BETA INVERSION EFFECT OF COVID-19 PANDEMIC USING CAPITAL ASSET PRICING MODEL

Mohammad Al-Dwiry *, Weaam Amira **

* *Corresponding author*, The Hashemite University, Zarqa, Jordan
Contact details: The Hashemite University, P. O. Box 330127, Zarqa 13133, Jordan
** Al-Ahliyya Amman University, Amman, Jordan

OPEN ACCESS

How to cite this paper: Al-Dwiry, M., & Amira, W. (2023). Beta inversion effect of COVID-19 pandemic using capital asset pricing model [Special issue]. *Journal of Governance & Regulation, 12*(1), 252–259. https://doi.org/10.22495/jgrv12i1siart5

ISSN Print: 2220-9352
ISSN Online: 2306-6784

Received: 22.06.2022
Accepted: 07.03.2023

JEL Classification: G00, G10, G12
DOI: 10.22495/jgrv12i1siart5

Abstract

This paper aims to analyze the effect of the beta inversion on COVID-19 by applying the capital asset pricing model and difference-in-differences (DiD) model in the US covering the five-year period from April 26, 2017, to April 22, 2022. Coronavirus induced pandemic has altered the fundamentals of the market (Baker, Bloom, Davis, Kost, et al., 2020; Mazur et al., 2021). The higher the value beta, the greater the potential for better long-term returns, according to the capital asset pricing model (CAPM). This study showed that companies that appeared to be safe to invest in are suddenly more dangerous, and the opposite is also true. Such as industries that previously shown a contractionary effect — aviation and retail, during COVID-19 have shown more benign effects on the market. The DiD model also reveals the same. The World Health Organization (WHO) intervention had a negligible effect on the treatment group, according to the model. It is obvious that beta has been inverted before investing in these sectors. The companies that are expected to perform better like pharma and biotech, have underperformed. This study deploys the understanding of the capital asset pricing model to see how different markets performed during and before the pandemic.

Keywords: Capital Asset Pricing Model (CAPM), COVID-19, Asset Pricing, S&P Select Industry Indices, Beta and Jensen's Alpha

Authors' individual contribution: Conceptualization — M.A.-D. and W.A.; Methodology — M.A.-D. and W.A.; Software — W.A.; Validation — M.A.-D. and W.A.; Formal Analysis — M.A.-D. and W.A.; Investigation — M.A.-D. and W.A.; Resources — M.A.-D. and W.A.; Data Curation — M.A.-D. and W.A.; Writing — Original Draft — M.A.-D. and W.A.; Writing — Review & Editing — M.A.-D. and W.A.; Visualization — M.A.-D. and W.A.; Supervision — M.A.-D. and W.A.; Project Administration — M.A.-D.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

1. INTRODUCTION

The coronavirus disease, also known as COVID-19 or SAR-COV-2, is an infectious illness, that was initially discovered in late 2019 at the seafood market in Wuhan Huanan (World Health Organization [WHO], 2020). There is still a pandemic as a result of the disease's spread throughout the globe. Lockdown orders were issued by governments globally on a national or municipal level to limit commercial activities and mandate that households "remain at home" for social distance to restrict encounters and stop the infection from spreading. As a result of the epidemic, the effect on nations is unparalleled. Early in 2022, when this article was written, not only had it caused over a million lives, the socioeconomic costs had already outweighed the world's financial crises (United Nations Office for Disaster Risk Reduction [UNDRR], 2022). Nearly every sector has been impacted by the health crisis.

Additionally, the COVID-19 pandemic has hit the world hard. All industries are somehow affected by the pandemic. Financial markets were affected by widespread economic uncertainty as a result of COVID-19 (Baker, Bloom, Davis, & Terry, 2020; Sharif et al., 2020). That is the bond market's volatility is mostly caused by greater uncertainty and unpredictable business circumstances (Arnold & Vrugt, 2010; Bansal & Shaliastovich, 2013; Beber & Brandt, 2009; Ulrich, 2012, 2013; Viceira, 2012), although the interventions by the government can lower risks (Amengual & Xiu, 2018; Kizys et al., 2020). When economic uncertainty is reduced, COVID-19-induced uncertainty (Kizys et al., 2020) and, thus, bond volatility, may decrease (Amengual & Xiu, 2018). Therefore, if government actions reduce general uncertainty and raise corporate expectations, they will be successful.

Also, the government-induced lockdown has severely affected the markets and jolted their fundamentals. The uncertainty rates have increased significantly in the global market during the pandemic which led to an effect on economic activities (Baker, Bloom, Davis, & Terry, 2020), many researchers have investigated the consequences of the pandemic on the global economy during the short period of time. For example, Hassan et al. (2020) have studied the impact of COVID-19 on individual institutions. Jorda et al. (2020) have examined the long-term impact on the stock markets. Furthermore, Baker, Farrokhania, et al. (2020) have shown that consumer behavior has changed due to the pandemic outbreak. Baker, Bloom, Davis, Kost, et al. (2020) have exposed that the volatility in the US stock market has reached the maximum point in history.

Moreover, Fama and French (2017) have demonstrated that profitability is positively related to the average stock returns for developed markets while the average stock returns are negatively correlated to investment. McKibbin and Fernando (2020) have analyzed the impact of the pandemic in its early stage and how that affects emerging markets in the short term. Also, Ru et al. (2020) have highlighted that the stock markets in countries without SARs experience have corresponded to the pandemic. Finally, the US market is not aloof from this tragedy. The market peaked in February 2020 but since then the foundation of systemic risk is altered. The beta which is a measure of systemic risk has given weird readings. Industries that are expected to be hit hard like aviation, retail, aerospace, and homebuilders are performing better than the industries like pharma and biotechnology. The coronavirus pandemic has altered the fundamentals of the stock market world over and the fundamental nature of stock price changes.

The capital asset pricing model (CAPM) has been in making for several decades. Many scholars of financial economics have contributed to its emergence. Fama et al. (1969) build their model based on the "efficient market" which is "a market which adjusts rapidly to new information". Jensen (1978) held that stock market prices show the information to the point till the marginal benefits of acting on the information do not exceed the marginal costs of collecting it. And, Sharpe (1964), Lintner (1965), and Treynor (1965) (SLT) increase the scope of the mean-variance framework to make it an equilibrium pricing framework called the CAPM.

In the framework of CAPM, beta is the most important measure of comparison. It measures the relationship between the asset returns and the overall market and their movement together. Industries with a beta of more than 1 have greater systematic risk than the market as a whole. A beta of less than 1 indicates prices are less volatile than the overall market. While beta equal to 1 shows identical movement between the asset and the market. Also, the difference-in-differences (DiD) approach includes a before-after comparison for a treatment and control group. The treatment group is the one where the impact of policy intervention is expected to be seen. The control group is one where no impact is expected.

Hence, we can measure the beta for different industries and compare them with each other, we can make some estimation of how industries behave during the pandemic period. And we can investigate whether there is any true fundamental relationship between the type of industry and the market. Thus, the main question in the study:

RQ: Does COVID-19 affected the industries in a manner popularly believed?

The aim of this research is to test whether the popular notion of the risky industry giving higher return against less risky industries giving lower return hold true. And whether the COVID-19 pandemic has made a fundamental impact on the basics of the market like a beta.

The remainder of this paper is structured as follows. Section 2 presents the literature review. Section 3 concentrates on data and methodology. Section 4 presents the findings. Section 5 concludes the paper.

2. LITERATURE REVIEW

According to Ferguson et al. (2020), pandemics have happened throughout human history at various times. Economic losses are significant as a result of COVID-19 mortality and morbidity impacts (Viscusi, 2020). The socioeconomic effects of COVID-19 and the related government initiatives have been thoroughly reviewed by Brodeur et al. (2020), with an emphasis on the labor, health, gender discrimination, and environmental aspects. Mazur et al. (2021) and Baker, Bloom, Davis, Kost, et al. (2020) have studied the stock market performance and how businesses respond to the pandemic in the capital markets. By employing the Lotka-Volterra model, Del Giudice et al. (2020) were able to anticipate the house price dynamic in Campania.

Zhao (2020) used zip code-level data and nonparametric estimation to demonstrate that the Federal Reserve's historic monetary easing has sped up the growth rate of the median housing price from April to August 2020, which is faster than any four months in the run-up to the global financial crisis between 2007 and 2009. There has been a structural break since the pandemic breakout, as seen by the rise in home demand in reaction to decreased mortgage interest rates. This is another reason why Wuhan is the case in our investigation of the pandemic's effects on the housing market. There was no monetary policy in place that attempted to mask the pandemic's negative effects.

Sun (2020) looked into how the Fama–French five-factor model performed in the US market prior to and following the COVID-19 outbreak.

The researcher used the ordinary least squares (OLS) method on 49 Fama–French industrial combinations to examine the validity of the model during the pandemic, investigate the existence of inexplicable factors, and determine whether the Fama–French factor beta changes as a result of the epidemic. According to the study, the unexplained factor behavior has increased while the five-factor Fama–French model's effectiveness has increased following the epidemic across all industries. Fama–French factor betas have changed significantly in most industries as a result of the pandemic, which has also had a substantial impact on factor exposure and portfolio performance.

In addition, after the COVID-19 outbreak and subsequent economic reopening, Huang et al. (2020) assessed the housing market's performance in China. This analysis discovered that the COVID-19 outbreak had a substantial negative impact on transaction volume but only had a somewhat negative impact on property values, utilizing weekly housing price indices from 64 Chinese cities. Yang and Zhou (2021) even hypothesized that COVID-19 would have a favorable effect on housing costs in China's second- and third-tier cities. However, they are making use of the city-level average selling price of commercial real estate, which ignored the variation in property quality. To the best of our knowledge, the COVID-19 effects on the property market in Wuhan, the pandemic's epicenter, have not received enough attention thus far.

Finally, in their analysis of the consequences of the cholera epidemic in Paris in the 19th century and the plague in Amsterdam in the 16th and 17th centuries, Francke and Korevaar (2020) discovered that while property values fell by 5.5% to 13.4% during the epidemics, they immediately resumed their long-term trend. According to del Rio-Chanona et al. (2020), supply shocks affect the manufacturing sector whereas demand shocks target specialized industries like transportation. While certain industries — like entertainment, dining, and tourism — are affected by both, others — particularly e-commerce and the IT sector — are mostly insulated from the epidemic. The study by Ozili and Arun (2020) examined how COVID-19 affected various industries, concluding that the lockdown, monetary policy choices, and restrictions on international travel had a negative impact on the economy, whereas the restrictions placed on internal movement and increased fiscal spending had a positive impact. The number of confirmed cases does not appear to have a major impact on the level of economic activity.

3. RESEARCH METHODOLOGY

The aim of this study is to investigate how COVID-19 affected the US industries and the market as a whole. The CAPM beta has been taken as a comparative post-COVID-19 to study the pre- and post-COVID-19 effect on the excess stock return.

The pharma sector gained from COVID-19 while industries like aviation were hit hard. This study highlights the fact this is not the case. But before we proceed, we need to find the continuously compounded log retunes. Daily log return (R_t) is calculated as follows:

$$R_t = ln\,(p_t) - ln(p_{t-1}) \quad (1)$$

Calculating excess return: The excess return on a portfolio is the excess return of an asset minus the risk-free rate like Treasury bills. Here we have taken a 3-month Treasury bill as an anchor to a risk-free rate. Additionally, excess return on market is the market return minus the risk-free rate. Thus, two formulas to calculate excess return are:

$$(R_i - r_f) = Excess\ return\ on\ asset_i \quad (2)$$

$$(R_m - r_f) = Excess\ return\ on\ market\ portfolio\ or\ Market\ risk\ premium \quad (3)$$

Model 1: Capital asset pricing model (CAPM)

$$(R_i - r_f)_t = \alpha + \beta(R_m - r_f)_t + u_{it} \quad (4)$$

where,

$$E(\tilde{R}_i) = r_f + \overbrace{\underbrace{[E(\widetilde{R_m}) - r_f]}_{Market\ price\ of\ risk}\underbrace{\frac{\sigma_{im}}{\sigma_m^2}}_{Risk\,=\,\beta}}^{Risk\ premium}$$

R_i = Return on an asset *i*, where *i* = seven industries;
r_f = Risk-free rate;
α = Jensen's alpha;
β = Systematic risk;
R_m = Market portfolio return, i.e., SP500;
u_t = *Econometric error term;*
$(R_i - r_f)$ = Excess return on industry *i*;
$(R_m - r_f)$ = Excess market portfolio return.

Additionally, the difference-in-differences (*DiD*) model has also been incorporated. We have four groups and two periods, with a sample of data from the population, the *DiD* estimate of the WHO announcement of COVID-19 as a pandemic impact can be written as follows:

Model 2: Difference-in-differences (DiD)

$$DiD = (\bar{y}_{s=Treatment,t=After} - \bar{y}_{s=Treatment,t=Before}) - (\bar{y}_{s=Control,t=After} - \bar{y}_{s=Control,t=Before}) \quad (5)$$

where,
Treatment = Pharma and biotechnology industries;
Control = Retail and regional banks industries;

The estimated regression equation takes the form of:

$$y_{ist} = A_s + B_t + \beta I_{st} + \varepsilon_{ist} \quad (6)$$

where,
A_s = Treatment/control group fixed effects;
B_t = Before/after fixed effects;
I_{st} = A dummy equaling 1 for treatment observations in the after period.

The cutoff period for the dummy variable is taken as March 20, 2020. It is this day only when the WHO announced COVID-19 as a pandemic.

The database covers the five-year period from April 26, 2017, to April 22, 2022, and encompasses daily adjusted prices of seven S&P select indices and the market index of S&P 500 on the US stock exchange. The seven indices chosen are the S&P Pharmaceuticals Select Industry Index, S&P Aerospace & Defense Select Industry Index, S&P 500 Airlines, S&P Biotechnology Select Industry Index, S&P Retail Select Industry Index, S&P Regional Banks Select Industry Index, and S&P Homebuilders Select Industry Index. Additionally, the 3-month Treasury bill: Secondary Market Rate, Percent, Daily, Not Seasonally Adjusted is taken as a proxy of risk-free rate (r_f). The choice of industries is based on the fact that COVID-19 has influenced certain industries like pharma, airlines, aerospace, and others.

The given sample has been divided into two sub-samples, taken March 11, 2020, as the cut-off date. It is on this day only, the WHO has declared COVID-19 a pandemic. Therefore, the first sample ranges from April 26, 2017, to March 10, 2020. While the second sample ranges from March 11, 2020, to April 22, 2022. In this manner, two series are analyzed, i.e., one before COVID-19 and the other after COVID-19.

For the purpose of the DiD estimation, we have changed the time-series data into panel data with two time periods. One before WHO intervention and one after WHO intervention. There are two groups formed one with pharma and biotech and the second as retail and regional banking.

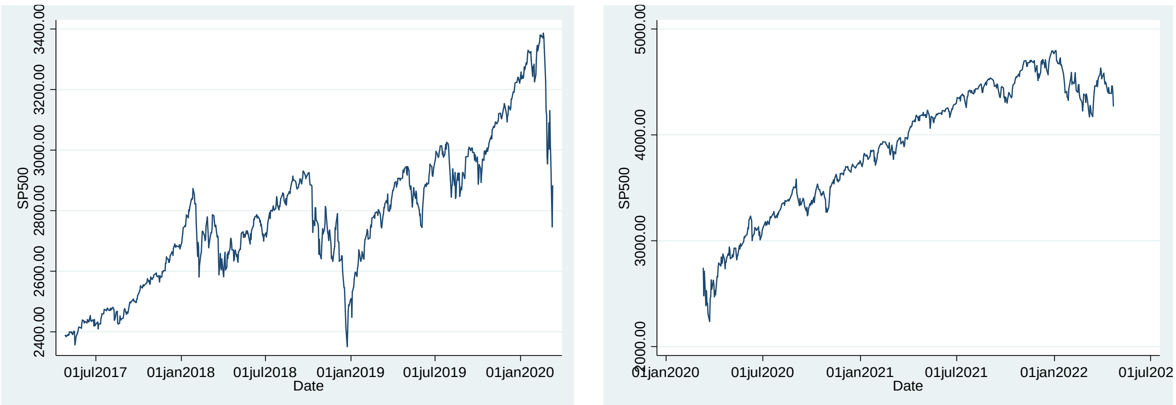
For the purpose of this study, data has been taken from the S&P Dow Jones Indices (https://www.spglobal.com/spdji/en/) and FRED (https://fred.stlouisfed.org/) databases.

4. EMPIRICAL RESULTS AND FINDINGS

4.1. Empirical outline

Data visualization: S&P 500 Index: In Figure 1, the pattern of time series random walk is manifestly evident. The S&P 500 market index before the arrival of the COVID-19 pandemic has shown an increasing trend with a sudden dip at the end suggesting the WHO announcement of COVID-19 as a pandemic. The after-COVID-19 pattern has shown less volatility and a sustained rise in the market index.

Figure 1. Random walk time series of raw data



The indices series shows a highly irregular (random walk) time series. It does not show any trend when plotted against time. It appears to be a non-stationary series.

Visualization of excess return on an asset and market portfolio using line plot: Before running the regression, plot the data to examine visually whether the series appear to move together. Following is a time-series plot of the two variables.

Figure 2. The excess returns at time t

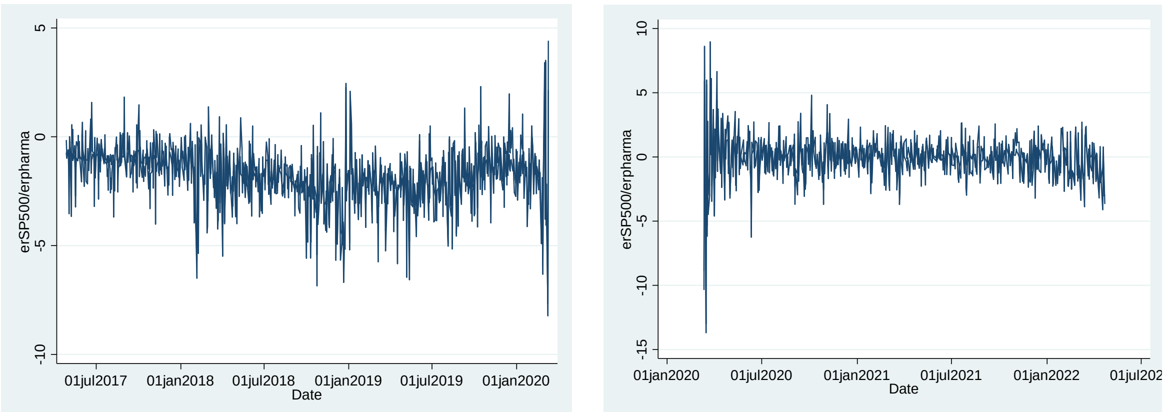


Figure 2 shows the excess returns at time t, which is the difference between the log of the industry price and the risk-free rate. The figure reflects how the excess return on S&P 500, and the pharma industry move together for a period of time.

Visualization of excess return on an asset and market portfolio using scatter plot: For a time-series plot of the two variables, a scatter plot may be more informative. As it shows the linear relationship more clearly.

Figure 3. The visual linear relationship between the Pharma industry and S&P 500

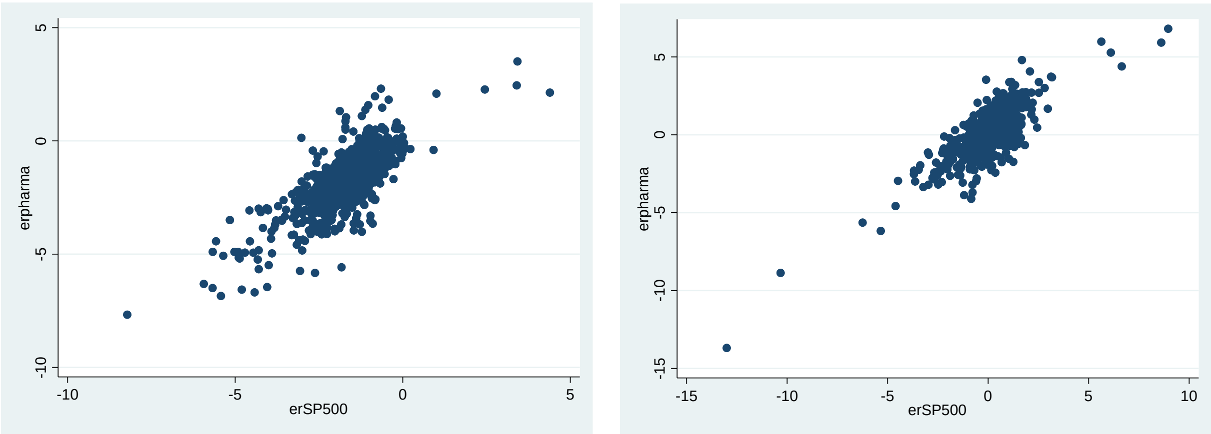


Figure 3 shows the visual linear relationship between the pharma industry and S&P 500. In the figure, the scatter plot suggests a linear relationship between the pharma and S&P 500 market index. The linear relationship suggests a one-on-one relationship between the two variables.

In this sub-section, we will also present a comparative summary/descriptive statistics after and before COVID-19 for all sectors of the study.

Table 1. Descriptive statistics (Before COVID-19)

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Pharma	4832.76	369.89	3993.23	5738.64
Aviation	334.28	20.29	229.14	390.53
S&P 500	2777.69	230.31	2351.14	3386.15
Aerospace and defense	1346.94	1946.84	10094.08	18254.85
Biotech	6680.71	591.83	5088	7863.13
Retail	4585.77	343.74	3826.67	5442.24
Regional bank	1762.53	141.72	1158.07	2056.03
Homebuilders	4078.71	352.92	3094.68	4956.21
T-bill	1.73	0.49	0.32	2.43

Table 2. Descriptive statistics (After COVID-19)

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Pharma	5375.27	519.96	3631.38	6449.76
Aviation	223.20	45.84	114.15	313.05
S&P 500	3892.60	617.40	2237.4	4796.56
Aerospace and defense	16885.35	2769.35	9746.82	21069.38
Biotech	9154.92	1604.26	5050.89	13513.12
Retail	7520.40	2308.97	2802.93	10846.47
Regional bank	1783.37	463.68	885.74	2476.52
Homebuilders	6298.78	1482.91	2486.19	8652.94
T-bill	0.12	0.14	-0.05	0.82

4.2. Normality test

Skewness/Kurtosis tests for normality are conducted to see if our data is normally distributed. The Chi-square test was applied for normality to the data set, the null hypothesis (H_0) is data sampled from a normal distribution. For our data all variables whether before or after COVID-19 appear to be non-normal as we reject the null hypotheses at a 5% level of significance.

4.3. Stationarity test

The unit root tests are frequently used to check the stationary for the selected variables in the model to determine whether the chosen variables belong to a stationary series. Eq. (7) and Eq. (8) represent the Dickey–Fuller (DF) test.

$$\Delta y_t = \psi y_{t-1} + u_t \tag{7}$$

The hypothesis of interest is *H_0: Series contains a unit root* against *H1: Series is stationary*.

$$Test\ statistic = \frac{\hat{\psi}}{S\hat{E}(\hat{\psi})} \quad (8)$$

The test statistics do not follow the usual *t*-distribution under the null hypothesis, since the null is one of non-stationarity, but rather they follow a non-standard distribution.

The purpose of the unit root test is to determine if a series is a "stationary" difference. Stationarity means that a series is stable over time. More formally, stationarity means that the mean and auto-covariances of the series do not depend on time. We have performed the unit root test in Stata with the DF method. Since the "DF test statistic", i.e, *z(t)* lies left of the critical values, the series is found to be stationary. The following table shows the result of the DF test with critical values at a 5% level of significance.

Table 3. Stationarity test

Industry	*Before COVID-19*		*After COVID-19*	
	Test statistic Z(t)	*Critical value (5% level)*	*Test statistic Z(t)*	*Critical value (5% level)*
erPharma	-22.196	-2.860	-28.531	-2.873
erAviation	-22.062	-2.860	-21.051	-2.873
erAD	-22.258	-2.860	-24.337	-2.873
erBiotech	-25.510	-2.860	-27.959	-2.873
erRB	-25.20	-2.860	-25.615	-2.873
erRetail	-21.35	-2.860	-25.284	-2.873
erHomebuilders	-22.73	-2.860	-24.179	-2.873
erS&P 500	-22.80	-2.860	-29.893	-2.873

Table 4. Difference-in-difference (DiD) estimation result

	Term	*Estimate*	*Std. Error*	*Statistic*	*P-value*
1	(Intercept)	2.23e-13	4.41e-13	0.482	0.630
2	Treat	-3.44e-13	6.24e-13	-0.552	0.581

The coefficient β_1 (Treatment group) is insignificant and not different from 0, which means that at time = 1, industries in the treatment and control groups had the same average price. This corroborates the findings of the CAPM model. Here also the expected positive impact on the pharma and biotechnology sector is not seen. The retail and regional banking sectors that have seen the little impact of COVID-19 are at par with the pharma and biotech sector.

COVID-19 has made a profound impact on the global economy. However, there are certain areas where the effect is expected to be more extreme than others. The pharmaceutical and aviation industry is expected to be impacted the most but in a different manner. The pharma sector is expected to gain while aviation takes a hit. Thus, these two sectors are expected to show a greater amount of volatility, unlike others. The eras "before COVID-19" and "after COVID-19" were estimated using Eq. (4).

Table 5. Regression output (Before COVID-19)

Industry	*α*	*β*
Pharma	-0.0548	0.9905*
Aviation	0.0131	1.0479*
Aerospace and defense	-0.0177	0.9807*
Biotech	0.4409	1.2576*
Regional bank	0.0661	1.0816*
Retail	-0.1824*	0.9205*
Homebuilders	-0.1070*	0.9470*

Table 6. Regression output (After COVID-19)

Industry	*α*	*β*
Pharma	-0.6626	0.8628*
Aviation	-0.0544	1.3165*
Aerospace and defense	-0.0158	1.1113*
Biotech	-0.0795	1.0572*
Regional bank	0.0344	1.2665*
Retail	0.0598	1.0613*
Homebuilders	0.0168	1.2607*

4.4. Analysis

Table 7 shows coronavirus-induced beta inversion where beta is a measure of the stock's volatility compared to the market index. The stock that moves higher than the market has a beta over 1. Such stocks are considered riskier to invest in but they provide a higher return. On the other hand, in a stock lower than the market, the beta has a lower risk but also a lower return.

Table 7. Beta comparison

Industry	*After COVID-19 β*	*Before COVID-19 β*	*Change in β*
Pharma	0.8628	0.9905	**-0.1277**
Aviation	1.3165	1.0479	**0.2686**
Aerospace and defense	1.1113	0.9807	0.1306
Biotech	1.0572	1.2576	**-0.2004**
Regional Bank	1.2665	1.0816	0.1849
Retail	1.0613	0.9205	0.1408
Homebuilders	1.2607	0.9470	0.3137

The coefficient estimate for β is interpreted as saying that, if x, i.e., *excess return on market portfolio* increases by 1 unit, y, i.e., *excess return on asset$_i$* will be expected, everything else being equal, to increase by β units.

For pharma sector, went from a beta of 0.9905 before COVID-19 to 0.8628 during the 4-month pandemic period. It means that in before-COVID-19 era, if the S&P 500 rose by 1%, the pharma industry would rise by 0.99%, on average. Now, when the market rises by 1%, pharma rises by 0.86%. Thus, there is a fall of 0.12% in the pharma sector. This is against the popular belief that the pharma sector has earned an enormous amount of wealth during a pandemic. This is clearly a case of beta inversion.

Similarly, the biotechnology sector went from a beta of 1.2576 before COVID-19 to 1.0572 during the 4-month pandemic period. It means that in before-COVID-19 era, if the S&P 500 rose by 1%, the biotechnology sector would rise by 1.25%, on average. Now, when the market rises by 1%, pharma rises by 1.05%. Thus, there is a fall of 0.20% in the biotechnology sector. This too defies the logic of an enormous amount of public funding getting into the research and development of vaccines. This is also a case of beta inversion.

For the aviation industry, the pandemic-induced lockdown shut down all flights across all the continents. This beta sector went from a beta of 1.0479 before COVID-19 to 1.3165 during the 4-month pandemic period. It means that in before-COVID-19 era, if the S&P 500 rose by 1%, the aviation industry would rise by 1.05% on average. Now, when the market rises by 1%, pharma rises by 1.32%. Thus, there is a rise of 0.26% in the aviation sector. This also defies the logic of lockdown-induced flights cancellation. For the aerospace, regional banks, retails, and household industries the beta has increased. This means that the return on these industries performs better during the COVID-19 period.

The before- and after-WHO policy intervention case-control study using difference-in-differences methodology has been implemented. The policy intervention has not made any significant impact on the treatment group. The finding is in line with our CAPM analysis.

5. CONCLUSION

The capital asset pricing model (CAPM) maintains the higher the beta value the higher the power for larger returns in the long run. Companies that seem to be safe to invest in are now risky and riskier companies seem to be safe. The COVID-19 pandemic has an upside-down market and, with it, the fundamental nature of stock price movements. The equity markets in the US had their peak in February 2020, and the basic bedrock of systematic risk (i.e., beta) in markets has become haywire since then. Stocks of the companies like pharmaceutical and biotech industries, for example, are used to enhance market movements, i.e., rising above when the market goes up and falling down when the market falls down. But during COVID-19, these industries have displayed volatility contrary to potential belief. On the other hand, industries that previously showed a contractionary effect — aviation and retail have shown more benign effects on the market. The same is also revealed by the DiD model. The model found an insignificant impact of WHO intervention on the treatment group. The inversion of beta is manifestly evident. Investors have to see closely how these industries work and what their fundamentals are before investing in them.

The primary limitation of our research is that it is only concerned with the examination of the American market. It could be beneficial to broaden the scope of the literature to cover additional European or Asiatic nations afflicted by the COVID-19 pandemic and do a comparative examination to find out the beta inversion effect of the COVID-19 pandemic. As well as the factors that affect how markets react globally. Moreover, further research of the topics in this article could include an investigation of the role and impact of COVID-19 in changes that occurred in the fundamentals of financial markets.

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