Eastern European Economics

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/meee20

Market Reactions to COVID-19: Does Systemic Risk Vary Across Industries? A Markov-Switching CAPM Approach

Emre Bulut, Cumali Marangoz & Muhammet Daştan

To cite this article: Emre Bulut, Cumali Marangoz & Muhammet Daştan (2024) Market Reactions to COVID-19: Does Systemic Risk Vary Across Industries? A Markov-Switching CAPM Approach, Eastern European Economics, 62:1, 69-88, DOI: 10.1080/00128775.2023.2173234

To link to this article: https://doi.org/10.1080/00128775.2023.2173234

Published online: 13 Feb 2023.

EASTERN EUROPEAN ECONOMICS
2024, VOL. 62, NO. 1, 69–88
https://doi.org/10.1080/00128775.2023.2173234

Market Reactions to COVID-19: Does Systemic Risk Vary Across Industries? A Markov-Switching CAPM Approach

Emre Bulut [a,b], Cumali Marangoz [c], and Muhammet Daştan [c]

[a]Department of Business, Ağrı Ibrahim Çeçen University, Ağrı, Turkey; [b]Faculty of Business Administration, Bilkent University, Ankara, Turkey; [c]Department of Economics, Ağrı Ibrahim Çeçen University, Ağrı, Turkey

ABSTRACT

Despite a broad consensus on the response of US stock market volatility to the coronavirus outbreak, our micro-level understanding of its variation across industries still needs to be improved. This study contributes to the existing literature by providing an industry-level analysis of the COVID-19 pandemic with two different states. Evidence from the MS-CAPM model indicates the role of portfolio diversification. Specifically, the results reveal that some industries, such as materials, real estate, communication, and utilities, have much higher expected returns. On the other hand, other sectors, including consumer discretionary, industrials, and information technology, become less volatile than the market during the lockdown period.

KEYWORDS
COVID-19; stock market volatility; the MS-CAPM

JEL CLASSIFICATION
C22; C58; G12

Introduction

Since the outbreak of COVID-19, numerous studies have examined its effects on the economy and financial system regarding several dimensions (Akhtaruzzaman, Boubaker, and Sensoy 2021; Amar et al. 2021; Ashraf, 2020, 2021; Baek, Mohanty, and Glambosky 2020; Choi 2020; Engelhardt et al. 2021; Goodell 2020; Sharif, Aloui, and Yarovaya 2020; Takyi and Bentum-Ennin 2021). Nevertheless, a limited number of studies have examined the impact of the pandemic on stock market volatility. The studies on volatility during the COVID-19 pandemic tend to focus on the entire market. For instance, Baker et al. (2020) examine the impact of COVID –19 on US stock market volatility and find that the pandemic harms US stock market volatility. Likewise, Albuquerque et al. (2020) analyze the interaction between financial market volatility and the COVID-19 pandemic in the US and the world. The results indicate that the pandemic increased volatility in US financial markets. Engelhardt et al. (2021) look into the impact of trust on stock market volatility during the pandemic for 47 countries. They report that the stock markets' volatility in high-trust countries was negatively and significantly affected. Besides, the authors find that trust in governments matters during pandemic times. Zaremba et al. (2020) analyze whether the government response to COVID –19 reduces international stock market volatility. They report a significant increase in stock market volatility in countries where governments took stricter measures.

Furthermore, Onali (2020) find a significant increase in volatility for US equity markets in response to reports of COVID-19 cases and deaths in several countries. On the other

CONTACT Cumali Marangoz cmarangoz@agri.edu.tr Department of Economics, Ağrı Ibrahim Çeçen University, Ağrı, Turkey

hand, some studies have focused on industry-level volatility. He et al. (2020) report for the Chinese stock market that the outbreak has affected the traditional industries adversely and more seriously, but it has helped bring opportunities for the development of high-tech industries. Hung, Hue, and Duong (2021) find that the impact of COVID-19 on stock market volatility in Vietnam is not robust across eleven sectors. Yagli (2020) reveals substantial volatility deterioration for all industries during the COVID-19 period in the Turkish stock market, with a greater impact on the service sector.

Despite a relatively large number of studies focusing on the sectoral impact of COVID-19 on stock market volatility, the US has not yet received enough attention[1]. Haroon and Rizvi (2020) examine whether coronavirus-related news causes a shift in industry-level volatility in the US and report that panic-laden news has led to greater volatility in sectors perceived to be affected most by COVID-19. Baek, Mohanty, and Glambosky (2020) analyze the relationship between COVID-19 and stock market volatility in the US and conclude that changes in systematic risk vary across industries. Investigating industry-level volatility in the U.S., Choi (2020) finds that COVID-19 has affected the volatility in all sectors and the magnitude is even larger than the global financial crisis.

Most industry-level analyses are mainly based on event study methodology (Kwan and Mertens 2020; Chowdhury and Abedin 2020; Ahmad, Kutan, and Gupta 2021) or linear models such as the liquidity network model (Farzami et al. 2021; Chebbi, Ammer, and Hameed 2021). In addition, a few studies perform the non-linear model applications of industry-level analyses. However, they neglect the volatility of asset prices (Salisu, Vo, and Lucey 2021; Haroon and Rizvi 2020; Corbet, Larkin, and Lucey 2020). In addition, many studies divide their sample as pre-Covid and Covid periods. Still, they do not consider the possible different structures (volatility) of the same periods, as investors do not restrict their investments only for a certain period. So they can spread their investments over different periods of the economy. Applying the Markov-Switching Capital Asset Pricing Model (MS-CAPM), this study aims to analyze the sectoral response of the US stock market volatility to the COVID-19 outbreak.

Unlike previous studies, we show that asset prices might have different volatility structures of beta coefficients at different periods, even in the pre-COVID period itself, on a sectoral basis during the COVID and pre-COVID periods, with the relatively novel MS-CAPM model. We compare the beta coefficients of sectors for similar regimes for both the pre-COVID and the COVID periods. As the pandemic is an ongoing phenomenon, our sample period is relatively large and allows us to examine the effect of the pandemic from a vantage point. Our findings reveal that most aggressive sectors, such as consumer discretionary, industrials, and information technology, with betas higher than one prior to the COVID-19 period, exhibit market risk decreases ranging from 0.01 (industrials) to 0.23 (information technology). While sectors with betas lower than one have the highest market risk increases ranging from 0.01 (consumer stables and communication) to 0.96 (real estate). As such, our results are in line with the findings of Alfaro et al. (2020) and Baek, Mohanty, and Glambosky (2020), and Dias and Serrasqueiro (2022) suggesting that at least some sectors - Information technology, consumer discretionary, telecom services, consumer staples, and energy) - show statistically significant differences. Overall, our findings for individual sectors show that the coronavirus outbreak contributed to volatility in the market in general, even if systematic risks in some sectors, including industrials, information technology, and consumer discretionary, decreases. In addition, we observe that the probability of transition from a low volatility regime to a high volatility regime is higher in the COVID period compared to pre-COVID times. That is, the probability of transition from one regime to another is comparably higher in extreme times.

The study proceeds as follows: Section two describes data and methodology, section three reports empirical results, and section four concludes.

Data and Methodology

Data

We retrieve sectoral returns and risk-free rates from spglobal.com and Kenneth French's data library, respectively. Our data starts a year before January 22, 2020, when the first case of COVID-19 in the US appeared, according to the Center for Disease Control and Prevention (CDC), and ends on January 22, 2022. That is, the data covers two separate periods. The first period defines pre-COVID data, while the second period determines the COVID period data. The study uses eleven sectors' daily adjusted returns for non-trading days. The sectors in the analysis are consumer discretionary, consumer staples, health care, industrials, information technology, materials, real estate, communication services, utilities, financials, and energy.

In the first phase of the analysis, we have investigated the descriptive statistics of the sectors and S&P 500 return series for pre and peri-COVID periods. As shown in Table 1, except for the energy sector, all sector means are positive in both periods. Almost all sectors exhibit a left tail feature in both periods, while utilities sector has a right tail in the COVID period. All sectors are more volatile in the COVID period compared to the pre-COVID period, and energy sector has the highest volatility. In contrast, consumer staples sector has the least in both periods. Besides, the kurtosis of the return series is close to normality before the COVID outbreak. Yet, after the pandemic, it has increased remarkably. That is, the normality of the series starts to spoil. Correspondingly, the results of the Jarque-Bera test are statistically significant, suggesting that all variables are not normally distributed. In addition, Figure 1 plots the returns series of the S&P 500 and 11 sectors for the entire period. It is clear that the volatility of all return series has increased, and the means of the series have a slide. Hence, MS-CAPM is a reasonable approach to apply.

Methodology

We analyze the importance of changing risk premiums and return variability over time. In this context, we first apply the traditional or standard CAPM and then the MS-CAPM for the sake of comparability.

Standard CAPM Model

The relationship between risk and expected return is a substantial challenge to the financial economy (Campbell 1996). One of the most common models used for addressing this problem is the capital asset pricing model (CAPM), which was first proposed by Sharpe (1964), Lintner (1965), and Mossin (1966) based on Markowitz's portfolio theory. The basic proposition of the CAPM is that the expected excess return on any asset is given by its sensitivity to the market (beta) times the market risk premium. The beta parameter (β),

Table 1. Descriptive statistics.

	Pre-COVID							COVID Period						
	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	J-B	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	J-B
S&P 500	0.08	0.74	−2.98	2.13	−0.89	2.66	4382.87*	0.08	2.17	−11.99	9.38	−0.55	7.80	654.86*
Consumer Discretionary	0.06	0.86	−3.15	2.63	−0.55	1.44	3144.25*	0.14	2.11	−12.09	8.63	−0.95	7.23	589.20*
Consumer Staples	0.07	0.66	−2.70	1.81	−0.58	1.43	1657.70*	0.02	1.76	−9.24	8.40	0.05	8.39	742.44*
Health Care	0.06	0.80	−2.90	2.20	−0.68	1.29	2053.33*	0.06	1.94	−10.00	7.58	−0.12	5.73	346.51*
Industrials	0.07	0.93	−3.00	2.36	−0.55	1.00	2417.26*	0.05	2.51	−11.45	12.75	−0.25	5.85	363.28*
Information Tecnology	0.16	1.06	−4.08	3.26	−0.56	1.67	2709.11*	0.16	2.56	−13.92	11.96	−0.30	6.75	484.26*
Materials	0.05	0.94	−3.26	3.41	−0.25	1.09	1922.69*	0.11	2.44	−11.44	11.63	−0.43	5.23	296.33*
Real Estate	0.07	0.78	−2.39	2.32	−0.41	0.16	5510.88*	0.00	2.56	−16.56	8.63	−0.90	8.40	301.91*
Communication Services	0.09	0.93	−3.07	3.73	−0.28	1.97	4432.81*	0.09	2.07	−10.45	9.20	−0.45	5.37	742.44*
Utilities	0.09	0.70	−2.16	2.13	−0.17	0.48	4699.65*	0.01	2.48	−11.55	13.11	0.29	7.54	602.94*
Financials	0.07	0.93	−3.57	2.70	−0.64	1.78	2895.47*	0.03	2.90	−14.00	13.22	−0.14	5.98	377.41*
Energy	−0.02	1.18	−4.13	3.28	−0.23	0.39	2480.69*	−0.06	3.84	−20.09	16.31	−0.32	5.31	301.91*

Note: J-B denotes Jarque-Bera test statistics. * indicates rejection of the null hypothesis referring that series are normally distributed.

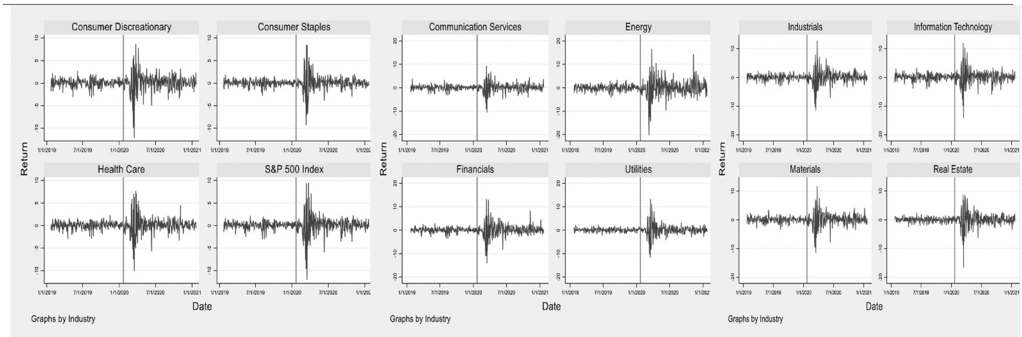

Figure 1. Returns of S&P 500 Index and Eleven Sectors in the Pre-COVID and the COVID Period.

indicating the level of sensitivity of the change in return on securities compared to the market as a whole, has a critical role in modern finance theory as a measure of systematic risk or volatility. Therefore, the most critical step in the CAPM framework is measuring the beta or asset systematic risk. Considering that the expected returns on a given asset are equal to the risk-free rate plus the portfolio's beta multiplied by the expected excess returns on the market portfolio (Chen and Huang 2007; Kayo et al. 2020), the beta is typically estimated by the following standard linear regression model (Korkmaz et al. 2010; Urom, Chevallier, and Zhu 2020; Yamaka and Phadkantha 2021).

$$\left(R_{i,t} - R_{f,t}\right) = \alpha + \beta * \left(R_{M,t} - R_{f,t}\right) + \varepsilon_t \tag{1}$$

where denotes the time horizon. $R_{i,t}$ is the rate of return of security i at time t, α is the fixed rate of return, $R_{f,t}$ is the risk-free rate, and is the rate of return of the market portfolio. Hence, $\left(R_{i,t} - R_{f,t}\right)$ presents the excess return on asset i while $\left(R_{M,t} - R_{f,t}\right)$ denotes the excess return on the market portfolio. The error term ε_t is assumed to be an independently and identically distributed random variable that follows the normal distribution ($\varepsilon_t \sim N(0, \sigma^2)$). Note that $\beta = 1$ means that the relevant security moves in the same direction as the market. That is, the systematic risk of the security and the market are equal. However, means that the security is more volatile or riskier than the market (but potentially more profitable), while means that the security is less volatile than the market.

Following the assumptions of the Sharpe-Lintner CAPM (Sharpe 1964; Lintner 1965), which assumes that performing the expectation operator $E_t(\bullet)$ of Equation (1) conditionally on information set up to time t, the condition below must hold:

$$E_t(r_i) = \beta E_t(r_m) \tag{2}$$

where r_i and r_m denote returns on asset i and market portfolio, respectively. The above condition implies that the intercept term α in Equation (1) must not be statistically different from zero (Cortazar, Kovacevic, and Schwartz 2013; He, O'Connor, and Thijssen 2018; Urom, Chevallier, and Zhu 2020).

Markov-switching CAPM Model

One of the most important assumptions in the standard CAPM is that investors focus on a single period. As a result, they consider the average return and volatility for only one period.

In addition, the beta of a risky asset estimated from the standard CAPM by employing the ordinary least squares (OLS) regression is assumed to be constant through time (Fama and MacBeth 1973; Bos and Newbold 1984). However, investors do not restrict their investments only for a certain period, so they can spread their investments over different periods of the economy or adjust their decisions over time according to the expectations of future investment opportunities. Therefore, investors can be curious about the covariances of asset returns with state variables that influence future investment opportunities, even if they favor high expected returns and low variance (Urom, Chevallier, and Zhu 2020). In this case, the constant beta coefficient assumption of the traditional CAPM is likely to fail in the real investment environment (Chen, 1981; Ang and Chen 2007; Vendrame, Guermat, and Tucker 2018). Several lines of evidence suggest that many beta coefficients tend to vary significantly through time rather than remain stable as the OLS model presumes because of macroeconomic and microeconomic factors affecting the investment decisions of companies and their cash flow balances, such as business cycle, technological change, and consumer preferences (see Blume, 1971; Levy, 1972; Blume and Friend 1973; Fabozzi and Francis 1977; Fama and French 1993; Jagannathan and Wang 1996; Groenewold and Fraser 1999; Ghysels 1998; Caporale 2012; Vendrame, Guermat, and Tucker 2018; Wang et al. 2021; Yamaka and Phadkantha 2021).

Furthermore, Lettau and Ludvigson (2001) and Beach (2011) revealed that the CAPM with a time-varying beta outperforms the standard CAPM with a constant beta. Therefore, the present study seeks to derive a reliable test by considering that the betas of underlying sectors can vary over time (as many economic time series) or be less stable over the business cycle. To this end, we apply the Markov-switching model proposed in Hamilton (1989) for the analysis of the non-stationary time series analysis of the business cycle to test whether there are regime shifts in those betas within the CAPM framework. Indeed, following Huang (2000), Huang (2001), and 2003), Chen and Huang (2007), Korkmaz et al. (2010), He, O'Connor, and Thijssen (2018), and Urom, Chevallier, and Zhu (2020) we try to find out if two different states exist between returns on the market portfolio and returns on asset *i*. We consider that Markov-switching model, which estimates regime shifting endogenously, allows beta to come from two different regimes. These regimes can be expressed as bull and bear due to the fact that when economic growth is expanding/contracting, the market is deemed to be bullish/bearish.[2]

Conversely, during recessionary/expansionary periods, correlations of assets with the market may increase/decrease depending on the industry (Urom, Chevallier, and Zhu 2020). As Vendrame, Guermat, and Tucker (2018) states, the main limitation of this idea is that the true market regime is unobservable. The sign of the market return is spurious because it is a deterministic predictor of market regimes. They tackle this problem by recognizing that, at any given period, a market's bull or bear regimes are random variables that can only be known with a certain probability. The Markov-switching model is helpful for determining these time-varying probabilities (Vendrame, Guermat, and Tucker 2018). Following Huang (2001), we denote s_t as a state variable that reflects the regime of the market at time t and assume that the market model is well specified in two different regimes. The Markov-switching CAPM equation, therefore, takes the form of equation (3) as follows:

$$\left(R_{i,t} - R_{f,t}\right) = \delta_{st} + \beta_{st}\left(R_{M,t} - R_{f,t}\right) + \varepsilon_{st} \tag{3}$$

where $\varepsilon_{st} \sim iid(0, \sigma^2)$ and δ_{st} indicates two states of the model. In this model, conditional betas are not constrained which makes the model tempting. s_1 and s_2 denote regime 1 and 2, respectively. The coefficient reflects the measure of correlation with the market for regimes 1 and 2. The unobserved state variable, s_t, takes only binary values of 0 and 1. Hence, it evolves according to the first-order Markov process as described in Hamilton (1989):

$$Prob[s_t = 1 | s_{t-1} = 1] = p \tag{4}$$

$$Prob[s_t = 1 | s_{t-1} = 2] = q \tag{5}$$

$$Prob[s_t = 1 | s_{t-1} = 2] = 1 - q \tag{6}$$

Note that p and q determined endogenously are the fixed transition probabilities of being in low and high volatility regimes.

Empirical Results

This study applies the methods introduced in the previous section to the database of eleven sectors (namely, consumer discretionary, consumer staples, health care, industrials, information technology, materials, real estate, communication services, utilities, financials, and energy) to form a basis for comparison. To this end, we first examine the standard CAPM with the traditional measure of market beta, and then we apply the MS-CAPM implying that the betas can vary over the business cycle.

CAPM Results

Applying the OLS regression model, the results of the CAPM are estimated based on equation (2). The null hypothesis is that beta coefficients are zero against a two-sided alternative, assuming that the fixed coefficients are not statistically significant from zero. To test whether standard CAPM holds, we construct excess returns by subtracting the risk-free return from the market return. In addition, we analyze the validity of the model using the Durbin-Watson test for residual autocorrelation and R-squared coefficients for the explanatory power of stock market returns for the sample sector returns.

Table 2 reports the beta coefficients and intercepts obtained from the standard CAPM. First, it is seen that the assumption of no intercept in the CAPM holds because all estimates (except for information technology and energy sectors in the pre-COVID period) are found to be statistically insignificantly different from zero. This result indicates that standard CAPM makes mainly correct estimations for the risk premium in our sampled sectors. Second, the beta coefficients or the systematic risk measures are highly statistically significant, with positive values in each period. The beta coefficient for Consumer Discretionary, Industrials, Information Technology, Communication, Financials, and energy is greater than one during the pre-COVID period, indicating that these sectors are more volatile or riskier than the market. This provides an opportunity for the investors of such sectors to have higher returns. On the other hand, the beta coefficient of consumer staples, health care, materials, real estate, and utilities sectors is lower than one during the pre-COVID period, indicating that securities of such sectors are less risky or less profitable than the market.

Table 2. Results of the CAPM model.

Sector	Consumer Discretionary	Consumer Staples	Health Care	Industrials	Information Technology	Materials	Real Estate	Communication	Utilities	Financials	Energy
Panel A					**Pre-COVID**						
Intercept	−0.02	0.03	−0.01	−0.02	0.05	−0.03	0.04	0.01	0.07	−0.02	−0.11
	[0.32]	[0.41]	[0.72]	[0.50]	[0.07][c]	[0.45]	[0.39]	[0.80]	[0.11]	[0.47]	[0.04][b]
Beta	1.05	0.56	0.83	1.09	1.34	0.97	0.39	1.03	0.20	1.08	1.08
	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]
R-squared	0.82	0.39	0.59	0.75	0.86	0.57	0.14	0.66	0.05	0.73	0.45
Durbin Watson	1.84	2.19	1.85	2.06	2.09	2.08	1.89	2.02	1.88	1.94	1.97
Panel B					**COVID Period**						
Intercept	0.07	−0.03	−0.00	−0.03	0.07	0.03	−0.08	0.02	−0.07	−0.06	−0.17
	[0.13]	[0.49]	[0.98]	[0.60]	[0.16]	[0.67]	[0.28]	[0.73]	[0.44]	[0.43]	[0.28]
Beta	0.91	0.72	0.82	1.06	1.13	1.03	1.05	1.15	0.94	1.20	1.33
	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]	[0.00][a]
R-squared	0.88	0.79	0.85	0.84	0.91	0.83	0.79	0.85	0.67	0.81	0.57
Durbin Watson	1.81	1.65	2.07	1.81	1.86	1.95	1.87	2.13	1.94	1.99	1.95

Note: [a], [b] and [c] represent significance of regime switching betas at 1%, 5% and 10%, respectively.

More importantly, the magnitude of beta estimates for consumer goods, the industrials, and the information sectors are lower. In contrast, the estimates for consumer staples, materials, real estate, utilities, financials, and communication sectors are higher in the COVID-19 period compared to the pre-COVID-19 period. This result shows that the consumer goods, the industrials, and the information sectors are adversely affected by COVID-19 whereas the pandemic positively impacts other sectors. Besides, there is no significant change in the health sector for both periods. This finding is consistent with Baek, Mohanty, and Glambosky (2020), suggesting that industries such as healthcare and medical exhibit less exposure to the pandemic.

The results indicate that household consumption priorities move toward basic needs during periods of uncertainty. Our findings show that discretionary and entertainment-related expenditure has declined relatively during the pandemic. As the government-imposed curfew is enforced, discretionary expenditure drops significantly. Meanwhile, people have started to spend more time at home and increase their demand for the utilities and communication sector, such as Netflix (Elhini and Hammam 2021). The positive impact of COVID-19 on the utility sector is consistent with the previous literature (Mazur, Dang, and Vega 2020). Also, the monetary policy implemented by the government and the stimulus package has positively affected the housing and financial markets during the COVID-19 period (Apergis 2021). In addition, the beta coefficient of the materials sector (including related chemicals, construction materials, mining, paper, and forest products) has increased due to the increase in demand during the COVID-19 outbreak.

MS-CAPM Results

Considering that betas can vary over the business cycle, the study analyzes the impact of COVID-19 pandemic on eleven sectors in both high and low-volatility regimes[3] by employing MS-CAPM with two states. As Korkmaz et al. (2010) state, in models that allow regime change, the volatility in the regimes is interpreted by looking at the standard errors of coefficients. Table 3 summarizes the estimation results for pre and pre-COVID periods.

As is seen in the table, the total risk of underlined sectors has increased significantly during the COVID period (see Table 4). During the COVID period, the total systematic risk increased, ranging from 1.26 to 3.44 in low and high volatility regimes compared to the pre-COVID period. The rise in the utility and real estate sectors are the main factors that have affected the sectors' total risk. The finding is consistent with Alfaro et al. (2020) and Baek, Mohanty, and Glambosky (2020), suggesting that more capital-intensive and leveraged sectors are likely to experience larger shifts in systematic risks. Interestingly, except for financials and energy sectors, aggressive sectors such as consumer discretionary, industrials, and information technology with betas higher than one prior to the COVID-19 period exhibit market risk decreases ranging from 0.01 (industrials) to 0.23 (information technology). While sectors with betas lower than one have the highest market risk increases ranging from 0.01 (consumer stables and communication) to 0.96 (real estate). As such, our results are in line with the findings of Dias and Serrasqueiro (2022), suggesting that at least some sectors Information technology, consumer discretionary, telecom services, consumer staples, and energy) must show statistically significant differences. Overall, our findings for individual sectors show that the coronavirus outbreak contributed to volatility in the market

Table 3. Results of the MS-CAPM model.

Sector	Consumer Discretionary		Consumer Staples		Health Care		Industrials		Information Technology		Materials		Real Estate		Communication		Utilities		Financials		Energy	
PANEL A										**Pre-COVID**												
Regime 1		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**
Intercept	0.11	[0.23]	0.16	[0.04]	0.02	[0.03]	-0.06	[0.03]	0.08	[0.04][b]	-0.04	[0.04]	0.32	[0.13][b]	0.16	[0.04] [a]	0.08	[0.14]	0.01	[0.04]	-0.14	[0.06]
Beta	1.06	[0.08][a]	0.63	[0.06][a]	0.83	[0.03][a]	1.04	[0.04][a]	1.25	[0.06][a]	1.04	[0.06][a]	0.39	[0.16][a]	0.63	[0.06][a]	-0.38	[0.19][a]	1.11	[0.04][a]	1.11	[0.07][a]
Regime 2																						
Intercept	-0.10	[0.14]	-0.06	[0.07]	-1.13	[0.57][b]	0.06	[0.10]	-0.02	[0.07]	0.13	[0.33]	-0.21	[0.24]	-0.06	[0.07]	0.08	[0.07]	-0.08	[0.12]	0.13	[0.35]
Beta	1.05	[0.05][a]	0.52	[0.07][a]	0.67	[1.52]	1.23	[0.14] [a]	1.46	[0.12][a]	0.47	[0.45][a]	0.39	[0.15][a]	0.52	[0.07][a]	0.42	[0.09][a]	1.01	[0.13][a]	0.64	[0.55]
p12	0.72		0.45		0.99		0.70		0.88		0.95		0.56		0.45		0.62		0.80		0.97	
p21	0.83		0.65		0.68		0.34		0.80		0.46		0.61		0.65		0.82		0.52		0.83	
PANEL B											**COVID Period**											
Regime 1		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**		**SD**
Intercept	0.04	[0.04]	-0.06	[0.04]	-0.04	[0.05]	-0.20	[0.07][a]	0.16	[0.10]	-0.03	[0.07]	0.04	[0.11]	-0.06	[0.04]	-0.13	[0.18]	-0.04	[0.08]	-0.28	[0.14][b]
Beta	0.91	[0.02][a]	0.64	[0.03][a]	0.87	[0.06][a]	0.93	[0.04][a]	1.23	[0.06][a]	1.14	[0.07][a]	0.90	[0.04][a]	0.64	[0.03][a]	1.20	[0.05][a]	0.87	[0.09][a]	1.34	[0.12][a]
Regime 2																						
Intercept	0.13	[0.14]	0.08	[0.22]	0.12	[0.22]	0.24	[0.21]	0.01	[0.09]	0.06	[0.10]	-0.35	[0.18][a]	0.08	[0.22]	-0.02	[0.11]	-0.09	[0.14]	0.19	[0.53]
Beta	0.91	[0.04][a]	0.78	[0.06][a]	0.85	[0.06][a]	1.22	[0.07][a]	1.08	[0.04][a]	1.01	[0.03][a]	1.35	[0.07][a]	0.78	[0.06][a]	0.55	[0.06][a]	1.26	[0.05][a]	1.33	[0.14]
p12	0.91		0.97		0.98		0.87		0.60		0.93		0.90		0.97		0.77		0.97		0.99	
p21	0.81		0.87		0.95		0.80		0.76		0.95		0.73		0.87		0.90		0.97		0.95	

Note: [a] and [b] represent the significance of regime-switching betas at 1% and 5%, respectively whereas p12 and p21 refer to the probability of moving from one volatility regime to another.

Table 4. Systematic and total risk for pre-COVID and COVID periods.

Low Volatility Regime	β Pre-COVID	β COVID	β^{Δ}
Consumer Discretionary	1.05	0.91	−0.14
Consumer Staples	0.63	0.64	0.01
Health Care	0.83	0.85	0.02
Industrials	1.04	0.93	−0.11
Information Technology	1.25	1.08	−0.17
Materials	1.04	1.01	−0.03
Real Estate	0.39	0.9	0.51
Communication	0.63	0.64	0.01
Utilities	0.42	1.2	0.78
Financials	1.11	1.26	0.15
Energy	1.11	1.34	0.23
Total Risk			1.26
High Volatility Regime	$\beta^{\textbf{Pre-COVID}}$	$\beta^{\textbf{COVID}}$	β^{Δ}
Consumer Discretionary	1.06	0.91	−0.15
Consumer Staples	0.52	0.78	0.26
Health Care	0.67	0.87	0.2
Industrials	1.23	1.22	−0.01
Information Technology	1.46	1.23	−0.23
Materials	0.47	1.14	0.67
Real Estate	0.39	1.35	0.96
Communication	0.52	0.78	0.26
Utilities	−0.38	0.55	0.93
Financials	1.01	0.87	−0.14
Energy	0.64	1.33	0.69
Total Risk			3.44

in general, even if systematic risks in some sectors, including industrials, information technology, and consumer discretionary, decreased.

Table 5 summarizes the comparison of sectors to the market in the high and low volatility regimes for both pre-COVID and COVID periods. In the low volatility regime of the pre-COVID period, the estimates of beta coefficients of consumer discretionary, industrials, information technology, materials, financial, and energy sectors are statistically significant and more than one, meaning that these sectors are riskier than S&P 500 index. However, estimates of beta coefficients of consumer staples, healthcare, real estate, communication, and utilities are less than one and statistically significant except healthcare sector. That is, these sectors are less risky than the market in the low volatility regime of the pre-COVID period. On the other hand, in the low volatility regime of the COVID period, the estimates of beta coefficients of information technology, materials, utilities, financials, and energy sectors are statistically significant and more than one. Hence these sectors are riskier than the market in the mentioned period. In the low volatile regime of the COVID period, the estimates of beta coefficients of consumer discretionary, consumer staples, healthcare, industrial, real estate, and communication sectors are statistically significant and less than one. In the COVID period, these sectors are less risky than the market.

Besides, in the high volatility regime of the pre-COVID period, the estimates of beta coefficients of consumer discretionary, industrials, information technology, and financials sectors are significant and more than one. These sectors are riskier than the market. Yet, the beta coefficients of consumer staples, materials, real estate, communication, and utilities sectors are significant and less than one, showing that these sectors are less risky than the market. Meanwhile, the healthcare and energy sector beta coefficients are less than one but insignificant. In the high volatility regime of the COVID period, the beta estimates of

Table 5. Summary of estimates of beta coefficients of sectors.

	Pre-COVID $\beta > 1$	COVID-Period β>1
Low Volatility Regime	1. Consumer Discretionary 2. Industrials 3. Materials 4. Financials 5. Information Technology 6. Energy	1. Information Technology 2. Materials 3. Utilities 4. Financials 5. Energy
High Volatility Regime	1. Consumer Discretionary 2. Industrials 3. Information Technology 4. Financials	1. Materials 2. Real Estate 3. Energy 4. Industrials 5. Information Technology
Low Volatility Regime	1. Consumer Staples 2. Health Care 3. Real Estate 4. Communication 5. Utility	1. Consumer Discretionary 2. Consumer Staples 3. Health Care 4. Industrials 5. Real Estate 6. Communication
High Volatility Regime	1. Consumer Staples 2. Health care 3. Materials 4. Real estate 5. Communication 6. Utilities 7. Energy	1. Consumer Discretionary 2. Consumer Staples 3. Health Care 4. Communication 5. Utilities 6. Financials

information technology, materials, real estate, and industrials are more than one and statistically significant. Although the beta estimate of the energy sector is more than one, it is not statistically significant. In the same regime of the COVID period, consumer discretionary, consumer staples, healthcare, communication, utilities, and financials sectors have a beta coefficient of less than one. Also, the beta coefficients of these sectors are statistically significant. These results show that only the information technology sector is relatively stable for both regimes and periods. Its beta coefficient stays more than one, whereas it decreases during the COVID period. In addition, in the low volatility regimes, the transitivity of the beta coefficients of the sectors is more stable compared to high volatility regimes. In the high volatility regimes, the transitivity of beta coefficients of the sectors is much more than in low volatility regimes. Moreover, the beta coefficient of the utilities sector turns positive from negative during the COVID period. These findings imply that investors' perceptions differ too much in crisis periods and high volatility regimes.

Table 3 and Figure 2 tabulate the transition probabilities of one regime to the other. It is generally likely to switch from a low volatility regime to high volatility regime, as shown by high values of P12 for the pre-COVID period. The highest value of P12 is 0.99 for healthcare. However, the probability of transition from high volatility to low volatility is relatively lower, as indicated by P21 values. To illustrate, the P21 energy and consumer discretionary sectors are 0.83. These results are very similar in the COVID period, as well. Yet, we observe that the probability of transition from low volatility regime to high volatility regime is higher in the COVID period compared to pre-COVID times. These results suggest that the probability of transition from one regime to another is comparably higher in extreme times, supporting our findings. A possible interpretation of our results is that economic relief packages announced by the US government might have affected sectors differently as the outbreak of the COVID-19 pandemic forced governments to support the

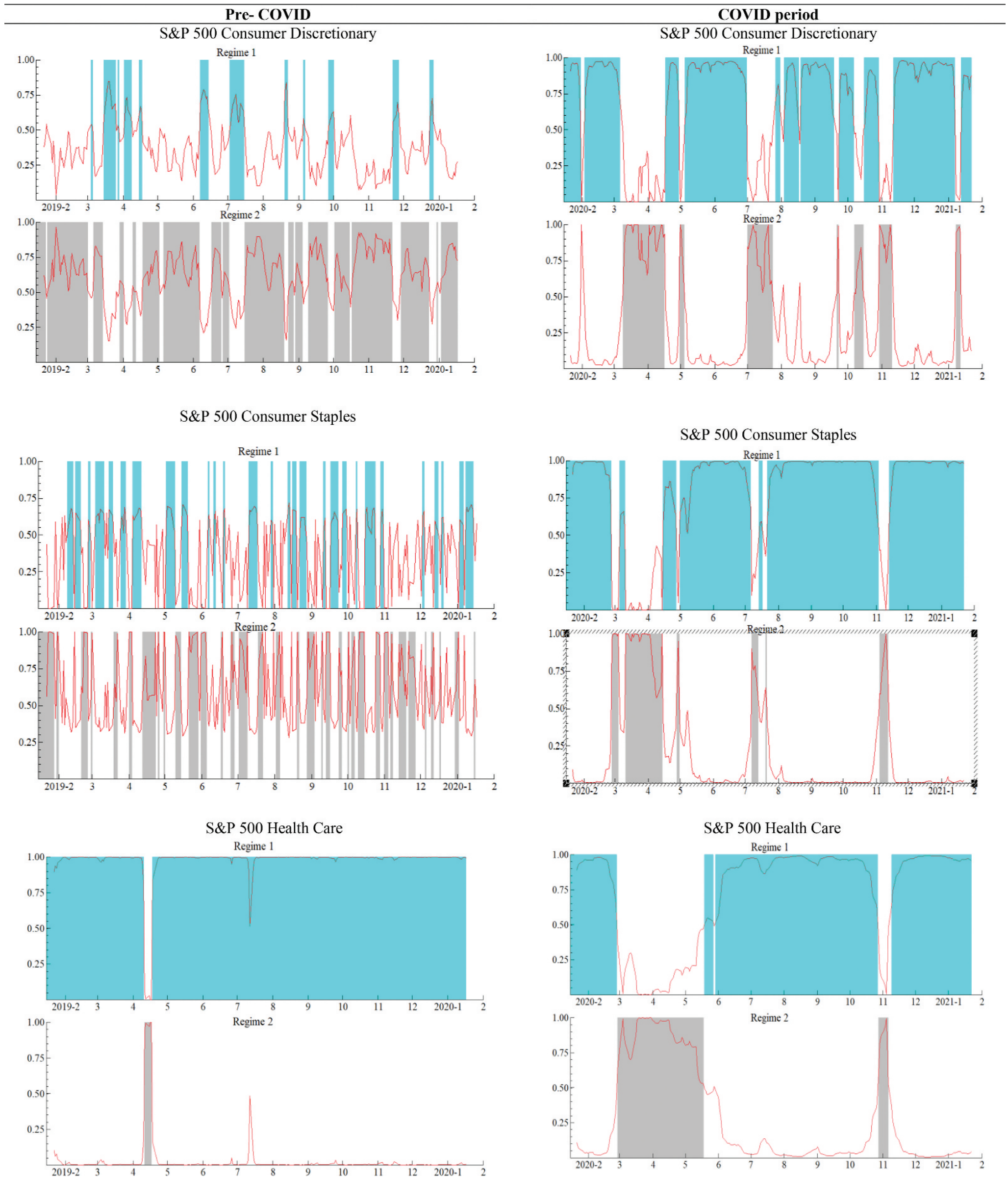

Figure 2. MS-CAPM state probabilities for eleven sectors.

economy with different kinds of fiscal and monetary actions. For instance, the US government has announced American Rescue Plan Six Month, Economic Impact Payments, Homeowner Assistance Funds, and Coronavirus State and Local Fiscal Recovery Funds to support the economy. These relief packages, for instance, propped up real estate sectors as many individuals have a chance to save more with the help of government cheques and buy a new house.

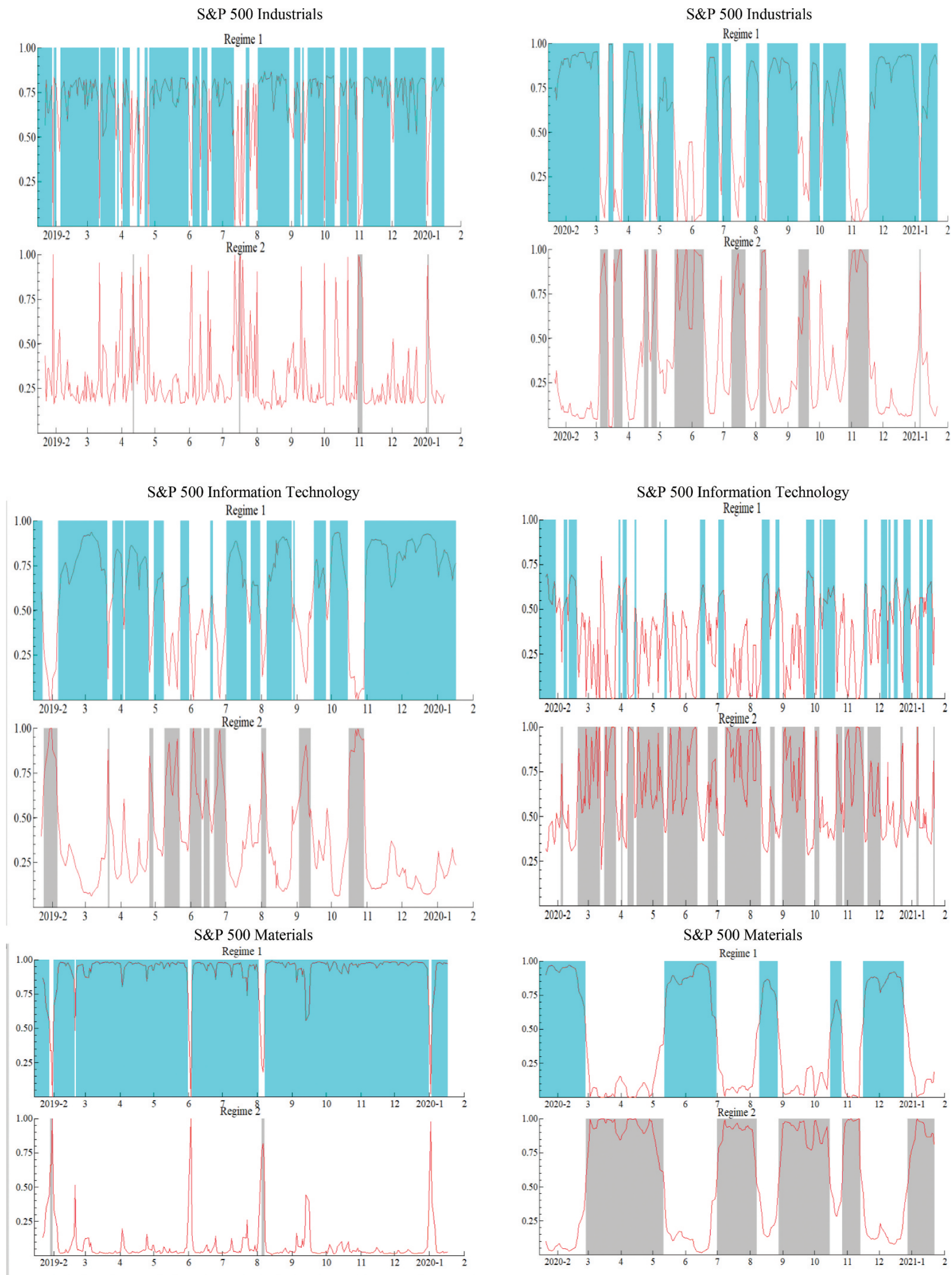

Figure 2. (Continued).

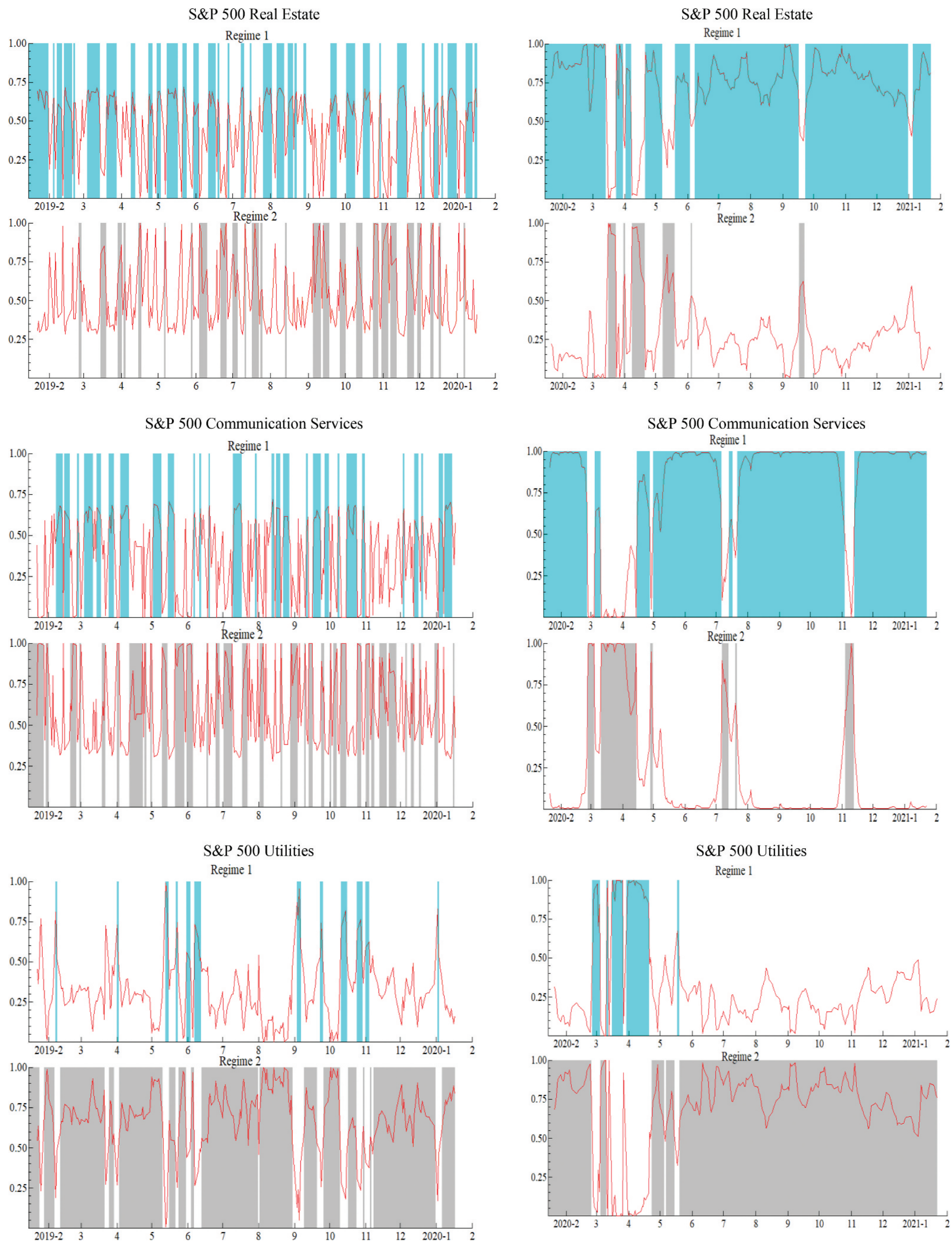

Figure 2. (Continued).

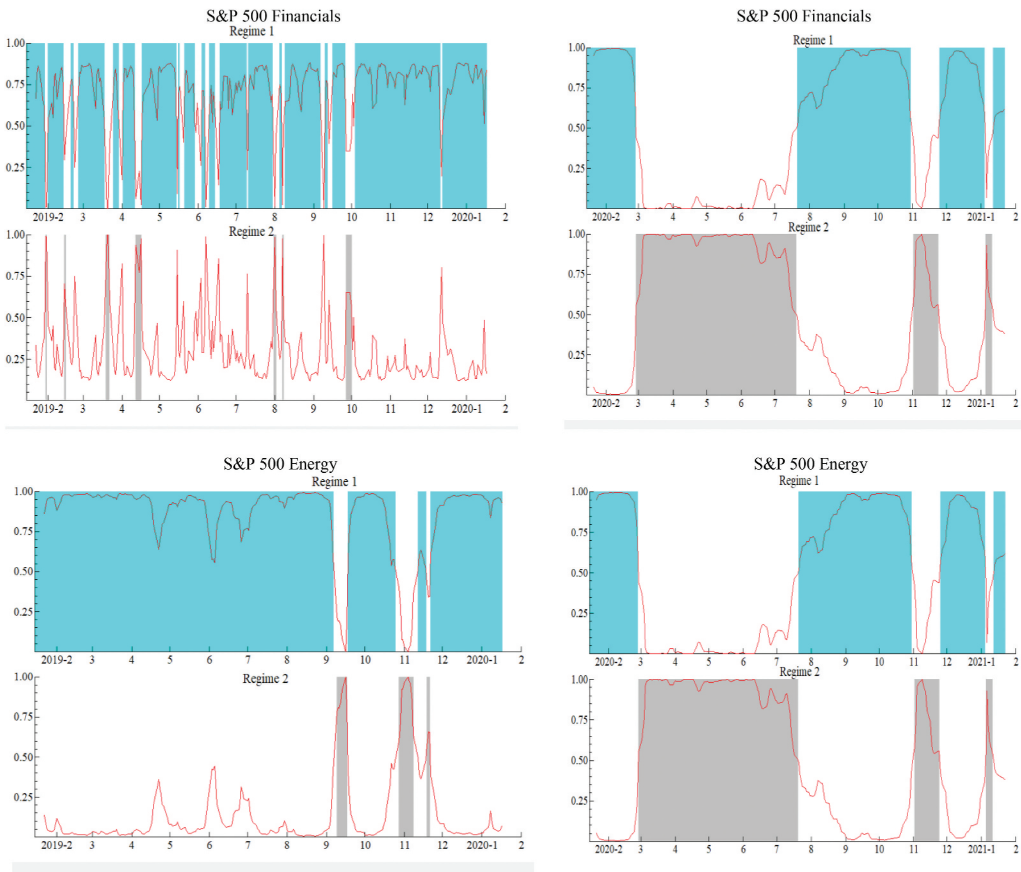

Figure 2. (Continued).

Concluding Remarks

This paper conducts an MS-CAPM model to examine the effect of the COVID-19 pandemic on the US stock market volatility. It makes mainly two contributions to the literature. First, to our knowledge, it is the first study that divides the sample into low-volatile and high-volatile regimes for both pre-COVID and COVID periods and analyses four betas for each economic sector. Second, we compare the standard CAPM model with the MS-CAPM model and show that even in normal times, the betas of the sectors depend on the volatility of the regime of the economy (high volatile or low volatile regime). Our findings for individual sectors show that the coronavirus outbreak contributed to volatility in the market in general, even if systematic risks in some sectors, including industrials, information technology, and consumer discretionary, decrease. In addition, we observe that the probability of transition from low volatility regime to high volatility regime is higher in the COVID period compared to pre-COVID times. That is, the probability of transition from one regime to another is comparably higher in extreme times. These results have significant implications for investors and policymakers interested in different sectors and monitor the economy, respectively. To illustrate, policymakers might focus on negatively impacted sectors and announce relief packages accordingly, and investors redesign their portfolios based on the changing volatility of sectors' returns.

Notes

1. Note that concentrating on the U.S. is due to the fact that markets in the U.S. are the main driver of the contagion effect around the world (Bekaert et al. 2011). As Aloui, Aïssa, and Nguyen (2011) assert, markets prone to commodity price risk start co-moving with the markets in the U.S. during higher levels of uncertainty. Hence the movements in the U.S. enable us to get a hint of movements in other markets across the globe.
2. Vendrame, Guermat, and Tucker (2018) defines the regimes as a bullish quiet regime and a bearish high volatility regime that might lead to swings between high positive and high negative returns.
3. Although financial market behavior is usually defined by two states (namely, bull and bear), this study also considers that the market may has more than two states. Therefore, the study has performed MS-CAPM with three and four states. However, the findings show that MS-CAPM with two states is the best suitable model for all sectors according to the loglikelihood, Schwartz Information Criteria (SIC), and Akaike Information Criteria (AIC). Results with three and four states is available upon request from the authors.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Emre Bulut is research assistant in the Faculty of Economics and Business at Agri Ibrahim Cecen University. He received his Ph.D. degree in Business Administration from Ihsan Dogramaci Bilkent University and his master's degree in Accounting from University of Texas at San Antonio. His research areas are mergers, financial crisis, asset pricing, industrialization.

Cumali Marangoz is assistant professor of economics in the Faculty of Economics and Administrative Sciences at Agri Ibrahim Cecen University. He studied Economics at Afyon Kocatepe University (BSc, 2009) and Graduate Program in Economic Development (GPED) at Vanderbilt University (MSc, 2013). He also holds a Ph.D. in Economics from Nevsehir Haci Bektas Veli University (2022). His research areas are tourism, business cycle, energy, economic growth, and structural change.

Muhammet Daştan is assistant professor of economics in the Faculty of Economics and Administrative Sciences at Agri Ibrahim Cecen University. He studied Economics at Anadolu University (BSc, 2015). He has a master`s degree in Economics from Anadolu University (2017). He also holds a Ph.D. (2021) in Economics from Erzurum Ataturk University (2021). His research areas are business cycle, economic growth, energy, macroeconomic activity, and uncertainty.

ORCID

Emre Bulut http://orcid.org/0000-0002-1468-2175
Cumali Marangoz http://orcid.org/0000-0002-0216-3490
Muhammet Daştan http://orcid.org/0000-0001-6067-8946

References

Ahmad, W., A. M. Kutan, and S. Gupta. 2021. “Black Swan Events and Covid-19 Outbreak: Sector Level Evidence from the US, UK, and European Stock Markets.” *International Review of Economics and Finance* 75:546–57. doi:10.1016/j.iref.2021.04.007.

Akhtaruzzaman, M, S Boubaker, and A. Sensoy. 2021. “Financial Contagion during COVID-19 Crisis.” *Finance Research Letters* 38(Jan): Epub 2020 May 23. PMID: 32837363; PMCID: PMC7245292. 101604. doi:10.1016/j.frl.2020.101604.

Albuquerque, R. A., Y. J. Koskinen, S. Yang, and C. Zhang. 2020. “Love in the Time of Covid-19: The Resiliency of Environmental and Social Stocks.” *SSRN Electronic Journal* doi: 10.2139/ssrn.3583611.

Alfaro, Laura, Anusha Chari, Andrew N. Greenland, and Peter K. Schott, 2020. “Aggregate and Firm-Level Stock Returns during Pandemics, in Real Time,” *NBER Working Papers* 26950, National Bureau of Economic Research, Inc.

Aloui, R., M. Aïssa, and D. Nguyen. 2011. “Global Financial Crisis, Extreme Interdependences, and Contagion Effects: The Role of Economic Structure?” *Journal of Banking and Finance* 35 (1): 130–41. doi:10.1016/j.jbankfin.2010.07.021.

Amar, Amine Ben, Fateh Bélaïd, Adel Ben Youssef, and Khaled Guesmi. 2021. “Connectedness among Regional Financial Markets in the Context of the COVID-19.” *Applied Economics Letters* 28 (20): 1789–96. doi:10.1080/13504851.2020.1854434.

Ang, A., and J. Chen. 2007. “CAPM over the Long Run: 1926–2001.” *Journal of Empirical Finance* 14 (1):1–40. 1. doi:10.1016/j.jempfin.2005.12.001.

Apergis, N. 2021. “The Role of Housing Market in the Effectiveness of Monetary Policy over the COVID-19ERA.” *Economics Letters* 200:109749. doi:10.1016/j.econlet.2021.109749.

Ashraf, BN. 2020. “Economic Impact of Government Interventions during the COVID-19 Pandemic: International Evidence from Financial Markets.” *Journal of Behavioral and Experimental Finance* 27(Sep): Epub 2020 Jun 29. PMID: 32835011; PMCID: PMC7323651. 100371. doi:10.1016/j.jbef.2020.100371.

Ashraf, B. N. 2021. “Stock Markets’ Reaction to Covid-19: Moderating Role of National Culture.” *Finance Research Letters* 41:101857. doi:10.1016/j.frl.2020.101857.

Baek, S., S. K. Mohanty, and M. Glambosky. 2020. “COVID-19 and Stock Market Volatility: An Industry Level Analysis.” *Finance Research Letters* 37(Nov): Epub 2020 Sep 3. PMID: 32895607; PMCID: PMC7467874. 101748. doi:10.1016/j.frl.2020.101748.

Baker, S., N. Bloom, S. Davis, K. Kost, M. Sammon, T. Viratyosin, and J. Pontiff. 2020. “The Unprecedented Stock Market Reaction to COVID-19.” *The Review of Asset Pricing Studies* 10 (4): 742–58. doi:10.1093/rapstu/raaa008.

Beach, Steven L. 2011. “Semivariance Decomposition of Country-Level Returns (October 1, 2011).” *International Review of Economics & Finance* 20 (4):607–23. Available at https://ssrn.com/abstract=1938003

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. Mehl. 2011. “Global Crises and Equity Market Contagion.” *SSRN Electronic Journal*. doi:10.2139/ssrn.1919553.

Blume, E. 1971. “On the Assessment of Risk.“ *Journal of Finance* 24: 275–288. doi:10.1111/j.1540-6261.1971.tb00584.x.

Blume, M.E., and I. Friend. 1973. “A New Look at the Capital Asset Pricing Model.” *The Journal of Finance* 28 (1): 19–34. doi:10.1111/j.1540-6261.1973.tb01342.x.

Bos, T., and P. Newbold. 1984. “An Empirical Investigation of the Possibility of Stochastic Systematic Risk in the Market Model.” *The Journal of Business* 57 (1): 35–41. doi:10.1086/296222

Campbell, J. 1996. “Understanding Risk and Return.” *Journal of Political Economy* 104 (2): 298–345. doi:10.1086/262026.

Caporale, Tony. 2012. “Time Varying CAPM Betas and Banking Sector Risk.” *Economics Letters, Elsevier* 115 (2): 293–95. doi:10.1016/j.econlet.2011.12.056

Chebbi, K., M. A. Ammer, and A. Hameed. 2021. “The COVID-19 Pandemic and Stock Liquidity: Evidence from S&P 500.” *The Quarterly Review of Economics and Finance* 81:134–42. doi:10.1016/j.qref.2021.05.008.

Chen, S. N. 1981. "Beta Nonstationarity, Portfolio Residual Risk and Diversification." *Journal of Financial and Quantitative Analysis* 16 (1): 95–111. doi:10.2307/2330668.
Chen, S., and N. Huang. 2007. "Estimates of the ICAPM with regime-switching Betas: Evidence from Four Pacific Rim Economies." *Applied Financial Economics* 17 (4): 313–27. doi:10.1080/09603100600749188.
Choi, S.-Y. 2020. "Industry Volatility and Economic Uncertainty Due to the COVID-19 Pandemic: Evidence from Wavelet Coherence Analysis." *Finance Research Letters* 37:101783. doi:10.1016/j.frl.2020.101783.
Chowdhury, E., and M. Abedin. 2020. "COVID-19 Effects on the US Stock Index Returns: An Event Study Approach." *SSRN Electronic Journal* doi:10.2139/ssrn.3611683.
Corbet, S., C. Larkin, and B. Lucey. 2020. "The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies." *Finance Research Letters* 35:101554. doi:10.1016/j.frl.2020.101554.
Cortazar, G., I. Kovacevic, and E.S. Schwartz, 2013. Commodity and Asset Pricing Models: An Integration (No. W19167). National Bureau of Economic Research.
Dias, Curto, José, and Pedro Serrasqueiro. 2022. "The Impact of COVID-19 on S&P500 Sector Indices and FATANG Stocks Volatility: An Expanded APARCH Model." *Finance Research Letters* 46 (PA): Elsevier.
Elhini, M., and R. Hammam. 2021. "The Impact of COVID-19 on the S&P 500 Index Sectors: A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model." *Journal of Chinese Economic and Foreign Trade Studies* 14 (1): 18–43. doi:10.1108/jcefts-08-2020-0049.
Engelhardt, N., M. Krause, D. Neukirchen, and P. N. Posch. 2021. "Trust and Stock Market Volatility during the COVID-19 Crisis." *Finance Research Letters* 38:101873. doi:10.1016/j.frl.2020.101873.
Fabozzi, F. J., and J. C. Francis. 1977. "Stability Tests for Alphas and Betas Over Bull and Bear Market Conditions." *The Journal of Finance* 32 (4): 1093–1099. doi:10.1111/j.1540-6261.1977.tb03312.x.
Fama, E.F., and K.R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56. doi:10.1016/0304-405X(93)90023-5
Fama, E. F., and J. D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3): 607–36. http://www.jstor.org/stable/1831028
Farzami, Y., R. Gregory-Allen, A. Molchanov, and S Sehrish. 2021. "Covid-19 and the Liquidity Network." *Finance Research Letters* 42:101937. doi: 10.1016/j.frl.2021.101937
Ghysels, E. 1998. "On Stable Factor Structures in the Pricing of Risk: Do Time-Varying Betas Help or Hurt?" *The Journal of Finance* 53 (2): 549–73. http://www.jstor.org/stable/117361
Goodell, J. W. 2020. "Covid-19 and Finance: Agendas for Future Research." *Finance Research Letters* 35:101512. doi: 10.1016/j.frl.2020.101512
Groenewold, N., and P. Fraser, 1999. "Forecasting Beta: How Well Does the 'Five Year Rule of Thumb' Do?," Economics Discussion/Working Papers 99-01, The University of Western Australia, Department of Economics.
Hamilton, J. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica* 57 (2): 357. doi:10.2307/1912559.
Haroon, O., and S. Rizvi. 2020. "COVID-19: Media Coverage and Financial Markets behavior—A Sectoral Inquiry." *Journal of Behavioral and Experimental Finance* 27:100343. doi: 10.1016/j.jbef.2020.100343
He, Z., F. O'Connor, and J. Thijssen. 2018. "Is Gold A Sometime Safe Haven or an Always Hedge for Equity Investors? A Markov-switching CAPM Approach for US and UK Stock Indices." *International Review of Financial Analysis* 60:30–37. doi: 10.1016/j.irfa.2018.08.010
He, P., Y. Sun, Y. Zhang, and T. Li. 2020. "COVID–19's Impact on Stock Prices Across Different Sectors—An Event Study Based on the Chinese Stock Market." *Emerging Markets Finance and Trade* 56 (10): 2198–2212. doi:10.1080/1540496X.2020.1785865.
Huang, H. 2000. "Tests of Regimes - Switching CAPM." *Applied Financial Economics* 10 (5): 573–78. doi:10.1080/096031000416451.
Huang, H.-C. 2001. "Tests of CAPM with non-stationary Beta." *International Journal of Finance and Economics* 6(3): river. 255–68. doi:10.1002/ijfe.146.

Huang, H.-C. R. 2003. "Tests of regime-switching CAPM under Price Limits." *International Review of Economics and Finance* 12 (3): 305–26. doi:10.1016/s1059-0560(03)00013-3.
Hung, D. V., N. T. Hue, and V. T. Duong. 2021. "The Impact of Covid-19 on Stock Market Returns in Vietnam." *Journal of Risk and Financial Management* 14 (9): 441. doi:10.3390/jrfm14090441.
Jagannathan, R., and Z. Wang. 1996. "The Conditional CAPM and the cross-section of Expected Returns." *The Journal of Finance* 51 (1): 3–53. doi:10.1111/j.1540-6261.1996.tb05201.x
Kayo, Eduardo K, Roy Martelanc, Eduardo O Brunaldi, and Walter E. da Silva. 2020. "Capital Asset Pricing Model, Beta Stability, and the Pricing Puzzle of Electricity Transmission in Brazil." *Energy Policy* 142(C): Elsevier. 111485. doi:10.1016/j.enpol.2020.111485.
Korkmaz, T., E. I. Çevik, E. Birkan, and N. Özataç. 2010. "Testing CAPM Using Markov Switching Model: The Case of Coal Firms." *Economic Research-Ekonomska Istraživanja* 23 (2): 44–59. doi:10.1080/1331677x.2010.11517411.
Kwan, Simon H., and Thomas M. Mertens. 2020. "Market Assessment of COVID-19." *Federal Reserve Bank of San Francisco*. Retrieved October 7 2021, from https://www.frbsf.org/economic-research/publications/economic-letter/2020/may/market-assessment-of-covid-19
Lettau, M., and S. Ludvigson. 2001. "Consumption, Aggregate Wealth, and Expected Stock Returns." *The Journal of Finance* 56 (3): 815–49. doi:10.1111/0022-1082.00347.
Levy, H. 1972. "Portfolio Performance and the Investment Horizon." *Management Science* 18 (12): B-645–B-653. doi:10.1287/mnsc.18.12.B645.
Lintner, J. 1965. "Security Prices, Risk, and Maximal Gains from Diversification." *The Journal of Finance* 20 (4): 587–615. doi:10.1111/j.1540-6261.1965.tb02930.x.
Mazur, M., M. Dang, and M. Vega. 2020. "Covid-19 and March 2020 Stock Market Crash. Evidence from S&P1500." *SSRN Electronic Journal* doi: 10.2139/ssrn.3586603.
Mossin, J. 1966. "Equilibrium in a Capital Asset Market." *Journal of Behavioral and Experimental Finance* 34 (4): 768. doi:10.2307/1910098.
Onali, E. 2020. "Covid-19 and Stock Market Volatility." *SSRN Electronic Journal* doi: 10.2139/ssrn.3571453.
Salisu, A., X. Vo, and B. Lucey. 2021. "Gold and US Sectoral Stocks during COVID-19 Pandemic." *Research in International Business and Finance* 57:101424. doi: 10.1016/j.ribaf.2021.101424.
Sharif, A, C Aloui, and L 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(Jul): Epub 2020 May 15. PMCID: PMC7227524. 101496. doi:10.1016/j.irfa.2020.101496.
Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *The Journal of Finance* 19 (3): 425–42. doi:10.1111/j.1540-6261.1964.tb02865.x.
Takyi, PO, and I. Bentum-Ennin. 2021. "The Impact of COVID-19 on Stock Market Performance in Africa: A Bayesian Structural Time Series Approach." *Journal of Economics and Business* 115(May–June): Epub 2020 Dec 8. 105968. doi:10.1016/j.jeconbus.2020.105968.
Urom, C., J. Chevallier, and B. Zhu. 2020. "A Dynamic Conditional regime-switching GARCH CAPM for Energy and Financial Markets." *Energy Economics* 85:104577. doi: 10.1016/j.eneco.2019.104577
Vendrame, Vasco, Cherif Guermat, and Jon Tucker. 2018. "A Conditional Regime Switching CAPM." Elsevier. *International Review of Financial Analysis* 56 (C):1–11.
Wang, F., R. Zhang, F. Ahmed, and S. M. Shah. 2021. "Impact of Investment Behaviour on Financial Markets during COVID-19: A Case of UK." *Economic Research-Ekonomska Istraživanja* 35 (1): 2273–91. doi:10.1080/1331677x.2021.1939089.
Yagli, Ibrahim, The Impact of COVID-19 on Emerging Stock Market Volatility: Empirical Evidence from Borsa Istanbul (December 29, 2020). YAĞLI, İ. The Impact of Covid-19 on Emerging Stock Market Volatility: Empirical Evidence from Borsa Istanbul. Ekonomi Politika ve Finans Araştırmaları Dergisi, 5(Özel Sayı), 269–79 (2020) https://ssrn.com/abstract=3760319
Yamaka, W., and R. Phadkantha. 2021. "A Convex Combination Approach for Markov Switching CAPM of Interval Data." *Soft Computing* 25 (12): 7839–51. doi:10.1007/s00500-021-05798-y.
Zaremba, A., R. Kizys, D. Y. Aharon, and E. Demir. 2020. "Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe." *Finance Research Letters* 35:101597. doi:10.1016/j.frl.2020.1015.