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The impact of COVID-19 on S&P500 sector indices and FATANG stocks volatility: An expanded APARCH model☆

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ABSTRACT

In this paper we hypothesize that not all stocks and sectors are affected equally by COVID-19 in terms of return volatility. Specifically, we hypothesize that at least some sectors (Information Technology, Consumer Discretionary, Telecom Services, Consumer Staples and Energy) must show statistically significant differences. We analyze eleven SP500 sectors and FATANG stocks, estimating an Asymmetric Power GARCH model including a dummy variable to account for the outbreak. Results reveal an exacerbation of volatility after February 2020 and validate our hypothesis with few exceptions. Based on a likelihood ratio test, the null hypothesis is rejected in most cases in favor of our APARCH(1, 1).

1. Introduction

Prior to the breakout of COVID-19, the USA witnessed a strong economic expansion, which had a large positive impact on US stocks and originated the longest bull market in US history. As the effects of pandemic transferred to the US economy and financial markets, the S&P 500 dropped 25% during March 2020. The year 2020 was thus characterized by unusual variations in stock prices leading to a period of extremely high volatility.

This paper concerns the impact of COVID-19 on the volatility of financial returns. While there is a general perception of impact, econometrical approaches are relevant to quantify the statistical significance of such perception. Bai et al. (2020) applied an extended GARCH-MIDAS model to financial returns and a newly developed volatility tracker (EMV-ID) is used to investigate the effects of COVID-19 on volatility of several markets, between January 2005 and April 2020. Results show that, up to a 24-month lag, the pandemic had significant positive impacts on the permanent volatility of international stock markets, even after controlling for the influences of realized volatility, global economic policy uncertainty and the volatility leverage effect. Shehzad et al. (2020) found, based on the Asymmetric Power GARCH model, that COVID-19 has significantly harmed the US and Japan's market returns to a greater extent than the Global Financial Crisis (GFC).

Assessing the impact of events on volatility has a long tradition in financial literature. Gribisch (2016) generalizes the basic Wishart multivariate stochastic volatility model by allowing for state-dependent (co)variance and correlation levels and state-dependent volatility spillover effects. The model is applied to five European stock index return series. Results show that the proposed regime-switching specification substantially improves the fit to persistent covariance dynamics relative to the basic model. Brix and Lunde (2015) investigate the finite sample performance of the Prediction-based estimating functions (PBEFs) – based estimator and compare its performance to that of the Generalized Method of Moments (GMM). Banerjee (2021) analyzes time-varying volatility spillovers between index future markets by applying an ADCC EGARCH (to address dynamic conditional correlations) on the

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residuals of a VAR model, concluding that most markets that had trade relations with China witnessed volatility contagion due the COVID-19 breakout as well as for the presence of asymmetric volatility.

Researchers have been prolific with respect to the impact of COVID-19 on financial markets. Apart from detecting statistical significance, several authors have attempted to provide an economic rationale underlying those relations. Baker et al. (2020) resorted to automated and human readings of newspapers, looking back to the year 1900, and found that no other extreme event has impacted the markets as strongly as the current pandemic. They suggest that such unprecedented impact may be due to the role of government restrictions on a service-oriented economy. Baek et al. (2020) applied a Markov-switching model to assess the impact of COVID-19 on total, systematic and idiosyncratic risk. While total and idiosyncratic risks have increased across all industries of the S&P500, systematic risk appears to have increased in defensive industries such as telecom and utilities and decreased in their agressive counterparts such as automobiles and business equipment. The authors attribute the difference between industries to their respective price elasticities. Additional contributions on the topic have been made by Mazur et al. (2021), Verma et al. (2021), Just and Echaust (2020) and Zaremba et al. (2020).

As the volatility of financial asset returns remains an important investigation topic in finance, and due to the lack of empirical analyses involving S&P500, FATANG stocks and S&P500 sector indices, the motivation of this study is to address and compare the impact of COVID-19 on return volatility of these classes of US stocks and indices. We wish to address how the three main stylized facts (see Cont, 2001) return volatility (clustering, persistence and asymmetry) compare differently among the eleven S&P500 sector indices and the six FATANG stocks, and to conclude if the impact of COVID-19 has been different in size and direction of financial returns.

Our contribution is threefold. Firstly, because Tesla has become an important player in technology sector, we include it in the set of FAANG stocks and refer to the new set jointly as FATANG. Second, we analyze COVID-19 impact on the volatility of all the 11 S&P 500 sector indices (Information Technology (IT), Health Care (HC), Financials (FI), Consumer Discretionary (CD), Telecom Services (TS), Industrials (ID), Consumer Staples (CS), Energy (EN), Utilities (UT), Real Estate (RE), and Materials (MT)) and on the volatility of FATANG stocks' returns (Facebook, Amazon, Tesla, Apple, Netflix and Google). Considering all sectoral indices, and not just the global index, as is common, also contributes to differentiate this investigation. Secondly, we include six stocks in the empirical analysis to conclude more generally about the impact of COVID-19 on the largest capitalization tech stocks. Finally, an extended Asymmetric Power GARCH (APARCH) model is proposed to assess the statistical significance of COVID-19 on stock volatility. Extreme events are, by definition, rare. We believe that taking the opportunity to test the econometrical toolbox in stressful conditions is a valuable contribution to the scientific community, not only in terms of descriptive but also predictive abilities.

Although it may be unsurprising that not all stocks/indices are affected in the same manner by COVID-19, it is important to assess if differences are statistically significant, and not merely by chance. Our research hypothesis is that at least some sectoral indices (IT, CD, TS, CS, EN) must show significantly different behavior in terms of volatility. As governments impose lockdown restrictions, IT and TS companies providing remote work tools saw a surge in demand, while more idling time may increase online purchases and therefore bring higher demand to Consumer Discretionary products and services. Spending more time at home should also significantly increase the purchase of Consumer Staples. We also hypothesize that the EN sector should be negative and significantly affected, as confinements halt the consumption of fuel for automobiles and airplanes.

The dataset includes prices and returns from March 9, 2009 (a market bottom after the 2008 subprime mortgage crisis) to May 24th, 2021. The time period was selected to include the longest bull market in the history of the US financial markets and to include different clusters of volatility (not just the one resulting from COVID-19) in the estimation process to better model, and describe the conditional heteroskedasticity of financial returns. Specifically, we estimate the APARCH model twice, including a dummy variable (0 before March 2020, 1 otherwise): once ending in December 2020 and another ending in May 24th 2021. In the second estimation, we include an additional dummy (from January 2021 through May 24th 2021) to anticipate, although it may be premature, and assess the impact of vaccination programs on volatility.

The paper is organized as follows: In Section 2 we discuss the econometrical methods used in the paper and describe our dataset. Time varying volatility is modeled in Section 3 by using an AR-APARCH specification. Inspection of the estimated models point to significant differences in parameter estimates, volatility clustering, volatility persistence and to an asymmetric effect. Section 4 concludes the analysis and sheds light on the volatility of returns for the financial assets under scrutiny.

2. Methodology

2.1. Econometrical framework

We start by establishing the typical representation of financial asset returns as a time series with a predictable and a random component:

$$r_t = E\left[r_t \mid \Phi_{t-1}\right] + u_t, \tag{1}$$

where Φ_{t-1} is the relevant (past) information set until (and including) time period $t-1$. A natural assumption for the conditional mean ($E\left[r_t \mid \Phi_{t-1}\right]$) is to model its dynamics as a white noise process, because the empirical distributions of returns under study relate to the most liquid and efficient global equity markets. However, anticipating our findings in the data analysis section, we specify the conditional mean equation as a fourth-order autoregressive process, AR(4), in order to remove the observed linear dependency in returns:

$$r_t = c + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \phi_3 r_{t-3} + \phi_4 r_{t-4} + u_t, \tag{2}$$

where $u_t = z_t \sigma_t$ and the standardized innovations (z_t) are assumed to be independently and identically distributed (i.i.d.) following a Student's t distribution (see Bollerslev, 1987): $z_t \sim t(v)$, where $t(v)$ is the zero-mean Student's t distribution with v degrees of freedom. This statistical distribution has a long tradition in econometrics as a popular choice from the set of fat-tailed distributions, because it has finite second moment, of its mathematical tractability, and is often found capable of capturing the excess of kurtosis observed in financial time-series. Other non-Normal alternative distributions have also been used in econometrical literature. Nelson (1991) proposed the Generalized Error distribution (GED), while the Laplace distribution has been employed by Granger and Ding (1995). Hsieh (1989) applied both the Student's t and GED as alternative distributional models for innovations. Stable Paretian distributions have been investigated, among others, by Liu and Brorsen (1995), Mittnik et al. (1998) and Curto et al. (2007).

To model the conditional variance of u_t: $E\left[u_t^2 \mid \Phi_{t-1}\right] = \sigma_t^2$, we apply the Asymmetric Power ARCH (APARCH) model proposed by Ding et al. (1993) in which the power of the conditional heteroskedasticity equation is estimated from the data:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \left(|u_{t-i}| - \gamma_i u_{t-i}\right)^\delta + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^\delta. \tag{3}$$

This model couples the flexibility of a varying exponent with the asymmetry coefficient, therefore accounting for the well-known leverage effect (see for example Tavares et al., 2007 and Curto and Pinto, 2012). APARCH is in fact a general class that encompasses seven other models, namely the GARCH in Standard Deviation [$\delta = 1$, $\gamma_i = 0$ $(i = 1, \dots, q)$] (Taylor, 1986 and Schwert, 1990), $GARCH(p, q)$ [$\delta = 2$, $\gamma_i = 0$ $(i = 1, \dots, p)$] (Bollerslev, 1986) and GJR [$\delta = 2$] (Glosten et al., 1993) models. As observed by Black (1976), volatility responds asymmetrically to the sign of any change in the price of the financial asset, i.e., volatility increases are greater after negative changes than after positive changes of the same magnitude. This phenomenon has become known as the leverage effect. By estimating an asymmetrical model, we attempt to capture the presence of this leverage effect in the indices and stock returns under analysis. We show that the Utilities sector and Tesla stock returns exhibit no leverage effect, i.e. positive and negative news have the same impact on volatility in the selected time period. However, the leverage effect is detected in the remaining sectors and FATANG stocks.

APARCH models are defined by their order, that is, the number of relevant dependence lags, given by parameters (p, q). Despite the theoretical interest of general (p, q) models, the $(1, 1)$ specification is, in general, satisfactory when modeling financial returns' volatility (see Bollerslev et al., 1992 and more recently Hansen and Lunde, 2005). To analyze the impact of COVID-19 on volatility we expand the standard APARCH(1,1) model by including a dummy (D_t) as exogenous variable that assumes the value 1 after the end of February, 2020 and 0 otherwise:

$$\sigma_t^\delta = \omega + \alpha \left(|u_{t-i}| - \gamma u_{t-1}\right)^\delta + \beta_i \sigma_{t-1}^\delta + \theta_1 D_t. \tag{4}$$

The model is estimated using maximum likelihood (MLE) and the APARCH model in (4) is used to analyze how the three stylized facts of the returns' volatility (clustering, persistence and asymmetry) compare differently among the eleven S&P 500 sector indices and the six FATANG stocks.

By comparing the MLE values from the unrestricted model (APARCH) with those from restricted models: $\delta = 1$ and $\gamma = 0$ (Taylor/Schwert), $\delta = 2$ and $\gamma = 0$ (GARCH) and $\delta = 2$ (GJR), a nested Likelihood Ratio (LR) test can be constructed to compare the in-sample goodness-of-fit of APARCH against either of the other three models, that is, the LR test serves as a procedure to select which model is likely to provide the best fit. Let l_0 be the maximum log-likelihood value under the null hypothesis that the true model is a Taylor/Schwert's GARCH in standard deviation, a GARCH or a GJR, and l_1 be the maximum log-likelihood value under the alternative that the true model is APARCH, then:

$$LR = 2(l_1 - l_0) \tag{5}$$

should have a χ^2 distribution with 2, 2 and 1 degrees of freedom, respectively, when the null hypothesis is true. Rejecting the null hypothesis in favor of the alternative that the true model is the proposed APARCH structure provides evidence in support of our model as the data generating process. Our analysis focuses therefore on detecting this asymmetric effect and testing the significance of the COVID-19 dummy variable when APARCH-modeled asymmetry is present.

2.2. Data

Our dataset consists of daily closing prices of the S&P 500, the eleven S&P 500 sector indices and six American stocks, five of which go under the acronym FAANG (Facebook, Amazon, Apple, Netflix and Google/Alphabet). We add Tesla as a sixth element and refer to the set of six stocks as FATANG. The period under analysis starts on March 9, 2009 (the market bottom after the 2008 crash. We note that this local minimum is not concurrent to all series — see Table 1). The two exceptions to the time period are Tesla and Facebook stocks, in which prices go back to their first trading day, which occurred later than the otherwise starting date of March 9, 2009. The end date is May 24, 2021 for all series. We performed two distinct analysis: one until December 31st 2020 and another until May 24th 2021, as per referee suggestion, to evaluate the impact of vaccination programs. All data was obtained from https://www.investing.com.

We compute the continuously compounded percentage rates of return as:

$$r_t = 100 \times \left[\ln\left(P_t\right) - \ln\left(P_{t-1}\right)\right]. \tag{6}$$

where P_t is the closing value for each index or stock at time t. Table 1 summarizes the basic statistical properties of the data. All results, with the exception of skewness (which is positive for two series), corroborate the stylized facts of financial returns.

Table 1
Summary statistics of r_t.

Index/Stock	Starting date	# Obs	Mean	Median	Min	Max	St Dev	Skew	Kurt	J-B
IT	9 Mar ’09	2981	0.08	0.12	−14.98	11.30	1.34	−0.47	12.19	0.000
HC	9 Mar ’09	2981	0.05	0.08	−10.53	7.31	1.07	−0.36	8.82	0.000
FI	9 Mar ’09	2981	0.05	0.07	−15.07	16.33	1.72	0.31	15.42	0.000
CD	9 Mar ’09	2981	0.08	0.13	−12.88	8.29	1.23	−0.59	9.99	0.000
TS	9 Mar ’09	2981	0.03	0.07	−11.03	8.80	1.14	−0.41	8.46	0.000
ID	9 Mar ’09	2981	0.06	0.08	−12.16	12.00	1.33	−0.41	10.84	0.000
CS	9 Mar ’09	2981	0.04	0.05	−9.69	8.07	0.88	−0.38	15.17	0.000
EN	9 Mar ’09	2981	−0.00	0.02	−22.42	15.11	1.73	−0.90	19.63	0.000
UT	9 Mar ’09	2981	0.03	0.09	−12.27	12.32	1.12	−0.28	19.54	0.000
RE	9 Mar ’09	2981	0.05	0.09	−18.09	16.24	1.70	0.07	16.93	0.000
MT	9 Mar ’09	2981	0.05	0.09	−12.15	11.00	1.41	−0.46	7.22	0.000
SP500	9 Mar ’09	2981	0.05	0.07	−12.77	8.97	1.14	−0.64	14.32	0.000
FACEBOOK	18 May ’12	2170	0.09	0.11	−21.02	25.94	2.34	0.34	15.11	0.000
AMAZON	9 Mar ’09	2981	0.13	0.10	−13.53	23.74	2.07	0.64	10.81	0.000
TESLA	29 Jun ’10	2646	0.19	0.12	−23.65	21.83	3.53	−0.04	6.05	0.000
APPLE	9 Mar ’09	2981	0.13	0.11	−13.77	11.32	1.79	−0.27	5.98	0.000
NETFLIX	9 Mar ’09	2981	0.15	0.05	−42.92	35.22	3.20	−0.30	23.34	0.000
GOOGLE	9 Mar ’09	2981	0.08	0.07	−11.77	14.89	1.62	0.29	9.67	0.000

S&P 500 sectors: Information Technology (IT), Health Care (HC), Financials (FI), Consumer Discretionary (CD), Telecom Services (TS), Industrials (ID), Consumer Staples (CS), Energy (EN), Utilities (UT), Real Estate (RE) and Materials (MT). Skew: Coeff. of Skewness, Kurt: Coeff. of Kurtosis and J-B is the $p-$ value associated to the Jarque–Bera test.

Table 2
Growth of stocks and S&P 500 sector indices.

	Prices			Growth	
Index/Stock	Mar 3 ’09	Dec 31 ’19	Dec 31 ’20	Dec 31 ’19	Dec 31 ’20
IT	199.62	1611.17	2291.28	707.12%	42.21%
HC	253.27	1188.20	1324.01	369.14%	11.43%
FI	83.77	511.39	490.43	510.47%	−4.10%
CD	125.72	986.29	1302.56	684.51%	32.07%
TS	88.10	181.64	221.92	106.17%	22.18%
ID	132.83	687.60	749.54	417.65%	9.01%
CS	199.80	646.97	696.32	223.81%	7.63%
EN	310.92	456.46	286.14	46.81%	−37.31%
UT	113.81	328.36	319.07	188.52%	−2.83%
RE	44.42	240.32	227.90	441.02%	−5.17%
MT	108.82	385.85	455.71	254.58%	18.11%
SP500	676.53	3230.78	3756.0701	377.55%	16.26%
FACEBOOK	38.23	205.25	272.00	436.88%	32.52%
AMAZON	60.49	1847.84	3256.93	2954.79%	76.26%
TESLA	4.77	83.67	705.67	1655.48%	743.44%
APPLE	2.56	72.78	130.20	2743.12%	78.89%
NETFLIX	5.50	323.57	540.73	5783.09%	67.11%
GOOGLE	144.50	1337.02	1752.64	825.27%	31.09%

S&P 500 sectors: Information Technology (IT), Health Care (HC), Financials (FI), Consumer Discretionary (CD), Telecom Services (TS), Industrials (ID), Consumer Staples (CS), Energy (EN), Utilities (UT), Real Estate (RE) and Materials (MT).

We note that average returns are all positive but close to zero (higher means correspond to the FATANG stocks), with the exception of the Energy sector. The distribution of returns appears to be asymmetric as reflected by negative and positive skewness estimates. All series exhibit heavy tails and show a strong departure from normality (the skewness and kurtosis coefficients are all statistically different from those of the Normal distribution). The Jarque–Bera normality test statistic is highly significant, which points to the departure of r_t from normality for all series.

In 2020, some sectors have seen a more definitive shock than others (positive or negative). The EN sector was down more than 37%, primarily because crude-oil prices entered a bear market, and have been battered by fears that the outbreak could hurt uptake of crude from China. Three other sectors stand out for their negative returns and impact of COVID-19: RE (−5.17%), FI (−4.10%) and UT (−2.83%). Returns of the remaining sectors have been positive. The best performers among the S&P 500’s sectors were IT (+42%), CD (+32%) and TS (+22%). The CS sector showed the weakest growth: 7.63%. Regarding FATANG stocks, the growth in price has been substantial, with Tesla standing out with a remarkable 743.44%. Apple, Amazon, Netflix, Facebook and Google fill the next ranks in terms of stock price growth, contributing significantly to the positive performance of the IT sector.

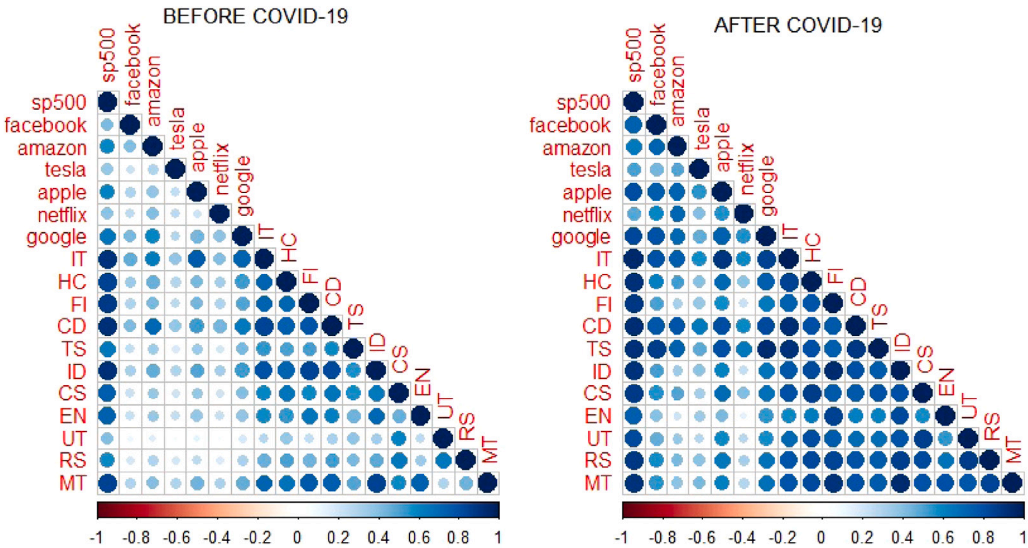

Fig. 1. Pearson correlation between FATANG stocks, S&P 500 and sectoral indices. S&P 500 sectors: Information Technology (IT), Health Care (HC), Financials (FI), Consumer Discretionary (CD), Telecom Services (TS), Industrials (ID), Consumer Staples (CS), Energy (EN), Utilities (UT), Real Estate (RE) and Materials (MT). We use the R `corrplot` package. Larger, darker circles represent stronger absolute value correlations.

In terms of correlation analysis, Fig. 1[1] shows positive correlations between all stocks and sectoral indices, i.e. all returns tend to move in the same direction. We note that correlations remain positive and generally increase (larger, darker circles) after March 2020 (after COVID-19). This corroborates the well known concern with portfolio theory that diversification benefits erode in face of extreme events (correlations increase and tend to +1).

3. Empirical results

In Table 3, we report the MLE APARCH(1,1) parameter estimates for the 18 return series. Volatility clustering is evident in all series, from the signal and significance of estimates for α and β. By 'volatility clustering' we mean persistence of high and low volatility, i.e. large (absolute) returns tend to be followed by returns of similar (large) magnitude.

Inspection of parameter estimates reveals that the ARCH effect (volatility clustering) is present in all series (α and β are significant across the board with only slight differences). For most series, APARCH(1,1) processes are highly persistent (almost-integrated: Facebook and Netflix) with the estimate for $\alpha + \beta$ ranging from 0.9492 to 0.9999, i.e. shocks on volatility not only cluster but also cancel out slowly, in line with the extant literature. These results are of practical relevance to practitioners, pointing to a slow decay of large (absolute) returns when dealing with FATANG stocks and S&P500 sectoral indices.

The leverage effect (γ) is statistically significant for all series, except for Utilities sector and Tesla. By leverage effect we mean the asymmetric impact of good and bad news on the volatility of financial returns. For the remaining series, where leverage is present, negative shocks (bad news) have a stronger impact than their positive counterpart (good news).

Considering the effect of COVID-19 on return volatility, results show that the estimate for the coefficient (θ_1) of the dummy variable is always positive, revealing an increase in volatility after February 1st, 2020. However, the estimate is statistically significant only for the IT, CD, TS, ID, CS and EN sectors, in spite of the significance of the asymmetric γ estimates. The statistical significance of $\hat{\theta}_1$ reinforces the impact of shocks (due to bad news) on volatility, i.e. COVID-19 exacerbated the leverage effect. From the performance of these sectoral indices in 2020 we can conclude that higher volatility had a positive impact on the returns of the first five, extending their uptrend in price, and a strong negative impact on the returns of the EN sector (see Table 2). For FATANG stocks, the estimate is statistically significant for Apple and Google only, and the volatility had a strong positive impact on their prices. For the remaining sectoral indices and prices, the impact of COVID-19 may be already included in the asymmetric γ estimate, reinforcing, but not increasing statistically, the effect of bad news on volatility.

In terms of the Likelihood Ratio test results, the rejection of the null in favor of the APARCH model occurs in most of the eighteen series under study. However, in the case of Tesla, we do not reject that the data may have been generated by the symmetric Taylor/Schwert or GARCH models. This conclusion is in accordance with the aforementioned insignificance of the γ estimate. Non-rejection of the null in favor of the asymmetric GJR model occurs in the IT, CD, UT and RE time series.

Our hypothesis is generally validated — sectors that seemed *a priori* candidates for a statistically significant impact of COVID-19 (IT, CD, TS, CS and EN) on volatility show in fact significance, most likely due to lockdown-induced behaviors such as remote work

[1] As per referee suggestion.

Table 3
APARCH(1,1) estimates and likelihood ratio test.

Indices/Stocks	α	β	$\alpha+\beta$	δ	leverage(γ)	covid (θ_1)	covid (θ_2)	vacc. (ϕ)	t−df	T/S	GARCH	GJR
IT	0.1130*	0.8696*	0.9826	0.9440*	1.000*	0.0458*	0.0478*	−0.0247	5.5099*	134.79*	127.55*	38.05*
HC	0.0886*	0.8858*	0.9744	1.0649*	0.925*	0.0084	0.0102	−0.0087	7.2675*	90.12*	73.75*	14.87*
FI	0.1225*	0.8731*	0.9956	1.1347*	0.5598*	0.0263	0.0317	−0.0023	5.8516*	71.61*	55.05*	8.84*
CD	0.1010*	0.8675*	0.9685	1.4660*	0.6516*	0.0399**	0.0565*	−0.0184	7.2462*	88.03*	65.72*	4.90***
TS	0.0641*	0.8858*	0.9499	1.5165*	0.5887*	0.0422**	0.0448**	−0.0083	5.8375*	37.78*	28.48*	2.28
ID	0.0826*	0.8950*	0.9776	1.4260*	0.7606*	0.0285**	0.0338***	−0.0126	6.6689*	93.03*	73.2*	6.23**
CS	0.0960*	0.8597*	0.9557	1.4183*	0.6098*	0.0191***	0.0184***	−0.0017	7.4517*	62.64*	44.57*	4.2
EN	0.0753*	0.9203*	0.9956	1.0362*	0.6413*	0.0319***	0.0376***	0.0042	8.535*	60.00*	51.84*	12.51*
UT	0.0593*	0.8899*	0.9492	2.5707*	0.1103	0.0428	0.0536	−0.0252	8.3229*	30.47*	7.55*	2.05
RE	0.0994*	0.8828*	0.9822	1.9573*	0.1821*	0.0283	0.0316	−0.0229	7.9654*	35.47*	10.77*	0.02
MT	0.0824*	0.9148*	0.9972	1.0543*	0.7910*	0.0132	0.0165	−0.0007	8.811*	81.83*	72.06*	19.36*
FACEBOOK	0.0765*	0.9333*	0.9999	0.9564*	0.4153*	0.0100	0.0121	−0.0033	3.8841*	16.46*	40.38*	22.53*
AMAZON	0.1003*	0.8888*	0.9891	0.793*	0.5156*	0.0225	0.0229	−0.0239	4.2747*	33.33*	90.49*	43.59*
TESLA	0.0785*	0.9106*	0.9891	0.9182*	0.1584	0.0747	0.0819	−0.0346	3.6068*	2.14	2.90	8.73**
APPLE	0.1145*	0.8493*	0.9638	0.8571*	0.7450*	0.0654**	0.0661**	−0.0434	4.986*	70.44*	92.99*	29.86*
NETFLIX	0.0716*	0.9285*	0.9999	0.5416*	0.5121*	0.0020	0.0024	−0.0131	3.3392*	28.56*	88.95*	68.62*
GOOGLE	0.0868*	0.8993*	0.9861	0.848*	0.6391*	0.0219***	0.0237***	0.0042	3.9208*	36.73*	74.42*	32.31*
SP500	0.1268*	0.8712*	0.9980	0.9487*	0.9999*	0.0251**	0.0267*	−0.0137	5.6529*	153.01*	140.31*	38.51*

S&P 500 sectors: Information Technology (IT), Health Care (HC), Financials (FI), Consumer Discretionary (CD), Telecom Services (TS), Industrials (ID), Consumer Staples (CS), Energy (EN), Utilities (UT), Real Estate (RS) and Materials (MT). $\alpha+\beta=1$ is the measure of volatility persistence. t-df represents the Student's t degrees of freedom. The LR test is shown under the names T/S (Taylor/Schwert), GARCH and GJR, respectively. θ_1 represents the effect of COVID-19 until December 31st, 2020 and θ_2 represents the effect of COVID-19 until May 24th, 2021. ϕ covers the period from January through May 24th 2021, to measure the impact of vaccination programs on volatility.

*Denote statistically significant at the 1%.

**Denote statistically significant at the 5%.

***Denote statistically significant at the 10%.

and increased consumption (the one exception is the ID sector, where we did not expect significance). Our results are generally in line with the financial COVID-19 literature: while most authors describe a relevant impact of COVID-19 on financial markets, Baek et al. (2020) finds that systematic risk has increased significantly for telecoms. Verma et al. (2021) and Mazur et al. (2021) observe significant downturns in the energy sector (specifically crude oil companies). The latter author also establishes the impact of COVID-19 in the food and software industries.

We have re-estimated our APARCH model to include the period from January 1, 2021 through May 24th 2021 and evaluate the impact of vaccination programs on volatility as well as leverage of the same stocks and sectoral indices.[2] To that effect, we introduced an additional dummy variable V_t in Eq. (4) (1 from January 1st 2021 through May 24th 2021, 0 otherwise):

$$\sigma_t^\delta = \omega + \alpha\left(|u_{t-i}| - \gamma u_{t-1}\right)^\delta + \beta_i \sigma_{t-1}^\delta + \theta_2 D_t + \phi V_t \tag{7}$$

Table 3 shows the estimate for θ_1, which represents the effect of COVID-19 until December 31st, 2020, while the estimate for θ_2 that represents the effect of COVID-19 until May 24, 2021 (the sample is increased by five months). The estimate $\hat{\phi}$ represents the impact of the vaccination on the US stock markets volatility. Re-estimating the model necessarily affected the initial estimates for the remaining parameters. New estimates show very small deviations, which, for clarity, we do not show. These results are available upon request to the authors.

The estimates for θ_2 (which include data from the first five months of 2021) are very close to those of θ_1 (which included data up until December 2020 only). Re-estimated values are slightly different, signs are maintained and only those estimates that were statistically significant so remain. Thus, it seems that COVID-19 impact on FATANG and S&P500 sectors did not change substantially in the first five months of vaccination. With regards to ϕ, estimates are almost all negative (except for EN sector and Google), indicating a negative impact of vaccination on volatility. However, none of the estimates is statistically significant. Therefore, we cannot yet conclude that vaccination had a statistically significant impact on US stock market volatility.

4. Conclusion

We compared the impact of COVID-19 on US stock prices and volatility by analyzing the continuously compounded returns of the eleven S&P 500 sectors and the six FATANG stocks from March 9th, 2009 to May 24th, 2021.

We note the remarkable growth of US stocks since the subprime crisis in 2008 until December, 2019. In 2020, however, we observed mixed results, as some sectors were more heavily impacted than others. All year-to-year returns of FATANG stocks have exceeded 30%, and a similar performance was only achieved by the IT and CD sectors.

To assess the effect of COVID-19 on return volatility we proposed an expanded Asymmetric Power GARCH (APARCH) model (by introducing a dummy variable controlling for the breakout of COVID-19). Results show that the estimate for its coefficient is

[2] As per referee suggestion.

always positive, revealing an increase in volatility after February 2020. The estimate is statistically significant for the IT, CD, TS, ID, CS and EN sectors. For FATANG stocks, the estimate is statistically significant for Apple and Google. These results generally validate our research hypothesis (with the exception of increased volatility of Apple and Google), and serve as reminder to portfolio and risk managers that while it may be unsurprising that not all sectors of the economy are affected equally in terms of volatility, there may be certain regularities in population behavior that impact specific sectors. COVID-19 should therefore serve as a learning experience to identify which sectors may be most affected by similar circumstances in the future.

Based on the likelihood ratio test, we conclude that the symmetrical GARCH model is rejected and the asymmetrical GJR model is the particular case of APARCH that is accepted more often in our data set. For most series, therefore, we conclude for the presence of the volatility leverage effect. Exceptions are the UT sector and Tesla, where good and bad news have the same level of impact.

APARCH processes are highly persistent for most series. The exceptions are the UT, TS, CS, CD sectors, and Apple, where the effect of shocks on volatility is less persistent, canceling out quickly.

Concluding, we can retrospectively state that the COVID-19 outbreak did not hit all the US sectors and all the US stock prices in the same manner, and our analysis provides an attempt at quantifying those differences. The higher volatility has favored mainly FATANG stocks and the IT, CD, TS, ID and CS sectors, while the EN sector was the most negatively affected. Promising, albeit simple, explanations are the significant increase in remote work (IT and TS) and the stay-at-home population behavior (and needs), which became prevalent as a result of lockdown restrictions (CD and CS).

We have focused on the S&P 500 due to its dimension, recognition and importance for portfolio managers. Further research can be done by replicating our method to indices from different countries (e.g. EUROSTOXX 600) and asset classes (e.g. fixed income). As countries are still rolling out their vaccination programs, the available sample size to assess their impact may be too small. We did not find that vaccination has impacted return volatility in this time period. Re-estimating models when more data is available may also prove a valuable contribution to better understand the impact of pandemic events on stock market returns and volatility.

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