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COVID-19 Effects on the S&P 500 Index*

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Abstract

This paper investigates the effects of the coronavirus disease 2019 (COVID-19) cases in the U.S. on the S&P 500 Index using daily data covering the period between January 21st, 2020 and August 10th, 2021. The investigation is achieved by using a structural vector autoregression model, where a measure of the global economic activity and the spread between 10-year treasury constant maturity and the federal funds rate are also included. The empirical results suggest that having 1% of an increase in cumulative daily COVID-19 cases in the U.S. results in about 0.01% of a cumulative reduction in the S&P 500 Index after one day and about 0.03% of a reduction after one week. Historical decomposition of the S&P 500 Index further suggests that the negative effects of COVID-19 cases in the U.S. on the S&P 500 Index have been mostly observed during March 2020.

JEL Classification: F44, G15, I10

Key Words: Coronavirus; COVID-19; S&P 500 Index; Baltic Dry Index

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1 Introduction

The coronavirus pandemic 2019 (COVID-19) has killed $618,363$ people in the U.S. as of August 10th, 2021, with corresponding COVID-19 cases of $36,152,620$.[1] This has created a significant turmoil not only in the global economic activity (e.g., see Baldwin and di Mauro (2020) or Yilmazkuday (2020)) but also in financial markets around the world (e.g., see Cao, Li, Liu, and Woo (2020)). This turmoil can best be observed by the Standard & Poor's (S&P) 500 Index, which is the benchmark financial and economic indicator in the U.S. and fell from about $3,386.15$ on February 19th, 2020 to about $2,237.40$ on March 23rd, 2020, corresponding to about 41% of a fall, although it achieved a great recovery with record braking values such as $4,436.75$ on August 10th, 2021.[2]

This paper attempts to understand the reasons behind the volatility in the S&P 500 Index during COVID-19 by using daily data between January 21st, 2020 (when the first COVID-19 case was reported in the U.S.) and August 10th, 2021 (the latest day available when this paper was written). As this volatility in the S&P 500 Index may be due to COVID-19 or any other factor (e.g., the economic activity or interest rates), a formal analysis is required to identify the causal effects of COVID-19 on the S&P 500 Index. Such an investigation is achieved in this paper by using a structural vector autoregression (SVAR) model, where the S&P 500 Index is used together with a measure of the global economic activity (as in Fama (1981), Huang and Kracaw (1984) or Vassalou (2003)) and the spread between 10-year treasury constant maturity and the federal funds rate in the U.S. (as in Chen, Roll, and Ross (1986) or Petkova (2006)). Since COVID-19 is an exogenous shock, percentage changes in

[1] This is based on the New York Times data published at https://github.com/nytimes/covid-19-data.

[2] The S&P 500 Index is also globally important as it causes price movements in other financial markets according to studies such as by Lento and Gradojevic (2021).

cumulative daily COVID-19 cases in the U.S. are included as an exogenous variable in this framework.

Following several early or recent studies in the literature such as by Isserlis (1938), Tinbergen (1959), Stopford (2008), Klovland (2002), Kilian (2009), Fan and Xu (2011), Qiu, Colson, Escalante, and Wetzstein (2012) and Makridakis, Merikas, Merika, Tsionas, and Izzeldin (2020), the global economic activity is measured by the Baltic Exchange Dry Index (BDI). This is a daily published index by the Baltic Exchange in London, and it reflects the shipping costs (due to using vessels of various sizes covering multiple maritime routes) regarding the transportation of raw commodities (e.g., grain, coal, iron ore, copper). Since these shipping costs are determined by the supply and demand forces in the global market, they are robust to any speculative manipulation or any government intervention by construction (e.g., see Bildirici, Kayıkçı, and Onat (2015) or Graham, Peltomäki, and Piljak (2016)). Using BDI as a global economic activity within this framework is also consistent with studies such as by Graham, Peltomäki, and Piljak (2016) who have shown that changes in BDI are highly associated with equity returns. Finally, the spread between 10-year treasury constant maturity and the federal funds rate in the U.S. not only reflects the term premium (between long-run and short-run interest rates) but also the future expectations in the U.S. economy (e.g., see Chen, Roll, and Ross (1986) or Petkova (2006)).

This paper contributes to the literature in several dimensions. First, the elasticity of S&P 500 Index with respect to confirmed COVID-19 cases in the U.S. is estimated for alternative horizons; this is important to understand how the stock market risk associated with the COVID-19 pandemic is perceived by investors as indicated in studies such as by Cox, Greenwald, and Ludvigson (2020). Second, the elasticity of the spread between 10-year treasury constant maturity and the federal funds rate in the U.S. with respect to confirmed COVID-19 cases in the U.S. is estimated for alternative horizons; this is important to understand how future expectations in the U.S. economy and the corresponding policy uncertainty interact with the stock market risk that is associated with the COVID-19 pandemic as indicated in studies such as by Sharif, Aloui, and Yarovaya (2020). Third, the period over which the COVID-19 pandemic has negative affected the S&P 500 Index the most is identified; this is important to understand the timing of the risk perception in the stock market as it is essential for policy design and financial planning as indicated in studies such as by Ahundjanov, Akhundjanov, and Okhunjanov (2020).

The rest of the paper is organized as follows. The next section introduces the estimation methodology and the data set used. Section 3 depicts empirical results, while Section 4 concludes.

2 Data and Estimation Methodology

The formal investigation is achieved by using the SVAR model of $z_t = (\Delta b_t, \Delta s_t, \Delta p_t)'$ based on daily data, where Δb_t represents the percentage change in BDI, Δs_t represents the percentage change in the spread between 10-year treasury constant maturity and the federal funds rate in the U.S., and Δp_t represents the percentage change in the S&P 500 Index. Percentage changes in daily cumulative COVID-19 cases in the U.S., denoted by Δc_t, are included as an exogenous variable in this framework, since they are not affected by any economic variables.

The daily data cover the sample period between January 21st, 2020 (when the first COVID-19 case was reported in the U.S.) and August 10th, 2021 (the latest day available when this paper was written). Daily data on BDI are obtained from the web page of Trading Economics.[3] Daily data on the S&P 500 Index and the spread between 10-year treasury constant maturity and the federal funds rate in the U.S. are obtained from the Federal Reserve Economic Data (FRED of St. Louis Fed).[4] Daily data on the COVID-19 cases in the U.S. are obtained from the New York Times.[5] For estimation purposes, all variables are converted into demeaned weekly percentage changes to control for any seasonality concern by construction.

The series included in the estimation are depicted in Figure 1, where COVID-19 cases in the U.S. is compared with BDI, the spread between 10-year treasury constant maturity and the federal funds rate in the U.S., and the S&P 500 Index. As is evident, COVID-19 cases in the U.S. are positively correlated with the spread between 10-year treasury constant maturity and the federal funds rate in the U.S. during March 2020, whereas they are negatively correlated with the S&P 500 Index during the same period. Since changes in the S&P 500 Index may also be due to other factors, a formal investigation is required to identify the causal effects of COVID-19 on the S&P 500 Index, as we achieve next.

The formal investigation is based on the following SVAR model:

$$A_o z_t = a + \sum_{k=1}^{11} A_k z_{t-k} + \Phi \Delta c_t + u_t$$

[3] The web page is https://tradingeconomics.com/commodity/baltic.

[4] The web page is https://fred.stlouisfed.org/.

[5] The web page is https://github.com/nytimes/covid-19-data.

where u_t is the vector of serially and mutually uncorrelated structural innovations. For estimation purposes, the model is expressed in reduced form as follows:

$$z_t = b + \sum_{k=1}^{11} B_k z_{t-k} + \Omega \Delta c_t + e_t$$

where $b = A_o^{-1} a$, $B_k = A_o^{-1} A_k$ for all k, and $\Omega = A_o^{-1}\Phi$. The number of lags (of 11) has been determined by minimizing the Deviance Information Criterion across alternative lags (between 1 and 21) of which details are given in Figure 2. It is postulated that the structural impact multiplier matrix A_o^{-1} has a recursive structure such that the reduced form errors e_t can be decomposed according to $e_t = A_o^{-1} u_t$, where the sizes of shocks are standardized to unity (i.e., the identification is by triangular factorization). The recursive structure imposed on A_o^{-1} requires an ordering of the variables used in the estimation. Accordingly, we utilize the ordering in $z_t = (\Delta b_t, \Delta s_t, \Delta p_t)'$, where we also impose block exogeneity such that shocks on Δs_t or Δp_t cannot have an impact on Δb_t that is determined globally, whereas shocks on Δb_t can affect both Δs_t and Δp_t contemporaneously. Since the main objective of this paper is to investigate the COVID-19 effects on the S&P 500 Index, Δp_t is ordered the last in this framework.

The estimation is achieved by a Bayesian approach with independent normal-Wishart priors. This corresponds to generating posterior draws for the structural model parameters by transforming each reduced-form posterior draw. In particular, for each draw of the covariance matrix from its posterior distribution, the corresponding posterior draw for A_o^{-1} is constructed by using by triangular factorization so that the sizes of shocks are standardized to unity. In the Bayesian framework, a total of 2,000 samples are drawn, where a burn-in sample of 1,000 draws is discarded. The remaining 1,000 draws are used to determine the structural impulse responses that are necessary for the estimation of COVID-19 effects. While the median of each distribution is considered as the Bayesian estimator, the 16th and 84th quantiles of distributions are used to construct the 68% credible intervals (which is the standard measure considered in the Bayesian literature).

3 Estimation Results

The cumulative response of the S&P 500 Index Δp_t to the U.S. COVID-19 cases Δc_t is given in Table 1 for alternative horizons, whereas the corresponding continuous estimates are given in Figure 2. As is evident, having 1% of an increase in cumulative daily COVID-19 cases in the U.S. results in about 0.01% of a cumulative reduction in the S&P 500 Index after one day and about 0.03% of a reduction after one week. These statistically significant results (based on the 68% credible intervals) are in line with those in studies such as by Cao, Li, Liu, and Woo (2020) who have shown that the elasticity of stock market indices with respect to cumulative confirmed COVID-19 cases is about -0.028. Regarding the patterns over time, these effects converge to their long-run value in about three weeks according to Figure 2. It is important to emphasize that these results are robust to the consideration of changes in the global economic activity as well as the term premium, and they are significant based on the 68% credible intervals.

The cumulative response of BDI Δb_t to the U.S. COVID-19 cases Δc_t is also given in Table 1 and Figure 2, where the effects of COVID-19 on BDI are statistically insignificant (based on the 68% credible intervals). Finally, the cumulative response of the spread between 10-year treasury constant maturity and the federal funds rate Δs_t to the U.S. COVID-19 cases Δc_t is also given in Table 1. It is evident that COVID-19 effects on the spread are very small, although they are statistically significant based on the 68% credible intervals; this result is also supported by Figure 2 that represents the corresponding pattern over time.

The historical decomposition of the S&P 500 Index is given in Table 2 for different months (represented as averages across days of months) during the early COVID-19 period, whereas the complete decomposition over time is given in Figure 3. As is evident, the COVID-19 cases in the U.S. have been effective on the S&P 500 Index mostly during March 2020, although it has been effective also in February and April of 2020.

4 Discussion of Results and Concluding Remarks

This paper has investigated the effects of the COVID-19 pandemic on the S&P 500 Index based on a structural vector autoregression model employing daily data. The empirical investigation has resulted in important findings.

First, it has been shown that the stock market risk associated with the COVID-19 pandemic is statistically significant as higher number of confirmed COVID-19 cases has reduced the S&P 500 Index. Second, higher number of COVID-19 cases have resulted in a higher term premium, suggesting that the COVID-19 pandemic has increased the uncertainty of future policy. Third, negative effects of the COVID-19 pandemic on the S&P 500 Index have been observed between February-April 2020 and mostly during March 2020, suggesting that the stock market risk perceived by investors has taken its highest values during the initial months of the COVID-19 pandemic.

It is implied that as uncertainty through increased health concerns and reduced economic activity result in volatilities in stock markets, policy makers should focus on providing better information to the public as implied in studies such as by Ahundjanov, Akhundjanov, and Okhunjanov (2020), especially during the initial periods of an unexpected global development.

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Table 1 - Cumulative Impulse Responses to COVID-19 Cases

	After 1 Day	After 1 Week	After 1 Month
COVID-19 Effects on the S&P 500 Index (%)	-0.010^{*}	-0.028^{*}	-0.024^{*}
	$[-0.014, -0.007]$	$[-0.036, -0.020]$	$[-0.031, -0.017]$
COVID-19 Effects on the Baltic Exchange Dry Index (%)	-0.002	-0.008	-0.013
	$[-0.008, 0.004]$	$[-0.035, 0.019]$	$[-0.052, 0.029]$
COVID-19 Effects on the Spread (%)	0.000^{*}	0.001^{*}	0.001^{*}
	$[0.000, 0.000]$	$[0.000, 0.001]$	$[0.000, 0.001]$

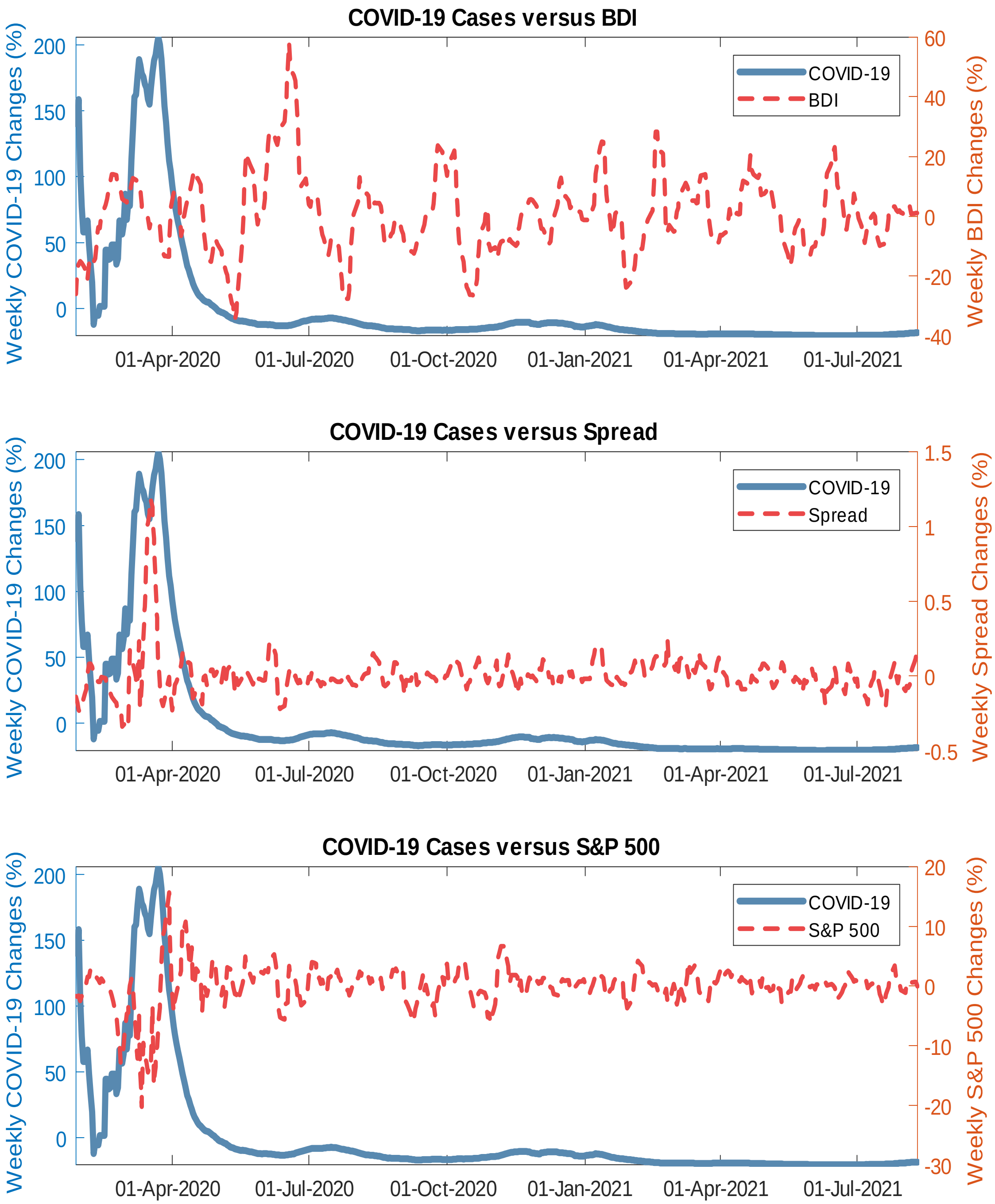
Notes: The estimates represent the median across 1,000 draws. Lower and upper bounds in brackets represent the 68% credible intervals, whereas * represents significance based on these intervals.

Table 2 - Historical Decomposition of the S&P 500 Index Changes (%)

Contribution of:	February 2020	March 2020	April 2020
COVID-19	-0.518^*	-3.870^*	-0.438^*
	$[-1.008, -0.030]$	$[-5.017, -2.721]$	$[-0.855, -0.054]$
Baltic Dry Index	-0.147	-0.054	-0.052
	$[-0.359, 0.032]$	$[-0.371, 0.251]$	$[-0.416, 0.296]$
Spread	-0.022	-0.004	-0.216
	$[-0.352, 0.302]$	$[-1.028, 1.024]$	$[-0.622, 0.166]$
S&P 500 Index	-1.894^*	-0.302	3.096^*
	$[-2.538, -1.251]$	$[-1.843, 1.179]$	$[2.532, 3.677]$

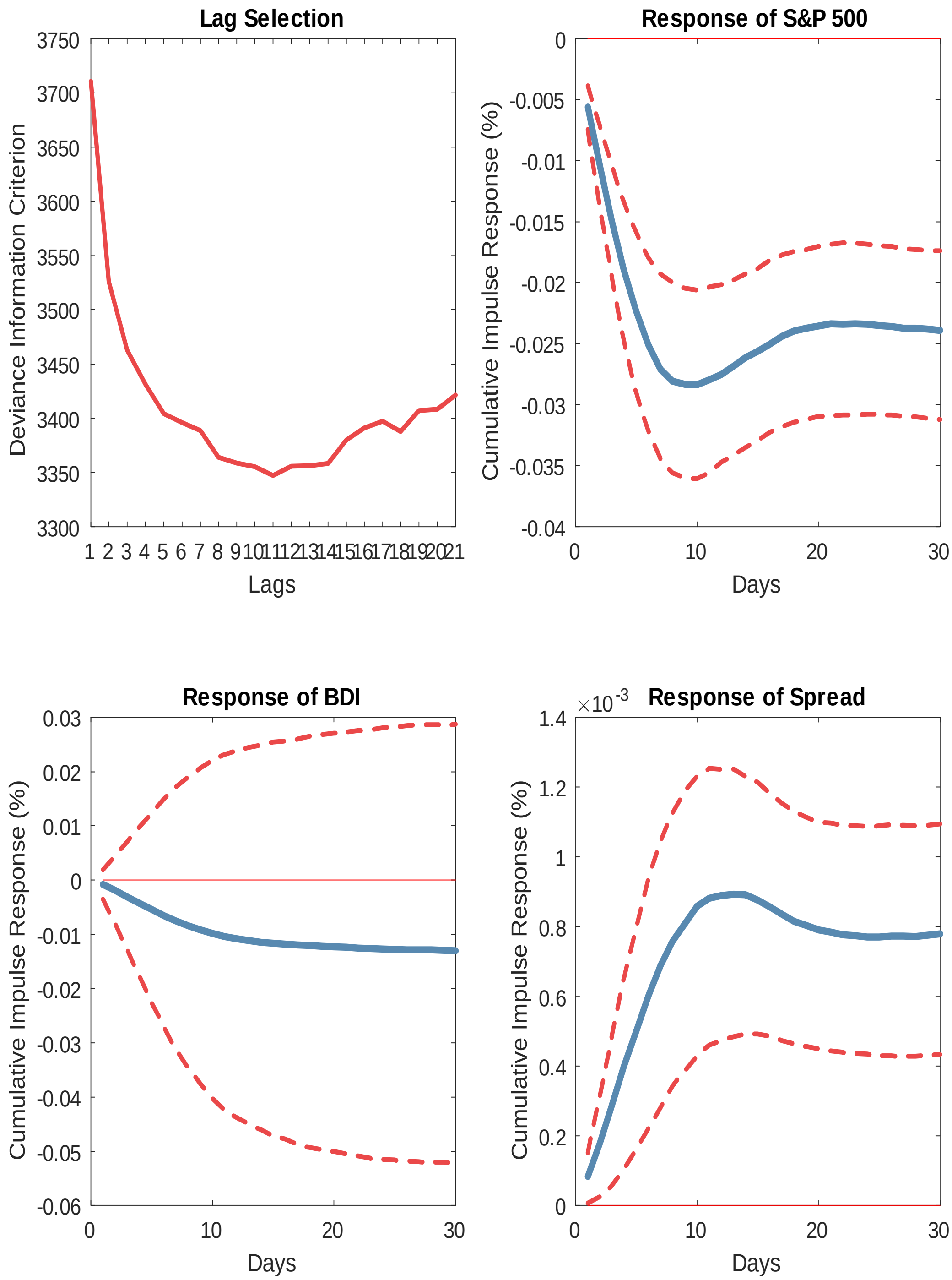
Notes: The numbers represent the average of estimates across days, where the estimates are the median across 1,000 draws. Lower and upper bounds in brackets represent the 68% credible intervals, whereas * represents significance based on these intervals.

Figure 1 - Descriptive Statistics



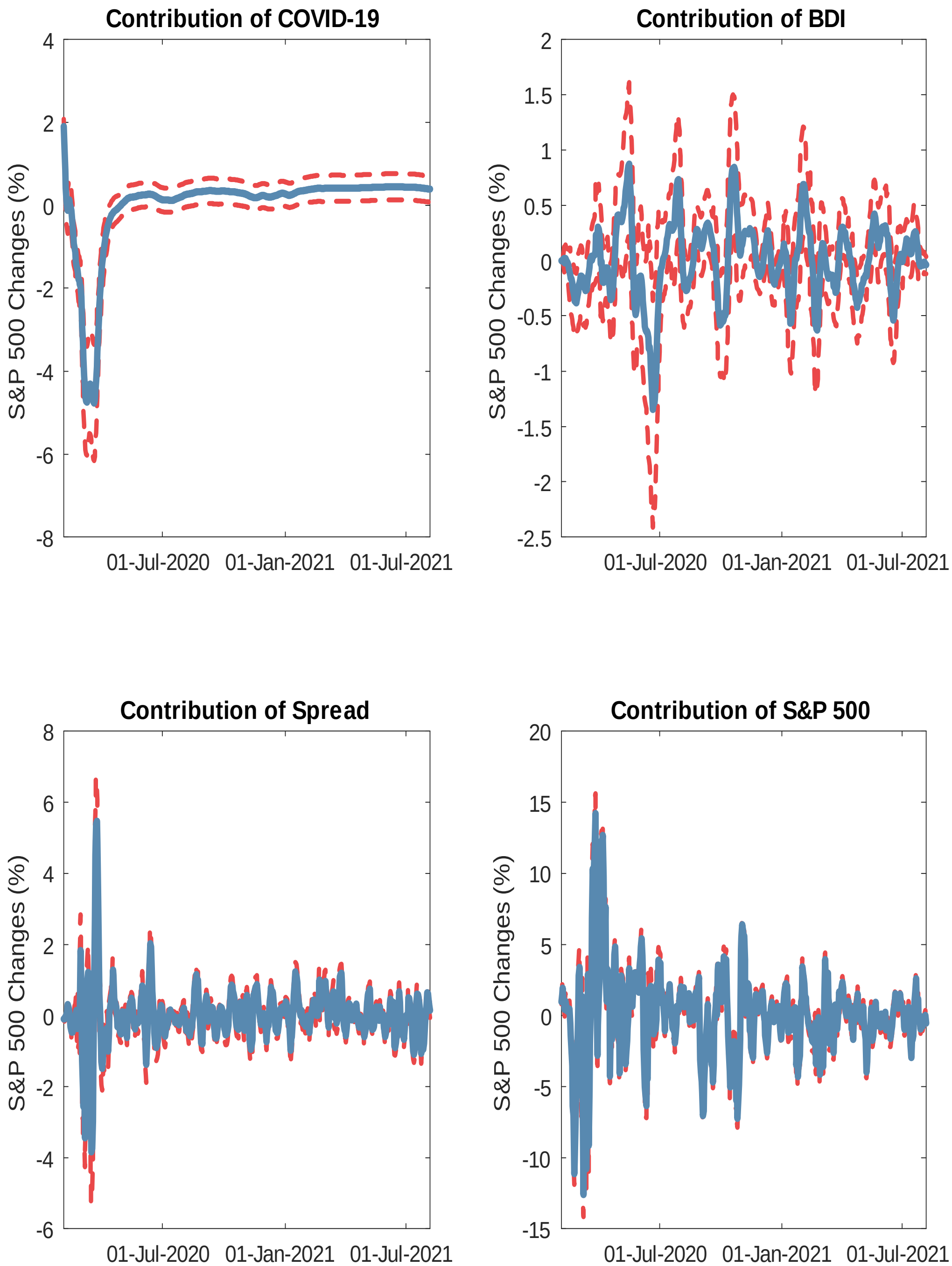
Notes: Series represent those used in the estimation.

Figure 2 - Effects of COVID-19



Notes: The solid lines represent the estimates, while dashed lines represent lower and upper bounds that correspond to the 68% credible intervals.

Figure 3 - Historical Decomposition of the S&P 500 Index



Notes: The solid lines represent the estimates, while dashed lines represent lower and upper bounds that correspond to the 68% credible intervals.