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What drives US stock markets during the COVID-19 pandemic? A global sensitivity analysis

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Received 11 March 2022; revised 3 July 2022; accepted 3 July 2022

Available online 15 July 2022

Abstract

This paper identifies robust determinants of US stock price movements in the economic shadow of the COVID-19 crisis and in the presence of model uncertainty, using several influential factors highlighted in relevant research. Our investigation performs an extreme bounds analysis (EBA), a global sensitivity framework capable of handling the problem of model uncertainty. We document that excess market returns, term spread, implied volatility, oil, Twitter-based economic uncertainty, and European and Chinese stock returns are the only variables that are robust to all possible variations in the condition set of information. The results also reveal the irrelevance of newly reported COVID-19 cases and deaths as novel drivers that contribute to the formation stock prices, thus lending support to the “psychophysical numbing” phenomenon.

JEL classification: E41; E42; G01; G10; G14

Keywords: COVID-19; Extreme bounds analysis; Price determinants; Psychophysical numbing; US stock Markets

1. Introduction

Mega-crises, whether economic, political, or biological, impinge on the welfare of individuals, businesses, and societies at large, because of their substantial scale, complexity, and impact on almost all aspects of life. The rapid spatiotemporal outbreak of the novel coronavirus (COVID-19) is one such example, sparking massive social and economic pandemonium in various parts of the world. As the virus spread throughout the world, and severe lockdowns were implemented, first in China and subsequently in most advanced economies, global economic activity plummeted in the early 2020. Worse still, the emergence of new mutations in the coronavirus and multiple waves of infection since the spring of 2020 have raised concerns about the speed of economic recovery. In terms of the number of infections and fatalities, the US is among the hardest hit by the pandemic. Since its rampant spread from the original epicenter in China beginning in January 2020, COVID-19 has taken a large toll on US public health. By the end of December 2021, the US had a cumulative 54.9 million infections, and the death toll had reached a grim milestone of 824,308, representing about 19 percent and 16 percent of the total worldwide infections and deaths, respectively.1 The financial markets have not been isolated from the vagaries of the pandemic. Amid the flows of negative news and the ensuing investor panic, major benchmark stock indices experienced an all-time decline in February–March 2020. Because of the dramatic price falls, the market-wide circuit breakers (MWCB) for US stock markets were tripped on March 9, 12, 16, and 18, suspending trading activity in the hope of assuaging investor fears. Concomitantly, the world’s most heavily traded indices (e.g., pan-European STOXX 600, London’s FTSE 100, Australia’s S&P/ASX

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Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

https://doi.org/10.1016/j.bir.2022.07.001

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200, Japan's Nikkei 225, Hong Kong's Hang Seng, Thailand's SET 100) suffered plunges in value of 10–40 percent.2

The continuing evolution of the virus and its widespread negative consequences have drawn attention in academic and industry circles. New avenues of research have emerged to determine the scale and severity of the multidimensional economic and financial calamities driven by the pandemic. The issues of concern include financial market performance (e.g., Alam et al., 2021; Baig et al., 2021; Bouri, Naeem, et al., 2021; Cao et al., 2021; O'Donnell et al., 2021), volatility (e.g., Bakry et al., 2021; Choi, 2020, Izzeldin et al., 2021; Uddin et al., 2021), liquidity (e.g., Chakrabarty & Pascual, 2022; Foley et al., 2022; Suardi et al., 2022; Zaremba et al., 2021), firm performance (e.g., Cui et al., 2021; Ding et al., 2021; Kaczmarek et al., 2021; Neukirchen et al., 2022), market connectedness (e.g., Abuzayed et al., 2021; Akhtaruzzaman et al., 2021; Bouri, Cepni, et al., 2021; Guo et al., 2021), investor behavior (e.g., Djalilov & Ülkü, 2021; Espinosa-Méndez & Arias, 2021; Sha et al., 2022; Smales, 2021), banking sector (e.g., Demir & Danisman, 2021; Demirgüç-Kunt et al., 2021; Foglia et al., 2022), and energy prices (e.g., Akyıldız et al., 2022; Ma et al., 2021; Narayan, 2022; Wu, Wang, et al., 2021).

One important issue, which seems to have been overlooked in the relevant literature, is identification of the factors that contribute to stock price formation in stressful periods, such as the ongoing COVID-19 pandemic. This empirical inquiry provides vital information regarding portfolio diversification and asset allocation for investors and fund managers as well as regulatory organizations charged with maintaining financial stability and protecting investors. Although revealing and understanding the drivers of stock price behavior are interesting discussion topics under normal circumstances, it is even more important in times of turmoil, when investors contemplate adjusting their expectations and trading strategies accordingly. Furthermore, given the well-documented significance of equity markets in economic growth, this research area has also macroeconomic policy relevance, which makes it appealing to academic and practitioner audiences.

Our chief objective is to address this gap in the literature. Our paper identifies the robust drivers of US stock price movements under the economic shadow of the COVID-19 crisis and in the presence of model uncertainty, using a large collection of potentially influential factors highlighted in pertinent studies. The primary focus of attention in our empirical investigation is the US stock market, in view of its unrivaled leading role in the world financial landscape and its lion's share of investor interest. According to the data from the World Bank, as of the end of 2019, the US aggregate market accounts for more than 38 percent of the stocks traded worldwide and about 40 percent of global market capitalization as a share of the gross domestic product (GDP).3 Rapach et al. (2013) and Nyberg and Pönkä (2016) suggest that the US market movements provide important clues for forecasting equity returns in major economies. In particular, the key questions that we explore are as follows:

- What factors are robustly associated with stock returns in the presence of a multitude of competing return-generating models?
- Do the human costs of the COVID-19 pandemic, in terms of infections and deaths, robustly affect stock returns?

As indicated by Chatfield (1995) and Avramov (2002), model uncertainty refers to situations in which one has no background knowledge of the factors that should be incorporated into the model specification, because of a lack of clear theoretical foundations. A given parameter is likely to have statistical significance in the context of a unique set of conditioning variables but is unlikely to do so in the context of a range of competing models. Therefore, the choice of explanatory variables is marred by ad hocery because of the temptation to experiment with various mixtures of parameters, each yielding different results. Cooper and Gulen (2006) argue that the literature on the ability to forecast asset returns tends to undertake data-fitting exercises, which, whether intentionally or unintentionally, present the most successful parts of an econometric analyses and hide the unsuccessful ones. Hence, scholars might cherry-pick results that agree with their self-interest, while disposing of those that do not. These practices are related to data-snooping biases, data-mining traps, and p-hacking (Black, 1993; Cooper & Gulen, 2006; Harvey, 2017; Learner, 1978; Lo & MacKinlay, 1990).

As a key contribution to the existing corpus of research, our inquiry relies on extreme bounds analysis (EBA), a global sensitivity framework, originally proposed by Leamer (1983, 1985) and Levine and Renelt (1992) and later enhanced by Sala-i-Martin (1997). The EBA sifts through the universe of independent variables to establish the robustness or fragility of a particular coefficient estimate to any minor variation in the condition set of information, thus tackling the issues of model uncertainty. The novelty of this technique is that it allows researchers to carry out a systematic sensitivity analysis to decide whether a regressor of interest is robustly related to a response variable, no matter which condition variables are added to the estimated model. Accordingly, the EBA deals effectively with data-snooping exercises on the entire gamut of model specifications could be conducted to determine the best-performing one, whose results are consistent with preconceived notions or beliefs. The EBA addresses these concerns by assessing the statistical sensitivity of the linkage between a response variable (e.g., stock returns) and a factor of primary interest (e.g., oil prices) to all possible groups of condition variables (e.g., volatility, term

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2 https://www.theguardian.com/business/2020/mar/31/fts-100-posts-largest-quarterly-fall-since-black-monday-aftermath/.
3 https://data.worldbank.org/indicator/CM.MKT.TRAD.CD/.
spread, investor sentiment, gold prices). Although the economics and politics literature is full of studies that adopt the EBA as the principal tool of analysis (e.g., Gassebner et al., 2013; Hartwig & Sturm, 2014; Moosa & Cardak, 2006; Moosa & Khatatbeh, 2021; Sturm & Williams, 2010; Walther & Hellström, 2021), only a few use this methodology to look at financial markets (e.g., Inekwe, 2018; Kim et al., 2019; Rahman et al., 2021). We are unaware of any studies in which the EBA is used to ascertain whether variables, previously shown to be correlated with equity returns, are still robust determinants to the multidimensional pressure of the global health crisis.

This paper fills this gap in the literature. In terms of practical implications, our evidence on the robust drivers of stock price movements could be added to the policy maker's toolbox for national authorities concerned about maintaining stability and resilience amid lingering pandemic-induced uncertainty in financial markets. Furthermore, the results could prove beneficial for investors adjusting their trading strategies in response to the challenging financial climate due to COVID-19.

The rest of the paper proceeds as follows. Section 2 contains a brief survey of the literature on the topic. Section 3 outlines the econometric methodology. Section 4 describes the dataset, while Section 5 reports and discusses our findings. Section 6 presents some robustness checks. Lastly, Section 7 concludes.

2. Related research

Because the exponential spread of the virus triggered a misasmasma of global uncertainty, a rapidly growing repository of research has emerged to investigate the impact on financial markets. Indeed, the literature on the economic and financial repercussions of the infectious disease can by no means be exhaustively reviewed, in view of its multiplicity and diversity. Specifically, existing studies on the nexus between the stock market and COVID-19 can generally be divided into three strands, based on the perspective of analysis. The first strand employs cross-sectional firm-level data to explore the ramifications of the pandemic outbreak on business operations and performance and to identify the unique characteristics that underlie corporate responses to the threats posed by coronavirus (e.g., Albuquerque et al., 2020; Bloom et al., 2021; Cui et al., 2021; Ding et al., 2021; Fahlenbrach et al., 2021; Gourinchas et al., 2020; Huang & Ye, 2021; Kaczmarek et al., 2021; Neukirchen et al., 2022; Ramelli & Wagner, 2020; Zhang & Hu, 2022; Zheng, 2021). For instance, Bloom et al. (2021) find that, in the second and third quarters of 2020, US small businesses had an average sales loss of 29 percent, and offline firms were much worse off than their online counterparts. In terms of demographic characteristics, female and Black owners have borne the brunt of harms from the pandemic. Cui et al. (2021) document that Chinese firms that adopted more conservative accounting practices had lower stock return declines during the COVID-19 crisis period. Investigating the joint impact of capital structure policies and corporate social responsibility (CSR) on firm risk during the pandemic, Huang and Ye (2021) demonstrate that firms with lower-than-optimal leverage are less exposed to stock return volatility, irrespective of their CSR activities. Ding et al. (2021) find that firms with larger (smaller) cash reserves, access to credit, profitability, and CSR practices (leverage, short-term debt, global supply chains, entrenched executives) have better stock price performance in response to the pandemic outbreak. Likewise, Zheng (2021) suggests that firm performance during the pandemic period is positively associated with the pre-2020 level of cash holdings, emphasizing the precautionary motive of corporate cash reserves.

As the pandemic crisis threatens to disrupt many global industries, a second stream of research focuses on assessing the differential vulnerability of industry sectors to the manifold ramifications of COVID-19 (e.g., Alam et al., 2021; Carter et al., 2022; Choi, 2020; He et al., 2020; Kanno, 2021; Liu et al., 2020; Lu et al., 2021; Mazur et al., 2021; Ntounis et al., 2022; Shahzad, Bouri, et al., 2021; Szczysigielski et al., 2021). For example, using an event-study approach, Liu et al. (2020) show that pharmaceutical manufacturing, information technology, software, and information services (warehousing and postal services, lodging and catering) posted abnormal cumulative positive (negative) returns in China during the pandemic period. Alam et al. (2021) find that food, pharmaceuticals, health care, and telecommunications (energy, transportation, technology) sectors perform well (worse) after the declaration of the COVID-19 outbreak in Australia. Mazur et al. (2021) find that, in the US, health care and medical devices, food and grocery distribution, software and technology, and natural gas (crude petroleum and oil services, hospitality and entertainment, and real estate) had the best (worst) performance throughout the market collapse in March 2020. Bouri, Naeem, et al. (2021) demonstrate that, in New Zealand, industry-level returns have heterogeneous reactions to COVID-19-related restrictions (mandatory lockdowns, the stimulus package, and travel prohibitions). These policies, nonetheless, appear to have a negligible impact on real estate, health care, and technology. Choi (2020) shows that economic uncertainty due to the pandemic exacerbates volatility in US sectoral stock returns. Szczysigielski et al. (2021) establish that COVID-19-related uncertainty has a negative influence on the risk-return profiles of the sample energy sectors, and those of net oil-exporting countries are more deeply affected than those of their net-importing peers. Shahzad, Naeem, et al. (2021) examine the time- and frequency-domain asymmetric volatility connectedness in China’s stock market. The results also suggest the dominance of bad volatility spillover shocks over their good counterparts during the COVID-19 pandemic.

The third stream of research takes a broader perspective by investigating whether, and to what extent, the pandemic influences primary aspects of the aggregate stock market portfolio, such as liquidity and risk-return profiles, in a single- or multi-country analytical framework (e.g., Ashraf, 2020; Baig et al., 2021; Bakry et al., 2021; Bouri et al., 2021a; Guo et al., 2021; Li et al., 2021; Orhun, 2021; O'Donnell et al., 2021; Smales, 2021; Topcu & Gulal, 2020; Uddin et al., 2021; Zaremba et al., 2021; Zhang et al., 2020). For instance, O'Donnell et al. (2021) find that the daily total count of positive cases plays an important role in explaining stock price changes in Italy, Spain, the US, and the UK. Smales
document that rising levels of investor attention to coronavirus-related news, proxied by Google search volume (GSV), tend to lower (exacerbate) returns (volatility) in the G7 stock markets. Bakry et al. (2021) find that COVID-19 case load and death rates both raise emerging-market volatility, whereas developed-market volatility is affected only by confirmed cases. Topcu and Gulal (2020) document that emerging stock markets were negatively affected by the coronavirus outbreak during the period March 10–April 10, 2020, after which the pandemic’s impact dwindled. Focusing on liquidity in global stock markets during the health crisis, Zaremba et al. (2021) demonstrate that government non-pharmaceutical interventions have a negligible effect on developed-market liquidity, whereas workplace and school closures modestly reduce emerging-market liquidity. Li et al. (2021) show that the spatiotemporal spread of the COVID-19 pandemic intensified the total volatility connectedness across the G20 stock markets. Bouri, Cepni, et al. (2021) explore the nature and magnitude of return shock spillovers between equities, bonds, foreign currencies, gold, and crude oil, using a TVP-VAR-based dynamic connectedness approach. They document a substantial increase in the overall connectedness among these assets in the wake of the pandemic. Furthermore, the results suggest that US stock and foreign exchange (bond) markets are the main transmitters of shocks before (during) the COVID-19 outbreak. Based on a couple of popular metrics of tail (extreme) risk (i.e., CoVaR and ΔCoVaR), Abuzayed et al. (2021) provide evidence of heightened systemic risk contagion between the global stock market and major stock counterparts in North America and Europe since the onset of the pandemic.

In short, notwithstanding its quantity and diversity, the extant research seems to be silent about which factors contribute to the stock price formation process during the new era of indefinite pandemic-induced uncertainty. Our paper is filled this literature gap.

3. Methodology

A large-scale sensitivity analysis, the EBA was initially developed by Leamer (1983, 1985) and Levine and Renelt (1992) and subsequently modified by Sala-i-Martin (1997). The first version is argued as too restrictive an exercise, due to its dichotomous criterion of fragility/robustness, whereas the second one is less stringent. This section briefly sheds light on both versions.

3.1. Leamer’s approach

The purpose of the EBA is to ascertain the robustness, or lack thereof, of the association between a given regressand, \( Y \), and an explanatory variable of interest, \( X \), to all possible changes in the conditioning information set. The robustness criterion is adequately satisfied only if (1) the estimated coefficient on \( X \) retains its statistical significance, and (2) the corresponding sign survives unaltered in the face of various subsets of other regressors included in the analysis. Leamer (1985) and Levine and Renelt (1992) point out that the EBA considers a real-life situation, in which one is interested in investigating the robustness of a specific factor, \( Qi \), in the presence of a large pool of \( U \) candidate factors recognized in the literature as potential drivers of an observable phenomenon (e.g., stock returns). The empirical implementation of the EBA consists of four steps. First, a baseline linear regression model of the form specified in Equation (1) is estimated:

\[
R_i = \alpha + \beta_i Q + \sum_{j=1}^{m} \eta_{ij} X_j + \sum_{k=1}^{n} \theta_{ik} Z_k + \nu_i \tag{1}
\]

where \( R \) represents daily stock returns, \( i \) indexes the continuum of regression models to be estimated, \( \alpha \) is an intercept, \( \beta \) denotes the factor in question (a.k.a. the focus variable), where \( Q \in U \), \( X \) is a vector of influential regressors (a.k.a. free variables) that appear in each model based on their strong theoretical or empirical pertinence, \( Z \) is a vector of additional potentially important covariates (a.k.a. doubtful variables) that may affect \( R \) and are included in each regression but in various combinations, where \( Z \in U \), and \( \nu \) is the disturbance term. For a particular focus variable, the total number of possible regression specifications, with a subset size of \( N \) doubtful variables taken from the remaining \( U - 1 \), is given by:

\[
P = \frac{(U-1)!}{N!(U-1-N)!} \text{ for } U-1 > N > 1 \tag{2}
\]

Second, we run Equation (1) \( P \) times, with every single regression run containing a different linear combination of \( Z \) variables. The estimated coefficient, \( \hat{\beta}_i \), associated with the factor of interest, \( Q_i \), and its corresponding standard deviation, \( \hat{\sigma}_i \), are both collected from each regression specification for subsequent analysis. Third, the maximum and minimum values of \( \hat{\beta} \) are identified and then employed to delineate its upper and lower bounds, respectively. The former is calculated as the largest value of \( \hat{\beta} \) plus \( \hat{\tau} \hat{\sigma} \), and the latter is defined as the lowest value of \( \hat{\beta} \) minus \( \hat{\tau} \hat{\sigma} \), where \( \tau \) is the z-values related to a confidence level (e.g., 1.96 and 2.58 for the 0.95 and 0.99 confidence levels, respectively). The last step deduces whether \( Q \) has robust explanatory power with respect to the response variable. Leamer (1985) indicates that the factor in question, \( Q_i \), is judged to be weak if either its extreme bounds (i.e., \( \hat{\beta}_{\max} + \hat{\tau} \hat{\sigma} \) and \( \hat{\beta}_{\min} - \hat{\tau} \hat{\sigma} \) have opposite signs or it loses statistical significance even once. Otherwise, \( Q \) is judged as robust in the sense that it withstands all changes in the model specifications. Some studies (e.g., Granger & Uhlig, 1990; Hendry & Krolzig, 2004; McAleer et al., 1985) critique Leamer’s EBA for being based on a more demanding inferential criterion that cannot be met in practice.

3.2. Sala-i-Martin’s approach

As a simple yet important refinement, Sala-i-Martin (1997) proposes relaxing the binary robustness criterion of Leamer’s EBA by considering the entire distribution of \( \hat{\beta} \) (i.e., \( \{\hat{\beta}_i\}_{i=1}^P \) instead of only its maximum and minimum bounds. He stresses that if most of \( \{\hat{\beta}_i\}_{i=1}^P \) is found to be on the left or right side of zero, then we can conclude that the underlying covariate is
robust. In the same paper, he suggests calculating the cumulative distribution function of \(\{\beta_i\}_{i=1}^P\) at zero (i.e., \(\{\text{CDF}(0)\}\)), using the mean and variance of the distribution. To this end, Equation (1) is estimated \(P\) times, and the coefficient of interest, \(\beta_i\), standard deviation, \(\hat{\sigma}_i\), and the integrated likelihood, \(L_i\), are extracted from each model output. Next, we perform a likelihood-weighting scheme, in which regressions with a better fit get a larger weight. Under this scheme, the weight, \(W_e\), of the \(e\)th model is calculated as:

\[
W_{Qe} = \frac{L_{Qe}}{\sum_{i=1}^{P} L_{Qi}}, \text{ where } \sum_{i=1}^{P} W_{Qi} = 1
\]  

(3)

As shown by Sala-i-Martin (1997), the \(\text{CDF}(0)\) is calculated in two mutually exclusive settings: (1) no specific distribution is assumed for all \(\beta_i\); and (2) a normal distribution is assumed for all \(\beta_i\). In the more generic case, \(\text{CDF}(0)\) is calculated for each of the \(P\) regression models, and the aggregate \(\text{CDF}(0)\) of \(\beta\) is constructed as an average of the respective values of \(\text{CDFs}(0)\), weighted by the integrated likelihoods. Put differently, if \(\Phi(Q_i(0 | \beta_i, \hat{\sigma}_i^2))\) represents the \(i\)th \(\text{CDF}(0)\), then we can calculate the aggregate \(\text{CDF}(0)\) for nonnormal \(\beta\) as follows:

\[
\Phi(Q(0)) = \sum_{i=1}^{P} W_{Qi} \Phi(Q_i(0 | \beta_i, \hat{\sigma}_i^2))
\]  

(4)

At the same time, under the assumption of a normal distribution, we can construct the mean estimates of \(\beta_i\) and \(\hat{\sigma}_i\) as follows:

\[
\overline{\beta}_Q = \sum_{i=1}^{P} W_{Qi} \beta_i
\]  

(5)

\[
\overline{\sigma}_Q^2 = \sum_{i=1}^{P} W_{Qi} \hat{\sigma}_i^2
\]  

(6)

After information about \(\overline{\beta}_Q\) and \(\overline{\sigma}_Q^2\) becomes readily available, \(\text{CDF}(0)\) can be obtained using the standard Gaussian distribution, such that \(\beta \sim N(\overline{\beta}_Q, \overline{\sigma}_Q^2)\). Sala-i-Martin (1997) highlights that a given focus variable can be reliably labeled as robust, if at least 95 percent of its density function is on the same side of zero. This implies that the corresponding coefficient estimates have the same sign and are statistically distinguishable from zero in no less than 95 percent of the regression models augmented with all feasible subset combinations of \(Z\) variables. As a visual supplementary output of the EBA, histograms can be deployed to illustrate the individual \(\text{CDFs}\). These bar graphs depict the amplitude and dispersion of the estimated coefficients across the entire range of regression runs. In addition, the statistical significance of \(\beta\) can be verified by examining the \(\text{CDF}\) of \(t\)-statistics, which shows the proportion of statistically significant coefficients at conventional levels.

4. Data description

Our empirical investigation employs multiple datasets of daily frequency (Monday to Friday) for the period January 22, 2020, to January 2, 2022. The beginning of the sample corresponds to the day on which the first positive case of COVID-19 was reported in the US. The dependent variable, US stock market behavior, is represented by the closing prices of the benchmark S&P 500 composite index. Globally recognized as the premier barometer of US large-cap stocks, the index comprises 500 leading constituents that make up about 80 percent of overall market capitalization. As of February 28, 2022, more than $13.5 trillion is benchmarked or indexed to the S&P 500, with indexed assets contributing nearly USD 5.4 trillion of this aggregate figure (S&P Dow Jones Indices, 2021). In terms of sectoral breakdown, information technology, health care, consumer discretionary, communication services, and finance are the dominant industry sectors in the index, accounting for 75.40 percent of the index market weight. Continuously compounded returns, \(R_t\), on the S&P 500 index are given by \(\ln(P_t/P_{t-1}) \times 100\), where \(P_t\) and \(P_{t-1}\) stand for closing index levels on consecutive days \(t\) and \(t-1\), respectively. A necessary step before the EBA is performed is to designate the free and doubtful variables. In what follows, we outline both regressor sets and offer some preliminary analysis.

4.1. Free variables

Free variables have widespread acceptance in the literature, thanks to their theoretical connection with, and empirical significance in, affecting a given dependent variable. In the relevant literature, the pandemic’s severity levels often are manifested in both daily infection counts and mortality. Numerous studies document that the health burden of COVID-19, in terms of confirmed cases and fatalities, weighs heavily on investor confidence and overall market sentiment, engendering downward pressure on asset prices in the US (e.g., Ali et al., 2020; Matos et al., 2021; O’Donnell et al., 2021), China (e.g., Fiti et al., 2021; Lee et al., 2021; Liu et al., 2021), Europe (e.g., Espinosa-Méndez & Arias, 2021; O’Donnell et al., 2021; Yu et al., 2021), and other parts of the world (e.g., Ashraf, 2020; Bakry et al., 2021; Topçu & Gulal, 2020). Seen in this light, the US stock markets’ exposure to pandemic-induced risk is quantified by two popular complementary indicators, laboratory-confirmed infections, CC, and fatalities, DC, per day. \(CC_t\) and \(DC_t\) are calculated as \(\ln(1 + \text{new positive cases})\) and \(\ln(1 + \text{new deaths})\), respectively, following Smales (2021) and Cao et al. (2021). Because our sample includes some days with neither new reported positive cases nor deaths, a constant value of one is included in the calculation of \(CC_t\) and \(DC_t\) to address the \(\log(0)\) problem. Both data series come from the “Our World in Data” website, which presents updated country-by-country interactive visualizations and statistics on the pandemic from the Johns Hopkins University and medicine coronavirus resource center.\(^4\)

\(^4\) https://ourworldindata.org/coronavirus#coronavirus-country-profiles/.
4.2. Conditioning information set

Extant research presents a diverse universe of candidate variables with reliable power to explain stock price changes. Such factors describe aspects related to financial, macroeconomic, political, behavioral, and global dimensions. The literature offers no clear consensus on a single factor that can consistently explain returns in different markets and over different periods. Many of those generally recognized determinants (e.g., book-to-market equity, interest rates, foreign exchange rates, crude oil, gold) prove statistically significant in some methodological contexts but fail to do so in others. With respect to our group of doubtful variables, we collect data for some methodological contexts but fail to do so in others. With respect to our group of doubtful variables, we collect data for 19 indicators that are widely cited in the literature as important determinants. Broadly speaking, these variables have a variety of drivers that potentially contribute to the stock price formation process, including stock market factors (excess returns, firm size effect, value effect, profitability effect, investment effect), investor attention (Wikipedia page views for coronavirus and S&P 500 index), market uncertainty (VIX, Twitter-based economic uncertainty), domestic economic fundamentals (US real economic activity, Treasury bill interest rates, term spread, inflation expectation rates, broad effective exchange rates of the US dollar), and global forces (European and Chinese stock markets, Bitcoin, oil, and gold markets).

Although other relevant, but unaccounted-for, factors might at play, we believe that this non-exhaustive set is adequately reflective of the different influences governing the behavior of stock prices. Levine and Renelt (1992) maintain that it is highly unlikely that the full continuum of forces with a bearing on a dependent variable can be identified and incorporated into an analytical model. Table 1 describes the variables and their respective data sources, with references for a sample of prior research in which they are reported.

4.3. Exploratory analysis

In the same spirit of Forbes and Rigobon (2002) and Yang and Zhou (2013), two-day rolling averages are calculated for all time series to address the bias from the non-synchronicity of data releases. Table 2 lists information on the univariate statistical properties of our variables, along with the results of normality and unit-root tests.

As seen in Table 1, the US stock market generates higher mean daily returns than do its European and Chinese counterparts. Bitcoin appears to be the best-performing asset class throughout this traumatic period, delivering an average daily return, 0.373 percent, whereas Chinese stocks yield the lowest average returns, 0.020 percent. In terms of the unconditional second moment, price changes in oil and Bitcoin seem to be the most volatile investment, with standard deviations of 5.963 and 5.242 percent, respectively. Such high levels of variability might be attributable to the historic oil market meltdown in 2020 and the inherently speculative nature of cryptocurrency prices. Returns associated with equities, Bitcoin, oil, and gold exhibit negative skewness and leptokurtosis, both of which are well-documented empirical regularities in financial time series (e.g., Aït-Sahalia & Lo, 1998; Campbell & Hentschel, 1992; Fama, 1965). The respective distributions of the variables are leptokurtic relative to the Gaussian distribution, except for that of the profitability factor. Based on the Jarque-Bera test results, we fail to reject the null hypothesis of normality for the profitability factor and Twitter-based economic uncertainty. The rest of the variables, however, show striking departures from normality at the 0.05 level of significance or better. The results of the augmented Dickey-Fuller test (Dickey & Fuller, 1979, 1981) and the Phillips-Perron test (Phillips & Perron, 1988) provide evidence against the null hypothesis of a unit root for all variables. Accordingly, our sample time series are stationary processes and can be modeled in the EBA without further transformation.

Because our investigation involves a large number of covariates, a glimpse at their dependence structure is appropriate at this early stage of analysis. Fig. 1 presents a heatmap visualization of pairwise correlation coefficients between all the variables. Empty cells imply statistically insignificant correlations. Cells in turquoise (yellow) denote a very weak positive (negative) relation, while those in dark blue (dark brown) show a very strong positive (negative) relation between two variables. A perusal of the heatmap grid reveals that the vast majority of cross-correlations either lack statistical significance (i.e., $r \geq 0.10$) or are low in strength (i.e., $|r| < 0.40$). Notable exceptions include the moderately positively (negatively) correlated pairs (i.e., $0.40 \leq |r| < 0.80$) of US real economic activity-relative Treasury bill rate, US-European stock markets, European-Chinese stock markets, size factor-value factor, investment factor-value factor, and investment factor-profitability factor (Bitcoin-VIX, US stock market-VIX, European stock market-VIX, gold-US dollar broad exchange rate, and European stock market-US dollar broad exchange rate). A remarkably strong positive association exists between confirmed infections and deaths, where $r_{CC, DC} \geq 0.80$. Given such extreme collinearity, we consider confirmed cases the sole free variable and omit deaths from the EBA.

As a safeguard against potential multicollinearity among the explanatory variables, Levine and Renelt (1992) suggest capping the total number of regressors at seven or fewer in every regression. In light of this suggestion, we limit the subset size of doubtful variables to 3 (i.e., $N = 3$), which is consistent with several past works (e.g., Durham, 2004; Kim et al., 2019; Sala-i-Martin, 1997). Accordingly, the righthand side of the $i$th regression accommodates an intercept, a predefined free variable, a focus variable, and a combination of three doubtful variables. In addition, model specifications with a VIF\footnote{The variance inflation factor (VIF) is a metric that reveals the degree to which independent variables are collinear. As a rule of thumb, a value of 10 is often considered the maximum level of VIF, beyond which multicollinearity becomes a concern (Greene, 2018; James et al., 2014).} cutoff value $> 10$ are excluded from the analysis. These procedures are expected to address concerns about possible multicollinearity.
Table 1
Description of the conditioning variables.

| Variable (Label)                  | Definition                                                                 | Data source                      | References                                      |
|-----------------------------------|---------------------------------------------------------------------------|----------------------------------|------------------------------------------------|
| Excess market returns \( (MKT) \) | According to the benchmark three-factor asset pricing model of Fama and French (1993), market risk premium is a relevant factor for explaining average stock returns. \( MKT \) is calculated as the difference between value-weighted returns on a market portfolio comprised of all NYSE, AMEX, and NASDAQ stocks and the one-month Treasury bill rate. | Kenneth R. French's website     | Fama and French (1993), Griffin (2002), Gaunt (2004), Calcici et al. (2013), Hou et al. (2019) |
| Size factor \( (SMB) \)           | According to the three-factor asset pricing model of Fama and French (1993), firm size premium is an important risk factor for explaining market returns. \( SMB \) is the difference between average returns on a portfolio of small-cap stocks and average returns on a portfolio of large-cap stocks. | Kenneth R. French's website     | Fama and French (1993), Griffin (2002), Gaunt (2004), Calcici et al. (2013), Hou et al. (2019) |
| Value factor \( (HML) \)          | Based on the three-factor asset pricing model of Fama and French (1993), the value premium is also an important risk factor in explaining market returns. \( HML \) is the difference between average returns on stocks with a high book-to-market ratio (i.e., value stocks) and average returns on stocks with a low book-to-market ratio (i.e., growth stocks). | Kenneth R. French's website     | Fama and French (1993), Griffin (2002), Gaunt (2004), Calcici et al. (2013), Hou et al. (2019) |
| Investment factor \( (CMA) \)      | In later research, Fama and French (2015) extend the three-factor model to include the investment premium as a fourth risk factor. Analogous to both \( SMB \) and \( HML \), \( CMA \) is the difference between average returns on a portfolio of low-investment (i.e., conservative) firms and average returns on a portfolio of high-investment (i.e., aggressive) firms. | Kenneth R. French's website     | Fama and French (2015), Guo et al. (2017), Foye (2018), Kubota and Takehara (2018), Hou et al. (2019) |
| Profitability factor \( (RMW) \)   | The profitability premium is the fifth risk-factor component in the five-factor model of Fama and French (2015). \( RMW \) is the difference between average returns on a portfolio of stocks with robust operating profitability and average returns on a portfolio of stocks with weak operating profitability. | Kenneth R. French's website     | Fama and French (2015), Guo et al. (2017), Foye (2018), Kubota and Takehara (2018), Hou et al. (2019) |
| Wikipedia views for coronavirus \( (AWC) \) | Daily total number of page views for keywords related to the novel coronavirus in 2019 (i.e., “COVID-19,” “sars-cov-2,” “COVID-19_pandemic,” “coronavirus,” “coronavirus_disease,” “novel_coronavirus”) on Wikipedia. All data series are retrieved via Toolforge, a hosting environment administered by the Wikimedia Foundation developers. In the same spirit as Da et al. (2011) and Hervé et al. (2019), we use abnormal Wikipedia page views, A \( WC \), as a proxy for investor attention to COVID-19 pandemic developments. \( A \ WC = \ln(\text{WIKI}_{\text{median}}(\text{WIKI}_{1} \ldots \text{WIKI}_{n})) \). | https://pageviews.toolforge.org   | Colavizza (2020), Gozzi et al. (2020), O’Leary & Storey (2020), Roszkowski and Włodarczyk (2021) |
| Wikipedia views for US stock markets \( (AWS) \) | Daily total number of Wikipedia page views for the keywords “S&P 500” and “S&P 500 component.” A \( WS \) is deployed as a proxy for investor interest in the benchmark S&P 500 index. An \( WS \) is calculated in a similar fashion to \( A \ WC \). | https://pageviews.toolforge.org   | Moat et al. (2013), Hervé et al. (2019), Audrino et al. (2020), Behrendt et al. (2020), Boulton et al. (2021) |
| CBOE implied volatility index \( (VIX) \) | Known as the US market’s fear gauge, the VIX is a popular forward-looking barometer capturing investor expectations regarding price fluctuations in the S&P 500 index in the near future. Because it is derived from real-time prices of S&P 500 options, the VIX is basically a measure of implied volatility. First differences are taken for daily observations of the VIX. | https://fred.stlouisfed.org/      | Kang et al. (2019), Sarwar (2020), Wang et al. (2020), Megaritis et al. (2021), Xiao et al. (2021) |
| Twitter-based economic uncertainty \( (TEU) \) | Introduced by Baker et al. (2021), the \( TEU \) delivers an immediate measure of economic uncertainty as perceived and posted by Twitter users. The \( TEU \) construction is based on counting the number of tweets containing keyword variants related to both uncertainty and the US economy. The index is available on a daily basis since 2011. \( TEU \) values are transformed into logarithmic first differences. | https://www.policyuncertainty.com | Behera and Rath (2021), Wu, Tiwari et al. (2021) |
| US real economic activity \( (ADS) \) | We use the Aruoba-Diebold-Scotti (ADS) index of US business conditions (Aruoba et al., 2009) as a real-time indicator of overall economic activity. The \( ADS \) index has a zero average value. Therefore, incrementally larger positive (negative) values indicate steadily better- (worse)-than-average general conditions. First differences are taken for \( ADS \) values. | https://www.philadelphiaped.org   | Klemola (2019), Giovannelli et al. (2021), Mascio et al. (2021), Smales (2021), Subramaniam & Chakraborty (2021) |

(continued on next page)
Relative treasury bill rate (RTB)
The relative one-month Treasury bill rate serves as a proxy for developments in short-term interest rates. Following Hodrick (1992) and Peña et al. (1999), R \( TB \) is given by
\[
\ln \left( TB_t - \frac{1}{22} \sum_{t-22}^{t} TB_t \right),
\]
where the numerator is the one-month Treasury bill rate on day \( t \) and the denominator is a one-month (22 trading days) backward moving average. First differences are taken for \( R \ TB \) rates.

Term spread (TSD)
The term spread serves as a proxy for the US monetary policy stance. TSD is calculated as the yields on the ten-year Treasury bond minus the yields on the three-month Treasury bill. We take the first differences of TSD series.

Inflation expectation rates (INF)
The five-year forward inflation expectation rates are used as a measure of average anticipated US inflation. We take first differences of INF series.

US dollar broad exchange rate index (USD)
The USD index is a trade-weighted benchmark that assesses the strength of the US dollar against a broad basket of key developed- and developing-country currencies. Increases in the index indicate a strengthening of the US dollar against the index's foreign currency constituents, and vice versa. First differences are taken for USD rates.

European stock market (ESM)
Stock price movements in European markets are represented by the S&P Europe 350 index, which is float-adjusted market capitalization weighted. The index tracks the performance of the largest and most liquid 350 stocks in 16 major developed markets. Daily closing values of ESM are transformed into logarithmic first differences.

Chinese stock market (CSM)
China's stock market behavior is represented by the S&P China 500 index, which is float-adjusted market capitalization weighted. The index includes the largest and most liquid 500 stocks in a broad range of industry sectors. Daily closing values of CSM are transformed into logarithmic first differences.

Bitcoin price index (XBX)
The daily average exchange rate of one unit of Bitcoin against the US dollar on the world's principal cryptocurrency trading platforms. XBX data points are in logarithmic first-difference form.

Crude oil (OIL)
Daily spot prices of the West Texas Intermediate (WTI) crude oil expressed in US dollars per barrel. Oil prices are transformed into logarithmic first differences.

Gold (GLD)
Daily spot prices of gold quoted in US dollars per troy ounce (USD/oz). Gold prices are transformed into logarithmic first differences.

5. Empirical evidence

To provide a more comprehensive assessment, we investigate the robustness of each of the doubtful predictors by designating it as a focus variable in turn, while treating the remainder (18 variables) as doubtful ones. This setting implies that \( Q \) and \( Z \) are interchangeable. The ordinary least squares (OLS) estimator with heteroskedasticity-robust standard errors (White, 1980) is used to generate the EBA regression results.\(^6\)

In all hypothesis testing, we choose a 0.05 significance level to test the null hypothesis that the individual parameter coefficients of each model are not different from zero. Our results are based on a more realistic assumption that the parameter estimates, \( \hat{\beta} \), are not normally distributed. Following Durham (2004) and Walther and Hellström (2021), we conclude that the covariate of interest is robust only if its corresponding estimated coefficient has a CDF(0) \( \geq 0.95 \).

In Table 3, Panel A shows basic statistics for the estimated coefficients, \( \hat{\beta} \), associated with the free and focus variables, while Panels B and C present the EBA estimation results of Leamer's and Sala-i-Martin's versions, respectively. Panel A
Table 2
Basic statistics and results of unit-root tests.

| Variable                        | Mean   | Standard deviation | Skewness | Kurtosis | JB test | Unit-root tests |
|---------------------------------|--------|--------------------|----------|----------|---------|-----------------|
|                                 | ADF    | PP                 |          |          |         |                 |
| US stock returns (R)            | 0.096  | 1.854              | −1.003   | 15.053   | 2.33E+3*** | −5.251*** −25.672*** |
| New COVID-19 positive cases (CC)| 9.901  | 3.029              | −2.465   | 8.024    | 776.409*** | −5.126*** −25.749*** |
| New COVID-19 deaths (DC)        | 6.319  | 2.135              | −2.160   | 6.634    | 499.294*** | −3.965** −3.790** |
| Excess market returns (MKT)     | 0.106  | 1.859              | −0.743   | 13.512   | 1.76E+3*** | −5.321*** −26.020*** |
| Size factor (SMB)               | 0.041  | 1.054              | 0.216    | 5.667    | 114.438*** | −20.232*** −20.307*** |
| Value factor (HML)              | −0.046 | 1.533              | 0.226    | 4.317    | 30.371*** | −18.162*** −18.138*** |
| Investment factor (CMA)         | −0.007 | 0.517              | −0.215   | 5.676    | 115.165*** | −17.757*** −17.867*** |
| Profitability factor (RMW)      | 0.005  | 0.634              | 0.154    | 2.898    | 2.33E+3*** | −17.323*** −17.306*** |
| Wikipedia views for coronavirus (A WC)| 0.028 | 0.267              | 4.725    | 41.528   | 2.46E+4*** | −11.801*** −13.058*** |
| Wikipedia views for US stock markets (A WS)| 0.054 | 0.239              | 1.136    | 9.079    | 659.965*** | −9.312*** −10.694*** |
| CBOE implied volatility index (VIX)| 0.008 | 3.208              | 2.269    | 21.705   | 5.78E+3*** | −9.647*** −25.993*** |
| Twitter-based economic uncertainty (TEU)| −0.001 | 0.288              | 0.124    | 3.286    | 2.236    | −14.913*** −40.734*** |
| US real economic activity (ADS) | 0.003  | 0.498              | 1.177    | 23.826   | 6.86E+3*** | −3.978** −11.314*** |
| Relative Treasury bill rate (RTB)| 0.273  | 0.501              | 2.091    | 5.503    | 394.058*** | −4.482*** −18.921*** |
| Term spread (TSD)               | 0.003  | 0.069              | 0.357    | 13.150   | 1.61E+3*** | −22.059*** −22.566*** |
| Inflation expectation rates (INF)| 0.001  | 0.052              | −0.053   | 12.765   | 1.49E+3*** | −23.277*** −25.695*** |
| US dollar broad exchange rate index (USD)| −0.006 | 0.451              | 0.409    | 7.548    | 333.656*** | −18.338*** −18.374*** |
| European stock market (ESM)     | 0.020  | 1.624              | −1.586   | 17.594   | 3.48E+3*** | −11.643*** −18.827*** |
| Chinese stock market (CSM)      | 0.078  | 1.367              | −0.538   | 4.676    | 61.985*** | −11.746*** −19.607*** |
| Bitcoin price index (XBX)       | 0.373  | 5.242              | −2.161   | 22.517   | 6.24E+3*** | −22.111*** −22.115*** |
| Crude oil (OIL)                 | 0.353  | 5.963              | −1.154   | 19.644   | 4.41E+3*** | −11.787*** −18.688*** |
| Gold (GLD)                      | 0.033  | 1.175              | −0.583   | 6.947    | 264.600*** | −19.736*** −19.981*** |

Notes: This table presents some univariate statistics of the variables under study, together with results of normality and unit-root tests. JB is the Jarque-Bera test statistic, which shows whether a given time series is normally distributed. ADF and PP denote the augmented Dickey-Fuller and the Phillips–Perron (PP) unit-root tests, which have the null hypothesis of a unit root. Based on MacKinnon (1996), the critical values for either the ADF or PP test, with drift and linear trend terms, are −3.983 and −3.422 at the 0.01 and 0.05 significance levels, respectively. *** and ** indicate rejection of the corresponding null hypothesis at the 0.01 and 0.05 significance levels, respectively.
has some interesting results. First, the coefficient estimate related to the free variable, the number of new positive cases, on average, takes a negative sign, which demonstrates the adverse impact of COVID-19 pandemic news on US stock price changes. Surprisingly, this effect lacks statistical significance in almost all specifications, because only 3.406 percent of the models have a corresponding slope coefficient that is statistically discernible from zero. Second, the coefficient estimates on excess market returns, size factor, profitability factor, Wikipedia views for the coronavirus, implied volatility, Twitter-based economic uncertainty, US real economic activity, and US dollar broad exchange rate index have, on average, a negative sign, which implies that those explanatory variables are inversely related to stock returns, whereas the remaining ones, on the whole, have a positive sign. Third, with respect to the magnitude of parameter estimates, the US dollar broad exchange rate index, Twitter-based economic uncertainty, and European stock market (US real economic activity, gold, value factor, and inflation expectation rate) appear to have the largest (smallest) effect, in absolute terms, on US stock returns. Fourth, the corresponding coefficients of VIX, term spread, oil, European and Chinese stock markets demonstrate statistical significance across the entire range of model specifications \(\{\text{i.e., } \text{Pct(Sig.)} = 100\, \%\}\), offering a clear indication that the behavior of US stock prices is fully correlated with those factors, regardless of which variables are in each regression. However, the respective coefficients of the size factor, value factor, investment factor, profitability factor, and US real economic activity are far from statistically different from zero in the vast majority of doubtful-variable combinations (i.e., Pct(Sig.) < 10 percent). For the remainder of the variables, between 12.255 percent (relative Treasury bill rate) and 93.873 percent (excess market returns) of the models have statistically significant slope coefficients. Hence, we conclude that, apart from those of the VIX, term spread, oil, European and Chinese stock markets, the individual explanatory power of the other covariates seem to be uncertain in the face of any slight change in the subset of doubtful variables.

Next, we turn our attention to the results from the stricter version of EBA. The lower and upper bounds of \(\hat{\beta}\) are shown in Panel B of Table 3. Three observations are worth mentioning. First, the extreme bounds of \(\hat{\beta}\) that pertain to the number of new infections have opposite signs. Thus, this variable is typically classified as a weak determinant of US stock returns, not only because of its statistical insignificance in most models (i.e., Pct(Sig.) = 3.406 percent), but also because of its failure to maintain the same sign across all feasible 3-Z variable combinations. This surprising finding is in stark contrast to

### Table 3

| Variable | Panel A: \(\hat{\beta}_Q\) statistics | Panel B: Leamer's approach | Panel C: Sala-i-Martin's approach |
|----------|--------------------------------------|---------------------------|---------------------------------|
|          | \(\hat{\beta}_Q\) \(\pm SE\) \(\times\) Pct (Sig.) | Lower \(\hat{\beta}\) | Upper \(\hat{\beta}\) | Classification | CDF(0) | Classification |
| CC       | -0.235 0.204 3.406 100.000           | -1.224 0.536 Weak       | -                      | Robust          | 86.135 | Weak          |
| MKT      | -0.165 0.039 93.873 100.000           | -0.432 0.017 Weak       | -                      | Robust          | 99.088 | Weak          |
| SMB      | -0.088 0.068 8.333 100.000           | -0.449 0.242 Weak       | -                      | Weak            | 87.190 | Weak          |
| HML      | 0.015 0.049 0.123 100.000           | -0.232 0.325 Weak       | -                      | Weak            | 67.122 | Weak          |
| CMA      | 0.206 0.141 9.069 100.000           | -0.453 0.953 Weak       | -                      | Weak            | 91.047 | Weak          |
| RMW      | -0.055 0.114 1.838 100.000           | -0.623 0.348 Weak       | -                      | Weak            | 66.611 | Weak          |
| AWC      | -0.225 0.315 46.691 100.000         | -2.005 0.826 Weak       | -                      | Weak            | 60.948 | Weak          |
| AWS      | 0.480 0.291 16.667 100.000         | -1.062 1.314 Weak       | -                      | Weak            | 85.491 | Weak          |
| VIX      | -0.423 0.019 100.000 100.000        | -0.501 -0.313 Robust    | 100.000               | Robust          | 100.000 | Robust       |
| TEU      | -0.636 0.246 83.333 100.000         | -1.940 0.212 Weak       | -                      | Robust          | 96.253 | Robust       |
| ADS      | -0.009 0.010 14.167 100.000         | -0.068 0.020 Weak       | -                      | Weak            | 73.769 | Weak          |
| RTB      | 0.056 0.051 12.255 100.000         | -0.153 0.373 Weak       | -                      | Weak            | 81.624 | Weak          |
| TSD      | 0.037 0.010 100.000 100.000        | 0.007 0.084 Robust      | 100.000               | Robust          | 99.954 | Robust       |
| INF      | 0.031 0.014 73.284 100.000         | -0.032 0.135 Weak       | -                      | Weak            | 90.922 | Weak          |
| USD      | -0.691 0.173 85.417 100.000        | -1.968 1.046 Weak       | -                      | Weak            | 80.541 | Weak          |
| ESM      | 0.593 0.046 100.000 100.000        | 0.253 0.901 Robust      | 100.000               | Robust          | 100.000 | Robust      |
| CSM      | 0.298 0.054 100.000 100.000        | 0.010 0.652 Robust      | 100.000               | Robust          | 99.899 | Robust       |
| XBX      | 0.060 0.014 83.333 100.000         | -0.034 0.170 Weak       | -                      | Weak            | 90.720 | Weak          |
| OIL      | 0.259 0.062 100.000 100.000        | 0.002 0.651 Robust      | 100.000               | Robust          | 99.901 | Robust       |
| GLD      | 0.012 0.012 65.139 100.000         | -0.032 0.081 Weak       | -                      | Weak            | 63.427 | Weak          |

Notes: This table presents the EBA results, based on both Leamer's (1983, 1985) and Sala-i-Martin's (1997) versions. \(Q\) is the focus variable of interest, and its coefficient estimate is \(\hat{\beta}\). Each of our nineteen doubtful variables, \(Z\), is set as a \(Q\) variable in succession. \(\hat{\beta}_Q\) and \(SE\) are the respective weighted averages of \(\{\hat{\beta}_Q\}_{i=1}^P\) and their corresponding heteroskedasticity-robust standard errors. Pct (Sig.) is the percentage of regressions in which \(\hat{\beta}\) is found to be statistically different from zero at the 0.05 significance level. Lower (upper) \(\hat{\beta}\) denotes the minimum (maximum) value of \(\hat{\beta}\) minus (plus) 1.96 SE. CDF(0) shows the percentage of the cumulative distribution function of \(\{\hat{\beta}_Q\}_{i=1}^P\) located on the right or left side of zero, whichever is larger. The sign of \(\hat{\beta}_Q\) indicates whether most CDF(0) is above or below zero. Regression models with a VIF threshold > 10 are removed from the analysis. The estimates of \(\hat{\beta}\), across all possible Z-variable combinations, are assumed to be nonnormally distributed. A likelihood-based weighting scheme is used to calculate the aggregate CDF(0) of \(\hat{\beta}\). The overall number of possible 3-Z variable combinations is 3876. The number of regressions estimated for a particular \(Q\) variable is 816, and the number of models per variable passing the VIF test is 816 as well. A potential determinant is deemed robust if its corresponding CDF(0) ≥ 0.95. For variable labels, see Table 2.
those of many papers that confirm the adverse financial market impact of COVID-19 pandemic across different economies (e.g., Alam et al., 2021; Ashraf, 2020; Bakry et al., 2021; O’Donnell et al., 2021; Smales, 2021; Topcu & Gulal, 2020; Zhang et al., 2020). Xu (2021) establishes that daily stock returns in the US (Canada) respond symmetrically (asymmetrically) to the emergence of COVID-19 cases. In this regard, the apparent irrelevance of the COVID-19 infection toll as a driver of US stock markets can be better understood in the context of the “psychophysical numbing” effect, which was first coined by Lifton (1967, 1982) and later developed by Fetherstonhaugh et al. (1997) and Slovic (2010). In this paradoxical phenomenon, the recurrent exposure to life-threatening danger is likely to stimulate apathy, in which people often become less emotionally responsive to mass human suffering as the scale and intensity of such suffering rises over time (Friedrich et al., 1999). This baffling pattern of behavior, which entails low cognitive effort and involvement, might be a reaction to menacing perils, such as the likelihood of a nuclear holocaust, pandemics, bioterrorism, environmental disasters, and climate change. For instance, with no apparent end in sight for the present health crisis, people seem to be gradually desensitized to scary media reports of the pandemic (Stevens et al., 2021). Indeed, mounting COVID-19 cases and deaths might no longer elicit the same emotional response as was the case in the early phases of the outbreak. Similarly, financial market participants, who constitute a distinct segment of the general population, might develop the same apathetic attitude toward press releases about fear-inducing health news. In retrospect, when the pandemic started to take hold in the US in the first months of 2020, there were instances of stock prices that fell to record lows, reminiscent of the global financial meltdown in 2008. Over time, however, financial market anxiety appears to have abated, and investors’ cognitive and emotional reactions were blunted, despite the continuing spread and evolution of the virus. The evident dissociation between the COVID-19 outbreak and its socioeconomic shocks, on the one hand, and US stock market performance, on the other, throughout our sample period might be attributable to collective psychophysical numbing, in which investors, over time, are indifferent to the rising toll of infection and death and thus become less likely to make panic-induced investment decisions. In their analysis of three large corpora of text data incorporating news of deaths (i.e., New York Times articles, News on the Web, Reddit social media website), Bhatia et al. (2021) find that events accompanied by high death counts usually attract less public attention and are discussed with low emotional expression and a weak negative tone. Dyer and Kolic (2020) suggest that Twitter users’ affective responses to the pandemic tend to ease off as the daily COVID-19 death rate increases, providing evidence of the psychophysical numbing effect.

Second, among the doubtful variables, only five (namely, VIX, term spread, oil, European and Chinese stock markets) satisfy Leamer’s rigid criterion of robustness, because their respective coefficients have statistical significance and do not change sign across all possible Z trios. It is obvious that US stock price movements are positively (negatively) associated with term spreads, oil prices, and European and Chinese stock prices (investor fear proxied by the VIX). The term spread (oil) has the narrowest (widest) gap between its upper and lower bounds of $\hat{\beta}$, which might suggest greater (less) precision in its coefficient estimates. Third, the remaining explanatory variables are classified as non-robust, because their corresponding coefficients have their signs reversed at least once, hence failing to withstand any alterations in the doubtful-variable subset.

Finally, the results from Sala-i-Martin’s (1997) version of EBA are listed in Panel C of Table 3. Some observations stand out. First, as expected, two more explanatory variables (excess market returns and Twitter-based economic uncertainty) are no longer weak in this less stringent approach, which means that the number of robust determinants increases to seven. This finding confirms that, of the five risk factors suggested by Fama and French (1993, 2015), the only relevant one that is robustly capable of explaining US stock returns during the pandemic period is the market risk premium. Second, in terms of importance, both the VIX and European stock returns take the lead with $\text{CDF}(0) = 100$ percent, followed closely by the term spread, oil, Chinese stock returns, and market risk premium, with a CDF(0) of between 99.954 percent and 99.088 percent, and, last, Twitter-based economic uncertainty, with a CDF(0) = 96.253 percent. Third, the estimated CDFs for the term spread, oil, and European and Chinese stock returns (excess market returns, VIX, and Twitter-based economic uncertainty) are virtually on the right- (left-) hand side of zero, as shown by their respective $\hat{\beta}_O$, which reveal a mostly positive (negative) relationship with US stock returns across the full range of model specifications. Our results parallel those of previous research. For example, several studies demonstrate statistically significant linkage between stock price changes and each market risk premium (e.g., Choi & Jen, 1991; Fama & French, 1993; Flannery et al., 1997; Hung et al., 2004; Karolyi & Sanders, 1998), economic policy uncertainty indicators (e.g., Ahmed, 2019; Bali et al., 2017; Behera & Rath, 2021; Choi, 2020; Dzielinski, 2012; Wu, Tiwari, et al., 2021), implied volatility (e.g., Dennis et al., 2006; Fleming et al., 1995; Giot, 2005; Hibbert et al., 2008; Smales, 2016; Whaley, 2000), term spread (e.g., Fama & French, 1989; Fatra & Verona, 2020; Hjalmarsson, 2010; Patelis, 1997; Resnick & Shoesmith, 2002; Schwert, 1990; Zhou, 2010), and oil prices (e.g., Angelidis et al., 2015; Bouri et al., 2021a; Filis & Chatziantoniou, 2014; Jones & Kaul, 1996; Miller & Ratti, 2009; Sadorosky, 2001; Salisu & Gupta, 2021).

Fourth, interestingly, the rest of the doubtful variables (i.e., confirmed cases, size factor, value factor, investment factor, profitability factor, Wikipedia views for coronavirus, Wikipedia views for US stock markets, US real economic activity, relative

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7 Multiple papers that offer preliminary evidence on the substantial sensitivity of asset prices to the coronavirus outbreak focus on the first half of 2020, in which the negative consequences of the pandemic were felt mostly by global financial markets (e.g., Ali et al., 2020; Ashraf, 2020; Cepoi, 2020; Izzeldin et al., 2021; Matos et al., 2021; O’Donnell et al., 2021; Smales, 2021; Xu, 2021; Zhang et al., 2020).

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Treasury bill rates, inflation expectation rates, US dollar broad exchange rate index, Bitcoin price index, and gold) are labeled weak, because their respective coefficients do not reach the robustness benchmark of $\text{CDF}(0) \geq 95\%$. After a change in the composition of the doubtful-variable subset, the estimated coefficients on these regressors change their sign or lose statistical significance. Our findings are at odds with those of past works offering evidence on the association between stock price movements and the Fama-French common risk factors (e.g., Bakshi et al., 2020; Boulton et al., 2021; Colavizza, 2020; Gozzi et al., 2020; Moat et al., 2013; O’Leary & Storey, 2020; Roszkowski & Włodarczyk, 2021), US real economic activity (e.g., Giovannelli et al., 2021; Klemola, 2019; Mascio et al., 2021; Smale, 2021; Subramaniam & Chakraborty, 2021), Treasury bill rates (e.g., Ang & Bekaert, 2007; Gupta & Modise, 2013; Hodrick, 1992; Maio, 2013; Park, 2005), inflation (e.g., Anari & Kolari, 2001; Jarefio et al., 2016; Schwert, 1981; Wei, 2010; Zhou, 2010), foreign exchange markets (e.g., Ahmed, 2019; Caporale et al., 2014; Krishnamoorthy, 2001; Nieh & Lee, 2001; Reboredo et al., 2016), Bitcoin markets (e.g., Ahmed, 2021; Gil-Alana et al., 2020; Rehman et al., 2020; Symitsi et al., 2018; Uddin et al., 2020; Ünvan, 2021), and gold markets (e.g., Basher & Sadorsky, 2016; Baur & McDermott, 2010; Drake, 2021; Iqbal, 2017; Tufano, 1998; Tursoy & Faisal, 2018). Using robust penalized predictive regressions, Ciner (2021) demonstrates that investment-grade corporate bond ETFs and high-yield corporate bond ETFs are strong predictors of the US market returns in the S&P 500 index and its constituent sectors during the COVID-19 period.

Fig. 2 illustrates the empirical frequency distribution of the individual estimated regression coefficients, $\hat{\beta}_{i,j}^P$. In each histogram plot, the horizontal axis indicates the magnitude of $\hat{\beta}$ obtained from all possible model specifications, and the vertical axis shows the corresponding probability density. The curve in blue depicts the kernel density of the explanatory variable of primary interest, whereas the green curve is a normally distributed approximation of its coefficient estimates. The two curves show whether $\{\hat{\beta}_{i,j}^P\}_{i=1}^5$ follows a normal distribution. The vertical red line at zero denotes the value of $\hat{\beta}$ in the null-hypothesis significance test (i.e., $H_0: \beta = 0$). If most of the yellow bars are located on the right- (left-) hand side of zero, we infer that most of the coefficient estimates of a given regressor are positive (negative). A closer inspection of the individual histograms reveals that the coefficient estimates of excess market returns (MKT), implied volatility (VIX), and Twitter-based economic uncertainty (TEU) are almost completely on the left-hand side of the red line, whereas those of the term spread (TSD), European stock returns (ESM), Chinese stock returns (CSM), and oil (OIL) are located rightward away from the red line. For the rest of our regressors, however, the area under the density function of their respective coefficients is on both sides of the red line, which reflects their weakness. Importantly, the blue curves appear to have more than a single peak in the majority of histograms, implying multimodality of the distribution of the corresponding coefficient estimates. Furthermore, the plots justify our choice of the generic model of EBA, because the kernel density curve for each variable does not closely mirror the shape of an approximate normal distribution curve.

Finally, as is typically the case with research studies, our investigation has a limitation, which could be an interesting avenue for future research. The EBA is based on the OLS estimator, which assumes consistency in the regression coefficients over time, i.e., $\beta_\hat{\beta} = \beta_\hat{\beta} \forall \text{ and } t$. In reality, however, several potential events (e.g., policy shifts, sudden macroeconomic shocks, price crashes and jumps, or other unforeseen events) could trigger instability in parameter estimates. Indeed, it is highly likely that the economic effects of the pandemic and the concomitant market reactions are heterogeneous across successive waves of COVID-19 infection. This temporal heterogeneity requires separate assessments, because each is expected to yield different results and conclusions. For instance, various economies were adversely affected during the period before vaccines were available. Around the world, events such as declines in the value of stocks, reduced trade and economic activity, and increased market volatility have become commonplace. Nevertheless, later on, mass vaccination programs helped to build herd immunity, minimizing the risk of uncontrolled outbreaks of the pandemic and unexpected waves of infection. Hence, the ultimate consequence of vaccination programs is less risk of unexpected government policy changes, less economic uncertainty, and eventually more stability in financial asset prices. Accordingly, it is important to ask whether the factors that affect US stock returns change over time. Future research could be conducted to address this empirical question.

6. Further analyses

This section addresses potential concerns about our evidence. More explicitly, we confirm whether the results are driven by (1) the VIF cutoff values adopted; (2) the number of doubtful variables included in each regression; and (3) the weighting method used. Moreover, we also explore whether the number of new COVID-19 deaths, instead of cases, is a robust determinant of US market performance. Because of space considerations, we focus our discussion on the estimation results from Sala-i-Martin’s version of EBA.

6.1. Conservative VIF thresholds

To prevent multicollinearity, we adopt a common VIF cutoff of 10 in the main analysis. In this exercise, however, we use more restrictive thresholds of 5 and 3, to double check whether our evidence is plagued by possible traces of collinearity among the explanatory variables. The EBA output based on $\text{VIF} = 5$ and $\text{VIF} = 3$ is reported in Panels A and B of Table 4, respectively.
The estimation results under either threshold value are qualitatively and almost quantitatively the same as those in Table 3. The excess market returns, VIX, TEU, term spread, oil, and European and Chinese stock returns maintain their superiority as robust determinants, whereas the other regressors are still weak, regardless of the VIF cutoffs employed. A salient observation from Panel B of Table 4 is worth noting. For the value factor (HML) and European stock returns (ESM), the number of model specifications that pass the VIF test declines from a maximum of 816 to 799 and 800, respectively. This suggests that some of the coefficient estimates related to those variables exceed the threshold of 3 and hence are dropped from the EBA. Overall, the adoption of more conservative VIF thresholds does not affect our conclusions.

6.2. Expansion of the doubtful-variable subset size

Our analysis is based on the restriction that, for a given focus variable, each regression model incorporates only three doubtful variables (i.e., \( N = 3 \)). To ensure whether the findings are sensitive to the number of conditioning variables, we partially relax this constraint by increasing this number to 4 and 5. Because the inclusion of more regressors is likely to introduce multicollinearity into estimated models, we reduce the VIF threshold to 5. Panels A and B of Table 5 present the EBA parameter estimates for \( N = 4 \) and \( N = 5 \), respectively.

Qualitatively, the results are identical to those in Table 3. Even with increases in the size of the doubtful-variable subset, the same independent variables (namely, excess market returns, term spread, oil, implied volatility, Twitter-based economic uncertainty, and European and Chinese stock returns) retain their respective sign and statistical significance in almost all possible 4-Z and 5-Z variable combinations. That being so, those factors are still labeled robust determinants of US stock market performance. Twitter-based economic uncertainty has marginal robustness, with its estimated CDFs edging above the significance threshold of 95 percent, whereas the remaining robust regressors have the highest level of robustness, with their respective CDFs approaching 100 percent. In addition, the share of statistically significant coefficient estimates on excess market returns and Twitter-based economic uncertainty...
This table reports the results of Sala-i-Martin's (1997) variant of EBA. All $\hat{\beta}$ values are derived from regression models with a VIF lower than 5 and 3. No. of $\hat{\beta}_Q$ denotes the number of models per variable passing the VIF test. The number of possible trio-Z variable combinations is 3,876, and the total number of regressions estimated for a particular $Q$ variable is 816. A potential determinant is deemed robust if its corresponding CDF(0) $\geq$ 0.95. For other legends, see Table 3.

Table 5
Estimation results of EBA with four and five doubtful variables.

| Variable | Panel A: N = 4 | Panel B: N = 5 |
|----------|----------------|----------------|
|          | $\hat{\beta}_0$ | CDF(0) | Classification | $\hat{\beta}_0$ | CDF(0) | Classification |
| CC       | -0.242 5.495 87.133 Weak | -0.247 7.921 87.920 Weak |
| MKT      | -0.148 89.216 98.659 Robust | -0.134 83.403 98.147 Robust |
| SMB      | -0.093 13.333 88.198 Weak | -0.099 18.662 89.265 Weak |
| HML      | -0.019 0.556 62.612 Weak | 0.024 1.611 64.763 Weak |
| CMA      | -0.034 11.797 90.174 Weak | 0.202 13.889 90.467 Weak |
| RMW      | 0.067 3.431 69.013 Weak | -0.079 5.451 71.439 Weak |
| AWS      | -0.181 38.007 58.289 Weak | -0.143 31.081 55.765 Weak |
| VX       | -0.415 100.000 100.000 Robust | -0.408 100.000 100.000 Robust |
| TEU      | -0.586 77.810 95.710 Robust | -0.543 72.409 95.194 Robust |
| ADS      | -0.010 6.634 76.260 Weak | -0.010 9.104 78.588 Weak |
| RTB      | 0.058 13.660 82.485 Weak | 0.061 15.184 83.634 Weak |
| TSD      | 0.036 100.000 99.954 Robust | 0.035 100.000 99.954 Robust |
| INF      | 0.031 66.334 86.527 Weak | 0.026 59.734 81.835 Weak |
| USD      | -0.581 81.601 77.559 Weak | -0.490 77.953 74.733 Weak |
| ESM      | 0.560 100.000 100.000 Robust | 0.532 100.000 100.000 Robust |
| CRM      | 0.269 100.000 99.874 Robust | 0.245 100.000 99.851 Robust |
| XBS      | 0.050 77.778 86.229 Weak | 0.042 72.222 81.496 Weak |
| OIL      | 0.234 99.902 99.840 Robust | 0.214 99.699 99.790 Robust |
| GLD      | 0.010 54.412 59.744 Weak | 0.008 44.479 56.169 Weak |

Notes: This table reports the results of Sala-i-Martin's (1997) variant of EBA. All $\hat{\beta}$ values are derived from regression models with subsets of four and five doubtful variables (Z). The overall number of possible 4-Z (5-Z) variable combinations is 11,628 (27,132). If N = 4 (N = 5), the number of regressions estimated for a particular Q variable totals 3060 (8568), and the number of models per variable that pass the VIF test is 3060 (8568) as well. A potential determinant is deemed robust if its corresponding CDF(0) $\geq$ 0.95. For other legends, see Table 3.

Table 4
Estimation results of EBA with more conservative VIF thresholds.

| Variable | Panel A: VIF = 5 | Panel B: VIF = 3 |
|----------|------------------|------------------|
|          | $\hat{\beta}_0$ | CDF(0) | Classification | $\hat{\beta}_0$ | CDF(0) | Classification |
| CC       | -0.235 816 86.135 Weak | -0.235 816 86.135 Weak |
| MKT      | -0.165 816 99.088 Robust | -0.165 816 99.088 Robust |
| SMB      | -0.088 816 87.190 Weak | -0.088 816 87.190 Weak |
| HML      | -0.015 816 60.722 Weak | 0.014 799 60.497 Weak |
| CMA      | 0.206 816 91.047 Weak | 0.206 816 91.047 Weak |
| RMW      | -0.055 816 66.611 Weak | -0.055 816 66.611 Weak |
| AWS      | -0.225 816 60.948 Weak | -0.225 816 60.948 Weak |
| VIX      | -0.423 816 100.000 Robust | -0.423 816 100.000 Robust |
| TEU      | -0.636 816 96.253 Robust | -0.636 816 96.253 Robust |
| ADS      | -0.089 816 73.769 Weak | -0.009 816 73.769 Weak |
| RTB      | 0.056 816 81.624 Weak | 0.056 816 81.624 Weak |
| TSD      | 0.037 816 99.954 Robust | 0.037 816 99.954 Robust |
| INF      | 0.037 816 90.922 Weak | 0.037 816 90.922 Weak |
| USD      | -0.691 816 80.541 Weak | -0.691 816 80.541 Weak |
| ESM      | 0.593 816 100.000 Robust | 0.601 800 100.000 Robust |
| CSM      | 0.298 816 99.899 Robust | 0.298 816 99.899 Robust |
| XBS      | 0.060 816 90.720 Weak | 0.060 816 90.720 Weak |
| OIL      | 0.259 816 99.901 Robust | 0.259 816 99.901 Robust |
| GLD      | 0.012 816 63.427 Weak | 0.012 816 63.427 Weak |

Notes: This table reports the results of Sala-i-Martin's (1997) variant of EBA. All $\hat{\beta}$ values are derived from regression models with a VIF lower than 5 and 3. No. of $\hat{\beta}_Q$ denotes the number of models per variable passing the VIF test. The number of possible trio-Z variable combinations is 3,876, and the total number of regressions estimated for a particular $Q$ variable is 816. A potential determinant is deemed robust if its corresponding CDF(0) $\geq$ 0.95. For other legends, see Table 3.

decreases from 93.873 to 83.333 percent, respectively, when $N = 3$ (see Panel A of Table 3) falls to 83.403 and 72.409 percent, respectively, when $N = 5$. This decrease indicates that some of the statistically significant coefficients in the baseline case of $N = 3$ become insignificant after the number of conditioning variables is increased.
6.3. Weighting systems

In Section 4, model-specific likelihoods are employed to calculate the aggregate weighted CDF(0) of \( \hat{\beta} \) for all independent variables. In this section, we investigate whether using the adjusted \( R^2 \)-weighting scheme, in place of the likelihood-weighting counterpart, could change our results. Furthermore, some authors (e.g., Bernoth & Colavecchio, 2014; Gassebner et al., 2016; Sturm & De Haan, 2005) argue against relying on goodness-of-fit statistics to produce regression weights, because those statistics by no means reflect the probability that a given model is the true one. Consequently, we repeat the empirical exercise without assigning weights to the different regression models. Weighted and unweighted averages of the individual CDFs are reported in Panels A and B of Table 6, respectively.

A careful inspection of Panel A reveals that the results based on adjusted \( R^2 \)-weights are not qualitatively different from those based on the integrated likelihoods in Table 3. Thus, the likelihood-weighting scheme and adjusted \( R^2 \)-weighting scheme lead to the same conclusions. But when no weights are assigned, as in Panel B, the inflation expectation rates (INF) and Bitcoin returns (XBX) also become robust determinants, which exceed the robustness threshold of CDF(0) ≥ 95 percent. In the light of their respective \( \hat{\beta} \) signs, the two variables have, on average, a positive, though small, influence on US stock prices. Overall, our main findings remain qualitatively unaltered, even after a different weighting method is applied and even after an unweighted version of the individual CDFs is used.

6.4. Robustness of fatality counts

Because of its largely documented explanatory power over stock market movements in recent literature, the number of new COVID-19 positive cases is treated as the only independent variable in the preceding analysis. However, our results show that this covariate is not robust. In this section, we rerun all the regression specifications, using the number of new COVID-19 deaths, rather than infections, as the independent variable. One line of research (e.g., Ali et al., 2020; Bakry et al., 2021; Matos et al., 2021; Uddin et al., 2021) shows that the severity of the pandemic, in terms of daily death rates, tends to have a negative effect on financial markets. The EBA estimation results are listed in Table 7.

The coefficient estimate associated with the number of new deaths (DC), on average, has a negative sign, which indicates that news updates on the coronavirus death toll tend to cast a pall over US stock price performance. Nevertheless, this adverse influence lacks statistical support in the majority of regressions, because the share of models in which the corresponding slope coefficient is statistically distinguishable from zero is 39.732 percent. Moreover, this variable has a CDF(0) of 78.804 percent, which demonstrates its weakness. This finding offers further support for the psychophysical numbing effect. But the inclusion of daily death counts, as an alternative to the number of new infections, offers further support for the psychophysical numbing effect.

Table 6

| Variable | Panel A: Adjusted \( R^2 \)-based weights | Panel B: Unweighted |
|----------|------------------------------------------|-------------------|
|          | \( \hat{\beta} \) | \( SE \) | CDF(0) | Classification | \( \hat{\beta} \) | \( SE \) | CDF(0) | Classification |
| CC       | −0.239 | 0.209 | 85.880 | Weak | −0.264 | 0.237 | 84.932 | Weak |
| MKT      | −0.177 | 0.040 | 99.235 | Robust | −0.227 | 0.044 | 99.651 | Robust |
| SMB      | −0.085 | 0.070 | 85.760 | Weak | −0.075 | 0.081 | 79.510 | Weak |
| HML      | 0.015  | 0.050 | 60.225 | Weak | 0.012  | 0.059 | 56.960 | Weak |
| CMA      | 0.205  | 0.145 | 90.389 | Weak | 0.231  | 0.168 | 89.341 | Weak |
| RMW      | −0.050 | 0.117 | 64.666 | Weak | −0.050 | 0.136 | 62.378 | Weak |
| AWC      | −0.275 | 0.323 | 64.449 | Weak | −0.590 | 0.367 | 82.400 | Weak |
| AWS      | 0.439  | 0.299 | 83.226 | Weak | 0.222  | 0.344 | 68.144 | Weak |
| VIX      | −0.424 | 0.019 | 100.000 | Robust | −0.426 | 0.019 | 100.000 | Robust |
| TEU      | −0.686 | 0.252 | 96.810 | Robust | −0.932 | 0.283 | 98.631 | Robust |
| ADS      | −0.010 | 0.010 | 75.448 | Weak | −0.012 | 0.012 | 80.021 | Weak |
| RTB      | 0.055  | 0.052 | 80.284 | Weak | 0.064  | 0.061 | 79.985 | Weak |
| TSD      | 0.038  | 0.011 | 99.951 | Robust | 0.043  | 0.012 | 99.935 | Robust |
| INF      | 0.041  | 0.015 | 92.285 | Weak | 0.060  | 0.016 | 96.463 | Robust |
| USD      | −0.719 | 0.178 | 80.119 | Weak | −0.928 | 0.191 | 85.937 | Weak |
| ESM      | 0.611  | 0.047 | 100.000 | Robust | 0.638  | 0.048 | 100.000 | Robust |
| CSB      | 0.311  | 0.056 | 99.809 | Robust | 0.368  | 0.060 | 99.927 | Robust |
| XBX      | 0.067  | 0.015 | 92.452 | Weak | 0.090  | 0.016 | 96.464 | Robust |
| OIL      | 0.271  | 0.064 | 99.914 | Robust | 0.333  | 0.071 | 99.955 | Robust |
| GLD      | 0.015  | 0.001 | 68.127 | Weak | 0.029  | 0.014 | 86.183 | Weak |

Notes: Panels A and B of this table report the weighted and unweighted parameter estimates, respectively, of Sala-i-Martin’s (1997) version of EBA. All \( \hat{\beta} \) values are derived from regression models with subsets of three doubtful variables (Z). The overall number of possible 3-Z variable combinations is 3876. The number of regressions estimated for a particular Q variable totals 816, and the number of models per variable that pass the VIF test is 816 as well. A potential determinant is deemed robust if its corresponding CDF(0) ≥ 0.95. For other legends, see Table 3.
still include excess market returns, implied volatility, TEU, the term spread, oil, and European and Chinese stock returns.

7. Summary and concluding remarks

Large-scale crises, whether of a social, political, economic, or public health nature, continue to be an overarching predictive and causal risk factor for countries around the world. One such vivid example is the spatiotemporal diffusion of the novel coronavirus, which has wreaked havoc on the world economy. Financial markets, as a forward-looking barometer of the global economy, have not been immune to the vagaries of the pandemic. Developed and emerging markets alike have been subject to widespread pessimism about the virus’s lethal trajectory, which has sent investors into a panicked sell-off. Meanwhile, with the pandemic causing global uncertainty, a growing body of research has explored the impact on financial market dynamics. Notwithstanding its profusion and diversity, the existing literature appears to be silent about which factors contribute to the stock price formation process during this era of a new normal. Our main goal is to address this void in the literature. This paper identifies the robust drivers of US stock price movements under the economic shadow of the COVID-19 crisis and in the presence of model uncertainty, using a wide range of influential factors recognized by relevant works as important determinants of stock prices. The empirical analysis addresses model uncertainty issues by adopting an extreme bounds analysis. This approach sifts through the pool of independent variables to demonstrate the robustness or weakness of a given parameter to any change in the conditioning set of information. Our potential explanatory variables include new COVID-19 infections, new COVID-19 deaths, excess market returns, size, value, investment, profitability, Wikipedia views for US stock markets, Wikipedia views for coronavirus, CBOE implied volatility index (VIX), Twitter-based economic uncertainty, US real economic activity, relative Treasury bill rates, the term spread, inflation expectation rates, US dollar broad exchange rate index, European stock markets, Chinese stock markets, Bitcoin price index, oil, and gold.

The results of Leamer’s variant of EBA suggest that, out of the universe of doubtful variables, only five factors (VIX, term spread, oil, and European and Chinese stock markets) satisfy Leamer’s rigid criterion for robustness, because their respective coefficients have statistical significance and maintain the same sign across the entire range of model specifications. The remaining explanatory variables are classified as weak in the sense that the sign of their corresponding coefficients is reversed at least once and thus cannot withstand any alterations in the doubtful-variable subset. However, with Sala-i-Martin’s version of EBA, two further explanatory variables (excess market returns and TEU) are no longer weak. Hence, the number of robust determinants totals seven. In terms of importance, the VIX and European stock returns both take the lead with a CDF(0) = 100 percent, followed closely by the term spread, oil, Chinese stock returns, and market risk premium, with a CDF(0) between 99.954 percent and 99.088 percent, and, lastly, Twitter-based economic uncertainty, with a CDF(0) = 96.253 percent. Additionally, the estimated CDFs for the term spread, oil, European and Chinese stock returns (excess market returns, VIX, and Twitter-based economic uncertainty) are almost on the right-(left-) hand side of zero, which indicates a mostly positive (negative) relationship with US stock returns across the full range of model specifications. More interestingly, the health burden of COVID-19, in terms of infections and deaths, is a weak determinant of US stock returns—results that contradict those in recent literature. The disconnect between the COVID-19 outbreak and US stock market performance throughout our sample period might be attributable to collective psychophysical numbing, in which over time investors become indifferent to the rising toll of infections and deaths and thus less likely to make panic-driven investment decisions.

Taken together, our results offer three practical implications for investors and traders. First, in view of their robustness, the variables excess market returns, VIX, term spread, TEU, oil, and European and Chinese stock returns are informative and yield relevant information that helps to explain US stock price changes. Ergo, portfolio managers and investors searching for possible clues about the future trajectory of stock prices should closely track developments in these robust determinants. Second, from a risk management perspective, the weak sensitivity of the US stock market to Bitcoin and gold markets suggests that it could be used as an effective hedge against the vagaries of price swings in Bitcoin and gold. But the irrelevance of the COVID-19 infection count to the stock price formation process
during our sample period provides strong evidence that the recurrent exposure to life-threatening danger is likely to trigger apathy, in which people become less emotionally responsive to mass human suffering as the scope and severity of suffering rise over time. Similarly, financial market participants, who constitute a distinct portion of the general population, might also develop apathy toward press releases containing fear-inducing health news. Therefore, over time investors appear to grow indifferent to the rising toll of infections and deaths and thus less likely to be motivated by panic in making investment decisions.

Third, even though the relevant literature mentions multiple factors as primary drivers of stock price movement, only a few of them prove robust in the sense that their corresponding coefficient estimates are statistically significant and maintain the same sign across all possible changes in the conditioning information set. The concern with the extant studies is that they propose numerous models that seem to be well specified given the datasets at hand, but they reach mixed conclusions regarding which factors are important drivers of stock market performance. The proper specification of a model for explaining stock returns necessitates consideration of many potential factors, their relationships, and interactions. Uncertainty about the determinants in prior research and the structural form of their relations with stock markets emphasize the importance of accounting for model uncertainty in constructing models to explain and predict stock price behavior.

Conflict of interest

I hereby declare that I do not have any commercial or associative interest that represents a conflict of interest in connection with the article entitled “What drives US stock markets during the COVID-19 pandemic? A global Q1 sensitivity analysis”.

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