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Do lower environmental, social, and governance (ESG) rated companies have higher systemic impact? Empirical evidence from Europe and the United States

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Abstract

In recent years, companies have increasingly been characterized by environmental, social, and governance (ESG) scores, and investors and academics have raised questions concerning financial performance and investment risks. Now, as the European Banking Authority has acknowledged that ESG risks can potentially impact the economic and financial system, the debate on systemic risk has gained traction. Understanding the relationship between ESG merit and systemic risk is of utmost importance for the stability of the economic and financial system, still, research is limited. Relying on real-world European and United Stated data, we quantify systemic risk by means of QL-CoVaR. Empirical analyses of the entire period from 2007 to 2021 show that companies with high ESG scores tend to exhibit low QL-CoVaR values indicating a positive effect of ESG scores. Such evidence is confirmed by clustering the individual companies into ESG portfolios and focusing on COVID-19. Additional insights using the individual pillars are also provided.

KEYWORDS
CoVaR, ESG, sustainability, financial stability, systemic risks

1 | INTRODUCTION

Company characteristics are the key driver in determining performance and risk profiles. Besides financial information, non-financial information has recently gained relevant attention as investors also look for sustainability in their investment decisions. Companies are increasingly characterized by their non-financial information, more specifically by environmental, social, and governance (ESG) scores and the debate about the impact of ESG information on company performance and risk is still open.

Generally, ESG scores are designed by different rating providers (e.g., Bloomberg and Reuters) and aim to assess the ESG performance of companies by considering several criteria, measurements, and quantitative and qualitative methods; see, among others, Bhattacharya and Sharma (2019), and Berg and Lange (2020). ESG scores typically range between 0 and 100. More specifically, assets with higher ESG scores indicate a more responsible ESG behavior. Moreover, ESG scores are typically associated with a rating class (i.e., *A*,*B*,*C*, *D*) using thresholds or quartiles of the ESG score values.

This complementary non-financial information can have the potential to increase the accuracy of performance forecasts and risk assessments (Achim & Borlea, 2015). Technically, quantifying these aspects should help to reach one of the main objectives of the European Commission's 2018 Action Plan, which is "managing financial risks stemming from climate change, resource depletion, environmental degradation, and social issues" (European Banking

Authority, 2021, p. 15). To do so, it is crucial to understand how these factors translate into financial risks that may affect the whole financial system (European Banking Authority, 2021). In particular, the European Banking Authority (EBA) states that ESG risks can materialize when ESG factors have a negative impact on financial performance or solvency (European Banking Authority, 2020). Moreover, according to a recent report, "ESG risks can also impact the financial system and economy as a whole, with potential systemic consequences" (European Banking Authority, 2021, p. 33). This effect could be prominent in macroeconomic factors (i.e., economic growth, labor productivity, or sovereign debt) and hence impact different institutions through the whole economy (European Banking Authority, 2021). Thus, higher ESG scores could be connected to more prudent and sustainable actions leading to a reduction in the overall risk. Additionally, Cerqueti et al. (2021) argued that high ESG-ranked funds could comprise an intrinsic property of lowering systemic risk due to less overlap with other funds, lower contagion, and a long-term investment approach. Furthermore, companies with higher ESG scores are less exposed to the risk of future litigation (Cerqueti et al., 2021).

While this is an essential topic for the stability of the financial system and the economy as a whole, research is still limited and often provides ambiguous results. Boubaker et al. (2020) were among the first to find that better corporate, social, and responsibility (CSR) practices, measured by all qualitative dimensions (except corporate governance) of the MSCI ESG index, lead to lower financial distress and default risk, with positive effects on financial stability and more crisis-resilient economies. Later, Eratalay and Cortés Ángel (2022) proposed a VAR-MGARCH model, performing a principal component analysis (Billio et al., 2012) to obtain systemic risk indicators. They found that companies with higher ESG scores contribute 7.3% less to systemic risk. Focusing on the COVID-19 period and the individual pillars, Eratalay and Cortés Ángel (2022) found no significant effects for the E-Pillar. In contrast, the S- and G-Pillar had a statistically significant impact (positive and negative, respectively) on systemic risk. Similarly, building on network analysis, Cerqueti et al. (2021) showed that ESG funds, defined as interconnected components of a unified system, may be less vulnerable to systemic shocks and more resilient to contagion under lower-volatility regimes. Furthermore, active disclosure is a key factor in effectively reducing the systemic risk for Chinese listed companies (Waner, 2021).

When considering the banking sector, Murè et al. (2021) added that higher ESG scores are connected to a lower probability of sanctions for Italian banks. Ducassy (2013) argued that lowering environmental costs and risks can aid in promoting financial stability during crisis periods. Moreover, Chiaramonte et al. (2021) showed that higher ESG and individual pillar scores are associated with lower default risk for European banks during times of crisis. These findings are in line with Aevoae et al. (2022), who used the ΔCoVaR to show that higher ESG Combined Scores are connected to a reduction of system-wide distress using a sample of publicly listed banks. In addition, higher G-Pillar scores imply lower bank interconnectedness, lower systemic risk, and higher financial stability (Aevoae et al., 2022). Furthermore, the S-Pillar also seems to play an important role. Indeed Scholtens and Van't Klooster (2019) argued that higher sustainability scores could reduce the systemic risk contribution of banks. Similarly, Lupu et al. (2022) found evidence that the overall ESG score, as well as the individual pillar score, has a notable impact on the financial stability of banks in Europe, stressing that this influence is nonlinear. Additionally, the duration of ESG disclosure also plays a role, as Chiaramonte et al. (2021) showed that it can positively affect stability for European banks. On the other hand, the study of Anginer et al. (2018) highlighted that shareholder-friendly corporate governance is linked to higher systemic risk in the US banking sector.

Several approaches have been proposed to estimate systemic risk in the literature. Among them, the CoVaR and ΔCoVaR introduced by Adrian and Brunnermeier (2016) are some of the most widely used. Recently, Bonaccolto, Caporin, and Paterlini (2019) proposed the so-called QL-CoVaR, which extends the CoVaR by employing an estimation process that captures the state in which the response and the conditioning variables are jointly in distress. An accurate estimation of the magnitude of the distress degree in financial connections is of utmost importance during economic or financial crises when the correlation among companies increases and the risk of contagion can impact the stability of the whole system (Bonaccolto, Caporin, & Paterlini, 2019). This is achieved by linking the left tails of the company's return and systemic return distributions. Thus, the QL-CoVaR better captures the degree of distress a stressed company exerts on the market. In contrast, the CoVaR's coefficients reflect the stressed state of the response variable only. As shown by Bonaccolto, Caporin, and Paterlini (2019), the QL-CoVaR model provides improvements in terms of predictive accuracy and is more informative than the CoVaR during tail events.

In this paper, relying on a large sample of European (EU) and American (US) companies, we estimate the systemic risk by adopting the ΔQL-CoVaR and analyze the relationship between ESG merit and systemic risk, with a particular focus on crisis periods. Empirical analyses on the entire period from 2007 to 2021 show that A-rated companies tend to exhibit more limited ΔQL-CoVaR values than lower-rated companies. We also confirm these findings with a portfolio analysis, in which we cluster the individual companies into four ESG indexes during the COVID-19 pandemic, which turns out to be the most relevant event, in terms of systemic impact, from 2007 to 2021.

The paper is structured as follows. Section 2 introduces the QL-CoVaR. Section 3 describes the data and the empirical setup. Then, Section 4 reports the empirical results obtained from the ESG analysis, while Section 5 focuses on the individual E-, S-, and G-Pillars analyses. Finally, Section 6 concludes the paper.

2 | QUANTILE-LOCATED CONDITIONAL VALUE-AT-RISK

Let y_t and $x_{j,t}$ be, respectively, the returns of the economic system and of company j observed at time t, for $t = 1, \ldots, T$ and $j = 1, \ldots, N$. We also define $\mathbf{M}_t$ as the vector of a set of control variables observed at time t. Following Adrian and Brunnermeier (2016), we estimate the conditional τ-th and θ-th quantiles of $x_{j,t}$ and y_t, denoted as $Q_\tau(x_{j,t})$ and $Q_\theta^{(j)}(y_t)$, respectively, using the following quantile regression models (Koenker & Bassett, 1978):

$$Q_\tau(x_{j,t}) = \alpha_\tau^{(j)} + \boldsymbol{\beta}_\tau^{(j)} \mathbf{M}_{t-1}', \tag{1}$$

$$Q_\theta^{(j)}(y_t) = \delta_\theta^{(j)} + \lambda_\theta^{(j)} x_{j,t} + \boldsymbol{\gamma}_\theta^{(j)} \mathbf{M}_{t-1}', \tag{2}$$

where $\tau,\theta \in (0, 1)$.

In the CoVaR framework, θ and τ take low values, typically within the interval (0,0.05], to focus on left-tail relationships between y_t and $x_{j,t}$. After estimating the parameters $\alpha_\tau^{(j)}$, $\boldsymbol{\beta}_\tau^{(j)}$, $\delta_\theta^{(j)}$, $\lambda_\theta^{(j)}$ and $\boldsymbol{\gamma}_\theta^{(j)}$ in Equations (1) and (2), as well as $\widehat{Q}_\tau(x_{j,\tau}) = \widehat{\alpha}_\tau^{(j)} + \widehat{\boldsymbol{\beta}}_\tau^{(j)} \mathbf{M}_{t-1}'$, Adrian and Brunnermeier (2016) computed the Conditional Value-at-Risk (CoVaR) of the economic system conditional on the VaR of company j as follows:

$$\text{CoVaR}_{t,\theta,\tau}^{(j)} = \widehat{\delta}_\theta^{(j)} + \widehat{\lambda}_\theta^{(j)} \widehat{Q}_\tau(x_{j,t}) + \widehat{\boldsymbol{\gamma}}_\theta^{(j)} \mathbf{M}_{t-1}'. \tag{3}$$

Setting $x_{j,t} = \widehat{Q}_\tau(x_{j,t})$ allows us to estimate the VaR of the financial system conditional on institution i being in distress as described by Adrian and Brunnermeier (2016). Likewise, the CoVaR of y_t conditional on the median of company j is obtained by replacing τ with 1/2:

$$\text{CoVaR}_{t,\theta,1/2}^{(j)} = \widehat{\delta}_\theta^{(j)} + \widehat{\lambda}_\theta^{(j)} \widehat{Q}_{1/2}(x_{j,t}) + \widehat{\boldsymbol{\gamma}}_\theta^{(j)} \mathbf{M}_{t-1}'. \tag{4}$$

From the difference of the conditional quantiles defined in Equations (3) and (4), we then compute the ΔCoVaR introduced by Adrian and Brunnermeier (2016):

$$\begin{aligned} \Delta\text{CoVaR}_{t,\theta,\tau}^{(j)} &= \text{CoVaR}_{t,\theta,\tau}^{(j)} - \text{CoVaR}_{t,\theta,1/2}^{(j)} \\ &= \widehat{\lambda}_\theta^{(j)} \left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t}) \right], \end{aligned} \tag{5}$$

which quantifies the marginal contribution of company j to the overall systemic risk. Note that the parameters and coefficients in Equations (2)–(5) are functions of θ only, neglecting then the role of τ, which reflects the stressed state of $x_{j,t}$. In our study, we employ a generalization of the CoVaR, which builds on the quantile-on-quantile approach introduced by Sim and Zhou (2015) to measure the effects that the quantiles of oil price shocks have on the quantiles of the US stock return. After that, the quantile-on-quantile method was adopted by Bonaccolto, Caporin, and Panzica (2019) to estimate financial networks and introduced into the CoVaR framework by Bonaccolto, Caporin, and Paterlini (2019), who proposed the so-called Quantile-Located CoVaR (QL-CoVaR) model. The QL-CoVaR model builds on an estimation process depending on both θ and τ, capturing then the state in which y_t and $x_{j,t}$ are jointly in distress.

Taking into account the effects of both θ and τ, the model defined in Equation (2) is rewritten as:

$$Q_{\theta,\tau}^{(j)}(y_t) = \delta_{\theta,\tau}^{(j)} + \lambda_{\theta,\tau}^{(j)} x_{j,t} + \boldsymbol{\gamma}_{\theta,\tau}^{(j)} \mathbf{M}_{t-1}'. \tag{6}$$

Note that the parameters in (6) have both θ and τ as subscripts, as they depend on the quantile levels of both y_t and $x_{j,t}$, being estimated from the following optimization problem:

$$\underset{\delta_{\theta,\tau}^{(j)},\lambda_{\theta,\tau}^{(j)},\boldsymbol{\gamma}_{\theta,\tau}^{(j)}}{\arg\min} \sum_{t=2}^{T} \rho_\theta \left[y_t - \delta_{\theta,\tau}^{(j)} - \lambda_{\theta,\tau}^{(j)} x_{j,t} - \boldsymbol{\gamma}_{\theta,\tau}^{(j)} \mathbf{M}_{t-1}' \right] K\left(\frac{\widehat{F}(x_{j,t}) - \tau}{h} \right), \tag{7}$$

where $\rho_\theta(e) = e(\theta - \mathbf{1}_{\{e<0\}})$ is the asymmetric loss function characterizing the quantile regression method introduced by Koenker and Bassett (1978), $\mathbf{1}_{\{\cdot\}}$ is an indicator function, which takes the value of one if the condition in $\{\cdot\}$ is true, and the value of zero otherwise, whereas $K(\cdot)$ is a kernel function, with bandwidth h, that captures the impact of $x_{j,t}$ in the neighborhood of its τth quantile.

Following Sim and Zhou (2015), we employ a Gaussian kernel $K(\cdot)$ to weight the impact of $x_{j,t}$ in the neighborhood of its τ-th quantile, and use the following specification of $\widehat{F}(x_{j,t})$:

$$\widehat{F}(x_{j,t}) = T^{-1} \sum_{p=1}^{T} \mathbf{1}_{\{x_{j,p} < x_{j,t}\}}. \tag{8}$$

We then compute the QL-CoVaR at the (θ,τ)-th level as follows:

$$\text{QL-CoVaR}_{t,\theta,\tau}^{(j)} = \widehat{\delta}_{\theta,\tau}^{(j)} + \widehat{\lambda}_{\theta,\tau}^{(j)} \widehat{Q}_\tau(x_{j,t}) + \widehat{\boldsymbol{\gamma}}_{\theta,\tau}^{(j)} \mathbf{M}_{t-1}', \tag{9}$$

where $\widehat{Q}_\tau(x_{j,t}) = \widehat{\alpha}_\tau^{(j)} + \widehat{\boldsymbol{\beta}}_\tau^{(j)} \mathbf{M}_{t-1}'$ is obtained from Equation (1).

We also estimate the QL-CoVaR model with 1/2 in place of τ, and obtain the ΔQL-CoVaR: $\Delta\text{QL-CoVAR}_{t,\theta,\tau}^{(j)} = \text{QL-CoVaR}_{t,\theta,\tau}^{(j)} - \text{QL-CoVaR}_{t,\theta,1/2}^{(j)}$. Following Bonaccolto, Caporin, and Paterlini (2019), we decompose the ΔQL-CoVaR as follows:

$$\begin{aligned} \Delta\text{QL-CoVAR}_{t,\theta,\tau}^{(j)} = {} & \widehat{\delta}_{\theta,\tau}^{(j)} - \widehat{\delta}_{\theta,1/2}^{(j)} + \widehat{\lambda}_{\theta,\tau}^{(j)} \left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t}) \right] \\ & + \left(\widehat{\lambda}_{\theta,\tau}^{(j)} - \widehat{\lambda}_{\theta,1/2}^{(j)} \right) \widehat{Q}_{1/2}(x_{j,t}) \\ & + \left(\widehat{\boldsymbol{\gamma}}_{\theta,\tau}^{(j)} - \widehat{\boldsymbol{\gamma}}_{\theta,1/2}^{(j)} \right) \mathbf{M}_{t-1}'. \end{aligned} \tag{10}$$

We stress here the role of $\widehat{\lambda}_{\theta,\tau}^{(j)}$, which quantifies the sensitivity of y_t to $x_{j,t}$ when both are in distress (see Equation 6). As a result, when keeping the other components in Equation (10) constant, $\Delta\text{QL-CoVAR}_{t,\theta,\tau}^{(j)}$ would react more readily to the shocks of those companies with greater $\widehat{\lambda}_{\theta,\tau}^{(j)}$ values. However, $\widehat{\lambda}_{\theta,\tau}^{(j)}$ is multiplied by $\left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t}) \right]$ in Equation (10), and these two components are estimated from two different models; the ones defined in Equation (6) and (7), respectively. More specifically, $\left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t}) \right]$ quantifies the specific idiosyncratic risk of company j, when it moves from its own median to its own VaR and, therefore, does not depend on y_t.

TABLE 1 The table reports the descriptive statistics for the constituents of the EURO STOXX 600 and the S&P 500, respectively

Data set	j	T	$\widehat{\mu}$	$\widehat{\sigma}$	$\widehat{kurt}$	$\widehat{skew}$	*freq.*
EURO STOXX 600	294	4002	0.02	0.04	16.89	−0.37	Daily
S&P 500	323	4001	0.06	0.05	19.48	−0.36	Daily

Note: Columns 1–8 report the data set, the number of constituents (j), the number of observations (T), the average annualized mean ($\widehat{\mu}$), the average annualized standard deviation ($\widehat{\sigma}$), the average kurtosis ($\widehat{kurt}$), the average skewness ($\widehat{skew}$) of the asset returns, and the sampling frequency (*freq.*).

As a result, risky companies with greater values of $\left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right]$ would have a moderate or non-relevant systemic impact if $\widehat{\lambda}^{(j)}_{\theta,\tau}$ approaches zero.

The component $\widehat{\lambda}^{(j)}_{\theta,\tau}\left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right]$ given in Equation (10) resembles the ΔCoVaR specification defined in Equation (5). However, $\widehat{\lambda}^{(j)}_{\theta,\tau} \neq \widehat{\lambda}^{(j)}_{\theta}$ due to the quantile-located effects.[1] In our study, we estimate the standard errors of the coefficients given in Equation (10) by employing a bootstrap method (Efron, 1979): the xy-pair approach of Kocherginsky (2003), which provides accurate results without any distributional assumption.

3 | DATA DESCRIPTION AND EMPIRICAL SET-UP

Firstly, we consider the daily logarithmic return, daily market capitalization, yearly environmental, social, and governance (ESG) and individual E-, S-, and G-Pillar data of 294 EU companies which are the constituents of the EURO STOXX 600 index and 323 US companies which are the constituents of the Standard & Poor' (S&P) 500 index whose observations are continuously available from January 2, 2007 to May 3, 2022. The return of each of these firms represents the variable $x_{j,t}$ from Equation (1) to Equation (10).[2] We employ the daily return of the S&P 500 index as the response variable y_t when focusing on the US firms, and the daily return of the EURO STOXX 600 index when considering the EU companies, spanning the time interval from January 2, 2007 to May 3, 2022.

We extract the time series and ESG data from Refinitiv, the financial and risk business unit of Thomson Reuters. Their rank-based ESG scores are based on publicly reported data (Refinitiv, 2021). ESG data are only sparsely available in the early 2000s from our data provider, thus we chose to start in 2007, allowing us to take into account different states of the economy. More specifically, we are looking at the 2007–2009 sub-prime crisis, the EU sovereign debt crisis beginning in late 2009, and the more recent COVID-19 pandemic and endemic, which made fundamental changes to the work life of many employees and employers (Microsoft, 2022).

Both data sets are similar in size, however, the US data exhibits stronger average kurtosis as shown in Table 1. Additionally, we find that the ESG scores of both data sets improve over time as companies are under pressure to improve their ESG performance and continue to disclose more information (see Table 2 and Figure 1) (Sahin et al., 2022).

In this research, we aim to shed light on a possible relationship between the ESG profile of a given firm and its systemic relevance considering the EU market and US market separately. For this purpose, we compute the average ESG score ($\overline{\text{ESG}}$) of each company in our data set from 2007 to 2022. We then cluster these companies into four different classes, from A to D, using the thresholds defined by Refinitiv. Specifically, class A includes those companies with $\overline{\text{ESG}} > 75$. The companies of class B have $50 < \overline{\text{ESG}} \leq 75$, whereas we require $25 < \overline{\text{ESG}} \leq 50$ for class C. Finally, class D has the companies with the lowest average scores: $\overline{\text{ESG}} \leq 25$. We provide the definition of these classes and the number of assets in Table 3.

In addition to $x_{j,t}$ and y_t, that we defined above, ΔQL-CoVaR$^{(j)}_{t,\theta,\tau}$ depends on the vector of control variables $\mathbf{M}_{t-1}$, the composition of which is described below. Starting from the EU market, we considered the lagged observations of the following variables: (i) the return of the EURO STOXX index (i.e., the lagged value of the response variable); (ii) the return of the EURO STOXX 50 Volatility Index (VSTOXX)[3]; (iii) the return of the New Composite Indicator of Systemic Stress (CISS) Index provided by the European Central Bank.[4] The additional variables from (iv) to (ix) are the European Fama–French research factors: (iv) the excess market return (MKT-RF); (v) Small Minus Big, the average return on the small stock portfolios minus the average return on the big stock portfolios (SMB); (vi) High Minus Low, the average return on the value portfolios minus the average return on the growth portfolios (HML); (vii) Robust Minus Weak, the average return on the robust operating profitability portfolios minus the average return on the weak operating profitability portfolios (RMW); (viii) Conservative Minus Aggressive, the average return on the conservative investment portfolios minus the average return on the aggressive investment portfolios (CMA); and (ix) the risk-free rate (RF).[5] From the principal component analysis on the control variables described above, we find that the first two components explain 89.61% of their overall variability. We then use these two components as entries of the $\mathbf{M}_{t-1}$ vector. As highlighted by Bonaccolto, Caporin, and Paterlini (2019), this choice allows us to exploit the near totality of the information conveyed by these control variables, with advantages in terms of computational costs.

[1]In our empirical analysis, we found that $\widehat{\lambda}^{(j)}_{\theta,\tau}$ estimated for the QL-CoVaR is typically greater than the CoVaR $\widehat{\lambda}^{(j)}_{\theta}$ coefficient, highlighting the fact that the co-movement between the overall system and the individual companies becomes more relevant when capturing their joint distress. These additional results are available upon request.

[2]Date of retrieval of the ESG data were April 28, 2022 and September 6, 2022 of the E, S, and G Pillar data.

[3]This time series is available at https://www.stoxx.com.

[4]Further information about the CISS Index can be found online at https://sdw.ecb.europa.eu.

[5]The data on the variables from (iv) to (ix) were downloaded from the Kenneth R. French library at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Data set	j	T	$\widehat{\mu}$	$\widehat{\sigma}$	$\widehat{kurt}$	$\widehat{skew}$	*freq.*
EURO STOXX 600	294	16	62.35	76.53	3.09	−0.54	yearly
S&P 500	323	16	54.84	92.28	2.92	−0.42	yearly

Note: Columns 1–8 report the data set, the number of constituents (j), the number of observations (T), the average mean ($\widehat{\mu}$), the average standard deviation ($\widehat{\sigma}$), the average kurtosis ($\widehat{kurt}$), the average skewness ($\widehat{skew}$) of the asset returns, and the sampling frequency (*freq.*).

TABLE 2 The table reports the descriptive statistics for the ESG data of the constituents of the EURO STOXX 600 and the S&P 500, respectively

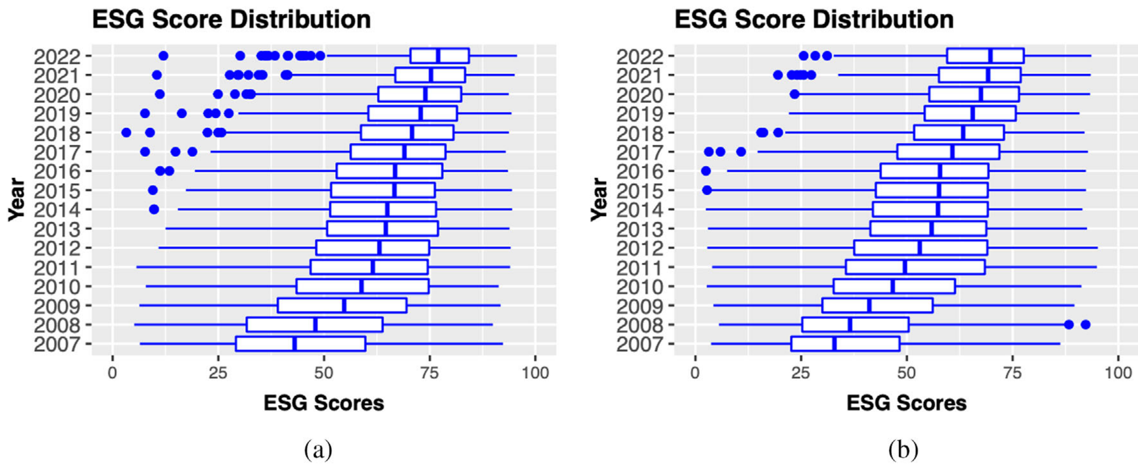


FIGURE 1 Boxplots of ESG scores over time (y-axis. We report the boxplots for the individual pillar scores in Appendix A. (a) EU companies (b) US companies [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Composition of ESG classes A, B, C, and D

ESG class	Condition	EU companies	US companies
A	($\overline{ESG}$ > 75)	71	33
B	(50 < $\overline{ESG}$ ≤ 75)	158	165
C	(25 < $\overline{ESG}$ ≤ 50)	59	117
D	($\overline{ESG}$ ≤ 25)	6	8

Note: From left to right, this table reports the definition of classes A, B, C, and D, the condition required for each class, and the number of EU and US companies within each of them.

Likewise, when using the US data, we employ the first two components of the lagged values of the following variables: (i) the return of the S&P 500 index (i.e., the lagged value of the response variable); (ii) the return of the VIX index[6]; (iii) the change in the Financial Stress Index (FSI) provided by the Office of Financial Research of the US Department of the Treasury.[7] The additional six variables are the same Fama–French research factors listed above for the EU data but are now obtained from the US market.[8]

In our empirical analysis, we set $\theta = \tau = 0.05$, so that we focus on the left tails of the conditional distributions of y_t and $x_{j,t}$. Finally, we set the bandwidth value h equal to 0.15. As explained by Bonaccolto, Caporin, and Paterlini (2019), this is a good compromise between the bias and the variance of the estimates.

4 | EMPIRICAL RESULTS FOR ESG INDEXES

In this section, we analyze the results obtained from the estimation of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ defined in Equation (10). ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ depends on different components. Among them, we highlight the central role of $\widehat{\lambda}^{(j)}_{\theta,\tau}$, which quantifies the sensitivity of y_t to the stressed state of $x_{j,t}$.

We first analyze in Figure 2 the boxplots of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ estimated for each firm included in our data set. We cluster the EU (Figure 2a) and US (Figure 2b) companies into classes A, B, C, and D, that we build according to their $\overline{ESG}$ values (see Table 3). Moreover, for each boxplot, we contrast $\widehat{\lambda}^{(j)}_{\theta,\tau}$ with $\widehat{\lambda}^{(j)}_{\theta,1/2}$ to assess the quantile-located effects. In general, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ take positive values (see Figure 2), highlighting the fact that there is a positive relationship between the return of a given company and the quantile of the overall system. Moreover, the greater $\widehat{\lambda}^{(j)}_{\theta,\tau}$ and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ are, the greater is the response of y_t in its θ-th quantile. Thus, we would observe a larger negative impact on systemic risk and financial stability. Additionally, it is notable that the $\widehat{\lambda}^{(j)}_{\theta,\tau}$ tend to be larger for the US sample compared with the EU sample indicating higher sensitivity.

For each class, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ is greater than $\widehat{\lambda}^{(j)}_{\theta,1/2}$, highlighting the fact that the relationships between the overall system and each firm become more relevant when they are both in distress. Focusing on the EU

[6]This time series has been downloaded from Thomson Reuters.
[7]Further information about the FSI can be found online at https:www.financialresearch.gov.
[8]These time series were downloaded from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

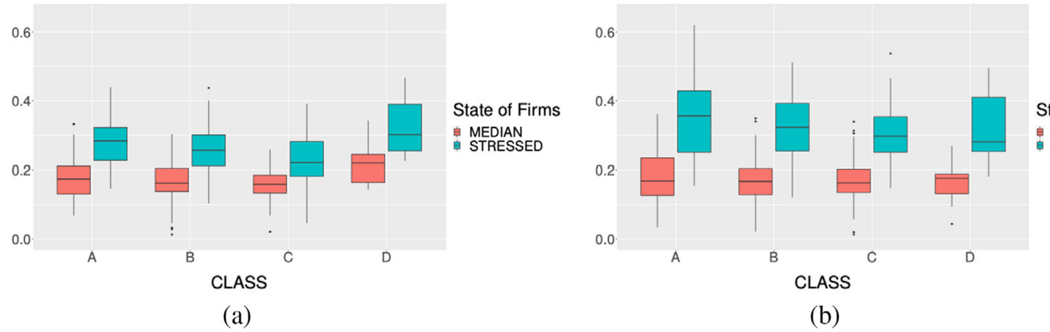


FIGURE 2 Boxplots of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ (STRESSED, cyan color) and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ (MEDIAN, red color) estimated for the EU and US companies clustered by $\overline{\text{ESG}}$ classes. (a) EU companies (b) US companies [Colour figure can be viewed at wileyonlinelibrary.com]

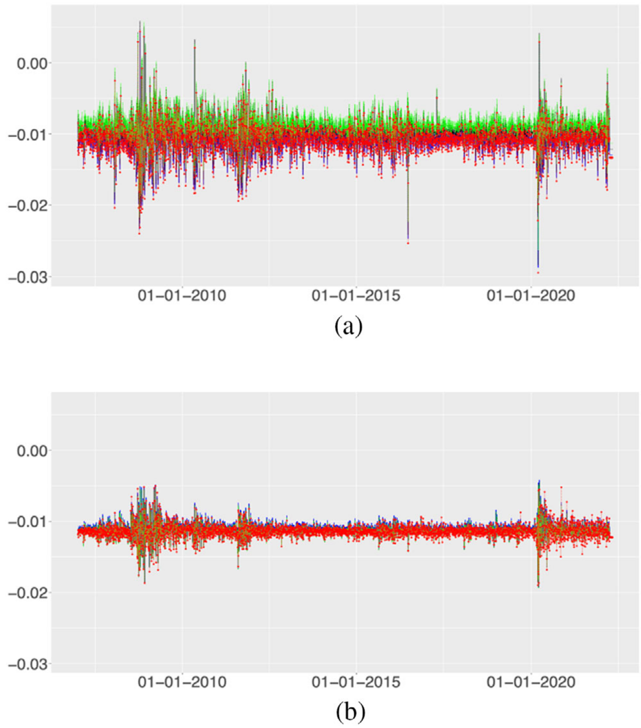


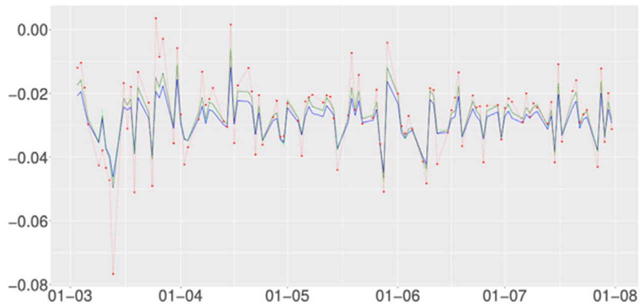
FIGURE 3 Average of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by $\overline{\text{ESG}}$ classes: A (blue line), B (black line), C (green line), and D (red line and red points) (a) EU companies (b) US companies [Colour figure can be viewed at wileyonlinelibrary.com]

companies (Figure 2a), $\widehat{\lambda}^{(j)}_{\theta,\tau}$ takes, on average, greater values for class D, followed by classes A, B, and C, with medians of 0.301, 0.282, 0.256, and 0.219, respectively. The third quartile of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ follows the same order across the four classes: 0.389 for class D, 0.322 for class A, 0.299 for class B, and 0.280 for class C. In contrast, the median of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ decreases from class A to class D in Figure 2b, where we focus on the US market: 0.356 for class A, 0.322 for class B, 0.296 for class C, and 0.279 for class D. However, we again find a U-shape behavior in the third quartile of $\widehat{\lambda}^{(j)}_{\theta,\tau}$, which takes higher values for the extreme A and D classes. Thus, as indicated by the greater $\widehat{\lambda}^{(j)}_{\theta,\tau}$, the economic and financial system is more sensitive to shocks of companies belonging to the extreme ESG classes A and D. Classes A and D might be attracting more attention from investors due to the positive and negative screening investment policies, respectively (Amel-Zadeh & Serafeim, 2018). In fact, best in class and worst in class are two investment criteria commonly used to decide which assets to focus on.

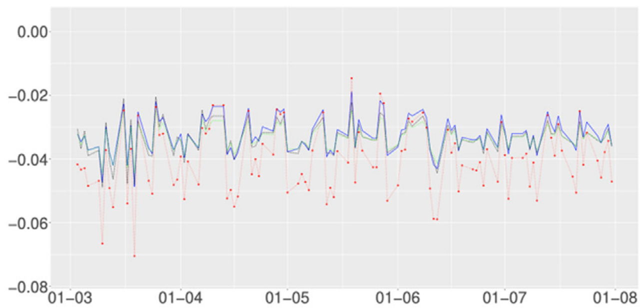
Thus, the boxplots in Figure 2 suggest substantial preliminary evidence: the VaR of both the EU and US markets tends to be more sensitive to the stressed state of companies that stand out from the crowd for more extreme ESG scores (such as the ones belonging to the A and D classes). This result is more notable for the D-rated companies in the EU market. Moreover, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ is almost always statistically significant at a 5% level, with a p-value greater than 0.05 for only three EU companies belonging to class C.

We now focus on the overall ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ time series to analyze the systemic impact of the conditioning EU and US companies. We remind the reader that more negative values of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ point out a greater systemic impact. Again, we evaluate the effects of the ESG classification. For this purpose, we compute, for each day t (with $t = 1, \ldots, T$), the mean of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ estimated for those companies belonging to class k, denoted as $\overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$, with $k \in \{\text{A, B, C, D}\}$. As a result, we obtain four-time series displayed in Figure 3. First, we highlight the strong impact of important tail events, such as the 2007–2009 sub-prime crisis and the EU sovereign debt crisis beginning in late 2009. However, the greatest impact is caused by the outbreak of the more recent COVID-19 pandemic. Specifically, the most extreme (negative) peak in the EU market was observed on March 13, 2020. The day before, on March 12, 2020, the European Central Bank (ECB) president Christine Lagarde had stated that "we are not here to close spreads, this is not the function or the mission of the ECB." This statement triggered the fears of investors, who interpreted it as refuting the "whatever it takes" policy advocated by the previous ECB president Mario Draghi (Moessner & de Haan, 2022). In contrast, the most extreme peak in the US market was detected on March 17, 2020, when Wall Street witnessed one of its worst days in history, given the threat of a possible global recession in the near term.

Second, we highlight (with the red points in Figure 3) the impact of the D-rated companies for the EU and US markets. Starting from the EU market (see Figure 3a), on average, the D-rated companies



(a)



(b)

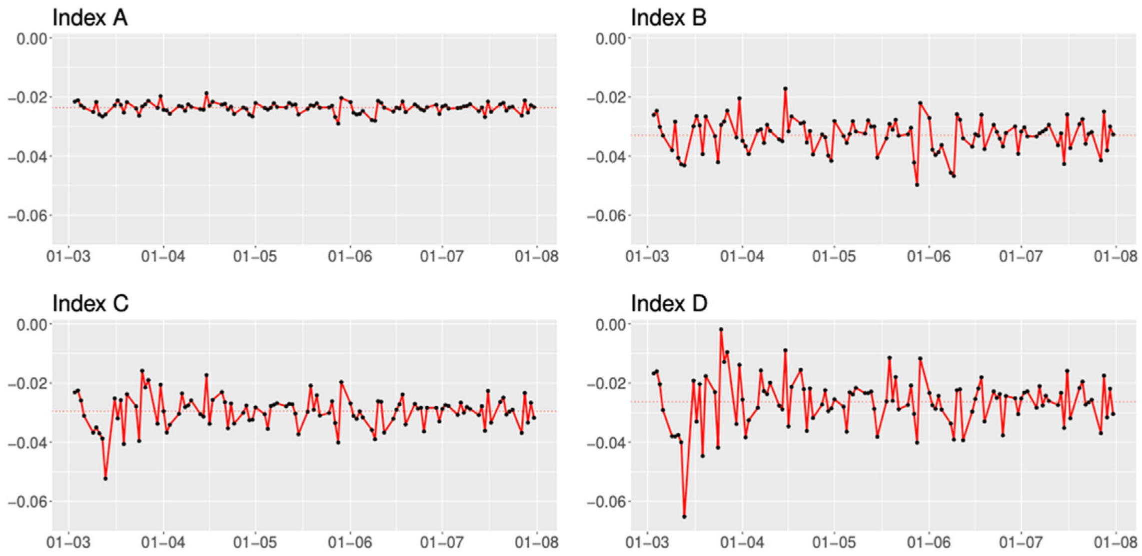
FIGURE 4 Average of $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by $\overline{\text{ESG}}$ classes: A (blue line), B (black line), C (green line), and D (red line and red points). The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020 (a) EU companies (b) US companies [Colour figure can be viewed at wileyonlinelibrary.com]

continuously have the greatest systemic impact from January 2, 2017, to May 3, 2022. Indeed, $\overline{\Delta\text{QL-CoVAR}}^{(D)}_{t,\theta,\tau} < \overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$ for $t = 1, \ldots, T$ and $k \neq D$. The A-rated companies continuously record, on average, the second greatest systemic impact for $t = 1, \ldots, T$. Therefore, the companies with extreme ESG classes (i.e., classes D and A) turn out to be, on average, more systemically relevant, consistent with the U-shape behavior of the boxplots given in Figure 2a. As for the US market (see Figure 3b), the D-rated companies record, on average, the greatest systemic impact on 2819 out of 4000 days. The C-rated companies have, on average, the greatest systemic impact on the remaining 1180 days. The latter result might appear quite surprising, given the moderate values of $\hat{\lambda}^{(j)}_{\theta,\tau}$ for class C in Figure 2b. However, in addition to $\hat{\lambda}^{(j)}_{\theta,\tau}$, $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ depends on other relevant components. For instance, we refer to $\hat{Q}_\tau(x_{j,t}) - \hat{Q}_{1/2}(x_{j,t})$: the risk of a given company when it moves from its median to its extreme τth quantile, regardless of the dynamics of y_t. Similar to the previous exercise, for each day t, we compute the mean of $\hat{Q}_\tau(x_{j,t}) - \hat{Q}_{1/2}(x_{j,t})$ estimated for those companies belonging to class k, with $k = \{A, B, C, D\}$.[9]

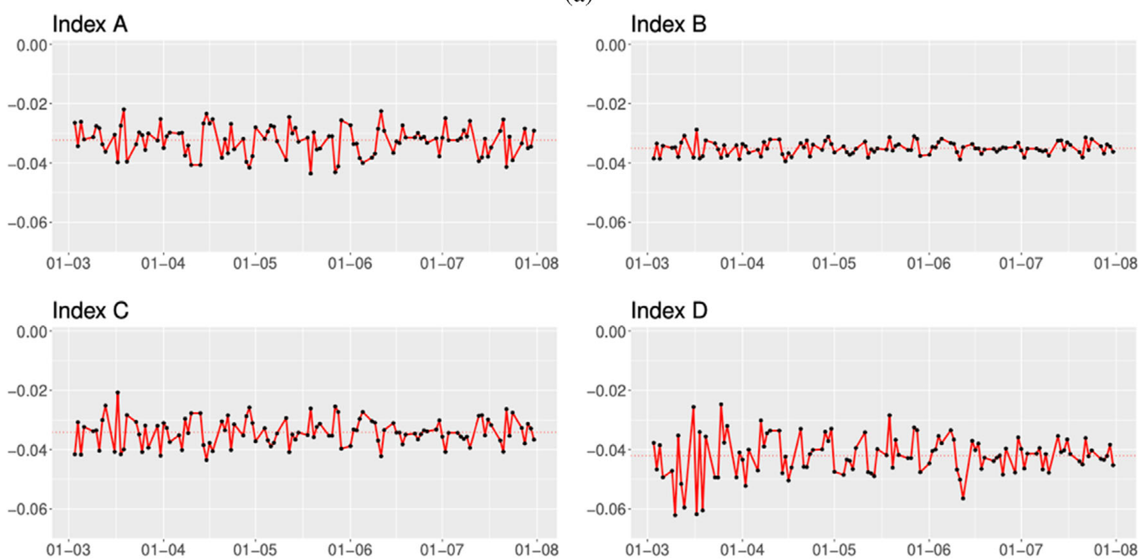
The full-sample analysis discussed so far provides important findings. However, it relies on time-invariant coefficients estimated from a relatively long interval spanning 16 years, characterized by a continuous alternation of stable and turbulent phases of the financial markets. Therefore, the effects of an important tail event would be smoothed by other events (possibly different in nature) along this long time interval and would not be properly captured using these full-sample coefficients. For this reason, we enrich our study with an additional exercise based on a shorter time interval. Among the different and relevant events we can consider from 2007 to 2022, we focus on the COVID-19 pandemic, as it has the greatest impact in terms of $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ on both the EU and US markets. Specifically, we re-estimate the QL-CoVaR model using the data from March 3, 2020, to July 31, 2020 and evaluate the contribution of each ESG class by computing the $\overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$ time series, that we display in Figure 4. In contrast to the previous full-sample analysis, where we clustered the EU and US companies of our data set according to $\overline{\text{ESG}}$, we now directly use the ESG scores of the year 2020 to be consistent with the sub-sample from which we obtain the new estimates. The systemic impact of class D in Figure 4 is clearer compared with Figure 3. Interestingly, the D-rated companies have, on average, the greatest impact on only 32 out of 109 days in Figure 4a. In contrast, the A-rated companies provide the lowest $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ on 71 days. As a result, it might seem that the latter have a greater systemic relevance during the time interval March 3, 2020–July 31, 2020. However, if we focus on the most relevant peaks, as well as on other bearish phases, class D has the greatest impact, with relevant values of the difference $\overline{\Delta\text{QL-CoVAR}}^{(D)}_{t,\theta,\tau} - \overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$ (with $k \neq D$). Moving to the US data, the D-rated companies have, on average, the greatest systemic impact on 89 out of 109 days.

So far, we have evaluated the link between ESG and systemic relevance by estimating the QL-CoVaR model for each company in our data set. In a second step, we aggregated the resulting estimates by ESG class. As a robustness analysis, we can also proceed differently, building on portfolio analysis. In a first step, we aggregate the individual companies into four indexes, according to their ESG scores observed in the year 2020, for both the EU and US markets. For instance, the constituents of Index A are the companies belonging to class A (i.e., the ones with ESG > 75). The return of Index A is computed as the weighted mean of the returns yielded by its constituents. The weight of each company is updated with a daily frequency and is calculated as its market capitalization observed on day t divided by the sum of the market capitalization of the other A-rated companies calculated on day t, for each day from March 3, 2020, to July 31, 2020. Likewise, we obtain the returns of Indexes B, C, and D. In a second step, we then estimate $\Delta\text{QL-CoVAR}^{(k)}_{t,\theta,\tau}$: the ΔQL-CoVaR that we obtain by replacing $x_{j,t}$ (i.e., the return of company j with the return of Index k, with $k \in \{A, B, C, D\}$. We display the results in Figure 5. We see that Index D has the greatest systemic impact during the outbreak of the COVID-19 pandemic in both the EU and US markets. It is interesting to see that the mean of $\Delta\text{QL-CoVAR}^{(D)}_{t,\theta,\tau}$ in the bottom-right panel of Figure 5a (depicted with the plotted-red line) is lower than the mean of $\Delta\text{QL-CoVAR}^{(B)}_{t,\theta,\tau}$ and $\Delta\text{QL-CoVAR}^{(C)}_{t,\theta,\tau}$ in the same figure. However, $\Delta\text{QL-CoVAR}^{(D)}_{t,\theta,\tau}$ reaches the minimum value of -0.065 on March 13, 2020. $\Delta\text{QL-CoVAR}^{(C)}_{t,\theta,\tau}$ also exhibits a relevant peak, but of a more moderate value of -0.052 on the same day. In contrast, $\Delta\text{QL-CoVAR}^{(B)}_{t,\theta,\tau}$ does not show any particular extreme value on March

[9]Similar results are obtained using the median instead of the mean as we observe a change of category for less than 12% of the companies.



(a)



(b)

FIGURE 5 Trend of ΔQL-CoVAR$^{(k)}_{t,\theta,\tau}$, with $k \in \{A,B,C,D\}$ clustered by $\overline{\text{ESG score}}$. The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020 to July 31, 2020 (a) EU companies (b) US companies [Colour figure can be viewed at wileyonlinelibrary.com]

13, 2020. ΔQL-CoVAR$^{(A)}_{t,\theta,\tau}$ continuously has a stable trend from March 3, 2020 to July 31, 2020 in the top-left panel of Figure 5a. Moving to the US market, ΔQL-CoVAR$^{(A)}_{t,\theta,\tau}$ and ΔQL-CoVAR$^{(C)}_{t,\theta,\tau}$ have a similar behavior, whereas ΔQL-CoVAR$^{(B)}_{t,\theta,\tau}$ is more stable (see Figure 5b).

5 | RESULTS FOR INDIVIDUAL E-, S-, AND G-PILLARS

So far, we have analyzed the systemic impact of the EU and US companies in our data set clustered by ESG scores. The ESG score of a given company is computed from three different components: the E-, S-, and G-Pillars. Hence, it is interesting to further develop our analysis by disentangling these three different pillars. Similar to Figure 1, we also find an increase in individual E-, S-, and G-Pillar scores throughout time as presented in Figure A1. Additionally, we point out that about a third to a half of the companies tend to change classes (A, B, C, or D) with a tendency toward higher levels (for instance, one asset might be in ESG class C and equally in individual E-, S-, or G-Pillar class B), therefore, the results might differ when using the individual pillar scores.

Madison and Schiehll (2021) showed that the individual pillars might have a different sensitivity to materiality issues. Moreover, Lupu et al. (2022) found that the impact of the individual pillars on systemic risk varies to a certain degree. Finally, according to the European Banking Authority (2021), especially the E-Pillar could

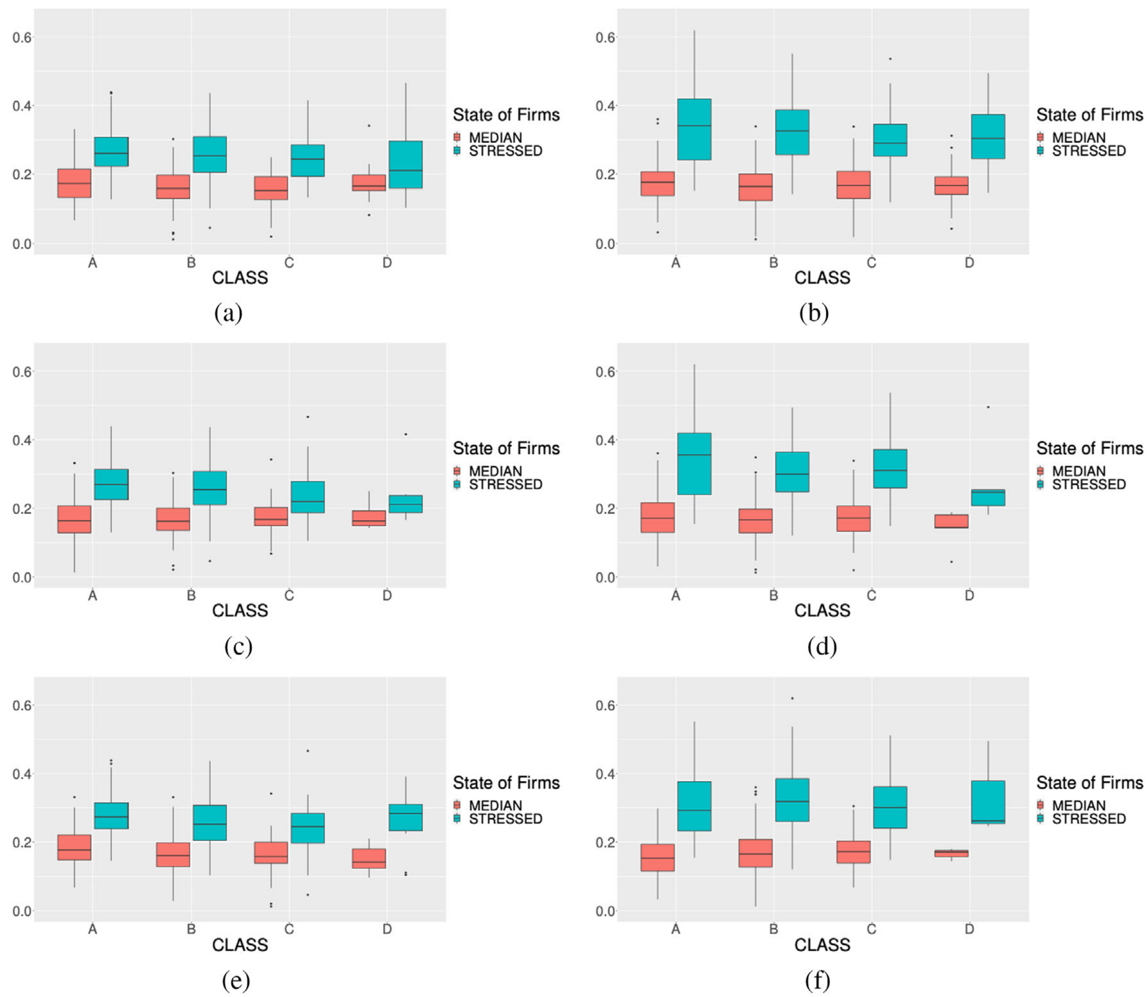


FIGURE 6 Boxplots of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ (STRESSED, cyan color) and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ (MEDIAN, red color) estimated for the EU and US companies clustered by the individual pillar classes(a) EU companies—clustered by $\overline{\text{E-Pillar}}$ classes (b) US companies—clustered by $\overline{\text{E-Pillar}}$ classes(c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes (d) US companies clustered by $\overline{\text{S-Pillar}}$ classes (e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes (f) US companies clustered by $\overline{\text{G-Pillar}}$ classes [Colour figure can be viewed at wileyonlinelibrary.com]

significantly affect the overall financial system due to the scale and complexity of the environmental risks. It is worth taking a closer look at this additional analysis, the results of which are reported and discussed below.

Following the same order adopted in Section 4, we start from the analysis of the $\widehat{\lambda}^{(j)}_{\theta,\tau}$ coefficients. Again, we cluster these coefficients according to the average scores of the individual EU and US companies, which are now computed for the three different pillars, denoted as $\overline{\text{E-Pillar}}$, $\overline{\text{S-Pillar}}$, and $\overline{\text{G-Pillar}}$, respectively. We display the results in Figure 6. Similar to the estimates depicted in Figure 2, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ tends to be greater than $\widehat{\lambda}^{(j)}_{\theta,1/2}$. Therefore, we again have evidence that the relationships between the overall system and the conditioning companies become more relevant when both are in distress. The U-shaped behavior previously found in Figure 2 is again present when using the G-Pillar on the EU data in Figure 6e. In contrast, in the other cases, the median of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ tends to decrease from higher to lower classes. Let us remember that the $\widehat{\lambda}^{(j)}_{\theta,\tau}$ coefficient quantifies the sensitivity of the ΔQL-CoVaR to $\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$; that is, the specific risk of company j when it moves from its median to its stressed state (see Equation 10). As a result, on average, the systemic risk would react more readily to the idiosyncratic risks or shocks of higher E-, S-, and G-Pillar classes for a given value of $\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$. Nevertheless, as discussed in Section 4, moderate values of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ could be offset by large values of $\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$ in determining the magnitude of the overall ΔQL-CoVaR measure. Focusing on the E-Pillar, we find larger variability in the $\widehat{\lambda}^{(j)}_{\theta,\tau}$ values of D-rated EU companies and A-rated US companies. Moving to the S-Pillar, D-rated companies show the lowest variability. It is also interesting to observe that the variability in the $\widehat{\lambda}^{(j)}_{\theta,\tau}$ values of both the EU and US companies is similar across the G-Pillar classes; see Figure 6e,f.

Similar to Figure 3, Figure 7 shows the time series of the cross-sectional mean of $\Delta\text{QL-CoVaR}^{(j)}_{t,\theta,\tau}$ estimated for the EU and US companies. Using the individual E-, S-, and G-Pillars still allows us to identify the impact of important tail events, such as the sub-prime crisis, the EU sovereign debt crisis, and the COVID-19 outbreak. In Section 4, we saw that, on average, the D-rated companies have the

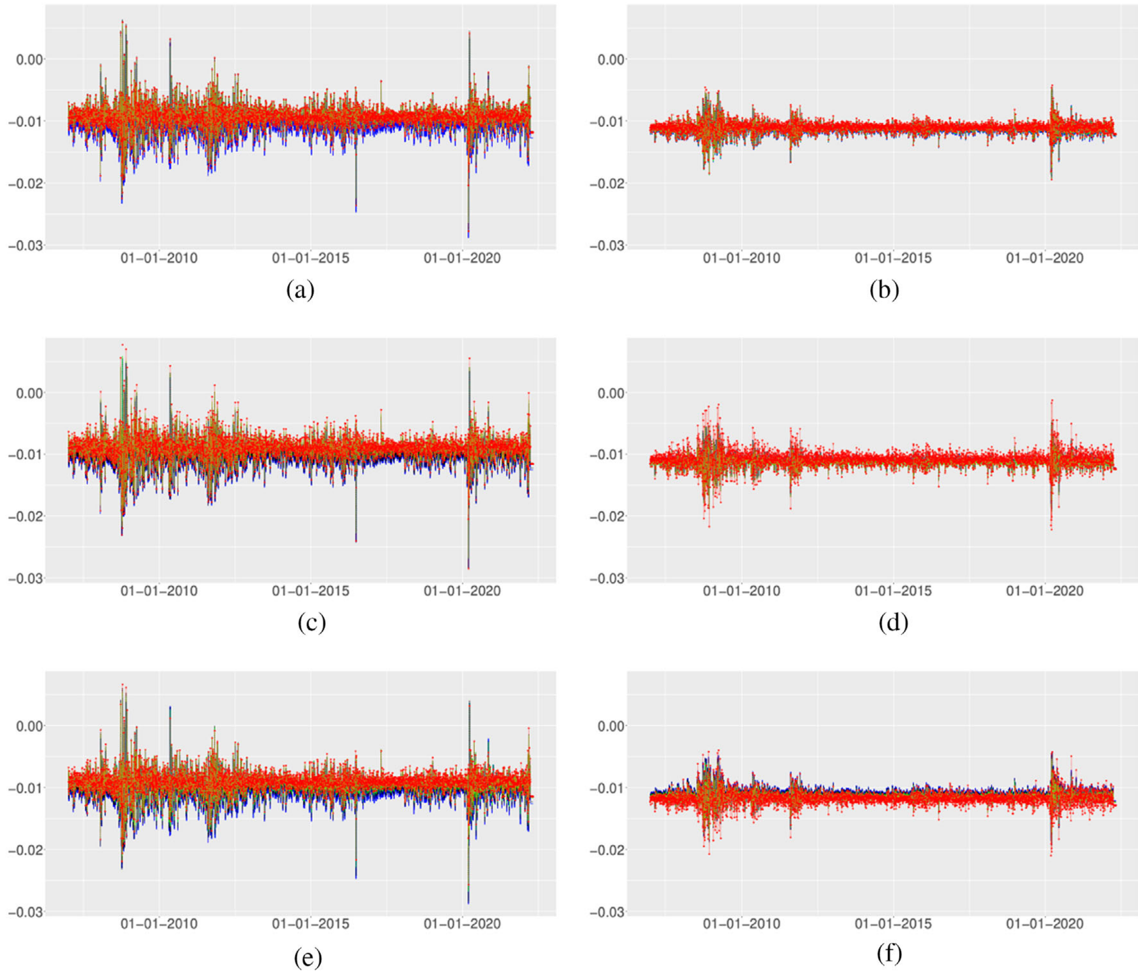


FIGURE 7 Average of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by individual pillar classes: A (blue line), B (black line), C (green line), and D (red line and red points). (a) EU companies—clustered by $\overline{\text{E-Pillar}}$ classes. (b) US companies—clustered by $\overline{\text{E-Pillar}}$ classes. (c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes. (d) US companies clustered by $\overline{\text{S-Pillar}}$ classes. (e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes. (f) US companies clustered by $\overline{\text{G-Pillar}}$ classes [Colour figure can be viewed at wileyonlinelibrary.com]

greatest impact, followed by the A-rated companies (see Figure 3). Now, the D-rated companies are the most critical contributors to systemic risk in the US market when employing the S- and G-Pillars (Figure 7d,f). However, the A-rated companies have a lower relevance in Figure 7d,f. As for the EU market, the systemic relevance of the A- and D-rated companies is evident when adopting the E- and S-Pillars, mainly during the tail events mentioned above (Figure 7a,c).

The results discussed above build on the estimates obtained from the full-sample data. Now, we present the results based on the estimates derived from the COVID-19 period. We find that, during the COVID-19 pandemic, the results obtained from the overall ESG scores are similar to those using the E-, S-, and G-Pillar scores on the EU data, and for the S-Pillar score on the US data as presented in Figure 8. However, we find notable differences in the US data when clustering the companies according to the E- and G-Pillar scores (Figure 8b,f). In Figure 8b, in which we focus on the E-Pillar score, C-rated companies show the highest systemic impact during the COVID-19 pandemic. In contrast, when considering the G-Pillar (Figure 8f), companies in the highest (A) rating class show the highest systemic impact. We highlight the fact that this class includes the companies that are generally top performers on the topics of Management, Shareholders, and CSR.[10] Thus, better governance does not necessarily imply less systemic risk. It is evident that the COVID-19 pandemic has impacted employees and employers and thus affected Management and CSR. Employees have reconsidered how they define the role of work in their lives and have raised their expectations toward their employer (Microsoft, 2022). These include the request for more flexibility and well-being. Additionally, 43% of the employees, especially Gen Z and millennials, are significantly more likely to change employers this year (Microsoft, 2022). As companies are already competing in the war for talent, possibly the threat of top performers leaving to work at a different company is more prominent in already responsible (i.e., high G-Pillar score)

[10]The G-Pillar score includes these three main categories Refinitiv (2021).

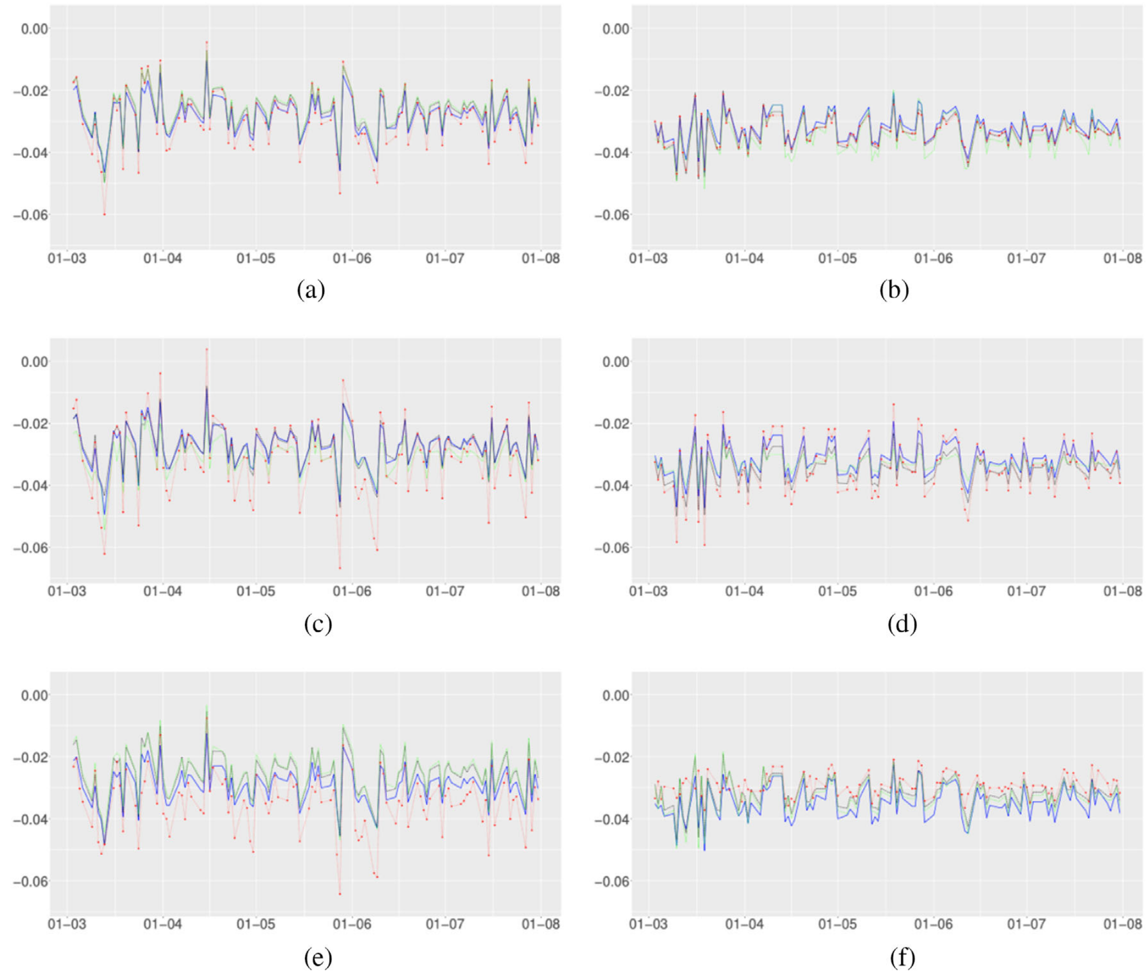


FIGURE 8 Average of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by the individual pillar classes: A (blue line), B (black line), C (green line), and D (red line and red points). The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020 (a) EU companies—clustered by $\overline{\text{E-Pillar}}$ classes (b) US companies—clustered by $\overline{\text{E-Pillar}}$ classes (c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes (d) US companies clustered by $\overline{\text{S-Pillar}}$ classes (e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes(f) US companies clustered by $\overline{\text{G-Pillar}}$ classes [Colour figure can be viewed at wileyonlinelibrary.com]

companies. Companies in lower categories might not be as severely affected as they are not competing for top performers in the first place.[11]

As a last analysis, we replace company j with the return of Index k, with $k \in \{A, B, C, D\}$. Now, in place of the mean ESG score, we use the mean of the individual pillar scores. Thus, for each pillar analysis, we have four indexes. Index A has low variability and impact in Figure 5. Now, for the E-Pillar (Figure 9b, top-left) on US data and the G-Pillar (Figure 9e,f, top-left) on EU and US data, we find larger variability for higher-rated indexes. It is also notable that the US Index B shows negligible variability and systemic impact when adopting the G-Pillar scores (Figure 9f, top-right). The fact that Index A shows a high impact could result from the increased attention and possibly the increased expectations and change in the workforce, as discussed previously. Similar to the analysis based on the overall ESG scores, we find, for all individual pillars in the EU market and the E- and S-Pillars in the US market, large variability and systemic impact for the Index D. Finally, we highlight the relevant peak observed for Index D built from the S-Pillar scores in March 2020. This highlights the social effects of the lockdown due to the outbreak of the COVID-19 pandemic, which were more severe for those companies characterized by low S-Pillar scores.

Overall, when looking at the individual pillars and the ESG score, we find a notable difference in the full sample as well as during the COVID-19 pandemic. Additionally, we find evidence of differences between the EU and US markets. In the EU market, especially the S- and G-Pillar show higher volatility compared with the ESG score for Index A during the COVID-19 pandemic. In contrast, we find some notable differences between the pillar and overall ESG scores in the US, especially when looking at the E- and G-Pillars during the COVID-19 pandemic.

[11]While aspects of employee relations are attributed to the S-Pillar (i.e., working conditions or career development), the G-Pillar also covers some aspects related to employees (i.e., compensation, committee structures, takeover defense.

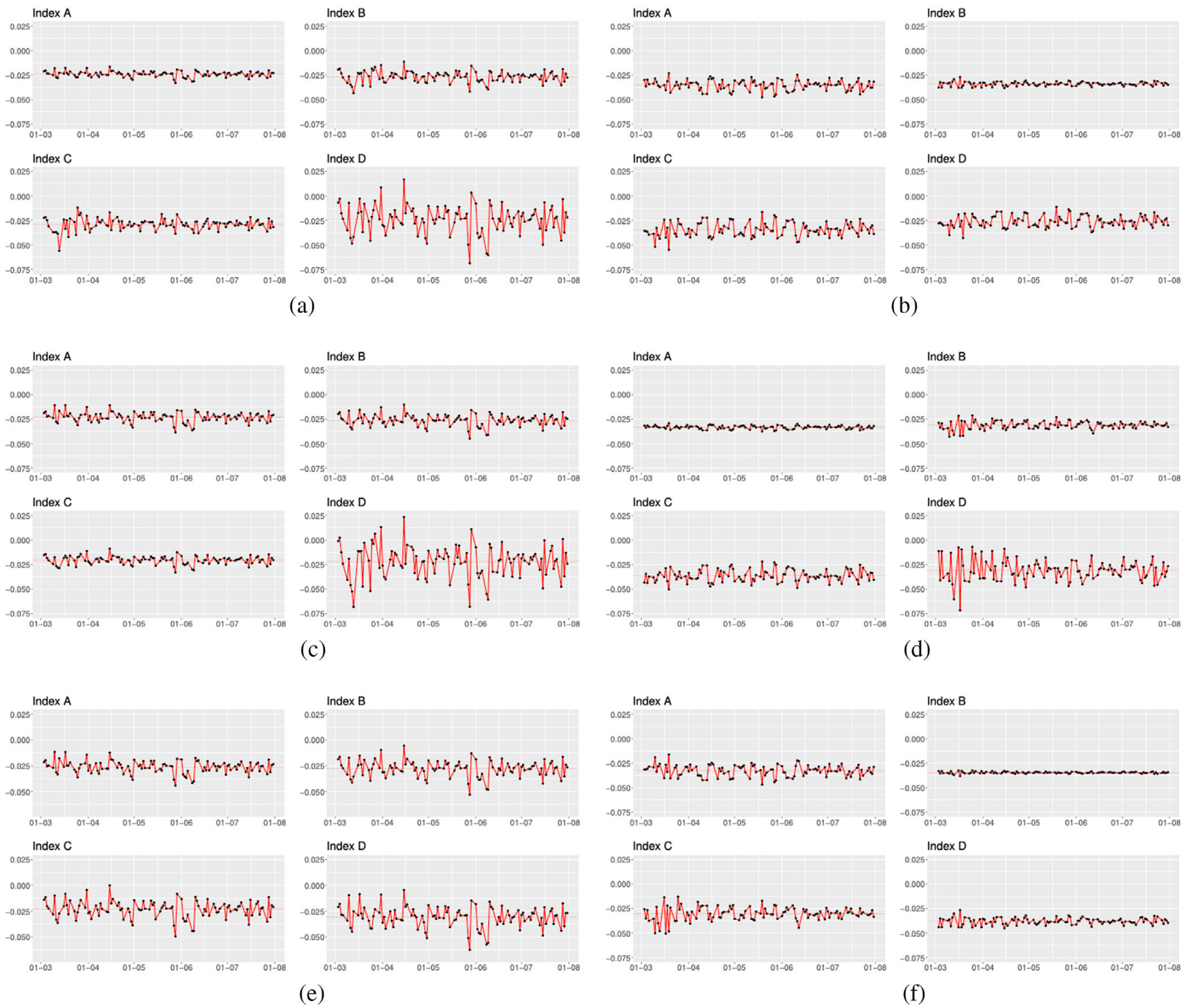


FIGURE 9 Trend of $\Delta\text{QL-CoVAR}^{(k)}_{t,\theta,\tau}$, with $k \in \{\text{A,B,C,D}\}$ clustered by individual pillar. The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020 (a) EU companies—clustered by $\overline{\text{E-Pillar}}$ classes (b) US companies—clustered by $\overline{\text{E-Pillar}}$ classes (c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes (d) US companies clustered by $\overline{\text{S-Pillar}}$ classes (e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes (f) US companies clustered by $\overline{\text{G-Pillar}}$ classes [Colour figure can be viewed at wileyonlinelibrary.com]

6 | CONCLUSION

The aim of this research is to analyze the relationship between ESG scores and systemic risk, the importance of which has been stressed recently by the EBA and has gained further traction. We do so by estimating the QL-CoVaR proposed by Bonaccolto, Caporin, and Paterlini (2019). By relying on a large sample of EU and US companies over a long time period, we are able to compare different economic states within two different markets. We highlight here the main results. By contrasting $\widehat{\lambda}^{(j)}_{\theta,\tau}$ with $\widehat{\lambda}^{(j)}_{\theta,1/2}$, we found that the relationships between the overall system and the conditioning companies become more relevant when focusing on a state in which they both are in distress. This evidence is also supported by the comparison of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ with $\widehat{\lambda}^{(j)}_{\theta}$ defined in Equation (5) for the CoVaR model (Adrian & Brunnermeier, 2016), with $\widehat{\lambda}^{(j)}_{\theta,\tau} > \widehat{\lambda}^{(j)}_{\theta}$.[12] On the one hand, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ tends to follow a U-shape behavior across the ESG classes, suggesting greater sensitivity of the VaR of the system to the stressed state of those companies belonging to the extreme A and D classes. Due to investment policies of best and worst in class, assets belonging to class A and D tend to receive more attention from the market and this could explain their greater sensitivities. Still, it could be reasonable to expect that class A assets could be more resilient and have less systemic impact due also to the overall evaluation they record with respect to non-financial

[12]For the sake of space, we do not report here the estimates obtained from the estimation of the CoVaR model (Adrian & Brunnermeier, 2016). However, these estimates are available upon request.

information, as captured by the ESG scores. In fact, the analysis of the overall ΔQL-CoVaR measure points out a greater systemic impact of the D-rated companies, due to their greater idiosyncratic risk. In contrast, the A-rated companies exhibit a lower idiosyncratic risk, leading to less relevant systemic effects. Therefore, on the one hand, companies with greater ESG scores are more attractive for rational investors and risk managers, who seek to reduce the risk of their financial portfolios within a more stable and resilient financial system. On the other hand, they offer important benefits for the entire society, stimulating the growth of sustainable and environmentally-friendly investments. It is reasonable to expect that companies with higher ESG scores should help to foster the stability of the economic and financial system, as they are more resilient and can absorb systemic shocks better. Thus, they contribute to the health of the economic and financial system. On the other hand, the fact that they are affected by best in class investment policies might moderate such result as they are subject to investors' attention.

Still, this evidence is clearer when focusing on the sub-sample characterized by the outbreak of the COVID-19 pandemic. This result is also confirmed, when clustering the individual firms into ESG indexes and estimating the systemic impact of the resulting portfolios. We, however, need to point out that results are not always consistent when considering the single pillars, as they focus on specific aspects of companies. For example, we find opposite evidence when considering the G-Pillar score for the US data, potentially implying that better governance results in higher systemic risk impact. Further analysis to disentangle further the impact of the single pillars rating is then needed to provide further insights on which company characteristics might impact the most its systemic relevance. Considering for example also the 10 categories on which the E, S, and G scores are computed (see Refinitiv, 2021) could allow to better detect which are the key company characteristics to monitor to develop even more reliable risk mitigation and management tools.

In our study, we draw some relevant findings for policymakers. The key message is that improvements in terms of ESG performance might lead to lower risk and more stable markets, while instead, companies in the lower ESG classes might contribute the most to systemic risk. Therefore, it is important to support disclosure policies of non-financial information, as ESG class D stocks typically are characterized by a lack of infrastructure and missing information (see Sahin et al., 2022) as well other policies, such as tax incentives, which stimulate companies to increase their efforts and investments in ESG-related activities, this resulting in improved ESG scores. By doing so, information on company characteristics, both financial and non-financial, would increase, providing further insights and knowledge, which we expect to lead to improved overall economic and financial stability, making the system less vulnerable even in times of turmoil. By disentangling the effect of the three pillars (E, S, and G) individually or even of the underlying pillar categories, we could also better point out the relevant company dimensions to be monitored and focus on the main drivers to develop effective risk mitigation policies. High on the agenda is investigating possible spillovers and interactions of the different pillars and of the different companies that could "simultaneously disrupt multiple parts of the financial system" as stressed by the European Banking Authority (2021, p. 33). Further analysis could include considering other sustainability measures and industry-focused analysis. Additionally, it could be interesting to consider the effect of different regulations set in place, that is, the Paris Agreement in 2015, and possible causal relationships. Research is still at an early stage and further investigations are needed, also considering alternative data providers and modeling tools for capturing systemic risk.

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APPENDIX A

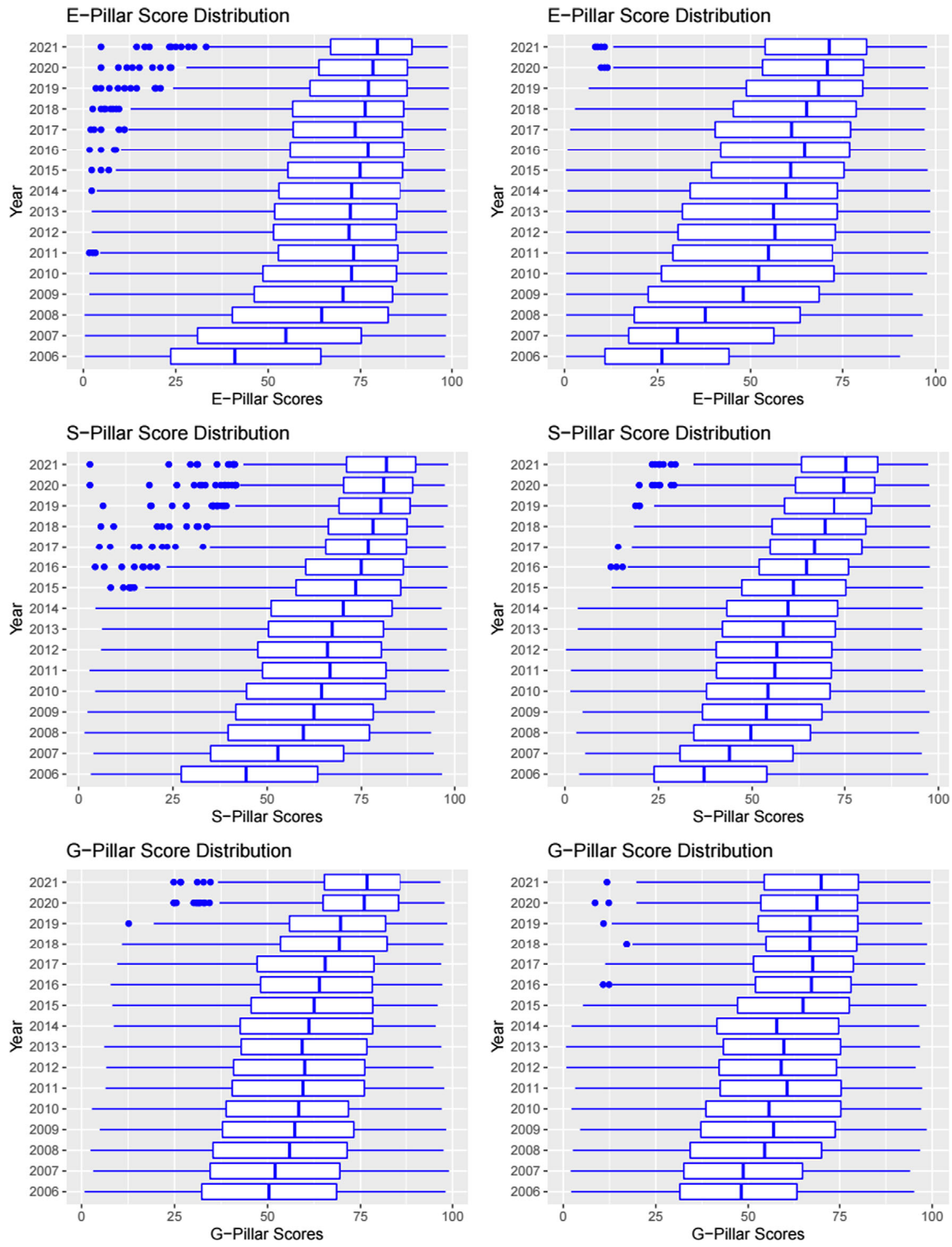

FIGURE A1 Distribution of individual pillar scores. [Colour figure can be viewed at wileyonlinelibrary.com]