Article

Modelling Global Bond Markets under Covid-19 Shadow

BIMTECH Business Perspective (BSP)
1–11

Saif Siddiqui[1] and Arushi Gaur[2]

Abstract

The spread of the novel coronavirus has had an impact on the world economy including the stock and bond markets. This paper investigates the linkages between bond and stock markets of Asia, USA, and Europe in pre-Covid and Covid period.

Daily data of Asia (Pan-Asia corporate bond), US (Treasury Bonds) and Europe (Eurozone-Investment-grade corporate bond) have been taken for two different periods. First period is from 1 November 2018 (pre-Covid) to 31 October 2019 and second period is from 1 November 2019 to 10 August 2020 (Covid period).

Descriptive statistics, correlation, ARDL method, Granger-Causality analysis and VAR Model were applied to examine the long-run and short-run associations among these indices /variables.

It is concluded that the correlation relationship of selected indices have changed from pre-Covid time to Covid time. One of the interesting findings is that long term association among the selected variables does not change between two periods. Few variables that were previously not influencing other variables have started affecting them during Covid period.

This study aims for portfolio managers and investors who are keen on taking decisions for investment purposes in pandemic period.

JEL Classification: G4

Keywords

bonds, co-integration, ARDL, VAR, Covid-19

Introduction

The pandemic of Covid-19 has wreaked havoc on the economy worldwide eliciting an exceptional economic unexpected stop. On 17 November 2019, in Wuhan, China, the first case was detected that eventually spread to 210 countries and territories. As of 9 August 2020, total of 20,024,263 cases and 733,995 deaths were confirmed (Worldometers, 2020).

[1] Associate Professor, Centre for Management Studies, Jamia Millia Islamia Central University, New Delhi, INDIA.
[2] Finance Professional and Consultant, Optima Finance, Texas, The United State of America.

Corresponding author:
Saif Siddiqui, Associate Professor, Centre for Management Studies, Jamia Millia Islamia Central University, Jamia Nagar, New Delhi-110025, INDIA
e-mail: drsaifsiddiqui@gmail.com

This time is very uncommon due to various factors including that the macroeconomic impact is higher than any other shattering events that have happened in the last forty years (Ludvigson et al., 2020). Moreover, the containment trials taken to restrain the blowout of this virus have put the worldwide economy into a synchronised halt. In addition to this, governments across the world, count on the combination of policies and strategy measures in order to save jobs and businesses.

In the month of February, from 24th to 28th, the worldwide stock markets wiped out approximately \$6 trillion US dollar of wealth. Moreover, during the same week, S&P 500 index had lost more than \$5 trillion US dollar. Though, Treasury Bonds (US) are considered as one of the most liquid and safest investments across the world, in past ten years, it was observed that US Treasury Bond (TB) had negative beta, which leads to a price rise when there is a fall in stock prices (Cieslak and Vissing-Jorgensen, 2020; Baele et al., 2019; He et al., 2019). During March 2020, positive correlation was observed between bond and stock returns (He et al., 2020).

While focussing on the present scenario of the pandemic affecting the financial sector worldwide, it becomes vital to examine the linkages between various bond markets and stock markets. Our purpose is to quantify the long-term and short-term relationships among Asian, European, and United States stock and bond market, before and during the Covid-19 period. For bond markets, we used S&P Treasury Bond for the US, S&P Asia Corporate Bond for Asia and S&P Eurozone Investment Grade Corporate Bond for Europe. For stock market, we used S&P 500 for the US, S&P Europe 350 for Europe and S&P Pan Asia BMI for Asia.

Literature Review

Andries et al. (2020) examined the European sovereign CDS during the Covid-19 crisis by applying an event study method. They found that with the rise in cases and death toll in Europe there was a significant rise in uncertainty among government bond investors. Moreover, in short run, this effect was magnified with the announcement of the government policies. Beirne et al. (2020) examined the daily data from 4 January 2010 to 30 April 2020 using structural VAR model and fixed effects panel model across emerging and advanced economies on exchange rates, stock prices and bond yields. They observed that quantitative measures taken by central banks helped to affect a rise in the prices of stock markets as well as lower the bond yields. Fleming (2000) used the US Treasury data from 08/1993 to 08/1994 to explain the changes in their price and their trading activities with respect to the release of any economic news information. It was observed that bond market's reactions were consistent in general to the announcement of new information.

Apart from this, Kim and Sheen (2001) used the data from January 1993 to July 1997 of futures market of Australian Commonwealth Bond to examine the efficiency of news response on the bond market. They observed that the prices of future market react significantly with economic news. In other words, a sharp decline in the future prices was observed when there is an announcement of inflation, deficient in current account, GDP etc, whereas the price rise with the news such as rise in unemployment. Thus, they concluded that the market adjusts within one minute from the release of news. But, volume of trading responded for at least one hour after the release of news. Goyenko and Ukhov (2009) used Granger-Causality to examine the integration between treasury bonds and stock markets. They observed that there is a bi-directional causal relationship between the two markets. Moreover, illiquidity in the bond market acts as a network, which helps in transferring the shocks in monetary policy into the stock market. Thus, a strong integration is observed in the bond and stock markets.

Moreover, Bollerslev et al. (2000) examined the 4-years data from 1994 to 1997 to investigate the volatility returns in future contracts of US Treasury bonds. It was observed that macroeconomic news such as employment reports, retail sales, producer price index (PPI), employment cost, etc., announced to general public affects the intraday volatility of bonds. Moreover, the volatilities were higher during the open and close of the day than in the middle of it.

Dean et al. (2010) examined the daily returns of Australian bonds and equity market from 1992 to 2006. They used bivariate Garch model to examine the spill over effect. It was observed that negative shocks in the return of bond market leads to spill over into lower returns in stock market. But, on the other hand the positive news from stock market returns leads to lower returns in bond market. Thus, they concluded that volatility spill over from bond market to equity market holds true but reverse is not true. Diaz et al. (2006) also investigated the volatility and liquidity in the Treasury bond market due to debt policy incorporated by Spanish government to enter the European Monetary Union (EMU). They used the daily data from year January 1993 to December 2002 and found that discount bonds were favoured more over premium bonds and high coupon bonds. Brenner et al. (2009) examined the linkages between real economy and financial market. They investigated the US stock, corporate and Treasury bonds by using DCCGARCH model. Daily data from 3 January 1986 to 14 February 2002 was used. It was observed that volatility and co-movement among the returns of Treasury, stock and corporate bond react inequitably to the surprise macroeconomic announcements.

Connolly et al. (2005) examined whether the return of Treasury bond and daily stock can be associated to understand the uncertainty measures of stock market. Daily data from 1986 to 2000 was studied. To estimate conditional volatilities in bond and stock returns, GARCH(1,1) was used. VAR regression model was applied on daily returns of bond and stock market to evaluate the issue of predictability. It was observed that returns in the bond market react in relation to the returns in stock market. Thus, they concluded that uncertainty in stock market plays a vital role in influencing cross market pricing. Moreover, the uncertainty in stock market also increases the benefits of diversification in stock and bond market. Grossman and Shiller (1980) investigated the linkages between the prices of stock market and interest rate by using the annual data from 1981 to 1989 (US) and 1918 to 1989 (UK). They found that there is a negative correlation between the changes in the prices of stock and changes in the long-term interest rates. In addition to this they also observed that in short run as well as in long run, stock market returns co-vary with bond market returns. Ghosh and Kanjilal (2016) investigated the relationship between equity market and oil prices for the period from 2003 to 2011, divided into three phases. They used Granger–Causality test and found that in phase 2 and 3, movement in international oil prices impacts stock market but not vice versa. Gokmenoglu and Fazlollahi (2015) examined the impact of volatility in oil and gold prices on equity market (S&P 500) for the period from January 2013 till November 2014. To examine the long-run association among the selected variables, they also applied ARDL method and found that all the variables under study are cointegrated in the long run, as they trend together.

It is witnessed that Jain and Biswal (2016) investigated the relationship between the prices of gold, oil, equity market, and exchange rate on the data from 2006 to 2015 using nonlinear causality test. They observed that the value of Indian currency and the Sensex depreciate with the fall in price of gold and oil. Further, Filis (2010) used data from 1996 to 2008 to examine the relationship between equity market, oil prices, industrial production, and CPI in Greece by using VECM and multivariate VAR model. They observed a positive effect on Greece CPI with oil and stock prices. Moreover, there is no relationship between industrial production and oil prices.

Rahaman and Mustafa (1997) examined the causality and long-term relationship between S&P 500 and US corporate bonds (short term) using error correction term and cointegration method. It was observed that both markets are cointegrated in long run. They also observed that in the long run US corporate bond Granger causes S&P 500 whereas two-way causality was observed between the two indices in the short run.

Though it was observed that sizable volume of literature is available on bond and equity markets but there is inadequate study available while considering all the selected variables considering the recent pandemic situation.

Objectives

Objectives of the study are as follows-

1. To examine the co-integration and co-movement among select bond and stock indices in pre-Covid-19 and during Covid-19 period.
2. To compare the risk return relationship of the select bond and stock indices in pre-Covid-19 and during Covid-19 period.
3. To examine lag relations among select bond and stock indices in pre-Covid-19 and during Covid-19 period.

Data and Research Methodology

Covid-19 cases started to appear in November 2019; daily closing data starting from 1 November 2019 to 10 August 2020 was taken into consideration for the purpose of this study. To make a comparative study, we also included the data of the select indices for 1 November 2018 to 31 October 2019 as pre-Covid period.

We have analysed Asian, European, and United States stock and bond market. For bond markets we used S&P Treasury bond for USA, S&P Asia Corporate Bond for Asia, and S&P Eurozone Investment Grade Corporate Bond for Europe. Whereas, for stock markets in USA, we used S&P 500, for Europe, S&P Europe 350, and for Asia, S&P Pan Asia BMI. Table 1 describes the variables used in the study.

In order to examine the long-run association among the selected variables we applied Auto Regressive Distributed Lag (ARDL) bound testing proposed by Pesaran and Smith (2001). The reason for using ARDL approach is because it can be applied to a small sample size. Moreover, it incorporates both the variations in short term with equilibrium in long term with the help of Error Correction Model (ECM).

Before the ARDL model, 'bound test' is applied to examine the co-integrating association in these variable which relies on F-statistics. A set of two critical values, i.e., I(1) and I(0) are generated. If the value obtained of F-statistics for a selected variable surpasses the higher critical value, then long-term association exists. But if the value obtained of F-statistics for a selected variable is less than the lower critical value, then there is no co-integration.

Table 1. Variables Assimilated

Variables	Symbols Pre-Covid	Symbols During Covid
S&P Treasury Bond	UB1	UB2
S&P Asia Corporate Bond	AB1	AB2
S&P Eurozone Investment Grade Corporate Bond	EB1	EB2
S&P 500	US1	US2
S&P Pan Asia BMI	AS1	AS2
S&P Europe 350	ES1	ES2

Source: Codes given by authors.

5. Analysis

5.1 Descriptive Statistics

Table 2 describes the basic characteristics of the selected variables for the whole period of study.

Here in Table 2a, we observed that the return of United States stock (S&P 500) is maximum as the mean value is highest, i.e., 0.000395, among all the variables whereas United States stock index (S&P 500) is highly volatile as compared to other indices as its standard deviation is the highest 0.009692.

In Table 2b, we observed that the returns for United States bond (S&P Treasury Bond) are maximum as the mean value is highest, i.e., 0.000394, among all the variables whereas United States stock index (S&P 500) is highly volatile as compared to other indices as its standard deviation is highest (0.024515). It was also observed that all the variables are negatively skewed except United States Bond (S&P Treasury Bond). As value of Kurtosis is more than 3 in all the variables, this proves that none of the variable lie in the verge of normality. Moreover, Jarque-Bera test also indicated that all variables are not normally distributed as the probability value is less than 5%.

During pre-Covid time, US stock returns were giving the maximum returns but during Covid, US bond was giving maximum returns.

Table 2a. Descriptive Statistics

	Asia		Europe		USA	
	AB1	AS1	EB1	ES1	UB1	US1
Mean	0.000159	0.000298	0.000126	0.000245	0.000374	**0.000395**
Median	–7.09E-05	0.000218	7.88E-05	0.000547	0.000412	0.00064
Maximum	0.009183	0.020725	0.010201	0.028526	0.007283	0.048382
Minimum	–0.01179	–0.02312	–0.00885	–0.02927	–0.00641	–0.03291
Std. Dev.	0.002535	0.007074	0.002977	0.008269	0.002131	**0.009692**
Skewness	0.056167	–0.2068	0.162131	–0.29242	–0.1433	–0.18276
Kurtosis	5.604861	3.922036	3.560587	4.11323	3.878255	6.504141
Jarque-Bera	73.9274	11.10569	4.561018	17.1968	9.281514	134.9872
Probability	0.000	0.004	0.002	0.000	0.00965	0.000

Table 2b. Descriptive Statistics

	Asia		Europe		USA	
	AB2	AS2	EB2	ES2	UB2	US2
Mean	0.000124	–7.45E-06	2.33E-05	–0.000461	0.000394	0.000210
Median	0.000205	0.000974	–8.10E-05	0.000264	4.05E-05	0.001008
Maximum	0.008277	0.054338	0.021937	0.085271	0.017846	0.089699
Minimum	–0.012074	–0.058802	–0.032254	–0.133415	–0.016848	–0.127639
Std. Dev.	0.002571	0.013776	0.006072	0.020278	0.003785	0.024515
Skewness	–0.347404	–0.36576	–1.041485	–1.534558	0.271109	–0.781358
Kurtosis	6.062015	6.640478	9.857228	14.51773	9.459160	10.08875
Jarque-Bera	73.94023	103.4115	385.2026	1065.581	315.1106	395.1938
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Source: Authors' calculations.

5.2 Correlation

Table 3 explains the correlation among the returns of selected variables.

Table 3a presents the correlation of pre-Covid period. Here, Asian bonds and stock markets have a positive relationship with all other indices except S&P Treasury bonds. However, United States Bond has a negative relation with all other indices.

During the Covid period, here, the relationships of Asian bond, Asian stock as well as European Stock market with all other variables except United Stated bond (S&P Treasury Bond) market are positive. Similar patterns were observed in the case of United States stock (S&P 500) as it had positive relation with all variables except United States Bond (S&P Treasury Bond.

The correlation relationship of selected indices has changed from pre-Covid time to Covid time.

5.3 Unit Root

In order to check the stationarity of the variables, Augmented Dickey Fuller (ADF) test is used. Null hypothesis of ADF test states that the variables are not stationary.

Using the pre-Covid data, Table 4a, does the unit root test. It is seen that variables are not stationary at level but at first difference, all variables become stationary as it was observed that their probability value is below 5%.

In the Table 4b of Unit root, since the probability value of all the variables Asian bond, Asian stock, European bond, European stock, American bond (S&P Treasury Bond), American Stock (S&P 500) is more than 5% (0.0952,0.655,0.3017,0.6933,0.8275,0.3689), which means that all the variables are not stationary at level. But at first difference they all become stationary as it was observed that their probability value is below 5%.

Table 3a. Correlation

	DAB1	DAS1	DEB1	DES1	DUB1	DUS1
DAB1	1	0.450979	0.145262	0.269469	–0.17425	0.105085
DAS1	0.450979	1	0.173309	0.404641	–0.15285	0.261152
DEB1	0.145262	0.173309	1	0.24865	0.1562	–0.00797
DES1	0.269469	0.404641	0.24865	1	–0.30047	0.508948
DUB1	–0.17425	–0.15285	0.1562	–0.30047	1	–0.48112
DUS1	0.105085	0.261152	–0.00797	0.508948	–0.48112	1

Table 3b. Correlation

	DAB2	DAS2	DEB2	DES2	DUB2	DUS2
DAB	1.000000	0.498161	0.262161	0.117302	–0.036806	0.071255
DAS	0.498161	1.000000	0.411034	0.704896	–0.209673	0.496368
DEB	0.262161	0.411034	1.000000	0.360629	0.312749	0.145025
DES	0.117302	0.704896	0.360629	1.000000	–0.257806	0.700900
DUB	–0.036806	–0.209673	0.312749	–0.257806	1.000000	–0.53624
DUS	0.071255	0.496368	0.145025	0.700900	–0.53624	1.000000

Source: Authors' calculations.

Table 4a. ADF Test for Non-Stationarity

		AB1	AS1	EB1	ES1	UB1	US1
At Level	**Lag Length**	0	0	0	0	0	0
	ADF Stats	–0.320738	–2.117127	–1.618562	–2.101131	–0.227769	–1.738206
	Prob.	0.9186	0.2382	0.4716	0.2445	0.9317	0.4108
At First	**Lag Length**	0	0	0	0	0	0
Difference	**ADF Stats**	–16.65835	–15.50743	–16.50948	–15.96986	–16.17950	–15.59026
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1% –3.467205, 5% –2.877636 (significance level)*, 10% –2.575430							

Table 4b. ADF Test for Non-Stationarity

		AB2	AS2	EB2	ES2	UB2	US2
At Level	**Lag Length**	0	1	1	0	0	7
	ADF Stats	–2.59844	–1.24385	–1.9661	–1.15508	–0.7596	–1.8221
	Prob.	0.0952	0.655	0.3017	0.6933	0.8275	0.3689
At First	**Lag Length**	0	0	0	0	0	0
Difference	**ADF Stats**	–15.7877	–10.9662	–8.88757	–12.4942	–13.13669	–18.8778
	Prob.	0	0	0	0	0	0
1% –3.467205, 5% –2.877636 (significance level)*, 10% –2.575430							

Source: Authors' calculations.

5.4 ARDL Bound Test Model

ARDL bound tests is conducted for understanding the long run association among each group of variables where one variable is considered as dependent variables while others are considered as independent variables.

It is seen in Table 5a that during pre-Covid time when, Asian bond, European bond, European stock and American bonds were taken as dependent variables individually while other selected variables as regressors, there was no long-run association among variables. Whereas during Covid-19, the result

Table 5a. ARDL Bound Test

	F-Stats	Selected Models	At 5%
AB|AS,EB,ES,UB,US	1.205056	2,4,4,4,4,0	No Cointegration
AS|AB,EB,ES,UB,US	2.241917	3,2,0,3,0,1	No Cointegration
EB|ES.AB.AS.UB,US	3.842045	3,1,0,1,2,4	Cointegration
ES| EB,AB,AS,UB,US	4.321486	4,1,0,3,4,1	Cointegration
UB|US,AB,AS,EB,ES	1.202914	1,2,1,0,1,3	No Cointegration
US|UB,AB,AS,EB,ES	5.092695	3,1,0,3,0,1	Cointegration
Critical Values with Case 3 - Restricted Constants &No Trends (K=5)			
	I(0)	I(1)	
At 10%	2.26	3.35	
At 5%	2.62	3.79	
At 1%	3.41	4.68	

Table 5b. ARDL Bound Test

	F-Stats	Selected Models	At 5%
AB|AS,EB,ES,UB,US	1.943278	2,1,2,1,0,3	No cointegration
AS|AB,EB,ES,UB,US	2.147431	2,1,0,4,1,0	No Cointegration
EB|ES.AB.AS.UB,US	8.097882	1,0,0,0,3,2	Cointegration
ES| EB,AB,AS,UB,US	8.082716	4,1,1,1,4,4	Cointegration
UB|US,AB,AS,EB,ES	1.030915	3,1,3,4,2,2	No cointegration
US|UB,AB,AS,EB,ES	7.10436	4,4,0,0,3,3	Cointegration
Critical Values with Case 3 - Restricted Constants &No Trends (K=5)			
	I(0)	I(1)	
At 10%	2.26	3.35	
At 5%	2.62	3.79	
At 1%	3.41	4.68	

Source: Authors' calculations.

of bound test, as shown in Table 5b, depicts that when Asian bond was taken as a dependent variable while other selected variables are regressors, then the calculated value of F-stats is less than the lower bound value at 5% significance level (1.943278 < 2.62), which proves that there is no long run association among the variables. When S&P Pan Asia BMI and S&P Treasury Bond are taken as dependent variable similar results are observed, similar results are observed. as Asian BMI was at 2.147431, which is lesser than 2.62, while American Bond was at 1.030915. But when European bond was taken as dependent variable, the calculated value of F-stats surpassed the highest critical value (98.097882 > 3.79) at 5% level of significance, which proves that a long-run association is possible. A similar result was observed when European stock and American stock (S&P 500) were taken as dependent variables as their calculated F-stats were greater than higher bond value (8.082716> 3.79) and (7.10436> 3.79) respectively.

Diagnostic test was also performed on the above three equations of bond test for ensuring stability via CUSUM test as well as no serial correlation in residuals via LM test. It was found that all the regression equations passed the diagnostic checks and thus we can say that models were stable and had no serial correlation.

Thus, we can conclude that there is long-term association among a few of the selected variables that does not change between two periods.

5.5 VAR Estimation

Tables 6a and 6b shows the influence of lagged prices on the selected variables.

The analysis of pre-Covid data is presented in Table 6a. It is witnessed that AB (-1) positively influence EB whereas AS(-1) has a positive influence on ES and US. Similarly, US (-1) has a positive influence on EB and ES.

In Table 6b, it was observed that AB (-1) negatively influence AB. But it was also observed that AS(-1) has a positive influence on ES. Similar result was observed in case of EB (-1) as it positively influenced some variables such as AB, AS, ES, and EB. But in the second period lag, EB influenced only itself and ES. On the other hand, UB(-1) has a positive influence on UB.

Table 6a. VAR Estimates with coefficients

	D(AB)	D(AS)	D(EB)	D(ES)	D(UB)	D(US)
D(AB(-1))	–0.059316	0.371797	0.174094	0.133955	0.065776	–0.336572
Probability	0.4163	0.0676	0.0396*	0.5339	0.2445	0.1208
D(AB(-2))	–0.014380	0.022935	0.004109	–0.265372	0.042152	–0.715827
Probability	0.8458	0.9117	0.9617	0.2239	0.4616	0.0011*
D(AS(-1))	0.035510	–0.094506	–0.027293	0.521105	–0.131222	0.960013
Probability	0.2096	0.2307	0.4052	0.0000*	0.0000*	0.0000*
D(AS(-2))	0.007770	–0.059143	–0.018058	0.296235	–0.038497	0.404851
Probability	0.8210	0.5366	0.6501	0.0035*	0.1480	0.0001*
D(EB(-1))	–0.060688	0.053563	0.019269	–0.001190	0.053126	0.207005
Probability	0.2975	0.7413	0.7753	0.9945	0.2390	0.2319
D(EB(-2))	0.047817	–0.154135	0.060827	–0.046349	0.058291	–0.378575
Probability	0.4122	0.3427	0.3680	0.7876	0.1968	0.0290*
D(ES(-1))	–0.028449	0.099408	–0.026646	–0.276681	0.003496	–0.044438
Probability	0.2705	0.1671	0.3732	0.0003*	0.8612	0.5625
D(ES(-2))	–0.042213	0.101971	0.002984	–0.150620	–0.023441	0.102825
Probability	0.0995	0.1532	0.9199	0.0464*	0.2374	0.1770
D(UB(-1))	–0.115726	–0.158338	–0.266256	–0.688313	–0.010448	–0.004381
Probability	0.1969	0.5262	0.0105*	0.0094*	0.8804	0.9869
D(UB(-2))	–0.044599	–0.075735	0.092616	–0.335297	0.058470	–0.105099
Probability	0.6231	0.7645	0.3786	0.2107	0.4055	0.6968
D(US(-1))	–0.010716	0.005514	–0.002337	–0.077591	0.046055	–0.232709
Probability	0.6555	0.9343	0.9331	0.2738	0.0134	0.0011*
D(US(-2))	0.026166	–0.034018	0.029571	–0.040742	0.013127	–0.191804
Probability	0.2214	0.5682	0.2330	0.5187	0.4282	0.0026*

Table 6b. VAR Estimates with coefficients

	D(AB)	D(AS)	D(EB)	D(ES)	D(UB)	D(US)
D(AB(-1))	–0.24292	–0.62846	0.149132	–0.36512	0.067594	0.239471
Probability	(0.0112)*	(0.1244)	(0.3577)	(0.3895)	(0.5615)	(0.8227)
D(AB(-2))	0.040515	0.155011	0.130248	–0.26058	0.143912	–1.41747
Probability	(0.6747)	(0.7071)	(0.426)	(0.5428)	(0.2208)	(0.1889)
D(AS(-1))	0.006389	0.226217	0.090734	0.728369	–0.02634	1.557787
Probability	(0.8289)	(0.0736)	(0.0704)	(0.000)*	(0.4641)	(0.000)*
D(AS(-2))	0.000522	0.086946	–0.03391	0.266892	–0.00659	0.595657
Probability	(0.9868)	(0.5179)	(0.5249)	(0.056)	(0.8634)	(0.0904)
D(EB(-1))	0.103816	0.637334	0.33436	0.571501	0.096053	1.246311
Probability	(0.0392)*	(0.0031)*	(0.0001)*	(0.0106)*	(0.1169)	(0.0268)
D(EB(-2))	0.090853	0.427955	0.177399	0.46473	–0.04522	–0.06218
Probability	(0.0779)	(0.0521)	(0.0423)*	(0.0421)*	(0.4707)	(0.9139)
D(ES(-1))	–0.02195	–0.03861	–0.11579	–0.14903	–0.07917	1.001503
Probability	(0.3646)	(0.7091)	(0.0049)*	(0.1654)	(0.0073)*	(0.0002)*
D(ES(-2))	–0.01128	–0.09948	–0.07518	–0.21286	–0.01356	0.235632
Probability	(0.6491)	(0.3477)	(0.0737)	(0.053)	(0.6531)	(0.3948)
D(UB(-1))	–0.19081	–0.17045	0.03105	–0.34382	0.228293	–0.9821
Probability	(0.0176)*	(0.6193)	(0.8195)	(0.3343)	(0.0196)	(0.2737)

(Table 6b continued)

(Table 6b continued)

	D(AB)	D(AS)	D(EB)	D(ES)	D(UB)	D(US)
D(UB(-2))	–0.02862	–0.01816	–0.46618	0.103766	–0.22339	0.445283
Probability	(0.7151)	(0.9568)	(0.0005)*	(0.7654)	(0.0194)*	(0.6113)
D(US(-1))	–0.00109	–0.06332	0.026016	–0.16264	0.057668	–0.93938
Probability	(0.9063)	(0.1097)	(0.0974)	(0.0001)*	(0.000)*	(0.000)*
D(US(-2))	0.004179	0.047462	0.026992	0.107826	0.00524	–0.03321
Probability	(0.6624)	(0.2462)	(0.0964)	(0.0112)*	(0.6529)	(0.7562)

Source: Authors' calculations.

ES(-1) influenced some variables negatively (EB, UB), whereas it positively influenced US. UB(-1) negatively influenced AB. But in the second period lag, UB influenced EB and UB negatively. On the other hand, US(-1) has a negative influence on ES and US and a positive influence on UB. But in the second period of lag, US has only a positive influence on ES.

It can be easily analysed that some variables, which were previously not influencing other variables have started affecting them during Covid period.

6. Summary and Conclusion

One of the most catastrophic crashes in the stock market was observed during March 2020 due to the occurrence of Covid-19 pandemic. The research contributions are twofold. First, we investigated whether the selected stock and bond markets are affected by the outbreak of Covid-19. Second, we examined whether the markets are associated with each other in long run. In this regard, we examined the daily price movements of three regions—Asia, America and Europe during pre-Covid and Covid era.

Pre-Covid analysis suggests that the return of United States stock (S&P 500) is maximum as the mean value is highest, i.e., 0.000395 among all the variables whereas United States stock index (S&P 500) is highly volatile as compared to other indices as its standard deviation is highest 0.009692.

Analysis of Covid period data suggest that United States bond (S&P Treasury Bond) is least volatile whereas United States stock index (S&P 500) is highly volatile. During the pandemic, it was observed that all variables are significantly correlated thus it is vital to examine the dynamics of the selected variables in short and long run. ARDL result shows that some variables when considered as dependent variables do not have long run association at 5% significance level. Also, VAR results explain that the lagged values of variables have both positive and negative influence on other variables.

It is concluded that the correlation relationship of selected indices have changed from pre-Covid time to Covid time. One of the interesting findings is that long-term association among the select variables does not change between two periods. Few variables that were previously not influencing other variables have started affecting them during Covid period.

This study is vital for financial professionals while taking decisions related to portfolio diversifications in pandemic situations like this. As a long-run relationship exists among the variables, therefore, market traders can take a decision related to the portfolio of securities, which they can trade in the long run.

References

Andries, A. M., Ongena, S., & Sprincean, N. (2020). The COVID-19 pandemic and sovereign bond risk. *Swiss Finance Institute Research Paper* (No. 20–42), 1–21.

Baele, L., Bekert, G., Inghelbrecht, K., & Wei, M. (2019). Fight to safety. *The Review of Financial Studies, 33*(6), 689–746.

Brenner, M., Pasquariello, P., & Subrahmanyam, M. (2009). On the volatility and co-movement of US financial markets around macroeconomic news announcements. *Journal of Financial and Quantitative Analysis, 44,* 1265–1289.

Bollerslev, T., Cai, J., & Song, F. M. (2000). Intraday periodicity, long memory volatility, and macroeconomic announcement effects in the US Treasury bond market. *Journal of empirical finance, 7*(1), 37–55.

Bouri, E., Jain, A., Biswal, P. C., & Roubaud, D. (2017). Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. *Resources Policy*, *52*, 201–206.

Cieslak, A., & Vissing-Jorgensen, A. (2020). The economics of the 'Fed put'. *NBER Working Papers 26894,* National Bureau of Economic Research, Inc.

Connolly, R., Stivers, C., & Sun, L. (2005). Stock market uncertainty and the stock-bond return relation. *Journal of Financial and Quantitative Analysis, 40,* 161–194.

Dean, W. G., Faff, R. W., & Loudon, G. F. (2010). Asymmetry in return and volatility spillover between equity and bond markets in Australia. *Pacific-Basin Finance Journal, 18*(3), 272–289.

DeJong, D. N., Nankervis, J. C., Savin, N. E., & Whiteman, C. H. (1992). The power problems of unit root test in time series with autoregressive errors. *Journal of econometrics*, *53*(1–3), 323–343.

Diaz, A., Merrick Jr, J. J., & Navarro, E (2006). Spanish Treasury bond market liquidity and volatility pre-and-post-European Monetary Union. *Journal of Banking & Finance, 30*(4), 1309–1332.

Filis, G. (2010). Macro economy, stock market and oil prices: Do meaningful relationships exist among their cyclical fluctuations? *Energy Economics*, *32*(4), 877–886.

Fleming, M. J. (2000). The benchmark US Treasury market recent performance and possible alternatives. *Economic Policy Review, 6*(1) *20–29.*

Ghosh, S., & Kanjilal, K. (2016). Co-movement of international crude oil price and Indian stock market: Evidences from nonlinear cointegration tests. *Energy Economics,* 53*, 111–117.*

Gokmenoglu, K. K., & Fazlollahi, N. (2015). The interactions among gold, oil, and stock market: Evidence from S&P500. *Procedia Economics and Finance*, *25*(Supp. C), 478–488.

Goyenko, R. Y., & Ukhov, A. D. (2009). Stock and bond market liquidity: A long-run empirical an*alysis*. *Journal of Financial and Quantitative Analysis, 44,* 189–212.

Grossman, S. J., & Shiller, R. J. (1981). The determinants of the variability of stock market prices. *American Economic Review, 71,* 222-227.

He, Z., Krishnamurthy, A., & Milbradt, K. (2019). A Model of Safe Asset *Determination. American Economic Review, 109,* 1230–1262.

He, Z., Nagel, S., & Song, Z. (2020). Treasury inconvenience yields during the covid-19 crisis (No. w27416). National Bureau of Economic Research, Inc.

Kim, S. J., & Sheen, J. (2001). Minute-by-minute dynamics of the Australian bond futures market in response to new macroeconomic information. *Journal of Multinational Financial Management*, *11*(2), 117–137.

Ludvigson, S. C., Ma, S., & Ng, S. (2020). Covid19 and the macroeconomic effects of costly disasters (Np. W26987). National Bureau of Economic Research, Inc

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric Methods*, *5*(4), 63–91.

Pantula, S. G., Gonzalez-Farias, G., & Fuller, W. A. (1994). A comparison of unit-root test criteria. *Journal of Business & Economic Statistics*, *12*(4), 449–459.

Phillips, P. C., &Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346.

Rahman, M., & Mustafa, M. (1997). Dynamic linkages and Granger causality between short-term US corporate bond and stock markets. *Applied Economics Letters*, *4*(2), 89–91.