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IS THE COVID-19 OUTBREAK A ROBUST DETERMINANT OF STOCK PRICES IN THE UNITED STATES?

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ABSTRACT

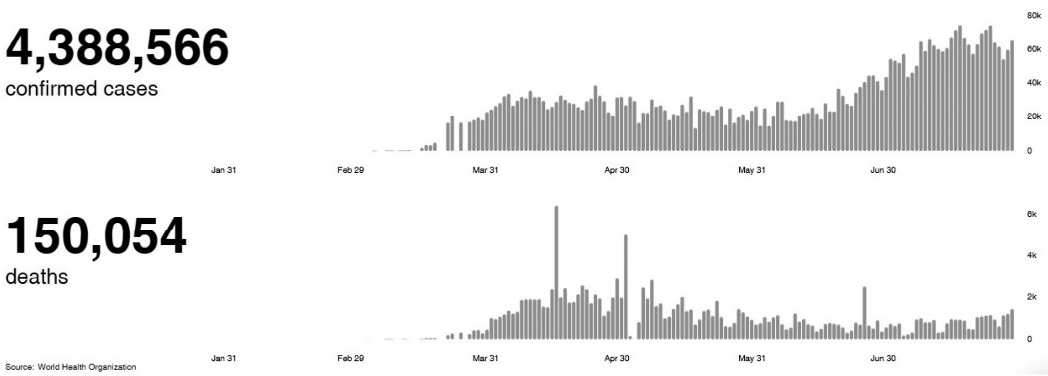
The aim of this paper is to assess the robustness of the impact of the COVID-19 outbreak on stock prices in the United States. Thus, building upon the literature related to the determinants of stock prices and based on data availability, five potential determinants of stock prices and two proxies for the COVID-19 outbreak were selected. Additional variables were taken into consideration to account for the trade war between the U.S. and China and the oil war between Russia and Saudi Arabia since both wars are believed to have a substantial impact on stock prices. The data set spanning from January 2, 2018 to July 16, 2020 was analyzed using the variants of the extreme bounds analysis developed by Leamer and Leonard and Sala-i-Martin. The results show that new confirmed cases of COVID-19 as well as new deaths do have a negative impact on stock prices in the U.S. even though the robustness of that impact depends on the proxy and the estimation technique used. Furthermore, in line with previous studies, it is also found that economic uncertainty, credit risk, investors' pessimism, inflation, and the on-going trade war are robust determinants of stock prices in the U.S.

1. INTRODUCTION

In December 2019, a new pathogen, the severe acute respiratory syndrome corovirus 2 or SARS-Cov-2, appeared in China and caused a wave of respiratory failure in the local population. On February 11, 2020, Tedros Ghebreyesus, Director General of the World Health Organization (WHO), gave the name COVID-19 to the disease caused by this new pathogen. The virus from natural and zoonotic origins (Di Gennaro *et al.*, 2020) spead rapidly across international borders and became a pandemic. Indeed, the WHO officially declared the COVID-19 a pandemic on March 11, 2020 when more than 118 countries were infected with over 118 000 confirmed cases and 4 000 deaths. Recent (July 31, 2020) WHO data[1] reveal that the disease has now spread to 216 countries/territories, the number of cases has risen to over 17 million, and the number of deaths is close to 700 000.

Figure 1a: Map of the COVID-19 pandemic

Figure 1b: Evolution of the COVID-19 outbreak in the United States

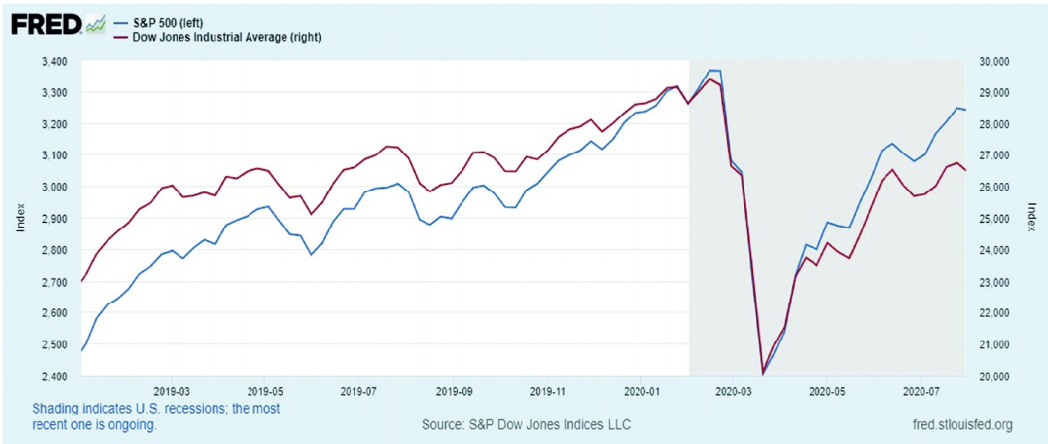


Source: World Health Organization

On the socioeconomic front, the COVID-19 has led more than 200 countries into partial or total lockdown, disrupted global supply chains, and induced a fall in both economic activity and financial asset prices (Gujrati and Uygun, 2020; Jowitt, 2020; Liu *et al.*, 2020; Ozili and Arun, 2020; Salisu *et al.*, 2020; Sansa, 2020; Elsayed and Abdelrhim, 2020). As represented on Figure 1a, the magnitude of the COVID-19 crisis is not uniform across the globe. Recent data show that the U.S. is the most-affected country with over 4 million cases and 150 000 deaths. Figure 1b sheds more light on that trend as it shows that the U.S. has experienced a second contamination wave in June 2020.

The economic and financial impact of the COVID-19 are unclear because the public health crisis is still unfolding. However, the initial contamination wave and the corresponding lockdown induced a significant fall in stocks prices in the U.S. Thus, as depicted on Figure

Figure 2: Evolution of stock prices in the United States



Source: Federal Reserve Economic Data (FRED)

2, between February 20 and March 20, 2020, the S&P 500 index fell from 3 373.33 to 2 267.40 while the Dow Jones Industrial Average (DJIA) fell from 29 219.98 to 19 173.98. Those stock indices have since recovered most of their losses even though the COVID-19 crisis is not yet over.

The seemingly sustainable rebound of financial markets has given rise to interrogations about the effect of the COVID-19 on stock prices. In other words, is the COVID-19 a robust determinant of stock prices in the U.S.? This paper aims to provide an answer to such a question. Thus, building upon the literature related to the determinants of stock prices (Oyama, 1997; Rahman *et al.*, 2009; Narayan *et al.*, 2014; Azar, 2014; Rjoub *et al.*, 2017; Mumo, 2017; Sin-Yu, 2017; Islam *et al.*, 2017; Demir, 2019) and based on data availability, five potential determinants of stock prices and two proxies for the COVID-19 outbreak were selected from the FRED and the Our World in Data (OWD) COVID-19 dataset. The paper also takes into consideration two proxies for the on-going trade war between the U.S. and China and a proxy for the oil war between Russia and Saudi Arabia because those events are believed to have a substantial impact on stock prices in the U.S. The sensitivity of each determinant is tested using the approaches of extreme bounds analysis(EBA) proposed by Leamer and Leonard (1983) and Sala-i-Martin (1997). The robustness of our findings is further checked with different U.S. stock indices.

The remainder of this paper is organized as follows: the next section presents the methodology; our findings are presented and discussed in section 3 and 4, respectively; and section 5 concludes the paper.

2. MATERIALS AND METHOD

2.1. Data

Testing the robustness of the impact of the COVID-19 outbreak on stock prices in the U.S., daily data were collected from the FRED and the OWD COVID-19 dataset. Inspired by the literature related to the determinants of stock prices (Oyama, 1997; Rahman *et al.*, 2009; Narayan *et al.*, 2014; Azar, 2014; Rjoub *et al.*, 2017; Mumo, 2017; Sin-Yu, 2017; Islam *et al.*, 2017; Demir, 2019) and based on data availability, five potential determinants of stock prices were selected to cover the period from January 2, 2018 to July 16, 2020.

The CBOE volatility index also known as VIX or fear index is used as a proxy for investors' sentiment. An increase in this variable is expected to lead to an increase in stock prices. The TED spread and the federal funds rate respectively account for credit risk and interest rate and are both expected to be negatively correlated with stock prices. As for the 5-year forward inflation expectation rate, it is used as proxy for inflation and is expected to have a negative impact on stocks. Finally, the equity market-related economic uncertainty index is used as proxy for the economic recession induced by the COVID-19 as Baker *et al.* (2015:2) argue that at the macro level, innovations in this variable ''foreshadow declines in investment, output, and employment in the United States''.

Two variables –the number of new cases per million and the number of new deaths per million– account for the COVID-19 outbreak. New cases and new deaths are preferred to total cases and total deaths because they convey more information about the dynamics of the pandemic. Three control variables are taken into consideration because they have a substantial effect on global demand, trade, and financial markets. The first control variable accounts for the oil war between Russia and Saudi Arabia that started in March when the two countries pulled out of the OPEC plus agreement. This oil war has induced a substantial fall in global oil prices and threatened U.S. shale oil production (Sukhantin, 2020). The severity of the oil shock has even led the Trump administration to announce on March 13, 2020 that the federal government will purchase 77 million barrels of U.S. oil for the country's Strategic Petroleum Reserve (Finley *et al.*, 2020). The other two control variables account for the trade war that began on July 06, 2018, between the U.S. and China. This trade war has adversely affected U.S. exporters, real income, and inflation among others (Amiti *et al.*, 2019; ISDP, 2020) and its overall impact on stock prices is still unclear.

The S&P 500 index accounts for stock prices in the U.S. and the Dow Jones Industrial Average is used for robustness check. The S&P 500 is known as the best proxy for large-cap U.S. equity market while the DJIA serves as proxy for the health of the overall U.S. economy. The definition of the variables used is presented in Table 1.

Table 1: Description of variables

Variable	*Definition*	*Source*
SP500	Log of S&P 500 stock index	FRED
Dow_Jones	Log of Dow Jones industrial average	FRED
Eco_Uncertainty	Equity market-related economic uncertainty index	FRED
New_Cases	New Covid-19 cases per million	OWD
New_Deaths	New Covid-19 deaths per million	OWD
VIX	CBOE volatility index	FRED
TED_Spread	TED spread	FRED
Inflation	5-year forward inflation expectation rate	FRED
Interest_Rate	Federal funds rate	FRED
China_US	China / U.S. foreign exchange rate	FRED
US_EME	Trade weighted U.S. dollar index: emerging markets economies, goods, and services	FRED
Crude_Oil	Crude oil prices: West Texas Intermediate - Cushing, Oklahoma	FRED

2.2. Extreme bounds analysis

Leamer (1983, 1985) criticizes the tendency of traditional econometrics to lead to fragile inference because small changes in the list of explanatory variables could lead to fundamentally different results. Thus, Leamer and Leonard (1983) propose a procedure to assess the robustness and sensitivity of the explanatory variables included in econometric models. The procedure called extreme bounds analysis is a relatively neutral procedure through which variables can be selected for an empirical model when the theoretical determinants of a phenomenon are ambiguous or conflicting (Chanegriha *et al.*, 2014).

Let us assume that stock prices can be explained by the following model:

$$P_t = \beta_0 + \beta_1 x_t + \beta_2 i_t + \beta_3 d_t + \varepsilon_t \tag{1}$$

Where t represents the days and P stands for stock price. x is a matrix containing variables that have an undeniable effect on stocks:this is the case for economic recession for instance. i is the variable of interest; that is, the determinant for which we want to test robustness and sensitivity. $d \in D$ is a matrix containing a limited number of other doubtful determinants of stock prices taken from the pool D of n available determinants. Finally, ε is the error term and β_i(i = 1, 2, 3) are parameters to be estimated.

The model is estimated for all the possible combinations of $d \in D$. For each regression, an estimate of β_2 and its corresponding standard error σ_2 are reported. The lower extreme bound is equal to the minimum $\beta_2 - 2\sigma_2$ and the upper extreme bound is equal to the maximum $\beta_2 + 2\sigma_2$. The decision rule for the variable of interest goes like this: if the lower extreme bound is negative and the upper extreme bound is positive, then the variable of interest is not a robust determinant of stock prices. Sala-i-Martin (1997) argues that such a robustness test is too restrictive because it takes only one regression (out of many) for which β_2 is insignificant or has another sign to conclude that the variable of interest is not robust. Sala-i-Martin (1997) then proposes an alternative form of EBA in which attention is paid to the entire distribution of β_2. In this alternative approach, the robustness of a variable is based on the fraction of the density function lying on the left and on the right of zero. Thus, if at least 95 percent of the cumulative distribution function (CDF) of β_2 lies in either side of zero, it is concluded that the variable of interest is robust.

EBA has been used to assess the determinants of economic growth (Levine and Renelt, 1992) and foreign direct investments (Moosa and Cardak, 2006; Chanegriha *et al.*, 2014). Young *et al.* (2007) and Ghosh and Yamarik (2014) have respectively used it to find out if the effect of black population on economic growth is robust and if the effect of regional trade arrangement on trade creation is robust. Despite its appealing characteristics, EBA is not a flawless procedure as it can lead to multicollinearity and the inflation of standard errors (Levine and Renelt, 1992). Besides, EBA is also criticized for replacing discretionary model selection with discretionary variable segmentation (McAleer *et al.*, 1985).

To address those issues, some restrictions are imposed upon the EBA used in this paper. Following Levine and Renelt (1992), the list of variables included in and allowed in all regressions has been reduced. Thus, only one explanatory variable (Eco_Uncertainty), an intercept, one variable of interest, and a combination of three doubtful variables are included all the models. Furthermore, for each variable of interest *i*, the pool of variables from which can be selected is restricted by excluding all the variables that, in theory, might point to the same phenomenon or be highly correlated. So, US_EME and China_US are not allowed in the same model. This is also the case for New_Cases and New_Deaths. Following Hlavac (2016), the variance inflation factor (VIF) is not allowed to exceed 7 to address multicollinearity. Moreover, to give more importance to estimation results from models with a better fit, each regression is weighted by its own likelihood ratio index (LRI).

3. RESULTS

To avoid spurious regressions, the stationarity of the data is tested using the augmented Dickey-Fuller test[2]. The results reported in Table 2 show that the series are not stationary at level but at first difference. Thus, all subsequent analysis will be done with data in their first difference. Table 3 presents the correlation matrix between stock prices in the U.S. and the COVID-19 outbreak. The table shows that there is positive and significant correlation between the S&P 500 and the Dow Jones as well as between new cases of COVID-19 and new deaths. It is also found that new cases and new deaths are both negatively and insignificantly correlated with stock prices in the U.S.

Table 2: Unit root test

	Level		*First Difference*	
	I	*TI*	*I*	*TI*
SP500	-2.646	-3.622**	-7.196**	-7.203**
Dow_Jones	-3.335**	-3.524**	-7.394**	-7.389**
Eco_Uncertainty	-2.624	-4.561**	-10.414**	-10.409**
New_Cases	2.887	1.971	-3.975**	-4.504**
New_Deaths	-2.747	-3.419**	-6.347**	-6.355**
VIX	-2.39**	-3.302**	-7.874**	-7.868**
TED_Spread	-4.515**	-4.515**	-5.611**	-5.607**
Inflation	-1.352	-2.906	-7.017**	-7.011**
Interest_Rate	-0.207	-1.224	-6.363**	-6.671**
China_US	-1.248	-1.409	-17.188**	-17.189**
US_EME	-1.438	-2.608	-6.902**	-6.891**
Crude_Oil	-1.315	-2.465	-16.244**	-16.238**

** denotes significance at the 5 percent level. I and TI respectively stand for intercept and trend and intercept.

Table 3 also shows that the correlation coefficient between new deaths and stock prices is superior to that between new cases and stock prices. Furthermore, it appears that the COVID-19 outbreak has more impact on the Dow Jones than on the S&P 500. After the correlation analysis, the EBA was carried out with the S&P 500 as dependent variable. Overall, 198 regressions were estimated and summarized in Table 4.

Table 3: Correlation matrix

	SP500	*Dow_Jones*	*New_Cases*	*New_Deaths*
SP500	1			
Dow_Jones	0.9838**	1		
New_Cases	-0.019	-0.038	1	
New_Deaths	-0.046	-0.069	0.448**	1

** denotes significance at the 5 percent level.

Table 4 shows the number of regressions in which each variable was included, its weighted mean coefficient, its weighted mean standard error, and the percentage of regressions in which the variable is significant. The EBA proposed by Leamer and Leonard (1983) is then carried out and reported in Table 5.

Table 4: Summary output (S&P500)

Variable	*Nb. Regressions*	*W.M. Beta*	*W.M. Std Error*	*% Significance*
Intercept	198	0.001	0.001	0.000
Eco_Uncertainty	198	0.001	0.001	39.899
New_Cases	58	0.001	0.001	36.207
New_Deaths	58	0.001	0.001	0.000
VIX	79	-0.002	0.001	100.000
TED_Spread	79	-0.015	0.005	100.000
Inflation	79	0.024	0.005	100.000
US_EME	58	-0.004	0.001	100.000
Interest_Rate	79	0.003	0.004	65.823
China_US	58	-0.031	0.009	100.000
Crude_Oil	79	0.001	0.001	46.835

Note: Nb. Regressions stands for number of regressions; W.M. Beta stands for the weighted mean of Beta; W.M. Std Error stands for the weighted mean of the standard error of Beta; and % Significance stands for the proportion of regressions in which each variable is significant.

Table 5 shows that the VIX, TED spread, inflation rate, trade weighted U.S. dollar index, and China/U.S. foreign exchange rate are robust determinants of stock prices in the U.S. The table also shows that the COVID-19 outbreak is not a robust determinant of stock prices since neither new cases nor new deaths have a robust effect on stocks.

Sala-i-Martin (1997) argues that the EBA proposed by Leamer and Leonard (1983)is too restrictive because it takes only one regression (out of many) for which the beta

Table 5: Leamer EBA (S&P500)

Variable	*Type*	*LEB*	*UEB*	*Decision*
Intercept	Free	-0.001	0.001	Fragile
Eco_Uncertainty	Free	-0.001	0.001	Fragile
New_Cases	Focus	-0.001	0.001	Fragile
New_Deaths	Focus	-0.001	0.001	Fragile
VIX	Focus	-0.002	-0.002	**Robust**
TED_Spread	Focus	-0.044	-0.001	**Robust**
Inflation	Focus	0.002	0.072	**Robust**
US_EME	Focus	-0.008	-0.002	**Robust**
Interest_Rate	Focus	-0.008	0.036	Fragile
China_US	Focus	-0.103	-0.007	**Robust**
Crude_Oil	Focus	-0.001	0.001	Fragile

Note: LEB and UEB stand for lower extreme bound and upper extreme bound, respectively.

coefficient is insignificant or has another sign to conclude that the variable of interest is not robust. We therefore carried out the EBA proposed by Sala-i-Martin (1997). But since this alternative approach pays attention to the entire distribution of the beta coefficients, two variants of the approach were estimated. In the first variant, the beta coefficients are assumed to be normally distributed across models while no assumption is made about their distribution in the second variant.

Table 6 reports the normal variant of the EBA proposed by Sala-i-Martin (1997). The table shows that economic uncertainty, new COVID-19 cases, VIX, TED spread, inflation, trade weighted U.S. dollar index, and China/U.S. foreign exchange rate are robust determinants of stock prices in the U.S. As for Table 7 reporting the generic variant of the EBA, it shows that economic uncertainty, VIX, TED spread, inflation, trade weighted U.S. dollar index, and China/U.S. foreign exchange rate are robust determinants of stock prices. Figure 3 shows the overall distribution function of each variable with the corresponding kernel density curves superimposed on the histogram. Those curves are non-parametric approximations of the shape of each variable's distribution.

In sum, using Leamer and Leonard's (1983) approach as well as Sala-i-Martin's (1997) generic approach, it is found that neither new COVID-19 cases nor new deaths are robust determinants of the S&P 500 while using Sala-i-Martin's (1997) normal approach, new cases are found to be robust determinants of the stock index.

Table 6: Sala-i-Martin EBA 1 (S&P500)

Variable	*Type*	*CDF (beta ≤ 0)*	*CDF (beta > 0)*	*Decision*
Intercept	Free	9.437	90.563	Fragile
Eco_Uncertainty	Free	**99.953**	0.047	**Robust**
New_Cases	Focus	**97.348**	2.652	**Robust**
New_Deaths	Focus	87.273	12.727	Fragile
VIX	Focus	**100.000**	0.000	**Robust**
TED_Spread	Focus	**99.794**	0.206	**Robust**
Inflation	Focus	0.000	**100.000**	**Robust**
US_EME	Focus	**100.000**	0.000	**Robust**
Interest_Rate	Focus	18.318	81.682	Fragile
China_US	Focus	**99.967**	0.033	**Robust**
Crude_Oil	Focus	84.364	15.636	Fragile

Note: Normal model, beta coefficients are assumed to be distributed normally across models. CDF (beta d" 0) and CDF (beta > 0) stand for fraction of the cumulative density function lying on the left and the right of zero, respectively.

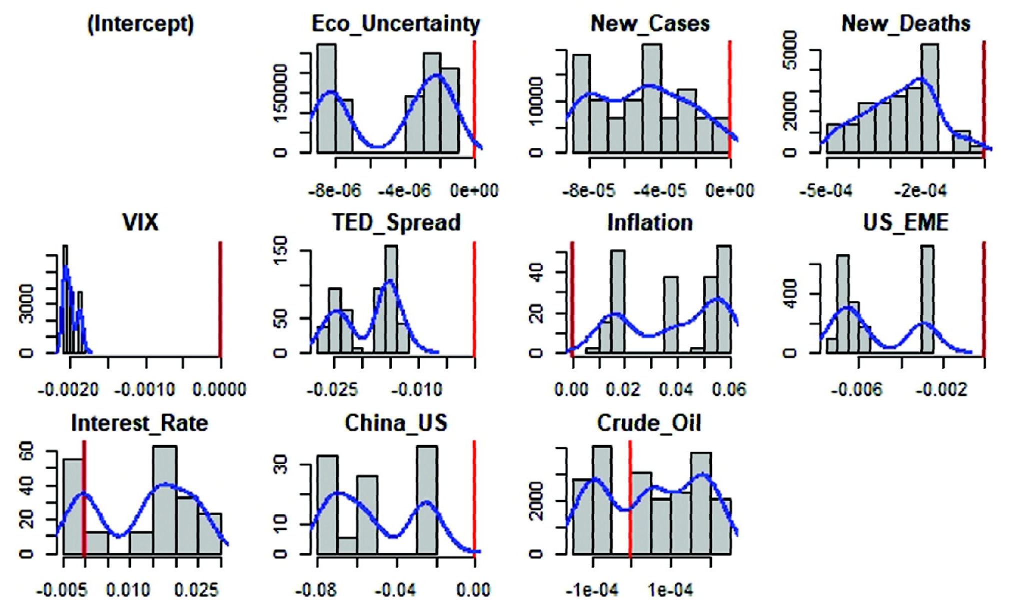
The EBA is then carried out with the DJIA as dependent variable. The approach proposed by Leamer and Leonard (1983) and the two variants proposed by Sala-i-Martin

Table 7: Sala-i-Martin EBA 2 (S&P500)

Variable	*Type*	*CDF (beta ≤ 0)*	*CDF (beta > 0)*	*Decision*
Intercept	Free	9.160	90.840	Fragile
Eco_Uncertainty	Free	**95.379**	4.621	**Robust**
New_Cases	Focus	93.380	6.620	Fragile
New_Deaths	Focus	87.304	12.696	Fragile
VIX	Focus	**100.000**	0.000	**Robust**
TED_Spread	Focus	**99.705**	0.295	**Robust**
Inflation	Focus	0.036	**99.964**	**Robust**
US_EME	Focus	**100.000**	0.000	**Robust**
Interest_Rate	Focus	44.238	55.762	Fragile
China_US	Focus	**99.903**	0.097	**Robust**
Crude_Oil	Focus	79.817	20.183	Fragile

Note: Generic model, no assumption about the distribution of beta coefficients across models. CDF (beta ≤ 0) and CDF (beta > 0) stand for fraction of the cumulative density function lying on the left and the right of zero, respectively.

Figure 3: Determinants of the S&P500



(1997) are estimated and reported in Table 8, 9, 10, and 11. Table 8 shows that 198 regressions were estimated and Table 9 reveals that the VIX, TED spread, inflation, trade weighted U.S. dollar index, and China/U.S. foreign exchange rate are robust determinants of the DJIA. As for Table 10 and 11, they reveal that economic uncertainty, new COVID-19 cases, new deaths, VIX, TED spread, inflation, trade weighted U.S. dollar index, and China/U.S. foreign exchange rate are robust determinants of the DJIA. Finally, Figure 4 shows the overall distribution function of each variable with the corresponding kernel density curves superimposed on the histogram.

In sum, using Leamer and Leonard's (1983) approach it is found that neither new COVID-19 cases nor new deaths are robust determinants of the DJIA while using both Sala-i-Martin's (1997) approaches, new cases and new deaths are found to be robust determinants of the stock index.

Table 8
Summary output (Dow Jones)

Variable	*Nb. Regressions*	*W.M. Beta*	*W.M. Std Error*	*% Significance*
Intercept	198	0.001	0.001	0.000
Eco_Uncertainty	198	0.001	0.001	39.899
New_Cases	58	0.001	0.001	36.207
New_Deaths	58	0.001	0.001	44.828
VIX	79	-0.002	0.001	100.000
TED_Spread	79	-0.017	0.006	100.000
Inflation	79	0.030	0.005	100.000
US_EME	58	-0.004	0.001	100.000
Interest_Rate	79	0.004	0.004	65.823
China_US	58	-0.035	0.010	100.000
Crude_Oil	79	0.001	0.001	40.506

Note: Nb. Regressions stands for number of regressions; W.M. Beta stands for the weighted mean of Beta; W.M. Std Error stands for the weighted mean of the standard error of Beta; and % Significance stands for the proportion of regressions in which each variable is significant.

Table 9: Leamer EBA (Dow Jones)

Variable	*Type*	*LEB*	*UEB*	*Decision*
Intercept	Free	-0.001	0.001	Fragile
Eco_Uncertainty	Free	-0.001	0.001	Fragile
New_Cases	Focus	-0.001	0.001	Fragile
New_Deaths	Focus	-0.001	0.001	Fragile
VIX	Focus	-0.002	-0.002	**Robust**
TED_Spread	Focus	-0.047	-0.001	**Robust**
Inflation	Focus	0.006	0.080	**Robust**
US_EME	Focus	-0.009	-0.002	**Robust**
Interest_Rate	Focus	-0.009	0.038	Fragile
China_US	Focus	-0.110	-0.007	**Robust**
Crude_Oil	Focus	0.001	0.001	Fragile

Note: LEB and UEB stand for lower extreme bound and upper extreme bound, respectively.

Table 10: Sala-i-Martin EBA 1 (Dow Jones)

Variable	*Type*	*CDF (beta ≤ 0)*	*CDF (beta > 0)*	*Decision*
Intercept	Free	19.045	80.955	Fragile
Eco_Uncertainty	Free	**99.956**	0.044	**Robust**
New_Cases	Focus	**99.461**	0.539	**Robust**
New_Deaths	Focus	**97.620**	2.380	**Robust**
VIX	Focus	**100.000**	0.000	**Robust**
TED_Spread	Focus	**99.812**	0.188	**Robust**
Inflation	Focus	0.000	**100.000**	**Robust**
US_EME	Focus	**100.000**	0.000	**Robust**
Interest_Rate	Focus	15.584	84.416	Fragile
China_US	Focus	**99.973**	0.027	**Robust**
Crude_Oil	Focus	52.185	47.815	Fragile

Note: Normal model, beta coefficients are assumed to be distributed normally across models. CDF (beta d" 0) and CDF (beta > 0) stand for fraction of the cumulative density function lying on the left and the right of zero, respectively.

Table 11: Sala-i-Martin EBA 2 (SP500)

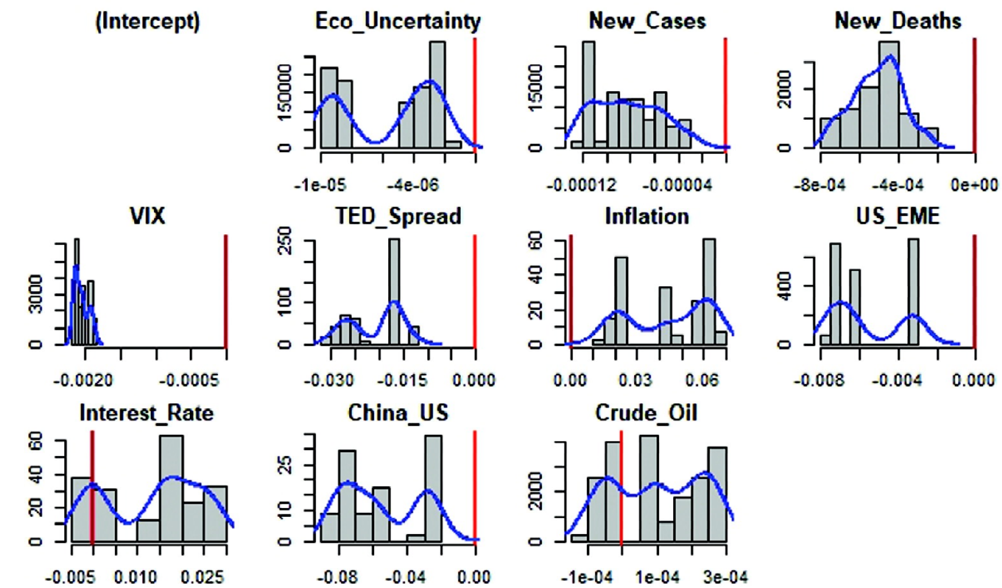
Variable	*Type*	*CDF (beta ≤ 0)*	*CDF (beta > 0)*	*Decision*
Intercept	Free	18.836	81.164	Fragile
Eco_Uncertainty	Free	**96.066**	3.934	**Robust**
New_Cases	Focus	**96.731**	3.269	**Robust**
New_Deaths	Focus	**96.655**	3.345	**Robust**
VIX	Focus	**100.000**	0.000	**Robust**
TED_Spread	Focus	**99.696**	0.304	**Robust**
Inflation	Focus	0.002	**99.998**	**Robust**
US_EME	Focus	**100.000**	0.000	**Robust**
Interest_Rate	Focus	40.057	59.943	Fragile
China_US	Focus	**99.903**	0.097	**Robust**
Crude_Oil	Focus	62.801	37.199	Fragile

Note: Generic model, no assumption about the distribution of beta coefficients across models. CDF (beta ≤ 0) and CDF (beta > 0) stand for fraction of the cumulative density function lying on the left and the right of zero, respectively.

4. DISCUSSION

In line with previous studies (Gujrati and Uygun, 2020; Jowitt, 2020; Liu *et al.*, 2020; Ozili and Arun, 2020; Salisu *et al.*, 2020; Sansa, 2020; Elsayed and Abdelrhim, 2020), the correlation matrix reveals that the COVID-19 outbreak is associated with a fall in stock prices. Our results also suggest that the fall in stock prices is more pronounced in the case

Figure 4: Determinants of the Dow Jones



of the DJIA. Such an impact could be due to the fact that the lockdown, social distancing, and other measures implemented to restrict the propagation of the COVID-19 adversely affect the real economy and the performance of those blue-chip companies (Coca-Cola, Disney, Caterpillar, Boeing, Microsoft, Apple, etc) included in the calculation of the DJIA.

It is also found that new deaths have more impact on stock prices that new cases. That is, stock markets are more sensitive to the lethal nature of the COVID-19 pandemic than they are to its infectious nature. It can thus be inferred that the discovery of an effective cure can be more beneficial for stock prices than that of a vaccine. Finally, The EBA supports the findings of the correlation analysis as it reveals that new COVID-19 cases and new deaths do have a negative impact on stock prices in the U.S. even though the robustness of that impact depends on the proxy and the estimation technique used.

Paying attention to other determinants of stock prices, the EBA shows that, as expected, increased economic uncertainty, credit risk (TED spread), and investors' pessimism (VIX) have a negative and robust impact on stock prices. These findings in line with Oyama (1997), Narayan *et al.* (2014), Sin-Yu (2017), and Islam *et al.* (2017) suggest that the bad news from the COVID-19 outbreak have triggered a flight-to-safety among investors.

The EBA also reveals that inflation and interest rate both have a positive impact on stock prices even though only the impact of the former is robust. These counter-intuitive findings could be due to the fact that since the Great Recession, inflation expectations are often subdue in the U.S. while the policy rate of the Fed has been kept close to its lower bound. Indeed, between February 1 to March 19, 2020 for instance, the 5-year forward inflation expectation rate has moved from 1.70 to 0.86. Similarly, between February 1 and April 6, 2020, the Fed drove its policy rate from 1.59% down to 0.05%. Thus, during this unprecedented public health crisis, an increase in any of those two variables can be perceived by investors as the sign of a potential rebound of economic activities.

It is also found that oil prices have a positive impact on stock prices, even though that impact is not robust. Such a finding is also related to investors' sentiment since an increase in oil prices is associated with an increase in global demand. Finally, the EBA shows that both proxies for the trade war between the U.S. and China have a negative and robust impact on stock prices in the U.S. Indeed, an increase in the trade weighted U.S. dollar index or in China/U.S. foreign exchange rate adversely affects the external competitiveness of the U.S. economy. For instance, that was the case between April 2018 and April 2020 when the trade weighted U.S. dollar index moved from 114.06 to 135.51. Such an appreciation of the dollar against the currency of emerging market economies could have fueled imports and impeded exports in the U.S. Similarly, 6.92 Chinese Yuan were exchanged for one dollar in January 2020 while up to 7.10 Yuan were needed in May 2020. Such a depreciation of the Yuan against the dollar could have supported China's export-led growth policy and inflated the U.S. trade balance with China.

5. CONCLUSION

The aim of this paper is to assess the robustness of the impact of the COVID-19 outbreak on stock prices in the U.S. Thus, building upon the literature related to the determinants of stock prices (Oyama, 1997; Rahman *et al.*, 2009; Narayan *et al.*, 2014; Azar, 2014; Rjoub *et al.*, 2017; Mumo, 2017; Sin-Yu, 2017; Islam *et al.*, 2017; Demir, 2019) and based on data availability, five potential determinants of stock prices and two proxies for the COVID-19 outbreak were selected. Additional variables were taken into consideration to account for the trade war between the U.S. and China and the oil war between Russia and Saudi Arabia. The data set was analyzed using the variants of the EBA developed by Leamer and Leonard (1983) and Sala-i-Martin (1997) and the results show that new confirmed cases of COVID-19 as well as new deaths do have a negative impact on stock prices in the U.S. even though the robustness of that impact depends on the proxy and the estimation technique used.

In line with previous studies (Oyama, 1997; Narayan *et al.*, 2014; Sin-Yu, 2017; Islam *et al.*, 2017), it is also found that economic uncertainty, credit risk, investors' pessimism, inflation, and the on-going trade war are robust determinants of stock prices in the U.S.

This paper is an early attempt to assess the financial impact of the COVID-19 outbreak because the public health crisis is still unfolding and nobody can really predict the future course of events. Thus, with the benefit of hindsight, future studies should take into consideration the other traditional determinants of stock prices –economic growth, trade openess, or foreign direct investment inflows, etc– that are not included in this paper because they are not available on a daily basis. Furthermore, future studies should also consider the strigency of government response in terms of lockdown, social distancing, and compulsory mask-wearing as well as the dynamics of monetary policy, current account balance, and sovereign debt during and after the pandemic. Finally, attention should be paid to catastrophe and pandemic bonds because they convey a great deal of information about policy responses to future pandemic.

NOTES

1. Available on: *https://covid19.who.int*
2. The lag length is automatically selected based on Akaike Information Criterion.

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