* 38 (January): 101690. https://doi.org/10.1016/j.frl.2020.101690.

MSCI. 2021. “GICS - Global Industry Classification Standard.” 2021. https://www.msci.com/our-solutions/indexes/gics.

Narayan, Paresh Kumar, and Rangan Gupta. 2015. “Has Oil Price Predicted Stock Returns for over a Century?” *Energy Economics* 48 (March): 18–23. https://doi.org/10.1016/j.eneco.2014.11.018.

Narayan, Paresh Kumar, and Susan Sunila Sharma. 2011. “New Evidence on Oil Price and Firm Returns.” *Journal of Banking & Finance* 35 (12): 3253–62. https://doi.org/10.1016/j.jbankfin.2011.05.010.

NBER. 2021. “Business Cycle Dating Committee Announcement July 19, 2021.” National Bureau of Economic Research: National Bureau of Economic Research. https://www.nber.org/news/business-cycle-dating-committee-announcement-july-19-2021.

Nelson, Daniel B. 1991. “Conditional Heteroskedasticity in Asset Returns: A New Approach.” *Econometrica* 59 (2): 347–70. https://doi.org/10.2307/2938260.

Nicola, Maria, Zaid Alsafi, Catrin Sohrabi, Ahmed Kerwan, Ahmed Al-Jabir, Christos Iosifidis, Maliha Agha, and Riaz Agha. 2020. “The Socio-Economic Implications of the Coronavirus Pandemic (COVID-19): A Review.” *International Journal of Surgery* 78 (June): 185–93. https://doi.org/10.1016/j.ijsu.2020.04.018.

Okorie, David Iheke, and Boqiang Lin. 2021. “Stock Markets and the COVID-19 Fractal Contagion Effects.” *Finance Research Letters* 38 (January): 101640. https://doi.org/10.1016/j.frl.2020.101640.

Onali, Enrico. 2020. “COVID-19 and Stock Market Volatility.” SSRN Scholarly Paper ID 3571453. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.3571453.

Pástor, Ľuboš, and Pietro Veronesi. 2013. “Political Uncertainty and Risk Premia.” *Journal of Financial Economics* 110 (3): 520–45. https://doi.org/10.1016/j.jfineco.2013.08.007.

Pilinkus, Donatas. 2010. “Macroeconomic Indicators and Their Impact on Stock Market Performance in the Short and Long Run: The Case of the Baltic States.” *Technological and Economic Development of Economy* 16 (2): 291–304. https://doi.org/10.3846/tede.2010.19.

Ramelli, Stefano, and Alexander F Wagner. 2020. “Feverish Stock Price Reactions to COVID-19*.” *The Review of Corporate Finance Studies* 9 (3): 622–55. https://doi.org/10.1093/rcfs/cfaa012.

Seong, Nohyoon, and Kihwan Nam. 2021. “Predicting Stock Movements Based on Financial News with Segmentation.” *Expert Systems with Applications* 164 (February): 113988. https://doi.org/10.1016/j.eswa.2020.113988.

Sharif, Arshian, Chaker Aloui, and Larisa Yarovaya. 2020. “COVID-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the US Economy: Fresh Evidence from the Wavelet-Based Approach.” *International Review of Financial Analysis* 70 (July): 101496. https://doi.org/10.1016/j.irfa.2020.101496.

Sharpe, William F. 1964. “Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk*.” *The Journal of Finance* 19 (3): 425–42. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x.

Smales, Lee A. 2020. “Investor Attention and the Response of US Stock Market Sectors to the COVID-19 Crisis.” *Review of Behavioral Finance* 13 (1): 20–39. https://doi.org/10.1108/RBF-06-2020-0138.

Smith, Colby, and Mamta Badkar. 2020. “US Stocks Post Weekly Drop as Investors Reach for Safety.” *Financial Times*, February 21, 2020. https://www.ft.com/content/45c718f4-54b9-11ea-8841-482eed0038b1.

S&P Dow Jones Indices LLC. 2020. “S&P 500 (USD) Factsheet.” S&P Dow Jones Indices. December 31, 2020. https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview.

Taylor, Derrick Bryson. 2021. “A Timeline of the Coronavirus Pandemic.” *The New York Times*, March 17, 2021, sec. World. https://www.nytimes.com/article/coronavirus-timeline.html.

Thorbecke, Willem. 2020. “The Impact of the COVID-19 Pandemic on the U.S. Economy: Evidence from the Stock Market.” *Journal of Risk and Financial Management* 13 (10): 233. https://doi.org/10.3390/jrfm13100233.

U.S. Bureau of Labor Statistics. 2020. “Consumer Price Indexes Overview.” U.S. Bureau of Labor Statistics. October 1, 2020. https://www.bls.gov/cpi/overview.htm.

World Health Organization. 2020. “WHO Timeline - COVID-19.” April 27, 2020. https://www.who.int/news/item/27-04-2020-who-timeline---covid-19.

Xu, Libo. 2021. “Stock Return and the COVID-19 Pandemic: Evidence from Canada and the US.” *Finance Research Letters* 38 (January): 101872. https://doi.org/10.1016/j.frl.2020.101872.

Yousfi, Mohamed, Younes Ben Zaied, Nidhaleddine Ben Cheikh, Béchir Ben Lahouel, and Houssem Bouzgarrou. 2021. “Effects of the COVID-19 Pandemic on the US Stock Market and Uncertainty: A Comparative Assessment between the First and Second Waves.” *Technological Forecasting and Social Change* 167 (June): 120710. https://doi.org/10.1016/j.techfore.2021.120710.

Zaremba, Adam, Renatas Kizys, David Y. Aharon, and Ender Demir. 2020. "Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe." *Finance Research Letters* 35 (July): 101597. https://doi.org/10.1016/j.frl.2020.101597.

Zhang, Dayong, Min Hu, and Qiang Ji. 2020. "Financial Markets under the Global Pandemic of COVID-19." *Finance Research Letters* 36 (October): 101528. https://doi.org/10.1016/j.frl.2020.101528.

Zhu, Huiming, Yawei Guo, Wanhai You, and Yaqin Xu. 2016. "The Heterogeneity Dependence between Crude Oil Price Changes and Industry Stock Market Returns in China: Evidence from a Quantile Regression Approach." *Energy Economics* 55 (March): 30–41. https://doi.org/10.1016/j.eneco.2015.12.027.

References Individual Part

116th Congress. 2020a. "Coronavirus Preparedness and Response Supplemental Appropriations Act, 2020." Legislation. 2019/2020. March 6, 2020. https://www.congress.gov/bill/116th-congress/house-bill/6074.

———. 2020b. "Families First Coronavirus Response Act." Legislation. 2019/2020. March 18, 2020. https://www.congress.gov/bill/116th-congress/house-bill/6201.

———. 2020c. "Coronavirus Aid, Relief, and Economic Security CARES Act." Legislation. 2019/2020. March 27, 2020. https://www.congress.gov/bill/116th-congress/house-bill/748.

Adams, Frederike. 2021. "Assessing Volatility Drivers during the Covid-19 Pandemic: A Sectoral Approach Using the GARCH Model." Individual Contribution of the Directed Research Project carried out by Frederike Adams and Catrin Hassdenteufel: Nova School of Business and Economics.

Adams, Frederike, and Catrin Hassdenteufel. 2021. "Measuring the Effect of Covid-19 on Volatility in the US Stock Market: Theoretical Approach, Literature Review and Model Selection." Joint Work of the Directed Research Project: Nova School of Business and Economics.

Anthes, Emily, Madeleine Ngo, and Eileen Sullivan. 2021. "Adults in All U.S. States Are Now Eligible for Vaccination, Hitting Biden's Target. Half Have Had at Least One Dose.," April 19, 2021.

Baker, Scott R, Nicholas Bloom, Steven J Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin. 2020. "The Unprecedented Stock Market Reaction to COVID-19." The Review of Asset Pricing Studies 10 (4): 742–58. https://doi.org/10.1093/rapstu/raaa008.

Cheng, Jeffrey, Tyler Powell, Dave Skidmore, and David Wessel. 2020. "What's the Fed Doing in Response to the COVID-19 Crisis? What More Could It Do?" https://www.brookings.edu/research/fed-response-to-covid19/.

Curto, José Dias, and Pedro Serrasqueiro. 2021. "The Impact of COVID-19 on S&P500 Sector Indices and FATANG Stocks Volatility: An Expanded APARCH Model." Finance Research Letters, June, 102247. https://doi.org/10.1016/j.frl.2021.102247.

Federal Reserve System. 2020a. "Federal Reserve Issues FOMC Statement." Board of Governors of the Federal Reserve System. March 3, 2020. https://www.federalreserve.gov/newsevents/pressreleases/monetary20200303a.htm.

———. 2020b. "Federal Reserve Issues FOMC Statement." Board of Governors of the Federal Reserve System. March 15, 2020. https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm.

Firestone, Melanie J. 2021. "First Identified Cases of SARS-CoV-2 Variant P.1 in the United States — Minnesota, January 2021." MMWR. Morbidity and Mortality Weekly Report 70. https://doi.org/10.15585/mmwr.mm7010e1.

Funakoshi, Minami, and Travis Hartman. 2020. "S&P Drops, Triggers Market Wide Circuit Breakers." March 18, 2020. https://graphics.reuters.com/USA-MARKETS/0100B5L144C/index.html.

Harjoto, Maretno Agus, Fabrizio Rossi, and John K. Paglia. 2021. "COVID-19: Stock Market Reactions to the Shock and the Stimulus." Applied Economics Letters 28 (10): 795–801. https://doi.org/10.1080/13504851.2020.1781767.

Huang, Fred Imbert, Jesse Pound,Eustance. 2020. "Dow Plunges More than 700 Points despite the Fed Cutting Rates." CNBC. March 2, 2020. https://www.cnbc.com/2020/03/02/dow-futures-rise-about-150-points-in-early-trading-extending-mondays-huge-comeback-rally.html.

Knueven, Liz. 2020. “When the Fed Cuts Interest Rates, It Affects Everything from Your Savings Account to Your Auto Loans.” Business Insider, March 16, 2020. https://www.businessinsider.com/personal-finance/federal-reserve-interest-rates-cut-money-savings-loans.

Labonte, Marc. 2020. “Monetary Policy and the Federal Reserve: Current Policy and Conditions.” Congressional Reserach Service.

Li, Yun. 2020. “Wall Street’s Fear Gauge Closes at Highest Level Ever, Surpassing Even Financial Crisis Peak.” CNBC. March 16, 2020. https://www.cnbc.com/2020/03/16/wall-streets-fear-gauge-hits-highest-level-ever.html.

MSCI. 2021. “GICS - Global Industry Classification Standard.” 2021. https://www.msci.com/our-solutions/indexes/gics.

NBER. 2021. “Business Cycle Dating Committee Announcement July 19, 2021.” National Bureau of Economic Research: National Bureau of Economic Research. https://www.nber.org/news/business-cycle-dating-committee-announcement-july-19-2021.

Nicola, Maria, Zaid Alsafi, Catrin Sohrabi, Ahmed Kerwan, Ahmed Al-Jabir, Christos Iosifidis, Maliha Agha, and Riaz Agha. 2020. “The Socio-Economic Implications of the Coronavirus Pandemic (COVID-19): A Review.” International Journal of Surgery 78 (June): 185–93. https://doi.org/10.1016/j.ijsu.2020.04.018.

Pisani, Bob. 2021. “One Year Ago Stocks Dropped 12% in a Single Day. What Investors Have Learned since Then.” CNBC. March 16, 2021. https://www.cnbc.com/2021/03/16/one-year-ago-stocks-dropped-12percent-in-a-single-day-what-investors-have-learned-since-then.html.

Rabin, Roni Caryn. 2020. "First Patient With Wuhan Coronavirus Is Identified in the U.S." The New York Times, January 21, 2020, sec. Health. https://www.nytimes.com/2020/01/21/health/cdc-coronavirus.html.

Romo, Vanessa. 2020. "Illinois Gov. Issues Stay-At-Home Order To Fight Coronavirus." NPR, March 20, 2020, sec. The Coronavirus Crisis. https://www.npr.org/sections/coronavirus-live-updates/2020/03/20/819295135/illinois-gov-issues-stay-at-home-order-to-fight-coronavirus.

Singh, Maanvi, and Victoria Bekiempis. 2020. "US Reports Its First Known Case of New UK Covid Variant." The Guardian, December 30, 2020, sec. World news. https://www.theguardian.com/world/2020/dec/29/us-first-case-new-uk-covid-variant.

Smith-Schoenwalder, Cecelia. 2020. "Trump Administration Suggests Avoiding Gatherings of More Than 10 People," March 16, 2020.

Taylor, Derrick Bryson. 2021. "A Timeline of the Coronavirus Pandemic." The New York Times, March 17, 2021, sec. World. https://www.nytimes.com/article/coronavirus-timeline.html.

Thorbecke, Willem. 2020. "The Impact of the COVID-19 Pandemic on the U.S. Economy: Evidence from the Stock Market." Journal of Risk and Financial Management 13 (10): 233. https://doi.org/10.3390/jrfm13100233.

U.S. Bureau of Economic Analysis. 2021. "Personal Saving Rate." FRED, Federal Reserve Bank of St. Louis. FRED, Federal Reserve Bank of St. Louis. July 1, 2021. https://fred.stlouisfed.org/series/PSAVERT.

World Health Organization. 2020. "WHO Timeline - COVID-19." April 27, 2020. https://www.who.int/news/item/27-04-2020-who-timeline---covid-19.

Appendix Joint Part

Comments

Appendix Comment 1 *Descriptive Analysis of the S&P500 and the 11 GICS Sectors*

Across the S&P500 and its 11 sectors, mean returns range from a minimum of 0.02% in Energy to a maximum of 0.14% in the Information Technology sector. These returns are close to zero, which was to be expected as stock returns usually have a regressive tendency towards a long term value (Lin 2018). With a return of -20.14%, the overall minimum daily was achieved by Energy, while notably the same sector also contains the overall maximum return of 16.04%. The relatively low standard deviations propose that the returns do not differ significantly from their respective mean. The high kurtosis for all sectors suggests sharper peaks and fatter tails than in a normal distribution. Except for Utilities, left tails seem particularly extreme as indicated by the negative skews. With Jarque-Bera statistics well over the J-B value of the standard normal distribution (5.8825) we can conclude that the returns do not follow a normal distribution.

Appendix Comment 2 *Descriptive Analysis of the Independent Variables*

On average, there were 47560 new reported Covid-19 cases per day in the United States with a maximum of 303007 on 08 January 2021. Starting with a high of 2.26% in the beginning of the sample period, interest rates dropped to a minimum of 0.00% on 25 March 2020 and remained at low levels. While, generally, inflation in the US moves around the 2% mark, the CPI experienced a fall following the weeks of 24 February 2020 with the sharpest decline of -3.24% on 16 March 2021. Following a stable couple of months, the BAA10Y spread expanded radically to an all-time high of 4.31% on 23 March 2020, only preceded by the financial crisis of 2007/08. The EPU ranged from a minimum of -84.24% to a maximum of 363.48%, which was reached in October 2019, prior to the Covid-19 outbreak. Returns on the Crude Oil Price Future dropped to a low of -305.97% on 20 April 2020 amid the oil price war between Saudi

Arabia and Russia. They recovered quickly after with their maximum of 37.66% only two days later. IR, CPI and BAA10Y all have a relatively low standard deviation below 0.1, indicating that they generally do not disperse much from their respective mean values while EPU and Oil have higher standard deviations of 0.479 and 0.155 respectively. As a normal distribution usually shows a skewness of zero and a kurtosis below three, none of the independent variables seem to be normally distributed. This is confirmed by the high J-B statistics and the related low p-values.

Tables

Author	Year	Topic	Focus	Statistical Method	Factors	Time Periods
Abulescu	2021	VIX	US, Global	Ordinary Least Squares	EPU	11 March 2020 to 15 May 2020
Al-Awadhi et al.	2020	Returns	China	Panel data analysis	Sector Dummy Variables	10 January 2020 to 16 March 2020
Artega-Garavito et al.	2021	Returns	(Global) news	Equity returns, patterns	-	1 January 2020 to 18 October 2021
Ashraf	2020	Returns	64 Countries	Panel data analysis	-	22 January 2020 to 17 April 2020
Baek et al.	2020	VIX	Negative and positive news; 30 industries	Makro Switching AR Model	Among others VIX, EPU, Moody's AAA Corporate Bond Yield, WTI Crude Oil Price, Federal Fund Target Range	2 January 2020 to 30 April 2020
Baker at al.	2020	Pandemics	Stock market moves; News	Text-based method	-	2 January 1900 to 30 April 2020
Brescher et al.	2020	Returns	US states and firm level	Cross-section regression	Government and monetary policy	31 December 2019 to 20 March 2020
Curto and Serrasqueiro	2021	VIX	Sectors; FATANG stocks	APARCH model	Vaccination	9 March 2009 to 24 May 2021
Goodell	2020	Pandemics	Economic impact	-	-	-
Harjoto et al.	2021	Returns	WHO announcement; FED stimulus package	2 Event Studies	Developed, Emerging Markets; US large/small cap	26 February 2020 to 25 March 2020; 26 March 2020 to 23 April 2020
Haroon and Rivizi	2020	VIX	News; industries	EGARCH model	-	1 January 2020 to 30 April 2020
He et al.	2020	Returns	8(first affected) countries; spill-over effects	Conventional t-tests and nonparametric Mann-Whitney tests	-	1 June 2019 to 16 March 2020; Domestic and foreign timeline
Just and Echaust	2020	Returns; VIX	Implied volatility; implied correlation; implied liquidity	Markov Switching model	12 Countries	3 June 2019 to 12 June 2020

Appendix Table 1 Literature Review (continued)

Mazur et al.	2021	VIX	CRSP Daily, Stock File and Compustat Index Constituents; industries	Data Matching; Event Study	-	March 20
Okorie and Lin	2021	Returns; VIX	32 Countries	Detrended Moving Cross-Correlation Analysis and Detrended Cross-Correlation Analysis	-	1 October 2019 to 31 March 2020, differentiated in calm and incubation period
Onali	2020	VIX	Trading volume	GARCH model; Markov Switching model	-	8 April 2019 to 9 April 2020
Ramelli and Wagner	2020	Returns	China/ International trade; industries; Analyst calls	Event Study	Firm size, book-to-market, and profitability	2 January 2020 till 20 March 2020 differentiated in incubation, outbreak and fever period
Sharif et al.	2020	Returns; VIX	Oil price volatility	Wavelet-based approach	Geopolitical risk, EPU	21 January 2020 to 30 March 2020
Xu	2021	Returns	Canada; USA	GARCH model	-	21 January 2020 to 2 July 2020
Yousfi et al.	2021	Returns; VIX	USA; China	GARCH model	EPU	5 January 2011 to 21 September 2021
Zaremba et al.	2020	VIX	67 Countries; Stringency of policy response	Panel data regression	Among others school closing, workplace closing, cancelled public events	1 January 2020 to 3 April 2020
Zhang et al.	2020	VIX	10 Countries	Correlation matrix	-	1 February 2020 to 27 March 2020

	Mean	Median	Min	Max	SD	Skew	Kurt	Jarque-Bera	p-value
S&P500	0.0009	0.0015	-0.1198	0.0938	0.0164	-0.68	16.70	3954.28	0.00**
Real Estate	0.0005	0.0013	-0.1687	0.0853	0.0192	-1.54	20.00	6232.28	0.00**
Materials	0.0009	0.0017	-0.1101	0.1176	0.0187	-0.47	11.99	1704.26	0.00**
Energy	0.0002	0.0000	-0.2014	0.1604	0.0296	-0.43	12.18	1774.94	0.00**
Financials	0.0008	0.0018	-0.1371	0.1316	0.0218	-0.26	13.60	2351.72	0.00**
Industrials	0.0007	0.0011	-0.1134	0.1265	0.0191	-0.36	13.28	2214.82	0.00**
Information Technology	0.0014	0.0025	-0.1381	0.1173	0.0198	-0.35	13.41	2271.38	0.00**
Consumer Staples	0.0004	0.0008	-0.0940	0.0851	0.0134	-0.02	17.35	4299.49	0.00**
Utilities	0.0003	0.001	-0.1136	0.1279	0.0183	0.28	16.71	3930.86	0.00**
Health Care	0.0007	0.0009	-0.09.86	0.0771	0.0147	-0.22	13.18	2169.4	0.00**
Consumer Discretionary	0.0009	0.0015	-0.1267	0.0938	0.0168	-1.02	15.63	3415.41	0.00**
Communication Services	0.0011	0.0015	-0.1128	0.0899	0.0165	-0.75	12.31	1858.15	0.00**
									**significant at 1%

Appendix Table 2 *Summary Statistics of Dependent Variables*

	Mean	Median	Min	Max	SD	Skew	Kurt	Jarque-Bera	p-value
Cases	47560	27134	0	303007	63124	1.82	5.74	433	0.00**
IR	0.0065	0.0012	0	0.0226	0.0080	0.78	1.77	82	0.00**
CPI	0.0000	0	-0.0324	0.0146	0.0032	-3.13	31.40	17660	0.00**
BAA10Y	0.0242	0.0223	0.0184	0.0431	0.0048	1.54	5.18	297	0.00**
EPU	0.0270	-0.0502	-0.8423	3.6348	0.4792	2.44	15.19	3601	0.00**
Oil	-0.0059	0.0023	-3.0597	0.3766	0.1548	-16.41	312.81	2026118	0.00**
									**significant at 1%

Appendix Table 3 *Summary Statistics of Independent Variables*

	t-value (ADF)	p-value (ADF)
Covid-19 New Cases	-1.8867	0.3386
Covid-19 New Cases (+1) Logged	-1.6687	0.4466
Covid-19 New Cases (+1) First Difference	-5.7896	0.0000**
Covid-19 New Cases (+1) Logged, First Difference	-3.3587	0.0130*
		** significant at 1% *significant at 5%

Appendix Table 4 *Augmented Dickey-Fuller Test: Covid-19*

	t-value (ADF)	p-value (ADF)
IR	-1.9646	0.3027
IR First Diff.	-8.0961	0.0000**
CPI	-24.4120	0.0000**
BAA10Y	-1.9222	0.3220
BAA10Y First Diff.	-7.9609	0.0000**
EPU	-29.7721	0.0000**
OIL	-16.5610	0.0000**
		**significant at 1%

Appendix Table 5 *Augmented Dickey-Fuller Test: Independent Variables*

	t-value (ADF)	p-value (ADF)
S&P500	-6.2536	0.0000**
Real Estate	-12.6428	0.0000**
Materials	-8.0479	0.0000**
Energy	-6.4675	0.0000**
Financials	-7.3746	0.0000**
Industrials	-7.5086	0.0000**
Information Technology	-6.7966	0.0000**
Consumer Staples	-6.4694	0.0000**
Utilities	-6.3992	0.0000**
Health Care	-6.6450	0.0000**
Consumer Discretionary	-8.0229	0.0000**
Communication Services	-30.2825	0.0000**
		**significant at 1%

Appendix Table 6 *Augmented Dickey-Fuller Test: S&P500 and the 11 GICS*

	F-statistic	Prob. F(1.497)	Obs*R-squared	Prob. Chi-Square(1)
S&P500	16.10115	0.0001*	15.65866	0.0001**
Real Estate	24.09577	0.0000*	23.07405	0.0000**
Materials	8.126854	0.0045*	8.028281	0.0046**
Energy	14.76362	0.0001*	14.39541	0.0001**
Financials	5.933293	0.0152*	5.88689	0.0153*
Industrials	14.74688	0.0001*	14.37956	0.0001**
Information Technology	10.09141	0.0016*	9.930385	0.0016**
Consumer Staples	18.94103	0.0000*	18.3191	0.0000**
Utilities	2.344719	0.1263	2.3431	0.1258
Health Care	9.953759	0.0017*	9.797591	0.0017**
Consumer Discretionary	33.18689	0.0000*	31.23475	0.0000**
Communication Services	21.87032	0.0000*	21.03279	0.0000**
				**significant at 1% *significant at 5%

Appendix Table 7 *ARCH Test: S&P500 and the 11 GICS*

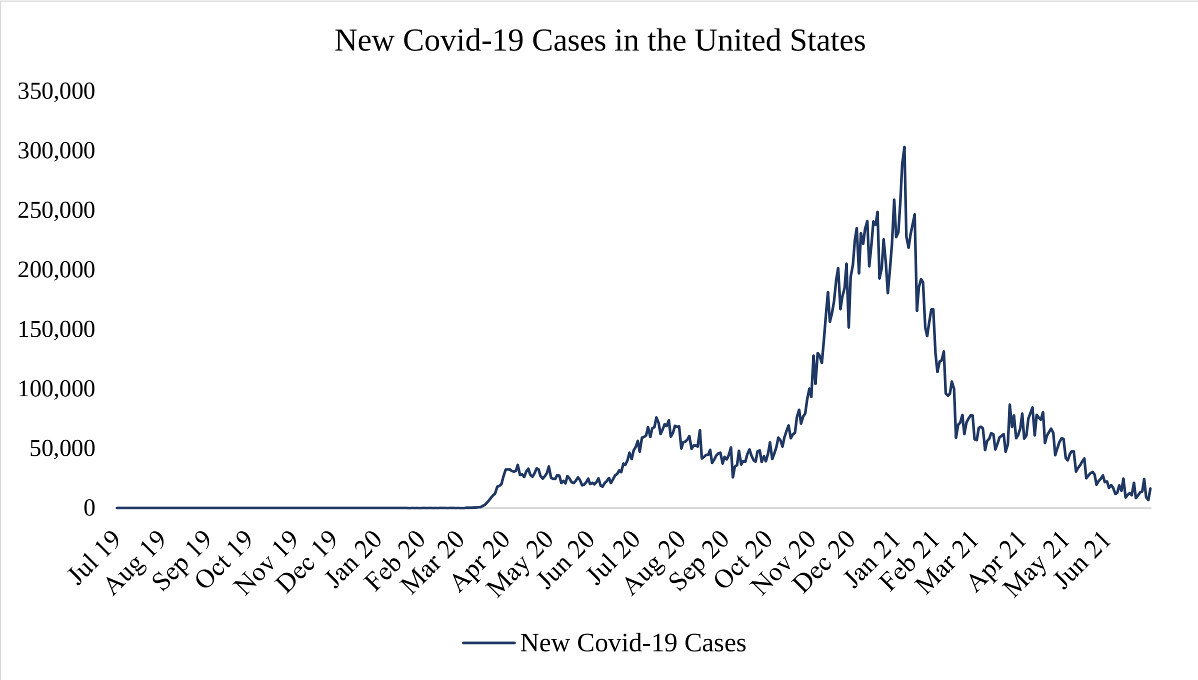
Variable	VIF
D_LN_New_Cases	1.09
IR	1.24
BAA10Y	1.329
CPI	1.147
EPU	1.004
Oil	1.018

Appendix Table 8 *Variance Inflation Factors*

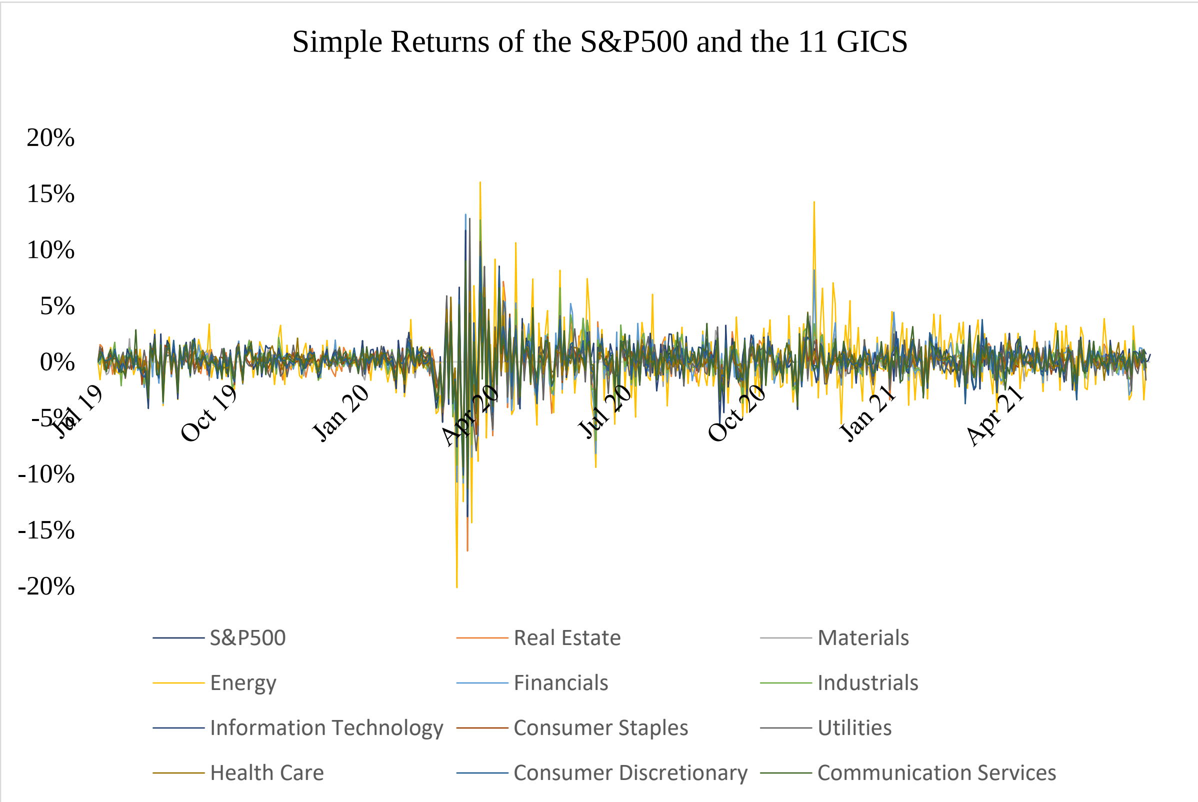
lambda	cond	const	Covid-19	IR	BAA10Y	CPI	EPU	Oil
1.781	1	0.012	0.066	0.136	0.14	0.087	0.004	0.013
1.102	1.271	0.175	0.247	0.024	0.018	0.177	0	0.194
1.025	1.318	0.471	0.02	0	0.036	0.003	0.009	0.399
1.001	1.334	0.018	0.027	0	0	0	0.942	0.003
0.851	1.447	0.254	0.186	0.006	0.001	0.243	0.031	0.382
0.694	1.602	0.005	0.451	0.416	0.04	0.296	0.011	0.01
0.545	1.808	0.064	0.002	0.416	0.765	0.193	0.002	0

Appendix Table 9 *Belsley-Kuh-Welsch Collinearity Diagnostics*

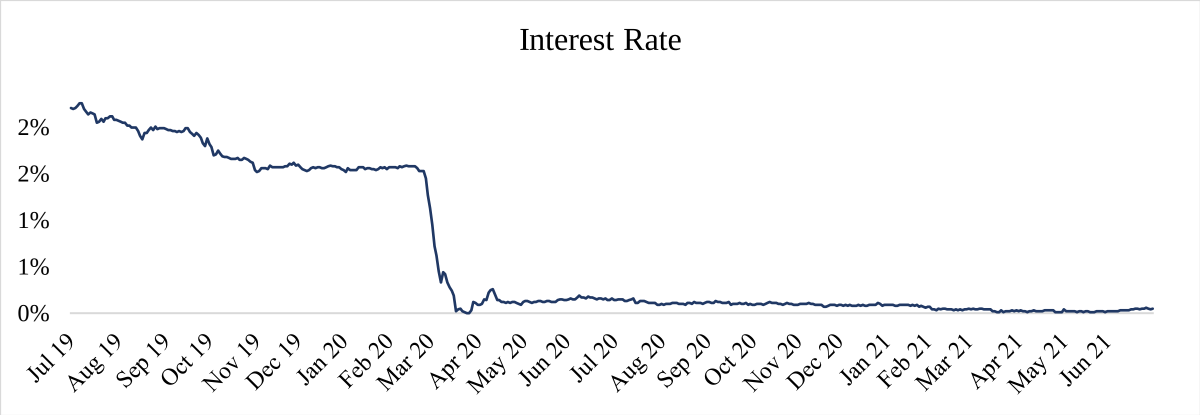
Figures



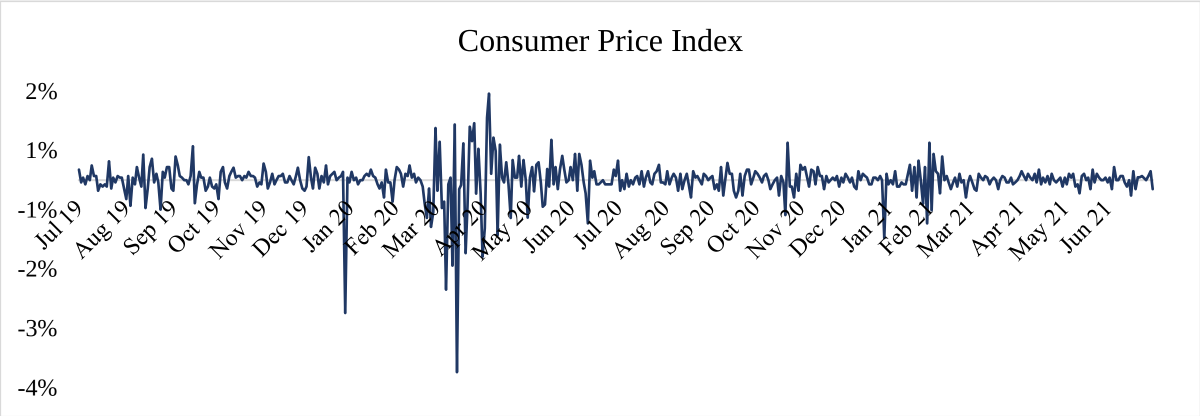
Appendix Figure 1 *New Covid-19 Cases in the United States (Own illustration with data derived from Our World in Data for the sample period of 22 January 2020 to 30 June 2021, values before this are denoted as zero)*



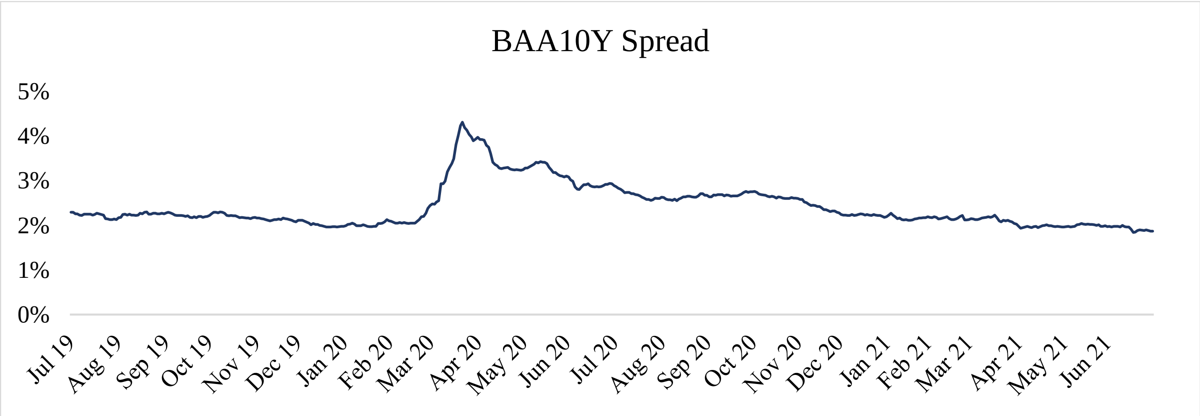
Appendix Figure 2 *Simple Returns of the S&P500 and the 11 GICS (Own illustration with data derived from investing.com for the sample period of 01 July 2019 to 30 June 2021)*



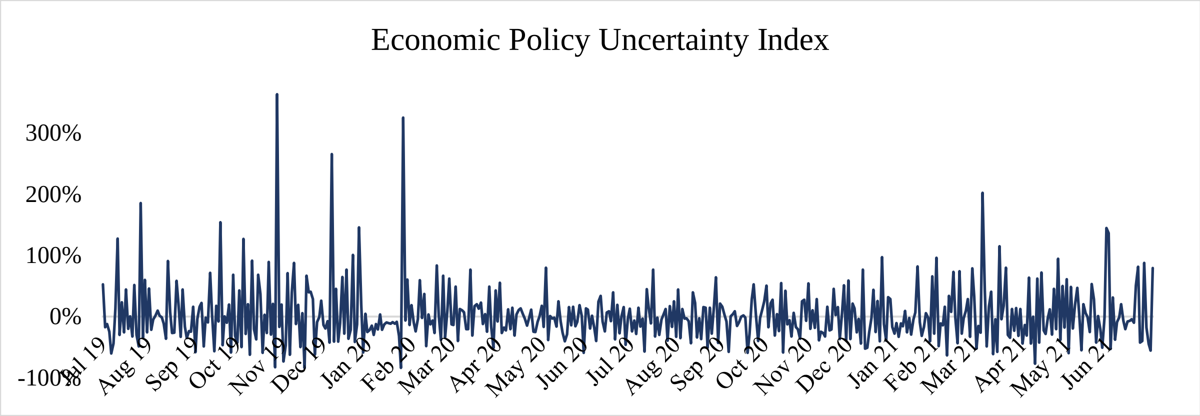
Appendix Figure 3 *Interest Rate (Own illustration with data derived from the Federal Reserve Website)*



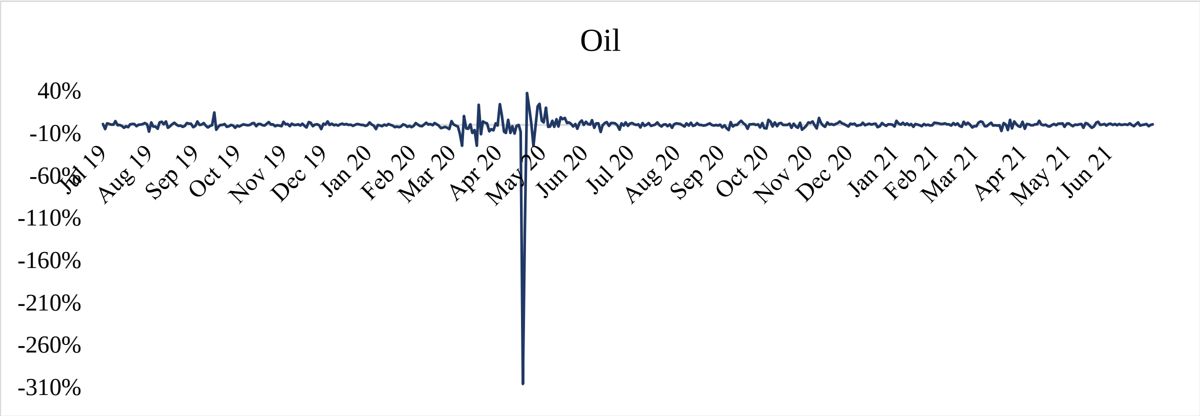
Appendix Figure 4 *Consumer Price Index (Own illustration with data derived from investing.com)*



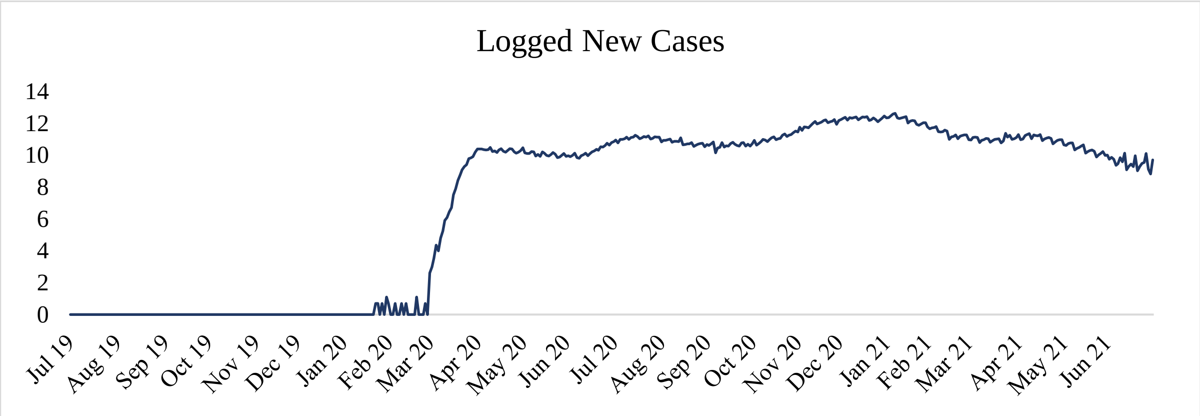
Appendix Figure 5 *BAA10Y Spread (Own illustration with data derived from https://fred.stlouisfed.org/series/BAA10Y)*



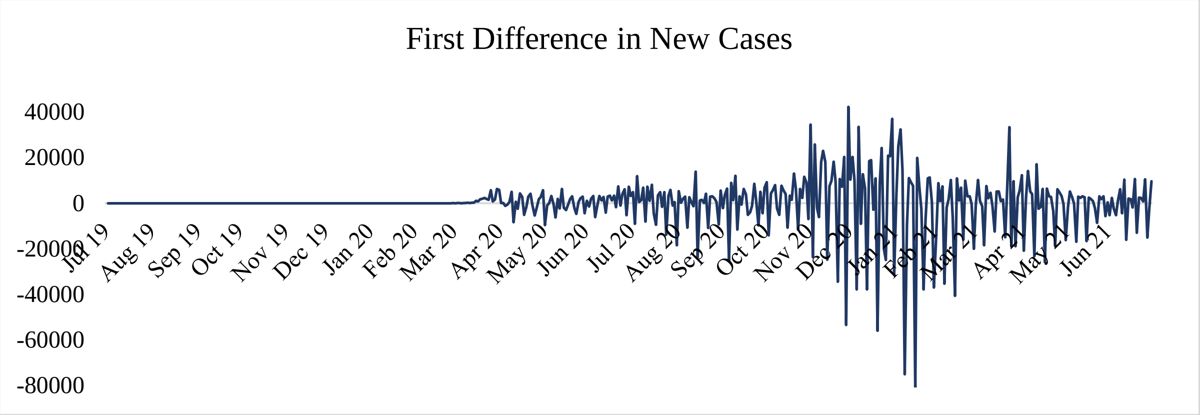
Appendix Figure 6 *Economic Uncertainty Index (Own illustration with data derived from https://fred.stlouisfed.org/series/USEPUINDXD)*



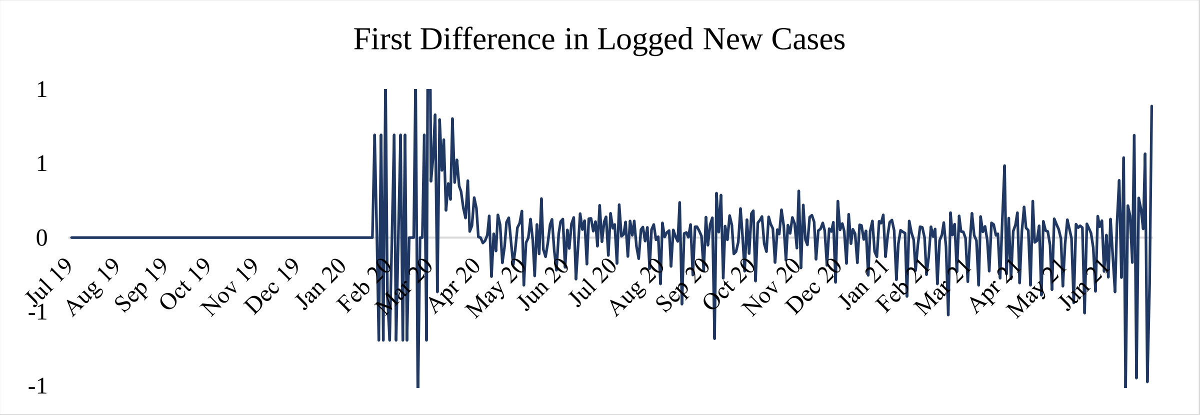
Appendix Figure 7 *Oil (Own illustration with data derived from investing.com)*



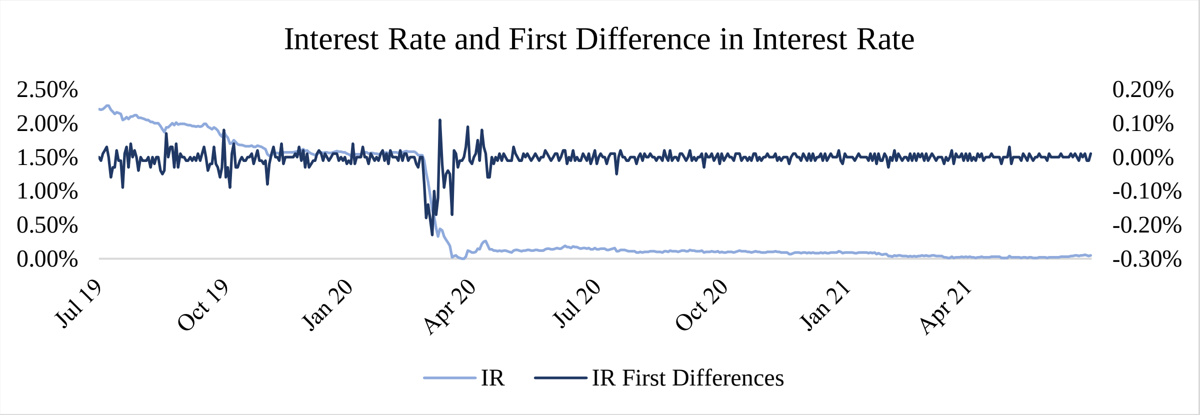
Appendix Figure 8 *New Covid-19 Cases Logged (Own illustration with data derived from Our World In Data)*



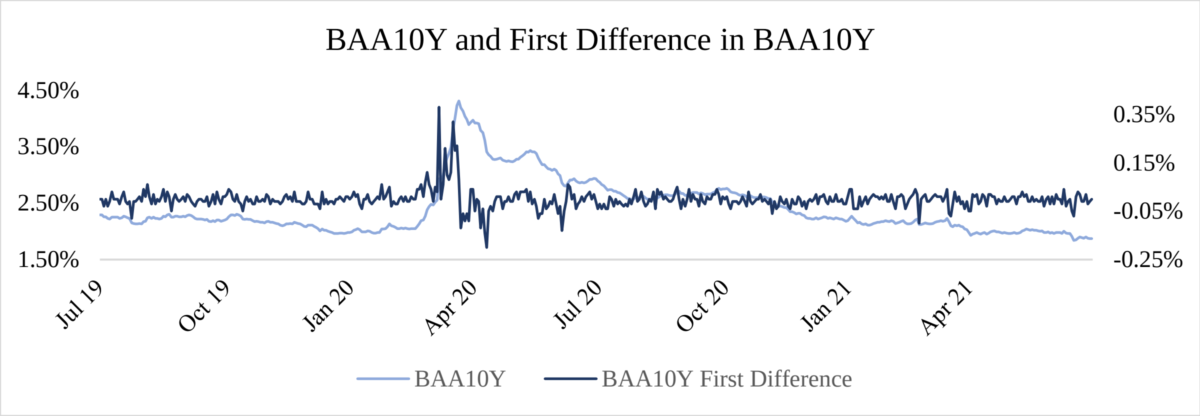
Appendix Figure 9 *First Difference in New Covid-19 Cases (Own illustration with data derived from Our World In Data)*



Appendix Figure 10 *First Difference in Logged New Covid-19 Cases (Own illustration with data derived from Our World In Data)*



Appendix Figure 11 *Interest Rate and First Difference in Interest Rate (Own illustration with data derived from the Federal Reserve Website)*



Appendix Figure 12 *BAA10Y and First Difference in BAA10Y (Own illustration with data derived from https://fred.stlouisfed.org/series/BAA10Y)*

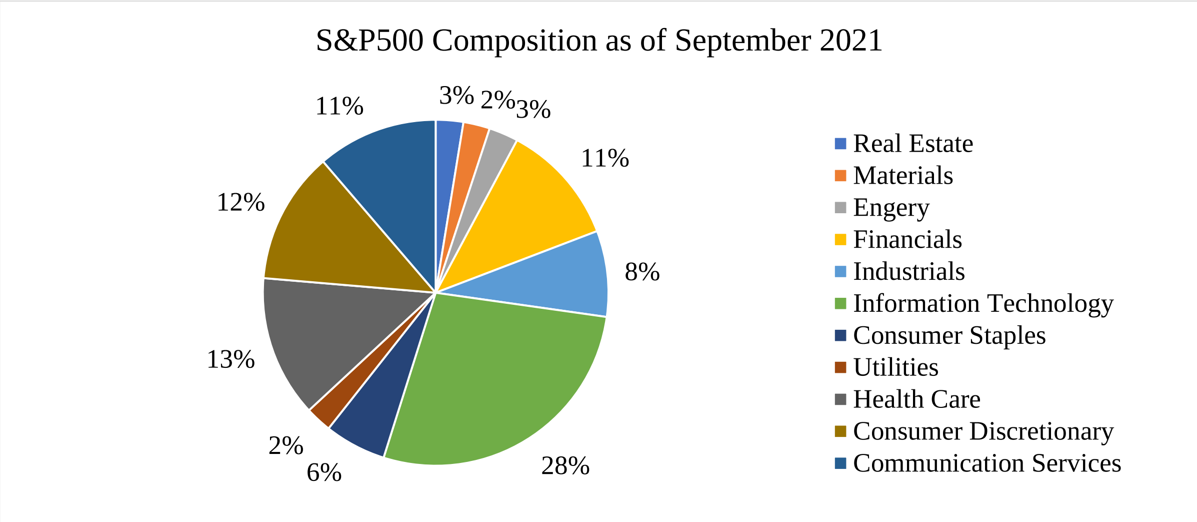
Appendix Individual Part

Tables

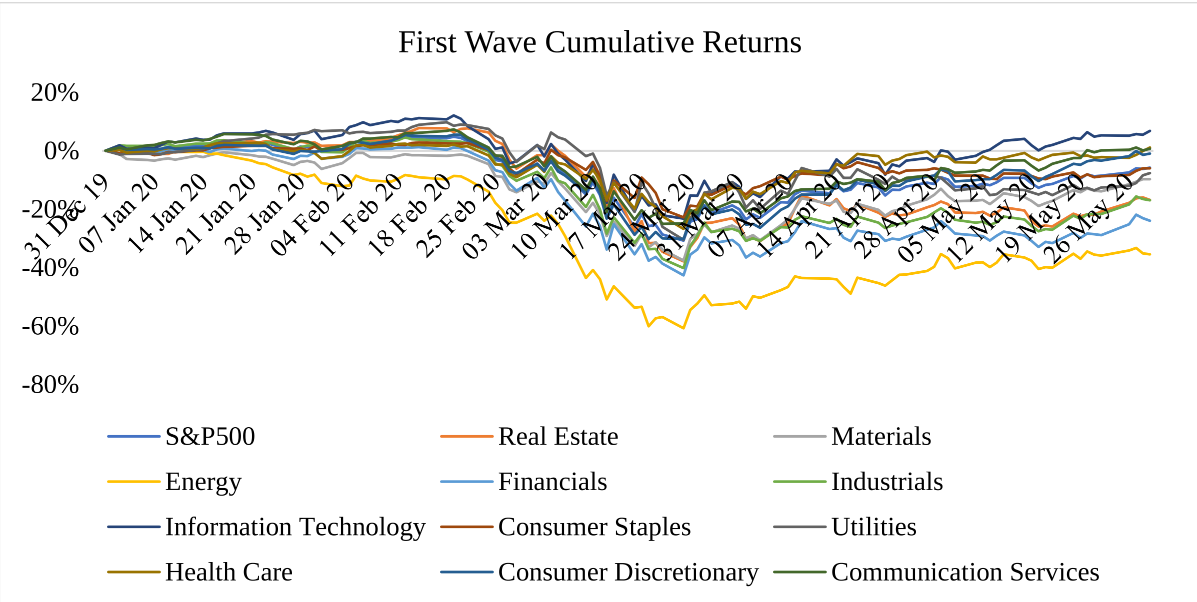
	Constant	Covid-19	IR	CPI	BAA10Y	EPU	OIL
S&P500	+	0	+	+	-	+	0
Real Estate	0	0	0	+	-	+	0
Materials	0	0	0	+	-	+	0
Energy	0	0	0	+	-	+	+
Financials	0	0	+	+	-	+	0
Industrials	0	0	0	+	-	+	0
Information Technology	+	0	0	+	0	+	0
Consumer Staples	0	0	0	+	-	+	0
Utilities	0	0	0	+	0	0	0
Health Care	0	0	0	+	0	+	0
Consumer Discretionary	0	0	0	+	-	0	0
Communication Services	+	0	0	+	0	+	0

Appendix Table 10 *Summarized Visualization of Mean Coefficients. A plus (minus) sign denotes a positive (negative) significant coefficient, zero stands for no significance*

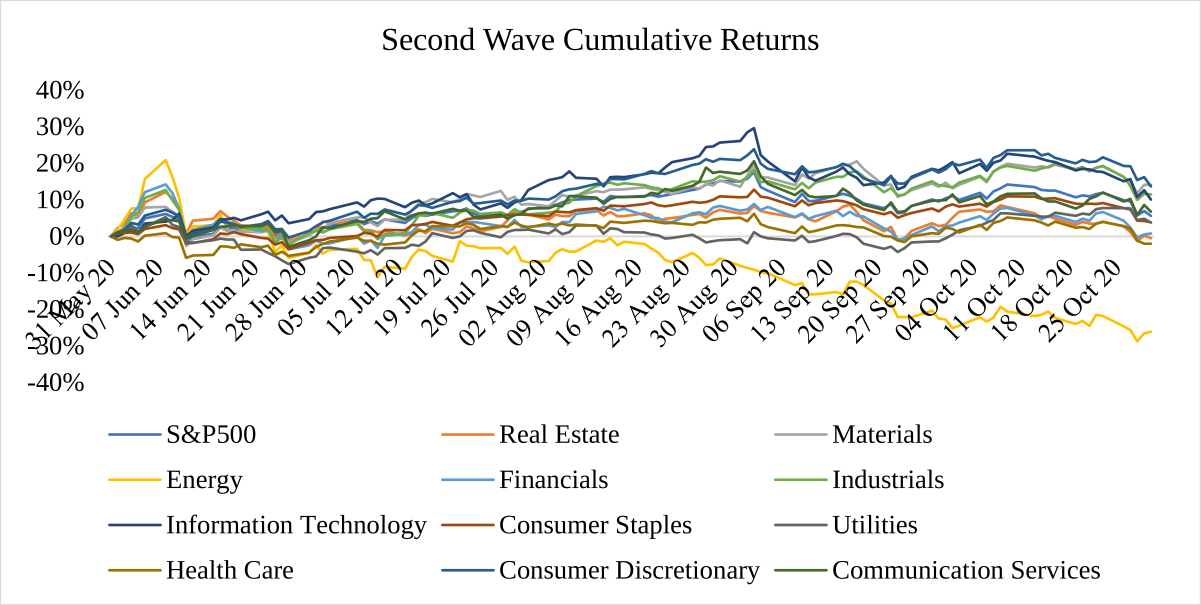
Figures



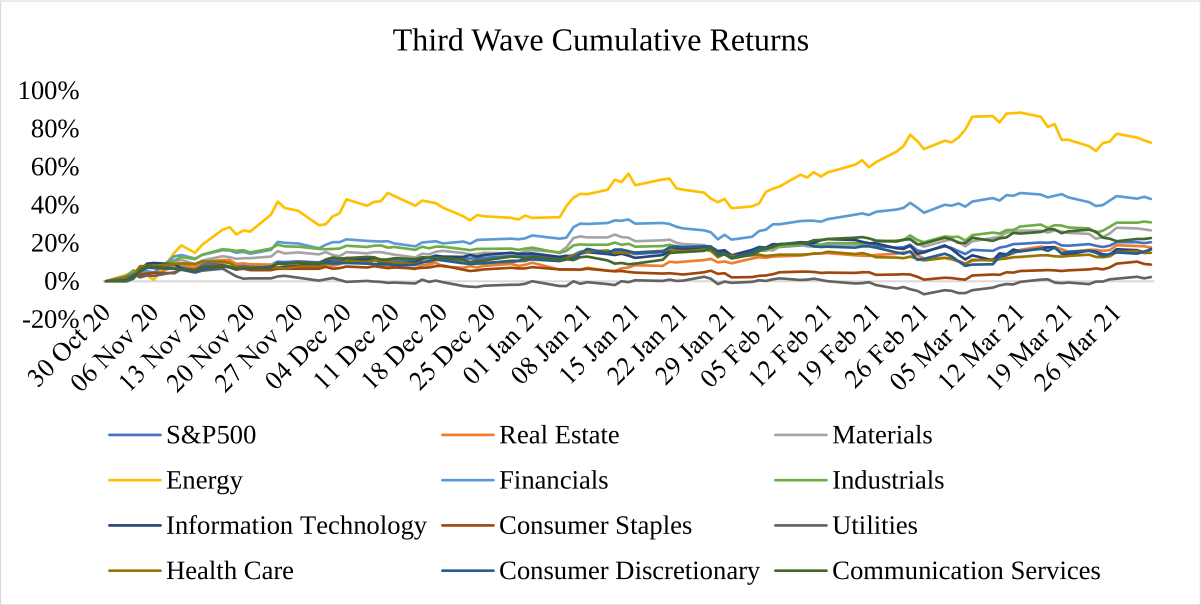
Appendix Figure 13 *S&P500 Composition as of September 2021 (Own illustration with data from Bloomberg)*



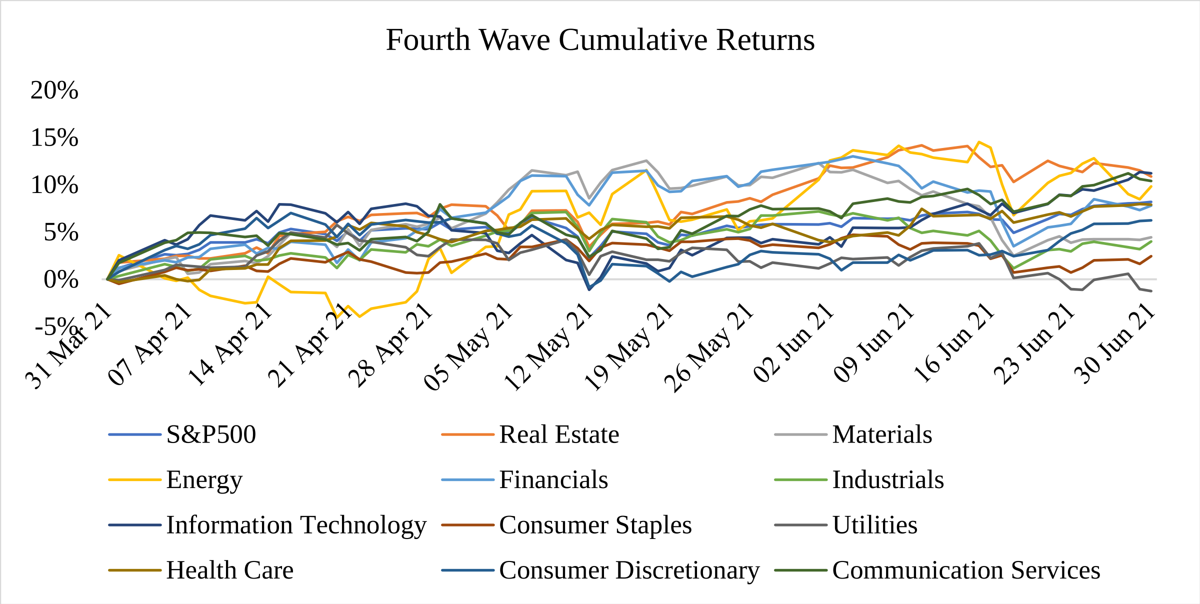
Appendix Figure 14 *First Wave Cumulative Returns (Own illustration with data from investing.com)*



Appendix Figure 15 *Second Wave Cumulative Returns (Own illustration with data from investing.com)*



Appendix Figure 16 *Third Wave Cumulative Returns (Own illustration with data from investing.com)*



Appendix Figure 17 *Fourth Wave Cumulative Returns (Own illustration with data from investing.com)*