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The Impact of ESG Ratings on the Systemic Risk of European Blue-Chip Firms

Mustafa Hakan Eratalay * and Ariana Paola Cortés Ángel

School of Economics and Business Administration, University of Tartu, Narva Mnt. 18, 51009 Tartu, Estonia; ariana.paola.cortes.angel@ut.ee
* Correspondence: hakan.eratalay@ut.ee

Abstract: There are diverging results in the literature on whether engaging in ESG related activities increases or decreases the financial and systemic risks of firms. In this study, we explore whether maintaining higher ESG ratings reduces the systemic risks of firms in a stock market context. For this purpose we analyse the systemic risk indicators of the constituent stocks of S&P Europe 350 for the period of January 2016–September 2020, which also partly covers the COVID-19 period. We apply a VAR-MGARCH model to extract the volatilities and correlations of the return shocks of these stocks. Then, we obtain the systemic risk indicators by applying a principle components approach to the estimated volatilities and correlations. Our focus is on the impact of ESG ratings on systemic risk indicators, while we consider network centralities, volatilities and financial performance ratios as control variables. We use fixed effects and OLS methods for our regressions. Our results indicate that (1) the volatility of a stock's returns and its centrality measures in the stock network are the main sources contributing to the systemic risk measure, (2) firms with higher ESG ratings face up to 7.3% less systemic risk contribution and exposure compared to firms with lower ESG ratings and (3) COVID-19 augmented the partial effects of volatility, centrality measures and some financial performance ratios. When considering only the COVID-19 period, we find that social and governance factors have statistically significant impacts on systemic risk.

Keywords: systemic risk; network centrality; sustainable; ESG; volatility; principal components; COVID-19

JEL Classification: C32; C33; C58; Q56

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1. Introduction

Since the 2008 financial crisis, there has been ever-growing interest in understanding the systemic risk concept. The term itself refers to the probability or the risk of a large number of financial institutions defaulting simultaneously (Lehar 2005). Many central banks and other institutions, such as the Systemic Risk Council formed in 2012 and the Systemic Risk Centre created in 2013, look into measuring systemic risk locally and globally. There has been an extensive amount of research on the topic. SRISK of Brownlees and Engle (2017) and CoVaR of Tobias and Brunnermeier (2016) are two of the many prominent works in the literature, while survey studies such as De Bandt and Hartmann (2000), Benoit et al. (2017) and Eratalay et al. (2021) cover many of the prevalent approaches.

As much as it is important to measure the systemic risk of a certain economy, it is also important to find out the key players in this economy: which firms are "too big to fail"?[1] For example, the works of Billio et al. (2012) and Tobias and Brunnermeier (2016) among many others look into the systemic risk contribution and exposure of firms. One interesting line of research that extends from here is analysing how sustainability influences systemic risk.

Sustainable firms exert effort in making their investments better in environmental, social and governance (ESG) terms, under which there are many subcategories. The study by Cerqueti et al. (2021) mentions that ESG investment could help reduce systemic risk and if firms comply with ESG requirements they would be less vulnerable to systemic shocks. His argument is that the firms with higher ESG ratings have less problems with their stakeholders, possibly due to more transparent governance. Second, he mentions that ESG-related investments rely on the longer term; therefore, the investors of ESG assets are not likely to sell off even in crisis periods. Lastly, he states that ESG related assets are not yet commonly preferred; therefore, they are less vulnerable to shocks. Leterme and Nguyen (2020) found some evidence that ESG factors can be considered systemic risk factors. There are also studies which found that there may be a negative or neutral relationship between ESG ratings and the financial performance of firms, while others found a positive relationship.[2]

In this study we aim to investigate the impact of the ESG ratings of firms on their systemic risk contribution and exposure. For this analysis we use the daily returns data on the stocks constituting the S&P Europe 350 index, which represents the blue-chip firms over 16 developed European countries and the ESG ratings data from S&P Global. We focus on the period of January 2016–September 2020, which covers days during the COVID-19 situation. If a firm's stock is central and has high volatility and this firm is performing poorly financially, it is likely that the firm is threatening the financial system it is in or being threatened by a shock from this financial system. This is even more true during the COVID-19 period. Hence, as control variables we consider financial performance ratios and two network centrality measures of these firms, volatility and a COVID-19 dummy variable. We would like to investigate whether, after controlling for the effect of the stock volatilities, financial ratios and the importance of the firms in the S&P Europe 350 network, we can still find statistical evidence that the ESG ratings increase or decrease the systemic risk contribution or exposure of a firm.

The analysis in this study brings together different tools from several fields. First of all, we estimate an econometric model following Eratalay and Vladimirov (2020) to extract the time-varying conditional correlation matrix. Using the Gaussian graphical model, we derive the dynamic partial correlation network of the stocks and calculate the local and global network parameters as in Cortés Ángel and Eratalay (2021). Then, we proceed to derive the systemic risk contribution and exposure of the stocks via the principal components method of Billio et al. (2012). Finally, we conduct a panel data analysis regressing systemic risk measures on volatility, ESG ratings, financial ratios and network metrics. The first contribution of this study is empirical, since we find the relation between systemic risk and ESG ratings, controlling for other factors that affect systemic risk, such as financial ratios and network parameters. Omitting these control variables could have misled previous research results. The second contribution of this study is in its methodology in combining different fields to extract these control variables. As mentioned above, there are many works studying the effect of ESG ratings on financial performance and some relate it to systemic risk. However, to our knowledge there is no work which has analysed the systemic risk contribution and exposures of the stocks in a stock market in relation to the ESG ratings and network centralities of these stocks.

Our results suggest that ESG ratings have a negative effect on the systemic risk contribution and exposure. However, this effect is marginal for small improvements in the ESG ratings. A firm that has an ESG rating that is 40 points higher benefits by reducing its systemic risk contribution and exposure by about 5%, reaching up to 7.3% for southern European countries.[3] We also find that the main factors determining the systemic risk contribution and exposure of a firm are the volatilities and network centralities. For the year 2020, we find that while the "social" factor in ESG ratings is positively related to systemic risk contribution and exposure, the "governance" factor negatively affects it. We did not find a significant effect from the "environmental" factor. Finally, during COVID-19, the partial effect of volatilities and network centralities increased.

This study is structured as follows. Section 2 gives a literature review on systemic risk and sustainability. Section 3 discusses the econometric model, network extraction and calculation of the systemic risk measure. Section 4 presents the data used for analysis. Section 5 discusses the results of the OLS and panel data regressions. Section 6 concludes.

2. Literature Review

2.1. Systemic Risk

The global financial crisis that occurred in 2007–2008 encouraged researchers to apply an interdisciplinary approach to studying systemic risk in the financial sector, with the purpose of predicting and controlling it.

In its simplest form, systemic risk can be understood as the risk of fracturing a system that can be triggered by the internal failure of any of its components or other external factors. It occurs much like a domino effect; if each component of the system represents one domino, it only takes one to fail (or fall in this case) in order to force all the components to collapse. In our analysis, the system is a stock market. The assumption that relates systemic risk in a stock market with the systemic risk in an economy is that the stock market represents a significant part of an economy. This could be the case if the stock market has many stocks, large market capitalizations, and large coverage of different industries. There are other studies that have used stock markets for systemic risk analysis. For example, Liu et al. (2020) analyse stock market indices of 43 countries to represent global financial markets, while Zhao et al. (2019) analyse the systemic risk of the Chinese stock market and Eratalay and Vladimirov (2020) focused on the Russian stock market.

Many studies have proposed methods for measuring systemic risk. To start with, Gray et al. (2007) used the risk-adjusted balance sheet and contingent claims analysis method to gauge the asset–liability mismatches between sovereign, corporate, household and financial sectors, and through stress-testing they depicted systemic instability due to an external factor. Tarashev et al. (2010) use a game-theoretic model, the Shapley value method, where the risk contributed by a bank was measured using the aggregate of the marginal contributions of the banking system. Additionally, Tobias and Brunnermeier (2016) define the conditional value-at-risk measures to appraise the individual and cumulative risk that an entity adds to the system. Similarly, Kritzman et al. (2011) apply the absorption ratio to asset prices to gauge the systemic risk in the US stock market, and Acharya et al. (2017) not only measure the systemic risk but also propose an optimal taxation policy to manage it.

Some studies go further to distinguish the systemic risk contribution and exposure of firms. Billio et al. (2012) use the principal components method, which uses the covariance matrix of returns (or return shocks) to capture the commonality between the returns, which would increase in turbulent times. Their systemic risk measure can identify the systemic risk contribution and exposure of firms, which are the same by construction. We use this methodology in our study, since it is straightforward and easily applicable using stock return shocks derived from our econometric model. Another study which discusses systemic risk contribution and exposure separately is by Tobias and Brunnermeier (2016), who base their methodology on value-at-risk measures.

For further reading we recommend Bougheas and Kirman (2015), which gives a detailed review of more non-network examples. On the other hand, Caccioli et al. (2018) delve into the topic of systemic risk utilizing network analysis as their primary tool. Please also see Bisias et al. (2012), Benoit et al. (2017), Silva et al. (2017) and Eratalay et al. (2021), among others.

2.2. Sustainability and Systemic Risk

One of the main concerns of humanity lies in the uncertainty of our future, due to all the damage caused to the planet. Entrepreneurs, investors and people in general have begun to become aware of this and have become more sensitive when making decisions. This has also had an impact on investors, who seek to contribute by investing in socially responsible and sustainable firms while being true to their values.

Socially responsible investing (SRI) and environmental, social and governance (ESG) investing are two of the most usual value-based investing strategies. In the case of the former, investors avoid investing in tobacco, weapons and gambling stocks Capelle-Blancard and Monjon (2012). In the case of the latter, for a firm to be qualified as ESG, its line of business (excluding tobacco firms, firms involved in any way with chemical or biological weapons and thermal coal generating firms) is considered along with the management of the risk inherent to it, such as management of human capital, business ethics, product and product governance, among others. These characteristics are taken into account to obtain ESG certification (see Drempetic et al. (2020), Dorfleitner et al. (2015), Friede et al. (2015) and Escrig-Olmedo et al. (2019)). It is worth mentioning here that there seems to be a question of the reliability of the ESG ratings by different firms. Berg et al. (2019) state that the ESG ratings of different sources tend to diverge.

When we search the literature, we find different views on whether investing in ESG related activities is beneficial for firms or not. Balcilar et al. (2017) show how socially responsible investment benefits reduce the volatility of conventional equity portfolios worldwide, using daily data from Dow Jones sustainable and conventional indices from around the world—North America, Europe and Asia-Pacific. Cortez et al. (2012) reveal that the performance of conventional and sustainable investments is quite similar for the US and European global socially responsible funds. Cortez et al. (2009) examine the performance of European socially responsible funds in greater depth and establish that their performance matches the performance of conventional and socially responsible standards, agreeing with Jain et al. (2019). Lööf et al. (2021) analyse over 5000 stocks from 10 stock markets and show that stocks with higher ESG ratings experience lower tail risk, while also keeping the upside return potential low. Giese et al. (2019) mentions that the ESG factor could mitigate tail risk and there may be a long-term ESG risk premium. There are also meta-analyses which argue in favour of ESG investing. Based on 2000 previous studies, Friede et al. (2015) document that there is evidence that ESG investing has a positive impact on financial performance. Clark et al. (2015) analyse 200 previous studies and report that 88% of them conclude that ESG practices affect stock prices positively. On the other hand, Revelli and Viviani (2015) report, based on 85 studies and 190 experiments, that socially responsible investments do not yield better financial performance than conventional investments. In line with this study, Lee et al. (2013) use a sample compiled from US stocks to show that there is no significant difference in the risk adjusted returns of the portfolios of high and low sustainability stocks.

From the systemic risk perspective, Cerqueti et al. (2021) show that ESG investments could help reduce systemic risk and make the funds that follow ESG requirements less vulnerable to systemic shocks. Boubaker et al. (2020) suggest that firms with higher ESG ratings have lower financial distress risk and are less likely to crash. Supporting this view, Lai et al. (2010) and Michelon (2011) suggest that corporate social responsibility of a firm creates a better reputation for the firm's name and therefore reduces the impact of negative news and the resulting risk. Murè et al. (2021) note that engaging in ESG practices reduces the probability of receiving sanctions for Italian banks, while Chiaramonte et al. (2021) show for European banks that ESG strategies enhance bank stability during financial turmoil. Oikonomou et al. (2012) find for the S&P 500 firms that corporate social irresponsibility is related strongly and positively to market risk, while corporate social responsibility is weakly and negatively related to firms' own systematic risk. Sun and Cui (2014) reach the conclusion that corporate social responsibility strongly reduces the firms' default risk. Klooster (2018) finds evidence that corporate social responsibility reduces a bank's default risk and reduces a bank's systemic risk contribution based on the SRISK measure but not based on the marginal expected shortfall measure. Bae et al. (2021) find that ESG ratings reduce a firm's stock price crash risk. However, if firms have larger financial constraints, they may tend to hide unfavourable news and hence this effect is suppressed. Gregory (2022) analyses the S&P 1500 stocks and shows that the non-financial firms which had better environment and governance scores performed better throughout the COVID-19 pandemic.

Sonnenberger and Weiss (2021) focus on the insurance firms and find that engaging in corporate social responsibility reduces tail risk and short and medium term exposure to systemic risk.

Notwithstanding the above, Lundgren et al. (2018), using a network approach and the Granger causality test, show that investing in European renewable energy stock is more risky compared with non-renewable energy stock. By network connectedness analysis using a wavelet method and a multivariate vector autoregression model, Reboredo et al. (2020) find that green bonds are significantly affected by corporate and treasure bond spillovers, although their transmission is unnoticeable besides the high connectivity among them in Europe and the USA. Friede et al. (2015) note that there are portfolio studies which find negative or neutral relations between ESG and financial performance. Maiti (2021), Jin (2018) and Leterme and Nguyen (2020) mention ESG related factors as a systematic risk of mutual funds in the Eurozone. Lopez-de Silanes et al. (2020) find that firms with higher ESG ratings have better disclosure of information and have less risk, but they find no evidence to support that ESG performance has an impact on risk adjusted financial performance. Waner (2021) supports this finding that active disclosure of information is a key to reducing systemic risk for China's ESG listed firms.

Given this diverging view on whether higher ESG ratings could be beneficial for firms in terms of mitigating systemic risk or not, our study finds a good place in the literature by providing evidence that ESG related investments could indeed reduce systemic risk contribution and exposures of firm stocks. Although the focus of the study is similar to that of Cerqueti et al. (2021) and Boubaker et al. (2020), we approach to the problem from a different angle, relating ESG ratings with the systemic risk measured in a stock market, where we can derive the importance of the firm's stock in this stock market through network centrality.

3. Methodology

3.1. Econometric Method

In the first step of our methodology, we needed to derive the dynamic volatility and dynamic correlation estimates, which were later used to obtain the systemic risk measure and network characteristics. Since there were many series to consider in this multivariate model, there were many parameters to estimate. Assuming normal distribution for the error term allowed us to estimate the model via quasi-maximum likelihood optimisation in three steps and avoid this curse of dimensionality. This estimation procedure is discussed in Eratalay and Vladimirov (2020), which is consistent and asymptotically normal (see Bollerslev and Wooldridge (1992) and Carnero and Eratalay (2014)).

3.1.1. Conditional Returns

Following a similar approach as in Eratalay and Vladimirov (2020), we modelled the conditional mean of the stock returns as a vector autoregressive model of order 1, VAR(1), with a common factor[4]:

$$\begin{aligned} r_t &= \mu + \beta r_{t-1} + c r_{t-1}^{MSWI} + \varepsilon_t \\ \varepsilon_t &\sim N(0_k, H_t) \end{aligned} \quad (1)$$

where r_t is a $kx1$ vector of returns. μ is a $kx1$ vector of intercept coefficients. β is a kxk non-diagonal matrix containing the vector autoregressive model coefficients, which allows for return spillovers. c is a diagonal vector of coefficients of the common observable factor. The error term, ε_t is assumed to be normally distributed with zero mean and a conditional variance-covariance matrix H_t.

Our approach differed here from Eratalay and Vladimirov (2020), as we considered an observable common factor, namely r_t^{MSWI}, which is the returns from the Morgan Stanley World Index (MSWI).[5] Considering MSWI allowed us to take into account the common trends in the world that may affect all the stocks in a similar manner. As Barigozzi and Brownlees (2019) states, the consideration of a common factor is essential. If ignored, it could yield a spuriously connected network. The typical stationarity restrictions apply on the coefficients β, such that all eigenvalues of the β matrix should be positive.

3.1.2. Conditional Variances

The conditional variance-covariance matrix of the error term ε_t is denoted by H_t such that:

$$\begin{aligned} \varepsilon_t &= H_t^{1/2} v_t \\ H_t &= D_t^H R_t D_t^H \\ D_t^H &= diag(h_{t,1}^{1/2}, h_{t,2}^{1/2}, ..., h_{t,k}^{1/2}) \\ h_{t+1} &= W + A\varepsilon_t^{(2)} + Bh_t \end{aligned} \tag{2}$$

In Equation (2), the conditional variance-covariance matrix H_t was constructed by the diagonal matrix, D_t^H, of conditional variances of each error term, multiplied by the correlation matrix. R_t. v_t denotes the standardized errors, and h_t is the vector of conditional volatilities. By this construction, each element of the variance-covariance matrix is equal to $H_{t,ij} = R_{t,ij} h_{t,i}^{1/2} h_{t,j}^{1/2}$, which is the well-known relation between covariance and correlation. W is a $kx1$ vector and A and B are kxk diagonal matrices of coefficients. This model therefore does not allow for volatility spillovers for simplicity. In fact, estimating a model with volatility spillovers with the data considered in this study would not be feasible. Under Equation (2), the volatility process for each series is given by:

$$h_{t+1,i} = w_i + a_i \varepsilon_{t,i}^{(2)} + b_i h_{t,i} \tag{3}$$

The conditional variances, $h_{t,i}$ are stationary under the usual assumption that $a_i + b_i < 1$. Moreover, they are positive as long as $w_i > 0$, $a_i \geq 0$ and $b_i \geq 0$.

3.1.3. Conditional Correlations

The conditional correlations, R_t, follow the consistent dynamic conditional correlation GARCH model of Aielli (2013):

$$\begin{aligned} R_t &= P_t Q_t P_t \\ P_t &= diag(Q_t)^{-1/2} \\ Q_{t+1} &= (1 - \delta_1 - \delta_2)\overline{Q} + \delta_1 \nu_t^* \nu_t^{*\prime} + \delta_2 Q_t \\ \nu_t^* &= diag(Q_t)^{1/2} \nu_t. \\ \nu_t &= [D_t^H]^{-1} \varepsilon_t \end{aligned} \tag{4}$$

where Q_t is the covariance matrix of the v_t^* and $\overline{Q}$ is the long run covariance matrix. $[D_t^H]^{-1}$ is the inverse of the D_t^H matrix. We used the correlation targeting approach of Engle (2002), where we replaced $\bar{Q}$ with the sample covariance matrix of the v_t^* during estimation. The scalar parameters, δ_1 and δ_2, of this model are restricted to be non-negative such that $\delta_1 + \delta_2 < 1$. To avoid the attenuation biases that occur when the cross-sectional dimension of the data is large, we used the composite likelihood approach of Pakel et al. (2020).

3.2. Partial Correlation Network

Following Anufriev and Panchenko (2015) and Eratalay and Vladimirov (2020), we used the Gaussian graphical model (GGM) algorithm. The GGM algorithm helps calculate the partial correlation matrices from the correlation matrices, which measure the conditional relation between any nodes in a network. We used partial correlations to isolate the correlation between two specific series, eliminating the indirect effect of other series and obtaining the true relationship between every two series. The matrix of partial correlations, P, can be obtained using the correlation matrix R:

$$P = -D_K^{-1/2} K D_K^{-1/2}. \tag{5}$$

where $K = R^{-1}$, and $D_K = diag(K)$ is the diagonal matrix that has the same leading diagonal as the K matrix. The details for the derivation of this equality can be found in Anufriev and Panchenko (2015).

In the model we constructed, the cDCC-GARCH approach from Section 3.2 provided us with the time varying conditional correlations. Therefore, we were able to construct a partial correlation network for each day in the time interval of our data. This gave us a dynamic network which took each firm's stock as a node. The strength of the connections between these nodes was obtained using the adjacency matrix, which was derived based on the partial correlations between the stock returns (see Jackson (2010)). A correlation matrix and the partial correlation matrix it implies are always symmetrical. Therefore, the adjacency matrix derived from the partial correlation matrix is also symmetrical. Consequently, this network's connections are bi-directional, meaning that there is no causal relationship. The adjacency matrix is defined as:

$$A = I + P = I - D_K^{-1/2} K D_K^{-1/2} \tag{6}$$

where I is the identity matrix. The identity matrix is added to the partial correlation matrix P, since the leading diagonal elements of P are equal to -1. Hence, now the leading diagonal elements of A matrix consist of zeros, implying that nodes are connected to each other but not to themselves. Another interesting point to note about this network is that, when there is an external shock to this network, all the nodes receive the shock simultaneously and the strength of the shock is defined through the partial correlations.

In our study, we are interested in two centrality measures that relate to systemic risk. The first is the eigenvector centrality which states that a node's centrality is proportional to its neighbours' centrality. In other words, a node's eigenvector centrality is high if its neighbours' eigenvector centralities are high. As Anufriev and Panchenko (2015) state, eigenvector centrality shows the extent to which a shock can propagate in a system. Second, we are interested in the closeness centrality, which focuses on the relative distance among nodes. To be more precise, it is the inverse of the total length of the shortest paths from this node to the other nodes. In this sense, closeness centrality relates to how fast and strongly the nodes react to a shock. As Eratalay and Vladimirov (2020) argues, in the GGM approach some partial correlations may turn out to be negative and this may imply that some entries of the adjacency matrix are negative. For this network, eigenvector centrality can be calculated even with negative partial correlations, although with closeness centrality this is not possible. (See Section 5.1. More details can be found in Eratalay and Vladimirov (2020) and Cortés Ángel and Eratalay (2021).)

3.3. Systemic Risk Measure

After obtaining the conditional correlation estimates that change over time, we derived the systemic risk measure using the principal components method from Billio et al. (2012). This approach detects the commonality between the stock returns through the correlations between them. When the commonality between the stock returns is large, the system is more connected. In turbulent times, the commonality between the stock returns, and therefore the connectedness between the stocks, increase. Therefore, there is a one-to-one relation between the systemic risk and commonality between the returns. The principal components analysis decomposes the original return vectors to orthogonal uncorrelated factors. These factors are ordered in decreasing explanatory power. Following the same notation above: let r_t^i be $kx1$ the vector of the returns of stock i. The system's aggregated return, r_t^S, therefore is given by:

$$r_t^S = \sum_i r_t^i \tag{7}$$

and the variance of the system's return, $\sigma_{t,S}^2$ is given by:

$$\sigma_{t,S}^2 = \sum_i \sum_j \sqrt{h_{t,i}}\sqrt{h_{t,j}} E(v_{t,i}v_{t,j}) \tag{8}$$

where $h_{t,i}$ and $v_{t,i}$ are the volatility and standardized residuals that correspond to stock return i as defined in Equations (3) and (4), respectively. The uncorrelated factors of the principal components method, ζ_i, have zero mean and have variance equal to λ_i, such that:

$$E(\zeta_k \zeta_l) = \begin{cases} \lambda_k, \text{ if } k = l \\ 0, \text{otherwise} \end{cases} \tag{9}$$

In fact, the λ_k is the k'th eigenvalue of the correlation matrix. In the context of our study, this correlation matrix is the conditional correlation matrix obtained from Equation (4). The principal components approach therefore decomposes the standardized residuals $v_{t,i}$ as:

$$v_{t,i} = \sum_k L_{ik}\zeta_k \tag{10}$$

where L_{ik} is the loading vector which is the eigenvector corresponding to the eigenvalue λ_k. Hence, the conditional correlation matrix can be written as:

$$\begin{aligned} R_t &= \sum_k \sum_l L_{ik} L_{jl} E(\zeta_k \zeta_l) \\ &= \sum_k L_{ik} L_{jk} \lambda_k \end{aligned} \tag{11}$$

and the variance of the system becomes:

$$\sigma_{t,S}^2 = \sum_i \sum_j \sum_k \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k \tag{12}$$

The principal components approach tries to explain a large percentage of the variation in the system with a few components. Hence, if we have k returns, we have n principal components, such that $n < k$. In periods of crisis, the n principal components can explain a large proportion of the total variation, since the commonality or correlation of these periods is expected to be high. Consequently, if the principal components can explain more than fraction H of the total variation, this indicates increased connectedness in the system. If the total risk of the system is defined as $\Omega = \sum_{k=1}^{N} \lambda_k$ and the risk captured by the first n principal components is measured by $\omega_n = \sum_{k=1}^{n} \lambda_k$, then the ratio $h_n \equiv \frac{\omega_n}{\Omega}$ shows the cumulative risk fraction. If this fraction is larger than the threshold H, then the system is highly connected and a few principal components can explain most of the variation in the system. Billio et al. (2012) derive the contribution of stock i to the risk of the system, when $h_n > H$:

$$PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_S^2} \frac{\partial \sigma_S^2}{\partial \sigma_i^2}\Big|_{h_n > H} \tag{13}$$

The authors also discuss that by construction, systemic risk exposure is the same as the systemic risk contribution of stock i:

$$PCAS_{i,n} = \frac{1}{2}\frac{\sigma_i^2}{\sigma_S^2}\frac{\partial\sigma_S^2}{\partial\sigma_i^2}\bigg|_{h_n>H} = \sum_{k=1}^{n}\frac{\sigma_i^2}{\sigma_S^2}L_{ik}^2\lambda_k\bigg|_{h_n>H} \tag{14}$$

In our study, the time varying conditional correlation matrix allows us to extract the systemic risk exposure of each stock i for each day.

Overall, the flow of the methodology was as follows. First, we applied the econometric model to the stock returns and obtained volatilities and dynamic conditional correlations. Then, from the volatilities and correlations we derived the systemic risk measures. From the conditional correlations, we derived the partial correlations which helped to construct the network of the stocks and to obtain network centrality measures. The obtained volatilities and network centralities along with financial performance ratios, ESG ratings and the COVID-19 dummy variable were used as regressors in fixed effects regressions, where the dependent variable was the systemic risk measure.

4. Data

4.1. Data Sources

For this study we collected the data from three sources. We collected the historical stock market data for the constituents of the S&P Europe 350 index[6] and for the Morgan and Stanley World Index (MSWI) from Yahoo Finance. For the constituents list, we made a formal request to SPGlobal[7]. We were provided with the list of all 362 constituents of S&P Europe 350 index as of December 2019. Afterwards, we collected daily closing values for these constituent stocks for the period of 5 January 2016–15 September 2020 from Yahoo Finance. Some stocks did not have data for the whole data period; therefore, we had to refine our data. The final list of stocks we considered is given in Tables A10–A17 in Appendix A. After pre-treating the data, we had 1202 observations for the prices of 331 stocks and the MSWI index. We detected the outliers following the Hampel filter as discussed in Pearson et al. (2015). We replaced the outliers with the local median in the 20 working days window. When detecting the outliers, we set the parameters of the Hampel filter such that the probability of observing an outlier was very small.[8]

Our second data source was the S&P Global website[9]. For the constituent stocks, we collected the yearly overall ESG ratings from 2016 to 2020. Moreover, we collected the dimension scores for environmental, social and governance/economic factors for 2020. Unfortunately, for some of the constituent stocks, the ESG data were not provided. We were able to collect the data for 308 stocks.[10]

Finally, our third dataset was firm level data of financial performance ratios obtained from the Orbis Europe system. We collected the data on current ratios, solvency ratios and profit margins as indicators of firm level financial performance. The data were annual and for the years 2016–2020. The stock market performance of the firms not only depends on the trading behaviour of the investors but also on the firms' profitability and riskiness. Hence, we can assume that the systemic risk contribution and exposure measures derived from the stock market relations should depend on the financial performance ratios. Unfortunately, the data on all these ratios were available for only 200 of the constituent stocks. We summarize the description of these three panels in Table 1 below.

Table 1. Short description of the panels.

Panels	Description	Number of Stocks
Panel 1	The stocks for which systemic risk, volatility and network centralities were calculated.	331
Panel 2	The stocks of Panel 1, for which we could obtain ESG ratings data.	308
Panel 3	The stocks of Panel 2, for which we could obtain financial performance ratios.	200

Notes: This table gives a summary of the panels used for the fixed effects regressions. For OLS and fixed effects regressions, we removed Wirecard AG from our samples, as explained in Section 5.2. Source: authors' calculations.

4.2. Descriptive Statistics

In Figure 1, we plot the returns after being processed through the Hampel filter. The high volatility caused by COVID-19 is visible towards the end of the sample. We marked the date 21 February 2020 with a vertical dashed grid line, which is when a cluster of cases occurred in Lombardy, Italy.[11] It can be seen from the figure that there are many extreme returns which were not eliminated by the Hampel filter. The most extreme negative return belongs to the return series of the company Wirecard, which declared insolvency in June 2020. We discuss more on this series in Section 5.2.

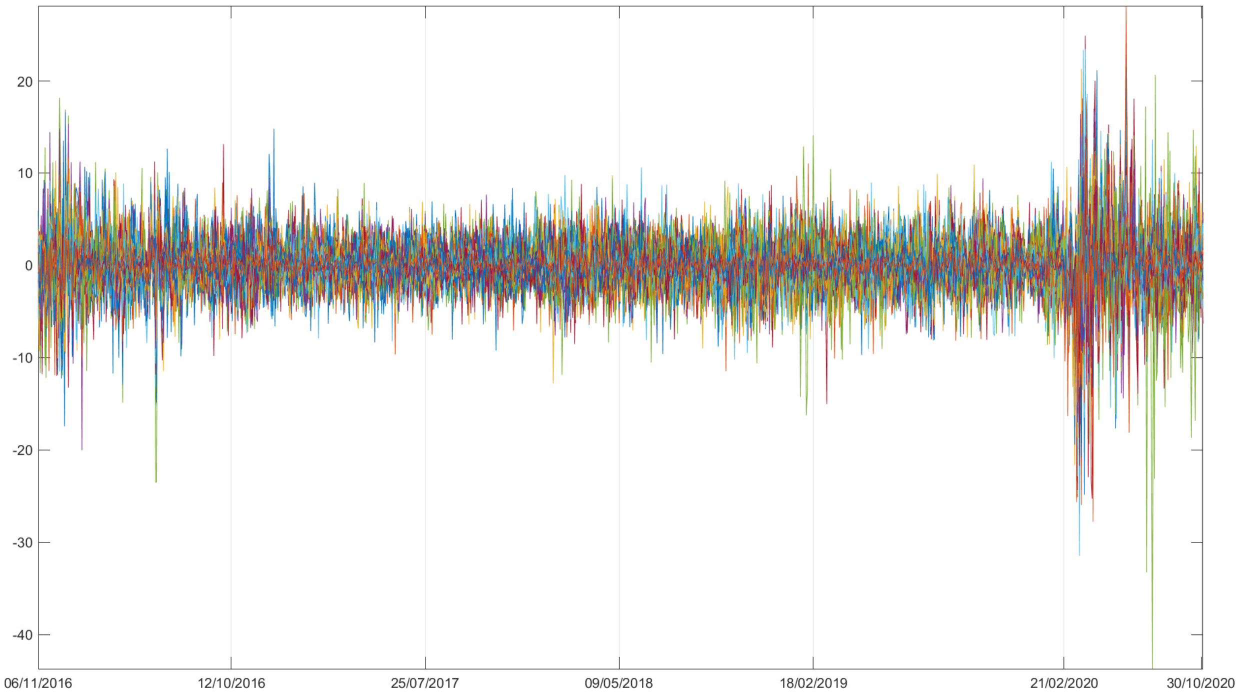


Figure 1. Returns of the S&P Europe 350 stocks, calculated as $100 * log(P_t/P_{t-1})$ where P_t is a stock price. This figure plots the returns of the stocks in the dataset, which contains 331 stocks from S&P 350 Europe. Period: 5 January 2016–15 September 2020. Source: authors' calculations.

In Figure 2, we give the descriptive statistics for the returns of the stocks in a box plot form.The descriptive statistics were calculated for each series, and then the box plots of each descriptive statistic were plotted. For example, the box plot for the means is for the average returns of each of the 331 return series. As we can see, the means of the returns are concentrated around zero for all the stocks, while the standard deviation varies between one and three but exceeds three for some series. For most stocks, the returns are negatively skewed and in some cases exceed the conventional threshold of unit skewness, indicating that the return distribution is highly skewed and implying that there are many negative extreme returns. We also observe that the kurtosis is very high for all the stocks. It is much above the kurtosis of normal distribution. This means that the sample distribution of the stock returns is leptokurtic and this is one of the stylized facts about financial time series data (Ghysels et al. 1996).

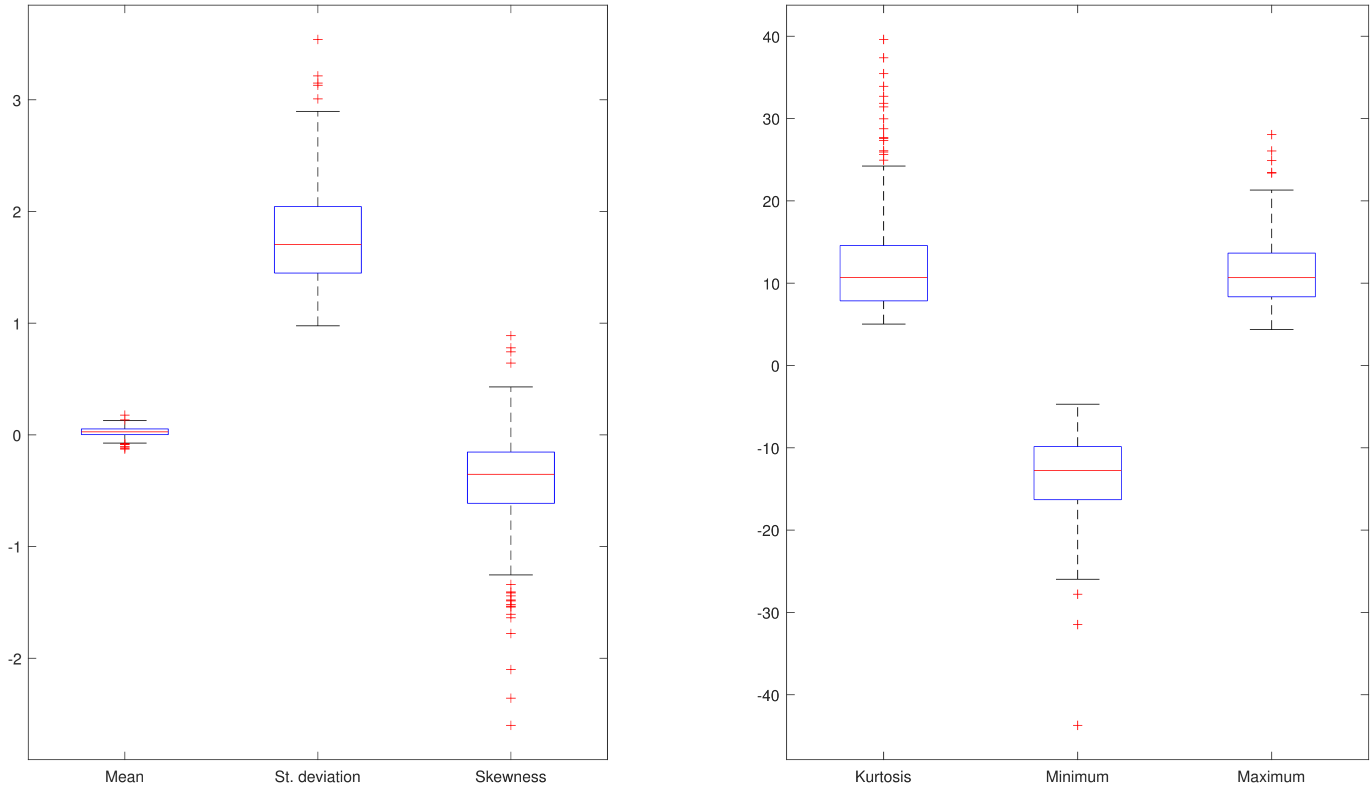
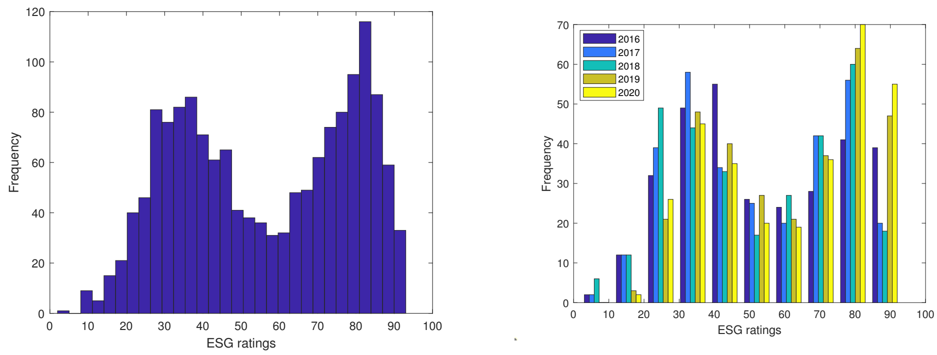


Figure 2. Box plots of basic descriptive statistics for S&P Europe 350 stocks. This figure shows the box plots of the mean, standard deviation, skewness, kurtosis, minimum and maximum of the returns of the stocks in the dataset. Period: 5 January 2016–15 September 2020. Source: authors' calculations.

We now discuss the ESG ratings data. In Figure 3, we present the histograms of (a) merged ESG ratings and (b) yearly ESG ratings. When we look at Figure 3a, we see that the distribution is bimodal and the difference between the modes is about 40–50 points. Figure 3b shows that the trend in ESG ratings over the years is different for these two modes. In particular, on the left side of the distribution, we see that the ESG ratings are decreasing over the years, while on the right side we see that they are increasing. This implies that over time the firms with lower (higher) ESG ratings reduced (increased) their ESG ratings further.

In Figure 4 we plot the 5th, 25th, 50th, 75th and 95th quantiles and the mean of the overall ESG ratings of the stocks from the S&P 350 Europe index. Although perhaps the mean and the median have a slightly positive trend, the other quantiles seem stable over time. What is also interesting is that the median is less than the mean before 2018 and more than the mean afterwards. This suggests that the ESG ratings distribution before 2018 was positively skewed, with a few firms with high ESG ratings. After 2018, the distribution became negatively skewed, with a few firms with low ESG ratings. This suggests that overall there is an increasing trend in the ESG ratings over the years. As we discussed in Figure 3, however, this increase is not for every quantile of the distribution.



(**a**) Merged (**b**) Per year

Figure 3. Histograms of merged and yearly ESG ratings. This figure shows the histograms of (**a**) merged and (**b**) yearly ESG ratings of the 308 stocks from the S&P 350 Europe index. Period: 5 January 2016–15 September 2020. Source: authors' calculations.

When we look at the averages per country over the years in Table 2, we can see that for many countries the ESG ratings have been decreasing over time, while for some they increased after a slight decrease. It is hard to comment on any country's efforts in creating and maintaining sustainable firms from this table, since only certain firms from each country are in this list. However, even for those countries where the number of stocks is higher, there is a visible decline of ESG ratings in general. The ESG ratings are higher for the Southern European countries, namely Italy, Spain, Portugal and to some extent France. These are all countries which can benefit from solar energy. This provides the motivation for analysing Southern European countries and other countries separately in Section 5.

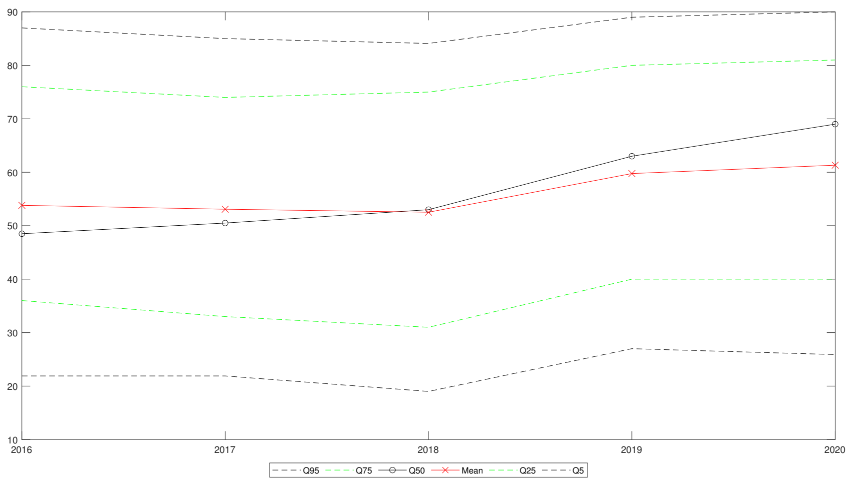


Figure 4. Quantiles and mean of ESG ratings over time. This figure shows the quantiles 0.95, 0.75, 0.5, 0.25, 0.05 and the mean of the ESG ratings of 308 stocks from the S&P 350 Europe index. Period: 5 January 2016–15 September 2020. Source: authors' calculations.

Table 2. Average overall ESG rating by country from 2016 to 2020.

Countries	2016	2017	2018	2019	2020	Count
Germany	57.79	56.24	48.68	50.11	49.97	38
France	70.82	69.24	61.11	60.42	59.93	45
Luxembourg	40.50	49.00	38.50	40.00	39.50	2
Ireland	46.22	46.56	37.22	37.44	38.11	9
Italy	70.38	69.31	67.69	70.62	72.31	13
Belgium	44.00	44.63	35.50	39.75	43.75	8
Denmark	53.10	50.40	41.00	37.80	35.90	10
Norway	53.57	50.00	43.43	43.71	43.43	7
Spain	75.12	73.94	67.41	68.65	71.41	17
Sweden	54.55	51.50	41.95	44.14	46.86	22
Netherlands	71.82	72.53	65.06	62.24	60.59	17
Portugal	84.00	84.00	80.50	86.00	85.00	2
Austria	55.00	59.00	58.00	61.00	61.50	2
Finland	62.78	58.56	52.33	50.22	51.78	9
Switzerland	59.00	57.86	52.45	52.79	54.59	29
United Kingdom	58.76	56.54	49.27	50.23	51.10	78

Notes: This table gives the average overall yearly ESG ratings of each country for the years 2016–2020. In total, there are 308 stocks for which ESG ratings were available. Source: S&P Global ESG ratings and authors' calculations.

In Table A1 in Appendix A, we show as an example 25 stocks that have the highest average ESG rating. It is interesting that there are many firms from electric and gas utilities. In terms of countries, Spain, Italy, Switzerland and the United Kingdom are leading. Interestingly, the United Kingdom, Germany, France and Switzerland have many firms in the S&P Europe 350 for which ESG ratings were available, but the average ESG ratings were not as high for these firms.

After obtaining the necessary regressors, we apply a fixed effects regression. However, to avoid the bias that it could introduce, we discard the data related to the company Wirecard. We discuss the reasons more clearly in Section 5.2. We construct panels considering (1) all 330 stocks for which systemic risk, volatilities and network centralities are available, (2) 307 of those 330 stocks for which ESG ratings are also available and (3) 199 of those 307 for which firm-level financial performance ratios are also available. Therefore, we have three panels of data to work with. Since some stocks get eliminated due to data limitations through these panels, it makes sense to discuss the content of these panels in terms of the represented countries and industries. In Figure A1 in Appendix A, we present word clouds to visualize the industries and countries which are dominant in these three panels. In the larger panels of 330 and 307 stocks, there are more stocks from industries such as banking, diversified financial services, machinery and electrical equipment, chemicals and insurance. In terms of countries, there are many stocks from Great Britain, Germany, Switzerland and France. When we look at the smaller panel of 199 stocks, we see that the industries of chemicals, telecommunication services, pharmaceuticals, machinery and electrical equipment and oil and gas upstream and integrated are more represented. In this panel there are more stocks from Great Britain, Germany and France. Therefore, when discussing the results, we should keep in mind that banks, diversified financial services and insurance industries dominate the bigger panels, while they do not play such a big part in the smaller panel.

5. Results

In this section, we first explain the findings from the network analysis of the constituent stocks of the S&P Europe 350 index. Afterwards, we discuss the results of the fixed effects and OLS estimations, which study the causal relationship between systemic risk and ESG ratings.

5.1. Partial Correlations Network

In this section, we use the partial correlations obtained from the estimation of the econometric model in Section 3 and calculated via Equation (5). As can be seen from the kernel density estimate in Figure 5, the partial correlations are primarily positive; however, there are also negative values. Therefore, some relationships among stocks have a negative sign. In other words, while some stocks react similarly (positive edges) to external news, others respond in the opposite way (negative edges). The positive and negative weights exist in the networks of each day since each day's network is constructed using the partial correlation matrices as the adjacency matrices. In fact, 51.45% of all correlations of all times are positive.

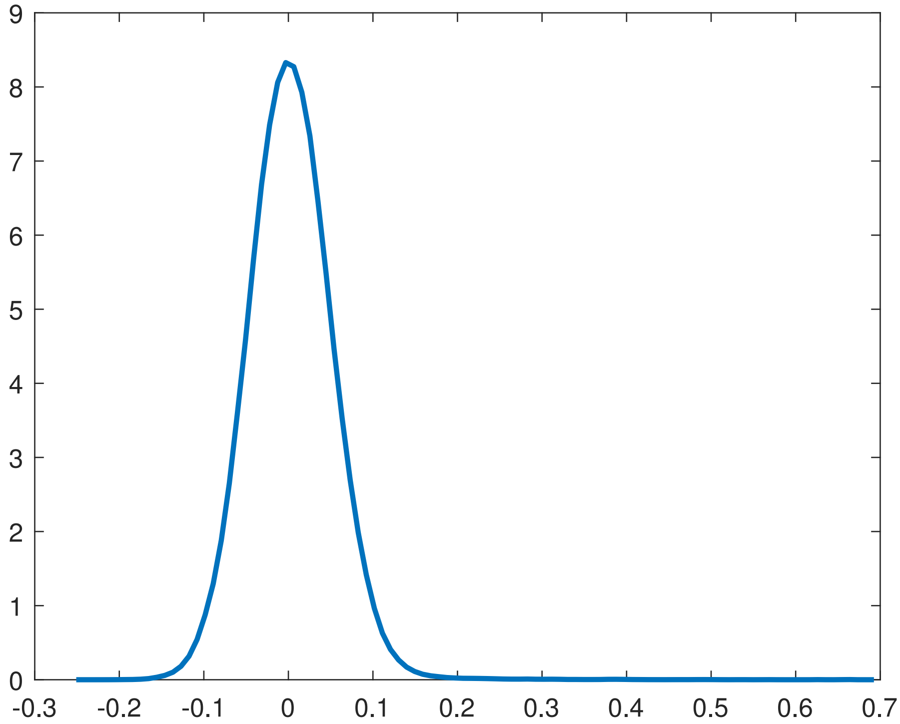


Figure 5. Kernel density estimate of all the partial correlations. This figure shows the kernel density estimate of all the partial correlations of 331 stock returns over time. The partial correlations are dynamic and obtained for the sample period. Period: 5 January 2016–15 September 2020. Source: authors' calculations.

Considering all positive and negative partial correlations, we calculate the normalized number of edges over time in Figure 6, which suggests that the normalized number of edges stayed more or less the same over time. In Figure 7, we see that the maximum eigenvalues reach an all time high just after the first news of COVID-19 patients and deaths appeared in Europe around 21 February 2020. The maximum eigenvalue is related to the eigenvector centrality, and its high values can be seen as an indicator of systemically risky times. In particular, when the maximum eigenvalues exceed one, it indicates that the system is unstable (Eratalay and Vladimirov 2020).

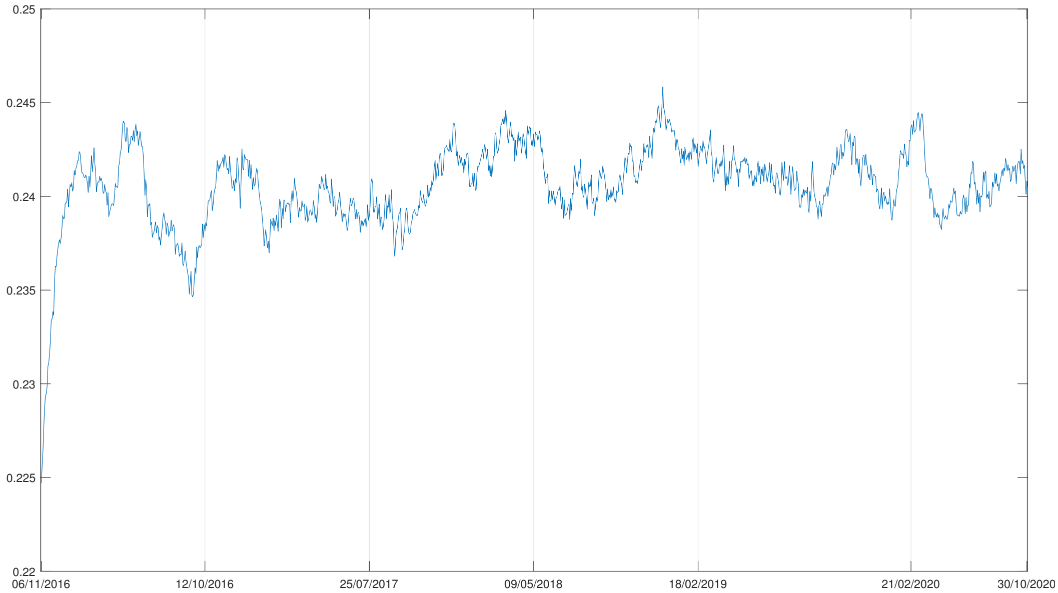


Figure 6. Normalized number of edges over time. This figure shows the normalized number of edges in the dynamic networks of the stocks in the S&P 350 Europe stock index during the data period 5 January 2016–15 September 2020. The normalization is done using the maximum number of possible edges. Source: authors' calculations.

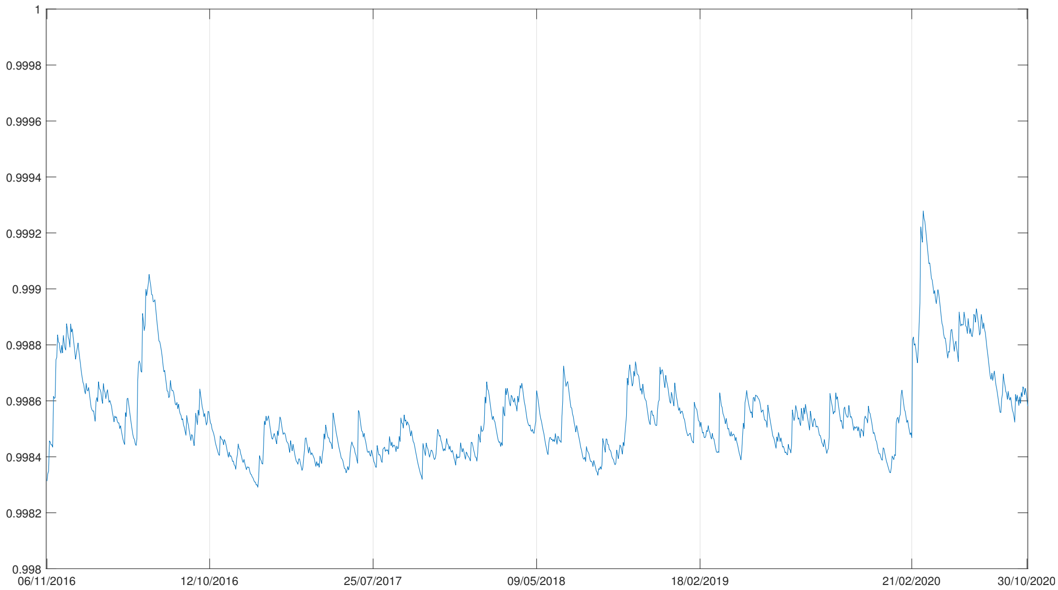


Figure 7. Maximum eigenvalues over time. This figure shows the maximum eigenvalue of the adjacency matrices in the dynamic networks of the stocks in the S&P 350 Europe stock index during the data period 5 January 2016–15 September 2020. Source: authors' calculations.

In this study, we calculated the eigenvector and closeness centrality measures based on the dynamic partial correlations networks of S&P Europe 350 for the years 2016–2020.[12] We calculated the eigenvector and closeness centralities considering whole daily partial correlation matrices. The eigenvector centrality considers the importance of a node's neighbours and those neighbours' connections. A node has a high eigenvector centrality if its neighbours have a high eigenvector centrality. A node's closeness centrality measures its distance to the rest of the nodes on the network. We can say that as a node is closer to the rest of the nodes, it has a higher closeness centrality. Therefore, if the node has a high closeness centrality, in the case of a shock, the rest of the network will have a quicker response to the shock. In terms of shock propagation, the closeness and eigenvector centralities help us measure the impact of a shock by considering the distance among stocks and the possible implications for the neighbouring nodes. This is why we selected these centrality measures.

When calculating the distances among nodes, we found negative cycles. Therefore, it was impossible to calculate any relative distance parameter for net partial correlations. Consequently, the closeness centrality was only calculated for absolute and positive partial correlations. Independently and additionally, positive and negative weights would offset each other when calculating closeness centralities. Therefore, we only considered the absolute value for the closeness centrality.

In Tables A2 and A3 in Appendix A, we present the top 25 central firms for which the ESG ratings were available for 2016–2019 and 2020, respectively. The most central firms were mostly the same in both periods. These most central firms were mostly from France and Germany and from the financial sector, namely from banking and insurance industries. We can also note that there is a clear correlation between the centrality measures and ESG ratings or systemic risk measures.

5.2. Systemic Risk Measure

Following the methodology in Section 5, we calculate the total systemic risk of the S&P Europe 350 stocks, given by Equation (8). In Figure 8, we plot this PCA-based total systemic risk along with the composite indicator of systemic stress of the European Systemic Risk Board and the stress sub-indices for financial and non-financial equities. These latter indices are calculated from the realized volatilities of the corresponding stock market indices. The data were obtained from the Statistical Data Warehouse of the European Central Bank.[13] This index is calculated for all the countries in the Euro area and uses the methodology of Hollo et al. (2012), which combines 15 raw mainly market-based financial stress measures.

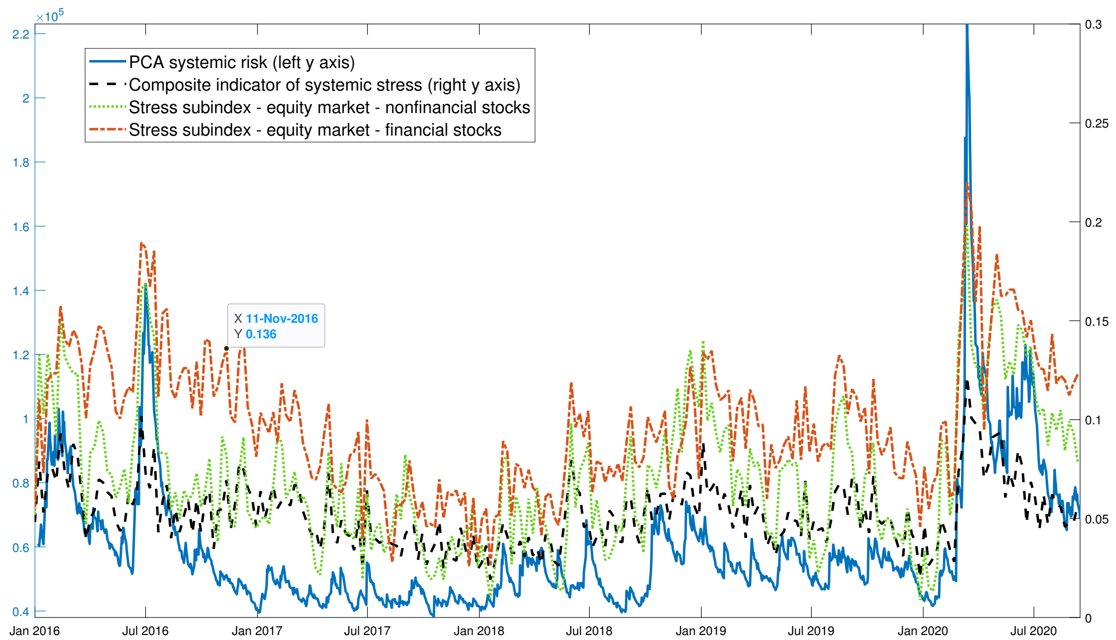


Figure 8. PCA systemic risk of S&P Europe 350 stocks versus the Composite Indicator of Systemic Stress of the ESRB. This figure shows the time series plots of the systemic risk index we calculated using the PCA method and the composite indicator of systemic stress, as well as the sub-indices for financial and non-financial equities of the European Systemic Risk Board. The latter indices are unit free and normalized to [0,1] interval. The correlation between the PCA based systemic risk and other series is 0.6474, 0.7790, 0.7477. The data period was 5 January 2016–15 September 2020. Source: ESRB and authors' calculations.

We find that the correlation of PCA-based systemic risk has a medium high correlation of approximately 0.65 with the ESRB composite indicator of systemic stress. Moreover, it is highly correlated with the stress sub-indices: approximately 0.78 with non-financial stocks and approximately 0.75 with financial stocks. It seems that the PCA systemic risk measure reacted more than the other measures when the systemic risk increased in the market in July 2016 and it reacted more clearly in early March 2020.

Tables A6 and A7 in Appendix A show 25 firms for which the systemic risk was very high in 2016–2019 and 2020, respectively. It can be seen that Wirecard AG from Germany had the highest risk and this risk was calculated as about nine times higher than the next company in line in 2020. This was probably related to the Wirecard scandal in 2019 and their declaration of insolvency in 2020. Interestingly, Wirecard AG's centrality measures were not very high.[14] In our regression analyses, we removed Wirecard AG from our dataset. According to Tables A6 and A7, Anglo American Plc, ArcelorMittal Inc, Bank of Ireland Group, Glencore Plc and Unicredit SpA Ord also had high systemic risk measures for 2016–2019. In 2020, Anglo American Plc, Glencore Plc and Unicredit SpA Ord improved their systemic risk measures, while Bank of Ireland Group, ArcelorMittal Inc. suffered in that respect.

Tables A8 and A9 in Appendix A show 25 firms for which the systemic risk was the lowest in 2016–2019 and 2020, respectively. We can easily see that most of these low risk firms are from Switzerland and there are many firms from the Communication Services and Consumer Staples sectors.

5.3. Systemic Risk and ESG Ratings

In this subsection we use the variables we obtained from the previous parts and from the datasets. We use the natural logarithm of systemic risk contribution and exposure as the dependent variable. As regressors, we use the eigenvector and closeness centralities, natural logarithm of volatility, ESG ratings and firm level financial performance ratios. In our regression analyses, we eliminate Wirecard AG from our list since it was an obvious outlier in terms of systemic risk.

A preliminary analysis of scatter plots of average systemic risk exposures in logarithm and ESG ratings of the remaining 307 firms for which the ESG data was available are given in Figure A2 in Appendix A. For each year and for the whole sample, the slope of the linear relation is negative but small in magnitude. We can also note that in 2018 and 2019, the magnitude of the slope is relatively higher. Hence, in general we can talk about a negative correlation between systemic risk exposure (and contribution) and the ESG ratings.

5.3.1. Fixed Effects Regressions

In this subsection, we discuss the fixed effects estimation results. As mentioned above, we have three panels to consider, with cross-section sizes 330, 307 and 199. In the larger panels, we have more stocks from many industries. However, in the smallest panel, although we have the variables for firm-level financial performance ratios, we do not have as many stocks from the banking and insurance industries. We discussed how different industries and countries are represented in these panels in Section 4.1.

The dependent variable in all these regressions is the natural logarithm of the systemic risk. Since it has some outliers and only has positive values, taking a logarithm of this variable helps to bring the distribution closer to normal. The main variables in these regressions are the net eigenvector centrality, absolute value closeness centrality, logarithm of volatility and the dummy variable that takes the value of one for 2020. We also added certain interactions of the variables. For example, it made sense to include the interaction of centralities with the logarithm of volatility, since a stock's high volatility becomes dangerous for the system if that stock is more central. A similar argument follows for the interaction of centralities with financial performance ratios. We also included interactions with the dummy variable since the partial effects might change during COVID-19. In all of the following regressions, we removed some of the interaction terms between regressors due to strong multicollinearity. Since we found that the ESG ratings of the firms from southern countries (Italy, Spain, France and Portugal) were relatively higher in Table 2, we performed the same regressions using sub-samples with respect to geographical location. Overall, the regressors and their interactions used in the regressions are presented in Table 3.

Table 3. List of variables.

Short Name	Variable
NetEC	Net eigenvector centrality
AbsCC	Absolute value closeness centrality
logVol	Natural logarithm of volatility
Dt	Dummy variable, equals 1 for year 2020
ESGrating	ESG rating of the company
CR	Current ratio
PM	Profit margin
SR	Solvency ratio

Notes: This table gives a summary of the variables used in the fixed effects and OLS regressions.

In Table 4, we present the fixed effects regression results using the large panel with 330 stocks. The estimation results suggest that both centrality measures are positively linked to the systemic risk of the stock. Similarly, higher volatility of a stock implies higher systemic risk contribution and exposure. As expected, the partial effect of eigenvector centrality and volatility increased in COVID-19 times.

Table 4. Fixed effects estimation results, using only the stock market and network data.

Sample →	All			Southern			Northern		
	Coef.	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**
NetEC	8.3727	2.1479	***	7.7652	4.3691	*	8.5689	2.5133	***
AbsCC	64.4704	7.4758	***	67.3261	15.7056	***	63.3571	8.5363	***
logVol	1.6429	0.0566	***	1.6423	0.1127	***	1.6603	0.0677	***
NetEC*logVol	−0.3447	0.8094		0.0288	1.4331		−0.8337	1.0174	
Dt	−0.4329	0.0156	***	−0.4449	0.0326	***	−0.4335	0.0189	***
NetEC*Dt	1.6016	0.3159	***	1.5794	0.6146	**	1.7127	0.3897	***
logVol*Dt	0.0833	0.0134	***	0.0897	0.0297	***	0.0811	0.0152	***
_cons	−3.7423	0.4821	***	−3.9077	1.0674	***	−3.6757	0.5399	***
Corr(u,X)	0.2968			0.1615			0.3548		
Pval_Ftest	0.0000			0.0000			0.0000		
R^2 within	0.8862			0.8984			0.8809		
R^2 between	0.8941			0.8834			0.8998		
R^2 overall	0.8923			0.8847			0.8967		
sigma_u	0.3159			0.2974			0.3220		
sigma_e	0.1082			0.1099			0.1080		
rho	0.8949			0.8799			0.8989		
N	330			90			240		

Notes: For this regression, yearly average of systemic risk, network characteristics and volatilities are used. Cross-section size is 330. The stock ticker was used as a panel id for the fixed effects regression. Other interaction terms were eliminated due to multicollinearity. Standard errors are calculated taking into account the clustering with respect to panel id. Significance: * 10%, ** 5%, *** 1%. Source: authors' calculations.

The coefficient estimates and their signs are similar for the stocks from southern and northern European countries. One difference is that for southern European countries, closeness centrality has a higher impact than for northern European countries. On the other hand, eigenvector centrality has a higher impact on northern European countries. One interpretation could be that for the stocks from southern European countries, being "close" to the rest of the stocks has more impact. In contrast, for northern European countries, the centrality of the neighbouring stocks matters more. The correlation between unobserved heterogeneity and the regressors validate that fixed effects is a better approach than the random effects method for these regressions.

In Table 5 we present the regression results with 307 stocks, where ESG ratings are also considered as a regressor. We again see similar relations that centralities and volatility are positively linked to systemic risk. Similar to before, we notice the way that the partial effects of centralities and volatility increase in 2020.

Table 5. Fixed effects estimation results, using the stock market, network and ESG ratings data.

Sample →	All			Southern			Northern		
	Coef.	St. Err.	Sig.	Coef.	St. Err.	Sig.	Coef.	St. Err.	Sig.
NetEC	8.7535	2.2502	***	9.6099	4.7321	**	8.4713	2.6003	***
AbsCC	68.5705	7.7649	***	67.5842	17.1712	***	68.8595	8.6944	***
ESGrating	−0.0007	0.0004	*	−0.0005	0.0008		−0.0009	0.0005	*
logVol	1.6316	0.0568	***	1.6710	0.1203	***	1.6373	0.0677	***
NetEC*logVol	−0.1281	0.7984		−0.3629	1.5245		−0.4371	0.9981	
Dt	−0.4264	0.0204	***	−0.4501	0.0535	***	−0.4252	0.0242	***
NetEC*Dt	1.5115	0.3464	***	1.7231	0.8141	**	1.5537	0.3977	***
logVol*Dt	0.0856	0.0145	***	0.0908	0.0329	***	0.0848	0.0164	***
ESGrating*Dt	0.0000	0.0002		−0.0000	0.0006		0.0000	0.0003	
_cons	−3.9823	0.5009	***	−4.0233	1.1596	***	−3.9669	0.5528	***
Corr(u,X)	0.2382			0.0669			0.3105		
Pval_Ftest	0.0000			0.0000			0.0000		
R^2 within	0.8896			0.9042			0.8832		
R^2 between	0.8895			0.8729			0.8976		
R^2 overall	0.8888			0.8766			0.8953		
sigma_u	0.3159			0.3068			0.3179		
sigma_e	0.1079			0.1102			0.1075		
rho	0.8955			0.8858			0.8973		
N	307			81			226		

Notes: For this regression, the yearly average of systemic risk, network characteristics, volatilities and ESG ratings are used. Cross-section size is 307. The stock ticker is used as panel id for the fixed effect regression. Other interaction terms are eliminated due to multicollinearity. Standard errors are calculated taking into account the clustering with respect to panel id. Significance: * 10%, ** 5%, *** 1%. Source: authors' calculations.

What is more in these results is that the ESG rating is negatively linked to systemic risk. The coefficient is significant at 10% and is small in magnitude. However, if we consider the approximately 40 point difference between the two modes in the histogram of Figure 3a, we can calculate that a 40-point increase in ESG ratings would decrease systemic risk contribution and exposure by 2.90%.[15] This means that firms with higher ESG ratings benefit from a lower systemic risk contribution and exposure compared to firms with lower ESG ratings. When we compare the results for southern and northern European countries, we see that the ESG ratings have no significant impact on systemic risk for southern European countries. For stocks from northern European countries, there was a higher impact, which would imply a 3.41% decline in systemic risk contribution and exposure for a 40-point increase in ESG ratings. Our findings do not support that the partial effect of ESG ratings was different in the COVID-19 period.

In Table 6, we further include the financial ratios of the firms in the regression. As we said before, due to lack of data, we end up with 199 stocks, among which there are fewer banks and insurance firms. As before, the coefficients of centrality measures are positive. In addition, we find that the partial effect of eigenvector centrality decreases as profit margin increases, but this does not depend on volatility or other financial performance ratios. This means that a stock becomes systemically less risky if the firm's profit margin is higher. The coefficient of log-volatility is positive, but the partial effect of volatility decreases when profit margin and solvency ratios are higher. This could mean that a stock's high volatility is less of a threat to the market if its profit margin and solvency ratios are higher. Financial performance ratios are positively linked to systemic risk contribution and exposure, but the sign of the partial effects quickly change for higher levels of eigenvector centrality and log-volatility, which implies that having better financial performance reduces systemic risk contribution and exposure further for central and volatile stocks.

The coefficient of the ESG rating is −0.0012 and it is significant at 5%. Following the previous discussion, an increase of 40 points in the ESG rating would mean a decrease of 4.87% in the systemic risk contribution and exposure. This implies that the high ESG-rating firms, in the right mode of the histogram in Figure 3a, are enjoying approximately 5% less systemic risk contribution and exposure compared to the low ESG-rating firms in the left mode of the same histogram. In the extreme case, the difference between the left and right tails of the ESG-rating distribution is over 80 points, and this implies about 9.5% less systemic risk contribution and exposure for the high ESG-rating firms. Another note is that the partial effects of eigenvector centrality and log-volatility are higher in 2020, but no such effect is seen for ESG rating and financial ratios.

Comparing the results for southern and northern European countries, we find that most coefficients are quantitatively and qualitatively very similar. We observe the difference that for southern countries the impact is much larger, yielding a 7.27% decrease in systemic risk contribution and exposure for a 40-point increase in ESG ratings, while for northern countries this impact is about 4.05%. This is a stronger result than that of the second panel, which has 307 stocks, and this is most likely due to the change in the stocks we considered. In this small panel, banks and insurance firms are not well represented due to lack of data. These results call for further research considering different industries, which we consider in Section 5.3.3.

Table 6. Fixed effects estimation results using the stock market, network, ESG ratings and firm level financial data.

Sample →		**All**			**Southern**			**Northern**	
	Coef.	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**
NetEC	9.8011	4.2693	**	14.0324	8.0976	*	8.4767	4.8918	*
AbsCC	78.7130	9.2521	***	81.1382	24.4414	***	79.4319	10.2511	***
ESGrating	−0.0012	0.0005	**	−0.0019	0.0010	*	−0.0010	0.0006	*
CR	0.0639	0.0298	**	0.0938	0.1230		0.0710	0.0310	**
PM	0.0048	0.0013	***	0.0012	0.0037		0.0044	0.0014	***
SR	0.0005	0.0035		−0.0012	0.0070		0.0003	0.0038	
logVol	1.7410	0.0815	***	1.4485	0.2155	***	1.7312	0.0887	***
NetEC*logVol	−0.4065	1.4020		3.0364	3.0377		−0.0675	1.6459	
NetEC*CR	−0.8164	0.6741		−1.5913	2.3496		−1.1342	0.7412	
NetEC*PM	−0.0702	0.0208	***	0.0059	0.0702		−0.0603	0.0276	**
NetEC*SR	0.0405	0.0774		0.0768	0.1223		0.0487	0.0874	
logVol*CR	−0.0198	0.0206		0.1562	0.1043		−0.0245	0.0215	
logVol*PM	−0.0017	0.0006	***	−0.0027	0.0018		−0.0017	0.0006	***
logVol*SR	−0.0028	0.0010	***	−0.0081	0.0030	***	−0.0023	0.0011	**
Dt	−0.3793	0.0320	***	−0.3194	0.1227	**	−0.3573	0.0351	***
NetEC*Dt	2.0518	0.4654	***	1.7539	1.1584		1.7616	0.5330	***
logVol*Dt	0.0424	0.0196	**	0.0510	0.0398		0.0442	0.0217	**
ESGrating*Dt	−0.0002	0.0003		−0.0007	0.0009		−0.0002	0.0003	
CR*Dt	−0.0067	0.0050		−0.0837	0.0465	*	−0.0033	0.0044	
PM*Dt	−0.0004	0.0007		−0.0005	0.0011		−0.0003	0.0008	
SR*Dt	−0.0003	0.0004		0.0027	0.0009	***	−0.0008	0.0004	*
_cons	−4.7024	0.5948	***	−5.0623	1.6964	***	−4.6851	0.6372	***
Corr(u,X)	0.3076			0.0330			0.3514		
Pval_Ftest	0.0000			0.0000			0.0000		
R^2 within	0.8673			0.8837			0.8646		
R^2 between	0.8770			0.6809			0.9025		
R^2 overall	0.8750			0.7033			0.8987		
sigma_u	0.3417			0.4237			0.3277		
sigma_e	0.1083			0.1053			0.1099		
rho	0.9087			0.9415			0.8988		
N	199			52			147		

Notes: For this regression, the yearly average of systemic risk, network characteristics, volatilities, ESG ratings and firm level financial data are used. Cross-section size is 199. The stock ticker was used as panel id for the fixed effects regression. Other interaction terms were eliminated due to multicollinearity. Standard errors are calculated taking into account the clustering with respect to panel id. Significance: * 10%, ** 5%, *** 1%. Source: S&P Global ESG ratings and authors' calculations.

Overall, we find that higher ESG ratings can be associated with lower systemic risk contribution and exposure, which is in line with the results of Cerqueti et al. (2021), Boubaker et al. (2020) and Oikonomou et al. (2012). We could not find evidence that the partial effect of ESG ratings is different in the pandemic period. This result does not coincide with the findings of Gregory (2022).

5.3.2. OLS Regressions for 2020

As explained in Section 4.1, we were able to collect data for the financial performances and the subcategories of the ESG ratings for the 199 firms in our smallest panel in 2020. To have a fair comparison, we ran three OLS regressions, one for each cross-section size in our panels: 330, 307 and 199. The stock tickers were used as a clustering variable to calculate the standard errors.

Using the 330 stocks of the first panel, we found similar results as in the fixed effects regression: the centralities and volatility significantly affect the systemic risk contribution and exposure. We present these results in Table 7. However, we should note that the coefficient for eigenvector centrality was negative and larger in magnitude for the stocks from southern European countries compared to the northern ones. For the 307 stocks that had ESG rating data available, we found similar coefficients in Table 8. Interestingly, in these regressions we found that ESG subcategories did not have an affect on the dependent variable. When we moved on to include the financial performance ratios in the OLS regressions in Table 9, we saw that eigenvector centrality and volatility regressors were significant, while in the sub-samples the former was not significant.

Table 7. OLS estimation results only using the stock market and network data for 2020.

Sample →		**All**			**Southern**			**Northern**	
	Coef.	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**
NetEC	−1.4137	0.3312	***	−1.5600	0.5433	***	−1.2293	0.3705	***
AbsCC	1.9125	0.9787	*	3.1472	1.6868	*	1.3937	1.2022	
logVol	2.0993	0.0185	***	2.0978	0.0305	***	2.1112	0.0214	***
NetEC*logVol	0.0004	0.3492		0.2293	0.5132		−0.3245	0.4147	
_cons	−0.1098	0.0616	*	−0.1844	0.1003	*	−0.0844	0.0757	
Pval_Ftest	0.0000			0.0000			0.0000		
R^2	0.9984			0.9983			0.9984		
N	330			90			240		

Notes: For this regression yearly average of systemic risk, network characteristics and volatilities are used. Cross-section size is 330. Other interaction terms were eliminated due to multicollinearity. Significance: * 10%, ** 5%, *** 1%. Source: S&P Global ESG ratings and authors' calculations.

Table 8. OLS estimation results using the stock market, network and ESG ratings data for 2020.

Sample →		**All**			**Southern**			**Northern**	
	Coef.	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**
NetEC	−1.5043	0.3474	***	−1.3615	0.6195	**	−1.3497	0.4002	***
AbsCC	2.2423	1.0341	*	2.4784	1.8449		1.9141	1.2944	
Esg_Env	−0.0003	0.0002		0.0001	0.0003		−0.0003	0.0002	
Esg_Soc	0.0001	0.0002		0.0005	0.0009		0.0000	0.0003	
Esg_GovEcon	0.0002	0.0003		−0.0003	0.0008		0.0003	0.0003	
logVol	2.0881	0.0199	***	2.0961	0.0316	***	2.0980	0.0240	***
NetEC*logVol	0.1710	0.3727		0.2201	0.5437		−0.1165	0.4639	
_cons	−0.1233	0.0645	*	−0.1743	0.1054		−0.1040	0.0803	
Pval_Ftest	0.0000			0.0000			0.0000		
R^2	0.9984			0.9984			0.9985		
N	307			81			226		

Notes: For this regression yearly average of systemic risk, network characteristics, volatilities and ESG ratings are used. Cross-section size is 307. Other interaction terms were eliminated due to multicollinearity. Significance: * 10%, ** 5%, *** 1%. Source: S&P Global ESG ratings and authors' calculations.

Table 9 also suggests that while the social factor in the ESG ratings is positively linked to systemic risk contribution and exposure, the governance/economic factor is negatively related. The latter is in line with the findings of Gregory (2022) that during the pandemic, non-financial firms with higher governance scores performed better. The coefficients are not very large, but for a 40-point improvement in these factors, the effect is 3.25% and −3.35%, respectively. We did not find a significant relation to the environment factor. Similar results can be observed for the sub-sample of stocks from northern European countries but not for the southern ones. These findings are in line with Ionescu et al. (2019), who analysed the impact of ESG factors on the market values of travel and tourism firms. They found that the governance factor had the highest positive impact on the market values and the social factor had a negative impact, while the environment factor had no significant impact. It is very likely that investors value the governance factor since it is a sign of stability for the firm. As Ionescu et al. (2019) also argue, the investors probably see social investments as risky.

Table 9. OLS estimation results using the stock market, network, ESG ratings and firm level financial data for 2020.

Sample →	**All**			**Southern**			**Northern**		
	Coef.	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**	**Coef.**	**St. Err.**	**Sig.**
NetEC	−1.4657	0.6431	**	−1.8380	1.1139		−1.2013	0.7311	
AbsCC	0.2549	1.1934		0.6408	2.8673		−0.2989	1.4799	
Esg_Env	−0.0001	0.0003		−0.0013	0.0012		0.0001	0.0003	
Esg_Soc	0.0008	0.0004	**	0.0013	0.0013		0.0007	0.0003	**
Esg_GovEcon	−0.0009	0.0003	***	−0.0007	0.0006		−0.0008	0.0003	**
CR	−0.0134	0.0087		−0.1310	0.0444	***	−0.0059	0.0079	
PM	0.0006	0.0006		0.0014	0.0010		0.0003	0.0007	
SR	0.0001	0.0007		0.0035	0.0021		0.0002	0.0008	
logVol	2.1108	0.0234	***	2.1396	0.0570	***	2.1115	0.0261	***
NetEC*logVol	−0.2389	0.4411		−0.8308	1.0937		−0.3030	0.5026	
NetEC*CR	0.2170	0.1769		2.0354	0.7527	***	0.1001	0.1482	
NetEC*PM	−0.0113	0.0109		−0.0314	0.0193		−0.0041	0.0133	
NetEC*SR	−0.0001	0.0115		−0.0534	0.0366		−0.0039	0.0131	
_cons	0.0079	0.0766		0.0608	0.1744		0.0151	0.0926	
Pval_Ftest	0.0000			0.0000			0.0000		
R^2	0.9985			0.9983			0.9988		
N	199			52			147		

Notes: For this regression yearly average of systemic risk, network characteristics, volatilities, ESG ratings and firm level financial data are used. Cross-section size is 199. Other interaction terms were eliminated due to multicollinearity. Significance: * 10%, ** 5%, *** 1%. Source: S&P Global ESG ratings and authors' calculations.

5.3.3. Further Regressions

In Table 10, we present the coefficients of the ESG ratings (ESG Coef) and their interaction with the dummy variable (D*ESG Coef) for 2020 in the fixed effects regressions we ran for each sector. The industries that constitute these sectors are given in Table A20 in Appendix A. As Hox et al. (2017) mention, when a panel data has less than 50 groups and less than five cases for each group, the standard errors for the fixed effects regressions might be too small. We need to keep this in mind when interpreting the results of Table 10. This is why we report the number of firms in each sector in the last column of this table.

If we consider the panel of 307 stocks, where the regressors are as in Table 5, we find significant coefficients for ESG ratings for energy, financial and utilities sectors. An increase of 40 points in ESG ratings in these sectors suggests a decrease of 16.60%, 6.07% and 17.56% in systemic risk, respectively. For these sectors, keeping ESG ratings high might have helped reduce the systemic risk contribution and exposure. Our finding for the financial sector is in line with the results of Sonnenberger and Weiss (2021) for insurance firms and Klooster (2018) and Chiaramonte et al. (2021) for banks. In 2020, this beneficial impact of the ESG rating was slightly offset for consumer discretionary and information technology sectors, while it was increased for the real estate sector. When we consider the panel of 199 stocks, where the regressors were as in Table 6, we see that for the health care, information technology and utilities sectors the ESG ratings coefficients are significant. For health care, the coefficient is as high in magnitude as to imply a 22.50% reduction in systemic risk contribution and exposure for a 40-point increase in ESG ratings. This impact is reduced to about 14.19% in 2020. For the information technology and utilities sectors, the impact of a 40-point increase in ESG ratings was about 13.20% and 18.74%.

Table 10. Fixed effects estimation results by sector.

Panel: 307 Stocks	ESG Coef	St. Err.	Pval	D*ESG Coef	St. Err.	Pval	N
Communication Services	−0.0025	0.0015		−0.0014	0.0011		19
Consumer Discretionary	0.0006	0.0010		0.0014	0.0006	**	32
Consumer Staples	0.0007	0.0013		−0.0006	0.0005		29
Energy	−0.0045	0.0020	*	0.0048	0.0028		10
Financials	−0.0016	0.0007	**	−0.0004	0.0005		59
Health Care	−0.0011	0.0023		0.0001	0.0010		21
Industrials	−0.0007	0.0009		0.0005	0.0006		64
Information Technology	−0.0026	0.0016		0.0022	0.0010	*	15
Materials	−0.0005	0.0008		−0.0006	0.0008		29
Real Estate	0.0004	0.0026		−0.0042	0.0021	*	10
Utilities	−0.0048	0.0012	***	−0.0010	0.0012		19
Panel: 199 Stocks	**ESG Coef**	**St. Err.**	**Sig.**	**D*ESG Coef**	**St. Err.**	**Sig**	**N**
Communication Services	−0.0015	0.0028		−0.0033	0.0013	**	14
Consumer Discretionary	0.0009	0.0018		−0.0008	0.0008		22
Consumer Staples	0.0013	0.0016		−0.0003	0.0009		23
Energy	−0.0061	0.0035		0.0102	0.0021	***	10
Financials	-	-	-	-	-	-	1
Health Care	−0.0064	0.0020	***	0.0025	0.0011	**	17
Industrials	−0.0003	0.0015		−0.0005	0.0009		49
Information Technology	−0.0035	0.0011	***	0.0026	0.0016		15
Materials	−0.0009	0.0008		−0.0004	0.0007		29
Real Estate	-	-	-	-	-	-	2
Utilities	−0.0052	0.0019	**	−0.0007	0.0020		17

Notes: Fixed effects regressions for each sector are presented for the panels with 307 and 199 stocks. *N* is the number of stocks in each sector. The focus is on the coefficients of the ESG-ratings variable and its interaction with the dummy variable for 2020. The stock ticker was used as panel id for the fixed effects regression. Standard errors are calculated taking into account the clustering with respect to panel id. Significance: * 10%, ** 5%, *** 1%. Source: S&P Global ESG ratings and authors' calculations.

Finally, we ran OLS regressions for each sector for 2020 using the panel with 307 stocks, where we used ESG sub-factors as ESG related regressors as in Section 5.3.2. In most cases, there were too few stocks in the sectors we wanted to analyse, which rendered these OLS regressions useless. There were 64 stocks in the Industrial sector and we found that the coefficient of the environmental factor was −0.0006, significant at 10%, while the other factors were not significant. On the other hand, for the financial sector, where there were 59 stocks, we found that the coefficients of social and governance/economic factors were −0.0008 and 0.0010, respectively, which were both significant at 1%. Harrell et al. (2001) suggest that for each regressor, one should have 10–20 observations per regressor, while Green (1991) suggests having at least 50+8*p number observations where p is the number of regressors. In these regressions we had seven regressors, which required at least 70 or 106 observations based on the suggestions of Harrell et al. (2001) and Green (1991), respectively. Therefore, it is possible that the results of these OLS regressions were suffering from a small sample size. To save space, we do not present the results of these regressions.

6. Conclusions

The ESG rankings provide us with particular information on the firms. With them, the firms state how they are in tune with investment preferences, treatment of their employees and the institution's financial health, etc. We can certainly imagine how susceptible a company is to an economic shock with this information. However, we question what happens when we also have information about the firm's role within the financial system. How influential is it? Is it likely to trigger a cascade effect if something happens to a specific entity or will bankruptcy not affect more entities? Furthermore, we wonder at what speed this will occur. We obtain this information from the eigenvector and closeness centralities.

In this study, we explored the effect of the ESG ratings of firms on the systemic risk contribution and exposure of their stocks. Our aim was to show that keeping ESG ratings high would benefit the firms by reducing the systemic risk they face. For this purpose, we used the daily returns of the stocks constituting the S&P Europe 350 index for the period 5 January 2016–15 September 2020 and yearly ESG ratings and firm performance ratios for these firms. We employed an interdisciplinary approach that connected financial econometrics, panel data econometrics and social networks. To be more precise, we fit a rigorous model to estimate the daily volatilities and dynamic correlations, and using the principal components method we derived the systemic risk contribution and exposure measures. Subsequently, we obtained dynamic partial correlations using Gaussian graphical modelling and constructed the daily partial correlation networks of stocks, which provided us with the network centralities. Finally, we employed panel data and OLS regressions, where the systemic risk contribution and exposure of each firm was the dependent variable and the volatility estimates, network centralities, ESG ratings and firm performance ratios were the regressors. We also considered a dummy variable for the year 2020 to take account of the effect of COVID-19.

Our results indicate that volatilities and network centralities are the main determinants of systemic risk contribution and exposure, and the impact of these variables increased during the COVID-19 period. We also found that the systemic risk contribution and exposure could be reduced by almost 5% through a 40-point increase in ESG ratings. When we consider the southern European countries (Italy, France, Spain and Portugal) alone, this effect rises to about 7.3%. This finding could be interpreted such that the firms to the higher end of the ESG ratings benefit from reduced systemic risk contribution and exposure compared to those with lower ESG ratings.

We were also able to analyse the effect of ESG subcategory ratings (environmental, social and governance/economic factors) for 2020, and we found no significant impact of the environmental factor. On the other hand, the results suggest a positive coefficient for the social factors and a negative coefficient for the governance/economic factors on the systemic risk contribution and exposure. These results may suggest that investors see social investments as risky but they value how the firms are governed.

The findings of this study are highly useful for firms. Although firms may find it costly or risky to engage in ESG related activities, our results show that it pays to keep ESG ratings high. In particular, firms should pay attention to governance/economic factors to satisfy the interests of their shareholders.

This work can be extended in multiple ways. The first would be to expand the dataset further, not only in terms of the number of stocks considered but also the ESG ratings and subcategories. For example, our data did not allow us to estimate regressions per sector, although this would have been a valuable analysis. Another interesting point could be to explore whether the systemic risk measures and firm performance ratios are simultaneously determined. Although it could provide a different insight into the possible relations between the variables, the firm-specific effects would not be captured by such a regression.

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Appendix A

Appendix A.1. Tables and Figures

Table A1. Average overall ESG rating by company for 2016–2020.

Stock Names	Countries	Industry	Average ESG Rating
Unilever NV	United Kingdom	Personal products	89.6
Koninklijke KPN NV	Netherlands	Telecommunication services	89.4
CNH Industrial NV	United Kingdom	Machinery and Electrical Equipment	88.8
Red Electrica Corporacion SA	Spain	Electric utilities	88.8
Energias de Portugal SA	Portugal	Electric utilities	88.6
Iberdrola SA	Spain	Electric utilities	88.2
Roche Hldgs AG Ptg Genus	Switzerland	Pharmaceuticals	88.2
Banco Santander SA	Spain	Banks	87.2
UPM-Kymmene Oyj	Finland	Paper and forest products	87.2
Allianz SE	Germany	Insurance	87
Enagas SA	Spain	Gas utilities	86.8
Enel SpA	Italy	Electric utilities	86.6
GlaxoSmithKline	United Kingdom	Pharmaceuticals	86.2
Telecom Italia SpA	Italy	Telecommunication services	86.2
Diageo Plc	United Kingdom	Beverages	86
Endesa SA	Spain	Electric utilities	85.4
Deutsche Telekom AG	Germany	Telecommunication services	85.2
Koninklijke Philips Electronics NV	Netherlands	Health Care Equipment & Supplies	84.6
Naturgy Energy Group SA	Spain	Gas utilities	84.6
UBS Group AG	Switzerland	Diversified Financial Services and Capital Markets	84.6
Clariant AG Reg	Switzerland	Chemicals	84.4
Lanxess AG	Germany	Chemicals	84.4
Schneider Electric SE	France	Electrical Components and Equipment	84.2
Adidas AG	Germany	Textiles, Apparel & Luxury Goods	84
CaixaBank	Spain	Banks	84

Notes: This table gives the 25 best stocks with the highest average of the yearly ESG ratings for the years 2016–2020. In total, there are 308 stocks for which ESG ratings were available. Source: S&P Global ESG ratings and authors' calculations.

Table A2. Centralities for 2016–2019, before COVID-19, by net eigenvector centrality.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
BNP Paribas	France	0.1028	0.0558	0.063	6.4293	81
Investor AB B	Sweden	0.0993	0.0588	0.0631	1.3355	40
Societe Generale	France	0.0965	0.061	0.0645	13.708	79
Banco Santander SA	Spain	0.0962	0.053	0.0629	9.4054	83
Allianz SE	Germany	0.0954	0.0583	0.0644	1.6231	87
Swiss Life Reg	Switzerland	0.0938	0.0578	0.0629	1.5106	51
Credit Agricole SA	France	0.0937	0.0568	0.062	9.2656	46
BASF SE	Germany	0.0926	0.0569	0.0631	2.806	37
Banco Bilbao V.A. SA	Spain	0.0899	0.0623	0.0659	9.592	87
Zurich Insurance Gr. AG	Switzerland	0.0898	0.0595	0.0627	1.3731	90
Industrivarden AB A	Sweden	0.0886	0.0527	0.0597	1.3141	30
Daimler AG	Germany	0.0881	0.0537	0.0603	4.59	25
ING Groep NV	Netherlands	0.0877	0.0572	0.062	6.3443	52
Porsche Automobil H. SE	Germany	0.0873	0.0518	0.059	8.0125	19
AXA	France	0.0865	0.0569	0.0625	3.1282	88
Bayer Motoren Werke AG	Germany	0.0861	0.0546	0.0601	3.6705	80
Sandvik AB	Sweden	0.0857	0.0573	0.0626	5.4072	76
Credit Suisse Group AG	Switzerland	0.0857	0.057	0.0643	10.308	65
TOTAL SA	France	0.0854	0.0565	0.06	2.7486	75
UBS Group AG	Switzerland	0.0836	0.0542	0.062	4.7065	84
Volkswagen AG	Germany	0.0832	0.0546	0.0593	5.4902	62
Repsol SA	Spain	0.0831	0.0584	0.0618	7.0166	38
SEB-Skand Enskilda B. A	Sweden	0.0827	0.0569	0.0628	2.7802	48
LVMH-Moet Vuitton	France	0.0826	0.057	0.0639	3.8778	69
BHP Group Plc	United Kingdom	0.0825	0.0576	0.0626	17.8649	43

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available, 2016–2019. The ordering was done with respect to net eigenvector centrality. Source: S&P Global ESG ratings and authors' calculations.

Table A3. Centralities in 2020, during COVID-19, by net eigenvector centrality.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
BNP Paribas	France	0.1008	0.0559	0.0633	12.4525	81
Investor AB B	Sweden	0.0977	0.0584	0.0632	1.7187	40
Societe Generale	France	0.0956	0.0615	0.065	31.57	79
Swiss Life Reg	Switzerland	0.0944	0.0565	0.0624	3.4205	51
Credit Agricole SA	France	0.0938	0.0563	0.0616	13.335	46
Banco Santander SA	Spain	0.0932	0.0534	0.0632	14.4758	83
Allianz SE	Germany	0.093	0.0573	0.0637	2.5602	87
BASF SE	Germany	0.0924	0.0567	0.063	4.5193	37
Banco Bilbao V.A. SA	Spain	0.0909	0.0625	0.0661	16.1662	87
Zurich Insurance Gr. AG	Switzerland	0.0889	0.0594	0.0629	2.7679	90
Daimler AG	Germany	0.0882	0.0534	0.0599	15.4757	25
Industrivarden AB A	Sweden	0.0873	0.0517	0.0596	1.7714	30
BHP Group Plc	United Kingdom	0.087	0.0577	0.0625	16.0257	43
Porsche Automobil H. SE	Germany	0.0869	0.0512	0.0591	6.9316	19
BP Plc	United Kingdom	0.0864	0.0541	0.0606	11.6752	48
ING Groep NV	Netherlands	0.0858	0.0568	0.0621	12.3155	52
Sandvik AB	Sweden	0.0856	0.0574	0.0628	7.1167	76
Bayer Motoren Werke AG	Germany	0.0855	0.0548	0.06	4.8539	80
Credit Suisse Group AG	Switzerland	0.0853	0.0566	0.064	9.406	65
Royal Dutch Shell Plc	Netherlands	0.0838	0.052	0.0606	10.135	68
TOTAL SA	France	0.0832	0.0572	0.0599	3.9101	75
AXA	France	0.0831	0.0575	0.0624	4.705	88
UBS Group AG	Switzerland	0.0828	0.0536	0.0615	5.3577	84
Siemens AG	Germany	0.0826	0.0525	0.0585	3.2297	81
Repsol SA	Spain	0.0825	0.0577	0.0615	11.8172	38

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available in 2020. The ordering was done with respect to net eigenvector centrality. Source: S&P Global ESG ratings and authors' calculations.

Table A4. Centralities for 2016–2019, before COVID-19, by ESG rating.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
Unilever NV	United Kingdom	0.0365	0.0527	0.0591	1.0489	91
Telecom Italia SpA	Italy	0.0406	0.0501	0.0565	15.1736	90
Zurich Insurance Gr. AG	Switzerland	0.0898	0.0595	0.0627	1.3731	90
CNH Industrial NV	United Kingdom	0.0551	0.0534	0.0595	13.8615	89
Deutsche Telekom AG	Germany	0.0544	0.0556	0.059	0.9918	89
Enel SpA	Italy	0.0603	0.0556	0.0605	1.9888	89
Koninklijke KPN NV	Netherlands	0.0331	0.0552	0.0603	2.4549	89
Red Electrica Corp. SA	Spain	0.0367	0.0541	0.06	1.1784	89
Roche Hldgs AG Ptg Gen.	Switzerland	0.0435	0.0531	0.0595	0.7459	89
AXA	France	0.0865	0.0569	0.0625	3.1282	88
Energias de Portugal SA	Portugal	0.0336	0.0551	0.059	1.8833	88
GlaxoSmithKline	United Kingdom	0.0344	0.0531	0.0592	1.2531	88
Schneider Electric SE	France	0.0795	0.0551	0.0621	3.5495	88
UPM-Kymmene Oyj	Finland	0.0598	0.06	0.0653	4.1734	88
Allianz SE	Germany	0.0954	0.0583	0.0644	1.6231	87
Banco Bilbao V.A. SA	Spain	0.0899	0.0623	0.0659	9.592	87
Burberry Group	United Kingdom	0.0417	0.0606	0.0622	8.5782	87
Diageo Plc	United Kingdom	0.0438	0.0613	0.0644	1.0848	87
Enagas SA	Spain	0.0393	0.0525	0.0601	2.2418	87
Endesa SA	Spain	0.0399	0.0542	0.0614	1.1404	87
Lanxess AG	Germany	0.0729	0.0532	0.0594	7.9381	87
Moncler SpA	Italy	0.0449	0.0586	0.0613	8.3403	87
Swiss Re Reg	Switzerland	0.0753	0.0518	0.0609	1.5014	87
Iberdrola SA	Spain	0.0511	0.0559	0.0607	1.2038	86
Naturgy Energy Gr. SA	Spain	0.0449	0.0566	0.0618	1.7394	86

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available for 2016–2019. The ordering was done with respect to ESG ratings. Source: S&P Global ESG ratings and authors' calculations.

Table A5. Centralities in 2020, during COVID-19, by ESG rating.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
Unilever NV	United Kingdom	0.0363	0.0512	0.0583	0.6753	91
Telecom Italia SpA	Italy	0.0409	0.0501	0.0561	14.4551	90
Zurich Insurance Gr. AG	Switzerland	0.0889	0.0594	0.0629	2.7679	90
CNH Industrial NV	United Kingdom	0.0536	0.0527	0.0589	14.949	89
Deutsche Telekom AG	Germany	0.0524	0.0562	0.0593	0.9406	89
Enel SpA	Italy	0.0618	0.0549	0.0598	1.91	89
Koninklijke KPN NV	Netherlands	0.0327	0.0551	0.0605	1.583	89
Red Electrica Corp. SA	Spain	0.0389	0.0541	0.06	0.9985	89
Roche Hldgs AG Ptg Gen.	Switzerland	0.0429	0.0524	0.0591	0.7583	89
AXA	France	0.0831	0.0575	0.0624	4.705	88
Energias de Portugal SA	Portugal	0.0313	0.0557	0.0594	1.9214	88
GlaxoSmithKline	United Kingdom	0.035	0.0536	0.0593	1.0876	88
Schneider Electric SE	France	0.0786	0.0557	0.0619	3.7223	88
UPM-Kymmene Oyj	Finland	0.0567	0.06	0.0648	2.8815	88
Allianz SE	Germany	0.093	0.0573	0.0637	2.5602	87
Banco Bilbao V.A. SA	Spain	0.0909	0.0625	0.0661	16.1662	87
Burberry Group	United Kingdom	0.043	0.0609	0.0626	8.7603	87
Diageo Plc	United Kingdom	0.0476	0.0626	0.065	1.0954	87
Enagas SA	Spain	0.0413	0.0537	0.0602	2.6524	87
Endesa SA	Spain	0.0422	0.0534	0.0609	0.994	87
Lanxess AG	Germany	0.0718	0.0532	0.0595	6.8079	87
Moncler SpA	Italy	0.0452	0.0584	0.0609	7.5916	87
Swiss Re Reg	Switzerland	0.0765	0.0515	0.0608	3.1312	87
Iberdrola SA	Spain	0.0538	0.0562	0.0605	1.5353	86
Naturgy Energy Gr. SA	Spain	0.0465	0.0567	0.0619	1.5673	86

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available in 2020. The ordering was done with respect to ESG ratings. Source: S&P Global ESG ratings and authors' calculations.

Table A6. Centralities for 2016–2019, before COVID-19, by systemic risk: most risky.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
Wirecard AG	Germany	0.0178	0.0537	0.0585	87.3601	11
Anglo American Plc	United Kingdom	0.063	0.0556	0.0623	69.7374	80
ArcelorMittal Inc	Luxembourg	0.0643	0.0525	0.0591	61.4661	49
Bank of Ireland Group	Ireland	0.0415	0.054	0.0577	50.872	44
Glencore Plc	Switzerland	0.0603	0.0539	0.0599	42.5701	41
Unicredit SpA Ord	Italy	0.0587	0.053	0.0601	42.048	49
Deutsche Bank AG	Germany	0.0509	0.0529	0.0599	28.2856	56
Commerzbank AG	Germany	0.0665	0.054	0.0583	26.2122	39
STMicroelectronics NV	Switzerland	0.0573	0.0544	0.0609	23.7928	80
ThyssenKrupp AG	Germany	0.054	0.0529	0.0604	23.2879	20
Banco de Sabadell SA	Spain	0.0558	0.0538	0.0621	21.9302	55
Easyjet	United Kingdom	0.0391	0.0578	0.0631	21.8589	18
TUI AG	Germany	0.0435	0.062	0.0645	21.8324	65
Pandora A/S	Denmark	0.0231	0.0526	0.056	20.5019	20
Valeo	France	0.0584	0.0521	0.0578	20.1379	76
Melrose Industries Plc	United Kingdom	0.0463	0.0502	0.0574	19.8368	15
Weir Group	United Kingdom	0.0609	0.0591	0.0615	19.52	36
Micro Focus International	United Kingdom	0.0327	0.05	0.0563	19.4467	17
GVC Holdings Plc	United Kingdom	0.0278	0.0542	0.0601	18.8734	63
BHP Group Plc	United Kingdom	0.0825	0.0576	0.0626	17.8649	43
Electricite de France	France	0.0377	0.0534	0.0586	17.538	84
Inter. Cons. A. Gr. SA	Spain	0.0522	0.0568	0.0619	16.8167	32
Mediobanca SpA	Italy	0.0628	0.053	0.0589	15.1757	53
Telecom Italia SpA	Italy	0.0406	0.0501	0.0565	15.1736	90
Ryanair Holdings Plc	Ireland	0.0348	0.0493	0.0577	15.0289	17

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available for 2016–2019. The ordering was done with respect to systemic risk in descending order. Source: S&P Global ESG ratings and authors' calculations.

Table A7. Centralities in 2020, during COVID-19, by systemic risk: most risky.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
Wirecard AG	Germany	0.0173	0.0551	0.0592	1050.2487	11
TUI AG	Germany	0.0445	0.0629	0.0648	138.6509	65
Bank of Ireland Group	Ireland	0.0424	0.0541	0.0576	96.2661	44
Carnival Plc	United Kingdom	0.0477	0.0534	0.0582	95.1087	47
ArcelorMittal Inc	Luxembourg	0.0647	0.0515	0.0587	66.7692	49
Inter. Cons. A. Gr. SA	Spain	0.0543	0.0573	0.0622	64.9675	32
Unibail Rodamco Westfield	France	0.0662	0.0565	0.0611	50.7264	41
ThyssenKrupp AG	Germany	0.0536	0.0531	0.0599	44.1727	20
Easyjet	United Kingdom	0.0407	0.0569	0.0632	42.9224	18
Rolls-Royce Holdings Plc	United Kingdom	0.0425	0.0547	0.0588	42.6259	74
Renault SA	France	0.0625	0.0549	0.0596	41.3718	45
Melrose Industries Plc	United Kingdom	0.0477	0.05	0.0578	40.107	15
Anglo American Plc	United Kingdom	0.0668	0.0557	0.0622	36.328	80
Commerzbank AG	Germany	0.0669	0.0545	0.0586	34.3686	39
Societe Generale	France	0.0956	0.0615	0.065	31.57	79
Micro Focus International	United Kingdom	0.0345	0.0505	0.0559	30.9013	17
Valeo	France	0.0568	0.0522	0.057	30.5707	76
Klepierre	France	0.0594	0.0581	0.0623	28.5112	40
Banco de Sabadell SA	Spain	0.0555	0.0546	0.0625	27.3305	55
Glencore Plc	Switzerland	0.0632	0.0532	0.0595	26.7761	41
Deutsche Bank AG	Germany	0.0509	0.0534	0.06	25.4111	56
GVC Holdings Plc	United Kingdom	0.0293	0.0539	0.06	23.5431	63
ABN AMRO Group NV	Netherlands	0.0577	0.0504	0.0593	22.6387	83
Ryanair Holdings Plc	Ireland	0.0362	0.0485	0.0573	22.2129	17
Unicredit SpA Ord	Italy	0.0579	0.052	0.0594	22.0486	49

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available in 2020. The ordering was done with respect to to systemic risk in descending order. Source: S&P Global ESG ratings and authors' calculations.

Table A8. Centralities for 2016–2019, before COVID-19, by systemic risk: least risky.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
Swiss Prime Site AG	Switzerland	0.031	0.0556	0.0612	0.3777	25
Swisscom AG Reg	Switzerland	0.0521	0.0539	0.0588	0.4423	58
Nestle SA Reg	Switzerland	0.0456	0.054	0.0578	0.4996	72
Beiersdorf AG	Germany	0.0438	0.054	0.0617	0.7235	29
Roche Hldgs AG Ptg Gen.	Switzerland	0.0435	0.0531	0.0595	0.7459	89
SGS-Soc Gen Surveil Hldg R.	Switzerland	0.0573	0.0521	0.0571	0.7497	85
Groupe Bruxelles Lambert	Belgium	0.0822	0.0508	0.0581	0.7744	38
Geberit AG Reg	Switzerland	0.0636	0.0556	0.0594	0.7797	37
Givaudan AG	Switzerland	0.0475	0.0526	0.0613	0.8175	37
Lindt & Sprungli AG R.	Switzerland	0.0324	0.0554	0.0584	0.8263	23
Heineken NV	Netherlands	0.0558	0.0581	0.0631	0.8693	82
Orkla AS	Norway	0.0222	0.0566	0.0605	0.9364	62
Novartis AG Reg	Switzerland	0.0506	0.0541	0.0593	0.945	73
Kuehne & Nagel Intl. AG R.	Switzerland	0.0466	0.0594	0.063	0.9477	48
Carlsberg AS B	Denmark	0.035	0.0543	0.0608	0.9688	24
Henkel AG & Co. K. N. P.	Germany	0.0464	0.0562	0.0597	0.9768	37
Partners Group Hldg	Switzerland	0.0552	0.0594	0.0628	0.9828	55
Danone	France	0.0468	0.0584	0.0609	0.991	69
Deutsche Telekom AG	Germany	0.0544	0.0556	0.059	0.9918	89
Unilever NV	United Kingdom	0.0365	0.0527	0.0591	1.0489	91
Telia Company AB	Sweden	0.0485	0.0528	0.0592	1.0531	32
Diageo Plc	United Kingdom	0.0438	0.0613	0.0644	1.0848	87
Pernod-Ricard	France	0.0472	0.0575	0.0623	1.0926	34
SEGRO Plc	United Kingdom	0.041	0.0515	0.0609	1.1128	58
Endesa SA	Spain	0.0399	0.0542	0.0614	1.1404	87

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available for 2016–2019. The ordering was done with respect to systemic risk in ascending order. Source: S&P Global ESG ratings and authors' calculations.

Table A9. Centralities in 2020, during COVID-19, by systemic risk: least risky.

Stock Tickers	Countries	Net EC	Abs. EC.	Abs. CC.	Sys.Rk.	ESG
Nestle SA Reg	Switzerland	0.0451	0.054	0.0575	0.3749	72
Swisscom AG Reg	Switzerland	0.0502	0.0543	0.0593	0.4261	58
Swiss Prime Site AG	Switzerland	0.0286	0.0558	0.0616	0.555	25
Beiersdorf AG	Germany	0.0447	0.053	0.0616	0.6034	29
SGS-Soc Gen Surveil Hldg R.	Switzerland	0.0549	0.0536	0.0573	0.6687	85
Unilever NV	United Kingdom	0.0363	0.0512	0.0583	0.6753	91
Givaudan AG	Switzerland	0.047	0.0515	0.061	0.6793	37
Lindt & Sprungli AG R.	Switzerland	0.0326	0.0552	0.0589	0.709	23
Novartis AG Reg	Switzerland	0.0494	0.0534	0.0591	0.7266	73
Roche Hldgs AG Ptg Gen.	Switzerland	0.0429	0.0524	0.0591	0.7583	89
Telia Company AB	Sweden	0.0472	0.0528	0.0588	0.7846	32
Danone	France	0.0458	0.0587	0.0611	0.7928	69
Orkla AS	Norway	0.022	0.0572	0.0601	0.8446	62
Schindler-Hldg AG Reg	Switzerland	0.0458	0.054	0.0604	0.9048	26
Henkel AG & Co. K. N. P.	Germany	0.0484	0.0566	0.0598	0.9162	37
Deutsche Wohnen AG BR	Germany	0.0291	0.0559	0.0613	0.9172	27
Deutsche Telekom AG	Germany	0.0524	0.0562	0.0593	0.9406	89
Ahold Delhaize NV	Netherlands	0.0259	0.0571	0.0613	0.9408	83
Geberit AG Reg	Switzerland	0.0605	0.057	0.06	0.9641	37
Endesa SA	Spain	0.0422	0.0534	0.0609	0.994	87
Kuehne & Nagel Intl. AG R.	Switzerland	0.0449	0.0597	0.063	0.9956	48
Red Electrica Corp. SA	Spain	0.0389	0.0541	0.06	0.9985	89
Elisa Corporation	Finland	0.0288	0.0536	0.0589	1.0182	31
Wolters Kluwer NV	Netherlands	0.0436	0.0518	0.0579	1.0284	30
Croda Intl	United Kingdom	0.0399	0.0554	0.0616	1.031	35

Notes: This table provides the net and absolute eigenvector centralities and absolute value closeness centralities of the top 25 central firms, for which the ESG ratings were available in 2020. The ordering was done with respect to systemic risk in ascending order. Source: S&P Global ESG ratings and authors' calculations.

(**a**) 330 firms—industries

(**b**) 330 firms—countries

(**c**) 307 firms—industries

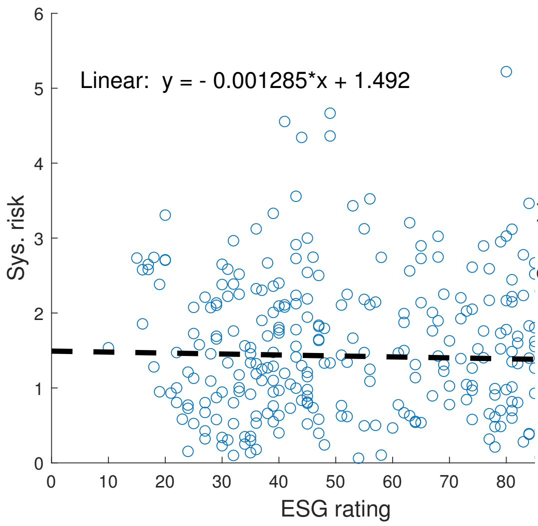
(**d**) 307 firms—countries

Figure A1. *Cont.*

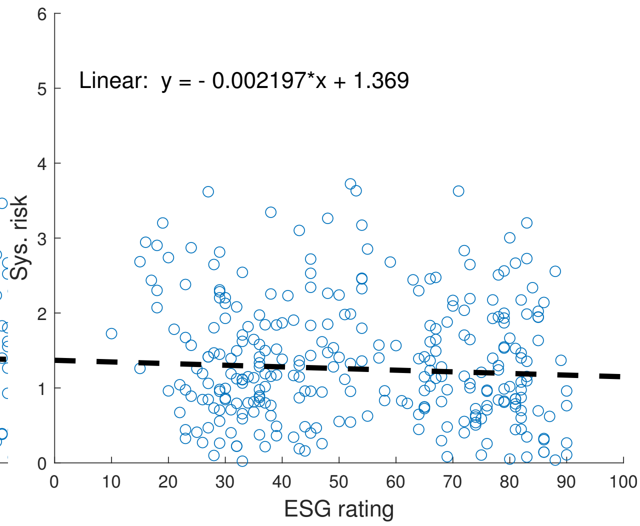
(**e**) 199 firms—industries

(**f**) 199 firms—countries

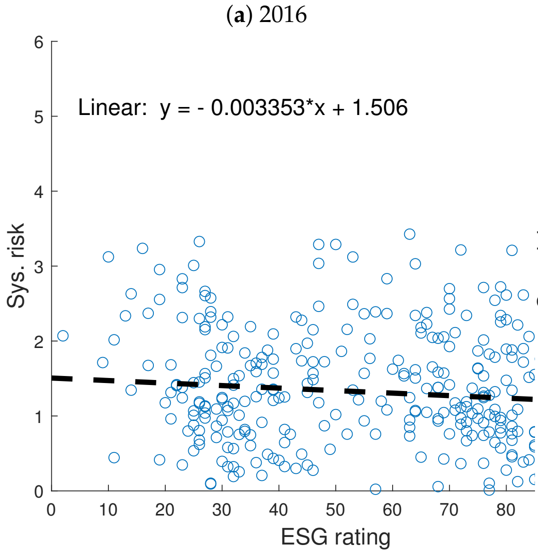
Figure A1. Word clouds to visualize the industries and countries of the firms in our dataset. In our dataset we have 330 firms, 307 of them have ESG rating data available, and 199 of them have both ESG rating and firm level financial ratios data available. Source: authors' calculations.



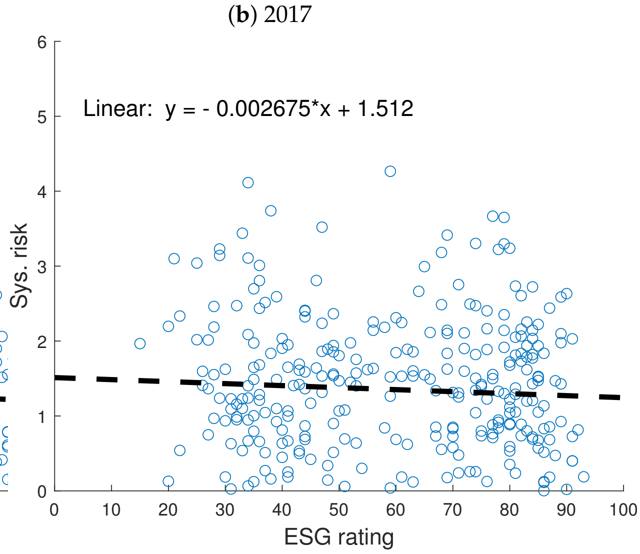
(**a**) 2016



(**b**) 2017

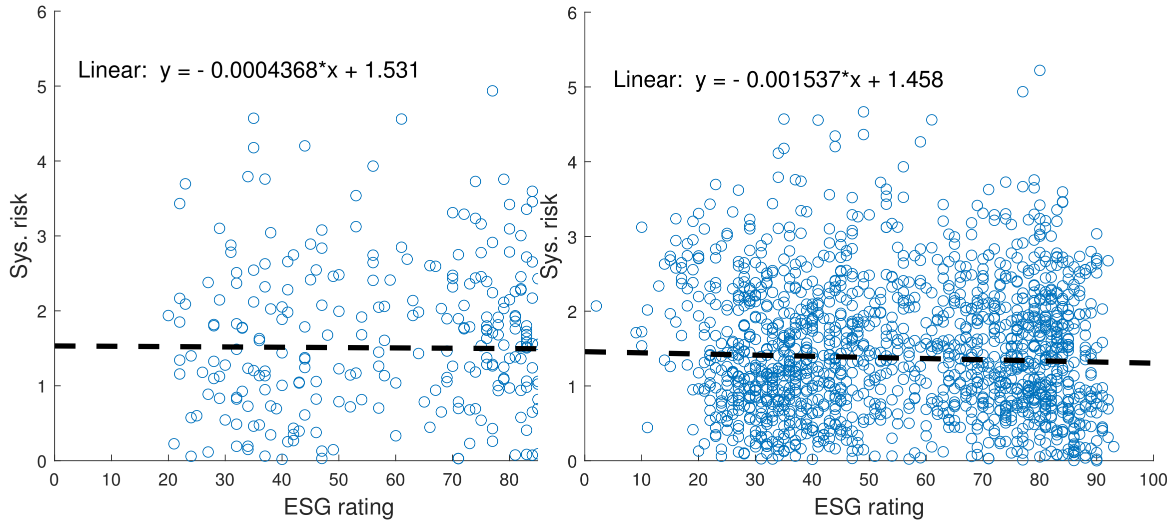


(**c**) 2018



(**d**) 2019

Figure A2. *Cont.*



(**e**) 2020 (**f**) 2016–2020

Figure A2. Scatter plots of average systemic risk per year versus the ESG ratings in that year.

Appendix A.2. Tables Related to Stock Data

Table A10. Firms part I.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
1COV.DE	Covestro AG	7585	DE	CHM	ooo
AAL.L	Anglo American PLC	35,532	GB	MNX	ooo
ABBN.SW	ABB Ltd	46,631	CH	ELQ	oo
ABF.L	Associated British Foods	24,306	GB	FOA	ooo
ABI.BR	Anheuser Busch Inbev NV	123,000	BE	BVG	ooo
ABN.AS	ABN AMRO Group NV	15,246	NL	BNK	oo
AC.PA	Accor	11,274	FR	TRT	ooo
ACA.PA	Credit Agricole SA	37,284	FR	BNK	oo
ACS.MC	ACS Actividades de Construccion y Servicios SA	11,217	ES	CON	ooo
AD.AS	Ahold Delhaize NV	26,391	NL	FDR	oo
ADP.PA	ADP Promesses	17,427	FR	PRO	o
ADS.DE	Adidas AG	58,080	DE	TEX	ooo
AENA.MC	Aena SA	25,575	ES	TRA	ooo
AGN.AS	Aegon NV	8523	NL	INS	oo
AGS.BR	AGEAS	10,450	BE	INS	oo
AHT.L	Ashtead Group	14,359	GB	TCD	ooo
AI.PA	L'Air Liquide S.A.	59,445	FR	CHM	ooo
AIR.PA	Airbus SE	101,000	FR	ARO	ooo
AKE.PA	Arkema	7242	FR	CHM	ooo
AKZA.AS	Akzo Nobel NV	20,643	NL	CHM	ooo
ALFA.ST	Alfa Laval AB	9490	SE	IEQ	ooo
ALO.PA	Alstom	9472	FR	IEQ	ooo
ALV.DE	Allianz SE	91,110	DE	INS	oo
AMS.MC	Amadeus IT Group SA	31,396	ES	TSV	ooo
ASML.AS	ASML Holding NV	112,000	NL	SEM	ooo
ASSA-B.ST	Assa Abloy B	22,025	SE	BLD	oo
ATCO-A.ST	Atlas Copco AB A	29,893	SE	IEQ	oo
ATL.MI	Atlantia SpA	17,153	IT	TRA	ooo
ATO.PA	AtoS SE	8115	FR	TSV	ooo
AV.L	Aviva	19,478	GB	INS	oo
AZN.L	AstraZeneca PLC	118,000	GB	DRG	ooo
BA.L	BAE Systems PLC	23,152	GB	ARO	ooo
BAER.SW	Julius Baer Group	10,284	CH	FBN	oo
BALN.SW	Baloise Hldg Reg	7859	CH	INS	o
BARC.L	Barclays	36,376	GB	BNK	oo
BAS.DE	BASF SE	61,859	DE	CHM	ooo
BATS.L	British American	94,014	GB	TOB	oo
BAYN.DE	Bayer AG	67,899	DE	DRG	oo
BBVA.MC	Banco Bilbao Vizcaya Argentaria SA	33,226	ES	BNK	oo

Notes: The last column indicates in which panels a stock was included. "o" indicates that the stock was in Panel 1, "oo" indicates that the stock was in Panel 1 and 2, and "ooo" indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors' calculations.

Table A11. Firms part II.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
BDEV.L	Barratt Developments Tobacco PLC	8981	GB	HOM	ooo
BEI.DE	Beiersdorf AG	26,875	DE	COS	ooo
BHP.L	BHP Group Plc	44,349	GB	MNX	ooo
BIRG.IR	Bank of Ireland Group	5270	IE	BNK	oo
BKG.L	Berkeley Group Holdings Plc	7860	GB	HOM	ooo
BLND.L	British Land Co	7108	GB	REA	oo
BMW.DE	Bayer Motoren Werke AG (BMW)	44,029	DE	AUT	oo
BN.PA	danone	50,625	FR	FOA	ooo
BNP.PA	BNP Paribas	65,744	FR	BNK	oo
BNR.DE	Brenntag AG	7490	DE	TCD	ooo
BNZL.L	Bunzl	8190	GB	TCD	ooo
BOL.ST	Boliden AB	6478	SE	MNX	ooo
BP.L	BP p.l.c	120,000	GB	OGX	ooo
BRBY.L	Burberry Group	10,719	GB	TEX	ooo
BT-A.L	BT Group	22,669	GB	TLS	ooo
BVI.PA	Bureau Veritas SA	10,512	FR	PRO	oo
CA.PA	Carrefour SA	12,068	FR	FDR	oo
CABK.MC	CaixaBank	16,736	ES	BNK	oo
CAP.PA	Capgemini SE	18,218	FR	TSV	ooo
CARL-B.CO	Carlsberg AS B	15,807	DK	BVG	ooo
CBK.DE	Commerzbank AG	6909	DE	BNK	oo
CCL.L	Carnival Plc	9321	GB	TRT	oo
CFR.SW	Richemont, Cie Financiere A Br	36,538	CH	TEX	oo
CHR.CO	Christian Hansen Holding A/S	9341	DK	LIF	oo
CLN.SW	Clariant AG Reg	6598	CH	CHM	ooo
CLNX.MC	Cellnex Telecom S.A.	14,784	ES	TLS	o
CNA.L	Centrica	6152	GB	MUW	ooo
CNHI.MI	CNH Industrial NV	13,325	IT	IEQ	oo
COLO-B.CO	Coloplast AS B	21,897	DK	HEA	ooo
CON.DE	Continental AG	23,052	DE	ATX	ooo
CPG.L	Compass Group	35,582	GB	REX	ooo
CRDA.L	Croda Intl	7981	GB	CHM	ooo
CRH	CRH Plc	28,198	IE	COM	ooo
CS.PA	AXA	60,928	FR	INS	oo
CSGN.SW	Credit Suisse Group AG	30,826	CH	FBN	oo
DAI.DE	Daimler AG	52,817	DE	AUT	ooo
DANSKE.CO	Danske Bank A/S	12,437	DK	BNK	oo
DASTY	Dassault Systemes SA	38,532	FR	SOF	ooo
DB	Deutsche Bank AG	14,295	DE	BNK	oo
DB1.DE	Deutsche Boerse AG	26,628	DE	FBN	oo

Notes: The last column indicates in which panels a stock was included. “o” indicates that the stock was in Panel 1, “oo” indicates that the stock was in Panel 1 and 2, and “ooo” indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors’ calculations.

Table A12. Firms part III.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
DCC.L	DCC	7836	IE	IDD	ooo
DG.PA	Vinci	59,918	FR	CON	ooo
DGE.L	Diageo Plc	97,310	GB	BVG	ooo
DLG.L	Direct Line Insurance Group	5078	GB	INS	oo
DNB.OL	DNB ASA	26,283	NO	BNK	oo
DPW.DE	Deutsche Post AG	41,805	DE	TRA	ooo
DSM.AS	Koninklijke DSM NV	21,063	NL	CHM	ooo
DSV.CO	Dsv Panalpina A/s	24,146	DK	TRA	ooo
DTE.DE	Deutsche Telekom AG	69,374	DE	TLS	oo
DWNI.DE	Deutsche Wohnen AG BR	13,100	DE	REA	oo
EBS.VI	Erste Group Bank AG	14,424	AT	BNK	oo
EDEN.PA	Edenred	11,211	FR	TSV	ooo
EDF.PA	Electricite de France	30,290	FR	ELC	ooo
EDP.LS	Energias de Portugal SA	11,931	PT	ELC	oo
EL.PA	EssilorLuxottica	58,853	FR	TEX	ooo
ELE.MC	Endesa SA	25,187	ES	ELC	ooo
ELISA.HE	Elisa Corporation	8190	FI	TLS	ooo
ELUX-B.ST	Electrolux AB B	6571	SE	DHP	oo

Table A12. *Cont.*

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
EN.PA	Bouygues	14,072	FR	CON	ooo
ENEL.MI	Enel SpA	71,827	IT	ELC	ooo
ENG.MC	Enagas SA	5428	ES	GAS	ooo
ENGI.PA	Engie	34,731	FR	MUW	ooo
ENI.MI	ENI SpA	50,318	IT	OGX	ooo
EOAN.DE	E.ON SE	25,155	DE	MUW	ooo
EQNR.OL	Equinor ASA	59,422	NO	OGX	ooo
ERIC-B.ST	Ericsson L.M. Telefonaktie B	23,660	SE	CMT	ooo
EXO.MI	EXOR NV	16,648	IT	FBN	oo
EXPN.L	Experian Plc	29,221	GB	PRO	oo
EZJ.L	Easyjet	6659	GB	AIR	ooo
FCA.MI	Fiat Chrysler Automobiles NV	20,446	IT	AUT	o
FER.MC	Ferrovial SA	19,942	ES	CON	ooo
FERG.L	Ferguson PLC	18,780	GB	TCD	ooo
FGR.PA	Eiffage	9996	FR	CON	ooo
FLTR.L	Flutter Entertainment plc	8465	IE	CNO	ooo
FME.DE	Fresenius Medical Care AG	20,259	DE	HEA	ooo
FORTUM.HE	Fortum Oyj	19,544	FI	ELC	ooo
FP.PA	TOTAL SA	131,000	FR	OGX	ooo
FR.PA	Valeo	7546	FR	ATX	ooo
G.MI	Assicurazioni Generali SpA	28,638	IT	INS	oo
G1A.DE	GEA AG	5320	DE	IEQ	oo
GALP.LS	Galp Energia SGPS SA	11,490	PT	OGX	ooo
GBLB.BR	Groupe Bruxelles Lambert	15,161	BE	FBN	oo
GEBN.SW	Geberit AG Reg	18,517	CH	BLD	ooo
GFC.PA	Gecina	12,155	FR	REA	oo

Notes: The last column indicates in which panels a stock was included. "o" indicates that the stock was in Panel 1, "oo" indicates that the stock was in Panel 1 and 2, and "ooo" indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors' calculations.

Table A13. Firms part IV.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
GFS.L	G4S Plc	3997	GB	ICS	ooo
GIVN.SW	Givaudan AG	25,757	CH	DRG	ooo
GLE.PA	Societe Generale	26,292	FR	INS	oo
GLEN.L	Glencore Plc	40,569	GB	MNX	ooo
GLPG.AS	Galapagos Genomics NV	12,060	BE	BTC	o
GMAB.CO	Genmab AS	12,880	DK	BTC	ooo
GRF.MC	Grifols SA	13,393	ES	BTC	ooo
GSK.L	GlaxoSmithKline	113,000	GB	DRG	ooo
GVC.L	GVC Holdings PLC	6041	GB	CNO	oo
HEI.DE	HeidelbergCement AG	12,889	DE	COM	ooo
HEIA.AS	Heineken NV	54,674	NL	BVG	ooo
HEN3.DE	Henkel AG & Co. KGaA Nvtg-Pref	16,426	DE	HOU	ooo
HEXA-B.ST	Hexagon AB	17,520	SE	ITC	ooo
HL.L	Hargreaves Lansdown Plc	10,846	GB	FBN	ooo
HLMA.L	Halma	9449	GB	ITC	ooo
HM-B.ST	Hennes & Mauritz AB B	26,521	SE	RTS	ooo
HNR1.DE	Hannover Ruck SE	20,778	DE	INS	oo
HO.PA	Thales	19,586	FR	ARO	ooo
HSBA.L	HSBC Holdings Plc	144,000	GB	BNK	oo
IAG.L	International Consolidated Airlines Group SA	14,713	GB	AIR	oo
IMB.L	Imperial Brands PLC	22,548	GB	TOB	ooo
IMI.L	IMI	3988	GB	PRO	o
INDU-A.ST	Industrivarden AB A	5938	SE	FBN	oo
INF.L	Informa PLC	12,676	GB	PUB	ooo
INGA.AS	ING Groep NV	41,645	NL	BNK	oo

Table A13. *Cont.*

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
IBE.MC	Iberdrola SA	58,403	ES	ELC	ooo
IFX.DE	Infineon Technologies AG	25,391	DE	SEM	ooo
IHG.L	InterContinental Hotels Group PLC	11,553	GB	TRT	ooo
III.L	3I Group	12,602	GB	FBN	oo
INVE-B.ST	Investor AB B	22,195	SE	FBN	oo
ISP.MI	Intesa SanPaolo	41,114	IT	BNK	oo
ITRK.L	Intertek Group PLC	11,119	GB	PRO	ooo
ITV.L	ITV PLC	7183	GB	PUB	ooo
ITX.MC	Inditex SA	98,018	ES	RTS	o
JMAT.L	Johnson, Matthey	7043	GB	CHM	ooo
KBC.BR	KBC Group NV	27,961	BE	BNK	oo
KER.PA	Kering	73,803	FR	TEX	ooo
KGP.L	Kingspan Group PLC	9888	IE	BLD	ooo
KINV-B.ST	Kinnevik Investment AB B	5280	SE	FBN	oo
KNEBV.HE	Kone Corp B	26,178	FI	IEQ	oo

Notes: The last column indicates in which panels a stock was included. “o” indicates that the stock was in Panel 1, “oo” indicates that the stock was in Panel 1 and 2, and “ooo” indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors’ calculations.

Table A14. Firms part V.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
KNIN.SW	KUEHNE & NAGEL INTL AG-REG	18,023	CH	TRA	ooo
KPN.AS	Koninklijke KPN NV	11,057	NL	TLS	oo
KYGA.L	Kerry Group A	19,531	IE	FOA	ooo
LAND.L	Land Securities Group PLC	8789	GB	REA	oo
LDO.MI	Leonardo S.p.a.	6041	IT	ARO	ooo
LEG.DE	LEG Immobilien AG	7237	DE	REA	o
LGEN.L	Legal & General Group	21,154	GB	BNK	oo
LHA.DE	Deutsche Lufthansa AG	7772	DE	AIR	ooo
LHN.SW	LafargeHolcim Ltd	30,439	CH	COM	ooo
LI.PA	Klepierre	10,406	FR	REA	oo
LISN.SW	Lindt & Sprungli AG Reg	10,701	CH	FOA	oo
LLOY.L	Lloyds Banking Group PLC	51,831	GB	BNK	oo
LOGN.SW	Logitech International SA	7301	CH	THQ	ooo
LONN.SW	Lonza AG	24,206	CH	LIF	oo
LR.PA	Legrand Promesses	19,234	FR	ELQ	oo
LSE.L	London Stock Exchange PLC	32,084	GB	FBN	oo
LXS.DE	Lanxess AG	5231	DE	CHM	ooo
MAERSK-A.CO	AP Moller-Maersk AS A	12,997	DK	TRA	o
MB.MI	Mediobanca SpA	8648	IT	BNK	oo
MC.PA	LVMH-Moet Vuitton	211,000	FR	TEX	ooo
MCRO.L	Micro Focus International	4561	GB	PRO	ooo
MKS.L	Marks & Spencer Group	4920	GB	FDR	oo
ML.PA	Michelin CGDE B Brown	19,645	FR	ATX	oo
MNDI.L	Mondi PLC	10,171	GB	FRP	ooo
MONC.MI	Moncler SpA	10,336	IT	TEX	ooo
MOWI.OL	Mowi ASA	11,942	NO	FOA	ooo
MRK.DE	MERCK KGaA	13,615	DE	DRG	ooo
MRO.L	Melrose Industries PLC	13,785	GB	IEQ	ooo
MRW.L	Morrison (WM) Supermarkets	5650	GB	FDR	ooo
MT.AS	ArcelorMittal Inc	15,888	LU	STL	ooo
MTX.DE	MTU Aero Engines AG	13,239	DE	ARO	ooo
MUV2.DE	Munich Re AG	37,955	DE	INS	o
NDA-FI.HE	Nordea Bank Abp	29,111	FI	BNK	oo
NESN.SW	Nestle SA Reg	287,000	CH	FOA	ooo
NESTE.HE	Neste Oyj	23,860	FI	OGR	ooo
NG.L	National Grid PLC	41,881	GB	MUW	ooo
NHY.OL	Norsk Hydro AS	6848	NO	ALU	ooo
NN.AS	NN Group N.V.	11,619	NL	INS	oo
NOKIA.HE	Nokia OYJ	18,561	FI	CMT	ooo
NOVN.SW	Novartis AG Reg	216,000	CH	DRG	ooo
NOVO-B.CO	Novo Nordisk AS B	96,373	DK	DRG	oo

Notes: The last column indicates in which panels a stock was included. “o” indicates that the stock was in Panel 1, “oo” indicates that the stock was in Panel 1 and 2, and “ooo” indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors’ calculations.

Table A15. Firms part VI.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
NTGY.MC	Naturgy Energy Group SA	22,044	ES	GAS	ooo
NXT.L	Next	11,049	GB	RTS	ooo
NZYM-B.CO	Novozymes AS B	10,350	DK	CHM	ooo
OCDO.L	Ocado Group PLC	10,685	GB	RTS	o
OMV.VI	OMV AG	16,389	AT	OGX	ooo
OR.PA	L'Oreal	147,000	FR	COS	ooo
ORA.PA	Orange	34,750	FR	TLS	ooo
ORK.OL	Orkla AS	9034	NO	FOA	ooo
PAH3.DE	Porsche Automobil Holding SE	10,204	DE	AUT	oo
PGHN.SW	Partners Group Hldg	21,805	CH	REA	ooo
PHIA.AS	Koninklijke Philips Electronics NV	39,397	NL	MTC	ooo
PNDORA.CO	Pandora A/S	3878	DK	TEX	ooo
PROX.BR	Proximus	8626	BE	ELQ	ooo
PRU.L	Prudential PLC	44,280	GB	INS	oo
PRY.MI	Prysmian SpA	5762	IT	ELQ	ooo
PSN.L	Persimmon	10,114	GB	HOM	ooo
PSON.L	Pearson	5876	GB	PUB	ooo
PUB.PA	Publicis Groupe	9701	FR	PUB	ooo
QIA.DE	QIAGEN NV	6913	DE	LIF	ooo
RACE.MI	Ferrari NV	28,681	IT	AUT	ooo
RAND.AS	Randstad NV	9960	NL	PRO	oo
RB.L	Reckitt Benckiser Group PLC	53,348	GB	HOU	ooo
RDSA.L	Royal Dutch Shell PLC	110,000	GB	OGX	ooo
REE.MC	Red Electrica Corporacion SA	9698	ES	ELC	ooo
REL.L	RELX PLC	45,300	GB	PRO	ooo
REP.MC	Repsol SA	22,271	ES	OGX	ooo
RI.PA	Pernod-Ricard	42,290	FR	BVG	ooo
RIO.L	Rio Tinto PLC	67,920	GB	MNX	ooo
RMS.PA	Hermes Intl	70,330	FR	TEX	o
RNO.PA	Renault SA	12,473	FR	AUT	oo
ROG.SW	Roche Hldgs AG Ptg Genus	203,000	CH	DRG	ooo
RR.L	Rolls-Royce Holdings PLC	15,590	GB	ARO	ooo
RSA.L	RSA Insurance Group PLC	6861	GB	INS	oo
RTO.L	Rentokil Initial	9836	GB	ICS	ooo
RWE.DE	RWE AG	16,813	DE	MUW	oo
RY4C.IR	Ryanair Holdings PLC	15,859	IE	AIR	ooo
SAB.MC	Banco de Sabadell SA	5840	ES	BNK	oo
SAF.PA	Safran SA	56,314	FR	ARO	ooo
SAMPO.HE	Sampo Oyj A	21,562	FI	INS	oo
SAN.MC	Banco Santander SA	61,985	ES	BNK	oo

Notes: The last column indicates in which panels a stock was included. "o" indicates that the stock was in Panel 1, "oo" indicates that the stock was in Panel 1 and 2, and "ooo" indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors' calculations.

Table A16. Firms part VII.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
SAN.PA	Sanofi-Aventis	113,000	FR	DRG	ooo
SAND.ST	Sandvik AB	21,857	SE	IEQ	ooo
SAP.DE	SAP SE	148,000	DE	SOF	ooo
SBRY.L	Sainsbury (J)	6008	GB	FDR	ooo
SCA-B.ST	SCA-B shares	5774	SE	FRP	o
SCHN.SW	Schindler-Hldg AG Reg	14,642	CH	IEQ	ooo
SCMN.SW	Swisscom AG Reg	24,437	CH	TLS	oo
SCR.PA	SCOR SE	6980	FR	INS	oo
SDR.L	Schroders PLC	8905	GB	FBN	oo
SEB-A.ST	SEB-Skand Enskilda Banken A	18,219	SE	BNK	oo
SECU-B.ST	Securitas AB B	5354	SE	ICS	oo
SESG.PA	SES	4793	LU	PUB	o
SEV.PA	Suez SA	8406	FR	MUW	ooo
SGE.L	Sage Group	9912	GB	SOF	ooo
SGO.PA	Saint-Gobain, Cie de	19,940	FR	BLD	oo
SGRO.L	SEGRO PLC	11,627	GB	REA	oo
SGSN.SW	SGS-Soc Gen Surveil Hldg Reg	18,624	CH	PRO	ooo
SHB-A.ST	Svenska Handelsbanken A	18,699	SE	BNK	oo
SIE.DE	Siemens AG	99,059	DE	IDD	ooo
SK3.IR	Smurfit Kappa Group PLC	8096	IE	CTR	ooo
SKA-B.ST	SKANSKA AB-B	8072	SE	CON	ooo
SKF-B.ST	SKF AB B	7588	SE	IEQ	oo

Table A16. *Cont.*

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
SLA.L	Standard Life Aberdeen	9100	GB	FBN	oo
SLHN.SW	Swiss Life Reg	15,019	CH	INS	oo
SMDS.L	DS Smith	6209	GB	CTR	o
SMIN.L	Smiths Group	7829	GB	IDD	ooo
SN.L	Smith & Nephew	19,295	GB	MTC	ooo
SOLB.BR	Solvay	10,936	BE	CHM	ooo
SOON.SW	Sonova Holding AG	13,127	CH	MTC	ooo
SPSN.SW	Swiss Prime Site AG	7821	CH	REA	ooo
SPX.L	Spirax-Sarco Engineering	7724	GB	IEQ	ooo
SREN.SW	Swiss Re Reg	32,752	CH	INS	oo
SRG.MI	Snam SpA	15,908	IT	GAS	ooo
SSE.L	Scottish & Southern Energy	17,583	GB	ELC	o
STAN.L	Standard Chartered	26,909	GB	BNK	oo
STERV.HE	Stora Enso OYJ R	7939	FI	FRP	ooo
STJ.L	St James's Place	7280	GB	FBN	oo
STM.MI	STMicroelectronics NV	21,820	IT	SEM	ooo
STMN.SW	Straumann AG Reg	13,888	CH	MTC	o
SU.PA	Schneider Electric SE	53,251	FR	ELQ	ooo
SVT.L	Severn Trent	7138	GB	MUW	ooo
SW.PA	Sodexo	15,578	FR	REX	ooo

Notes: The last column indicates in which panels a stock was included. "o" indicates that the stock was in Panel 1, "oo" indicates that the stock was in Panel 1 and 2, and "ooo" indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors' calculations.

Table A17. Firms part VIII.

Ticker	Company	Market Cap in Billion $	ISO Code	Industry Code	Model Inclusion
SWED-A.ST	Swedbank AB	15,047	SE	BNK	oo
SWMA.ST	Swedish Match AB	7821	SE	TOB	ooo
SY1.DE	Symrise AG	12,703	DE	CHM	ooo
TATE.L	Tate & Lyle	4187	GB	FOA	ooo
TEF.MC	Telefonica SA	32,331	ES	TLS	ooo
TEL.OL	Telenor ASA	23,032	NO	TLS	ooo
TEL2-B.ST	Tele2 AB B	8621	SE	TLS	oo
TELIA.ST	Telia Company AB	16,151	SE	TLS	ooo
TEMN.SW	Temenos Group AG	10,213	CH	SOF	o
TEN.MI	Tenaris SA	11,864	IT	OGX	ooo
TEP.PA	Teleperformance	12,735	FR	PRO	o
TIT.MI	Telecom Italia SpA	8459	IT	TLS	ooo
TKA.DE	ThyssenKrupp AG	7495	DE	IDD	ooo
TPK.L	Travis Perkins	4730	GB	TCD	ooo
TRN.MI	Terna SpA	11,913	IT	ELC	o
TSCO.L	Tesco	29,294	GB	FDR	ooo
TUI1.DE	TUI AG	6612	DE	TRT	ooo
UBI.PA	Ubisoft Entertainment SA	6939	FR	IMS	o
UBSG.SW	UBS Group AG	43,098	CH	FBN	oo
UCB.BR	UCB SA	13,790	BE	DRG	ooo
UCG.MI	Unicredit SpA Ord	28,956	IT	BNK	oo
UG.PA	Peugeot SA	19,272	FR	AUT	o
UHR.SW	Swatch Group AG-B	7663	CH	TEX	ooo
UMI.BR	Umicore	10,683	BE	CHM	ooo
UNA.AS	Unilever NV	79,136	NL	COS	oo
UPM.HE	UPM-Kymmene Oyj	16,448	FI	FRP	ooo
URW.AS	Unibail Rodamco Westfield	19,358	FR	REA	oo
UTDI.DE	United Internet AG Reg	6002	DE	TLS	ooo
UU.L	United Utilities Group Plc	7602	GB	MUW	ooo
VIE.PA	Veolia Environnement	13,332	FR	MUW	ooo
VIFN.SW	Vifor Pharma Group	10,567	CH	DRG	ooo
VIV.PA	Vivendi SA	30,564	FR	PUB	oo
VNA.DE	Vonovia SE	26,029	DE	REA	oo
VOD.L	Vodafone Group	49,971	GB	TLS	ooo
VOLV-B.ST	Volvo AB B	24,537	SE	AUT	oo
VOW.DE	Volkswagen AG	51,124	DE	AUT	ooo
VWS.CO	Vestas Wind Systems AS	17,918	DK	IEQ	ooo
WDI.DE	Wirecard AG	13,275	DE	FBN	
WEIR.L	Weir Group	4631	GB	IEQ	ooo
WKL.AS	Wolters Kluwer NV	17,751	NL	PRO	oo
WPP.L	WPP Plc	16,725	GB	PUB	ooo
WRT1V.HE	Wartsila Oyj ABP	5828	FI	IEQ	o
WTB.L	Whitbread	8407	GB	TRT	oo
YAR.OL	Yara International ASA	10,188	NO	CHM	ooo
ZURN.SW	Zurich Insurance Group AG	55,011	CH	INS	oo

Notes: The last column indicates in which panels a stock was included. "o" indicates that the stock was in Panel 1, "oo" indicates that the stock was in Panel 1 and 2, and "ooo" indicates that the stock was in all the panels. Source: S&P Global ESG ratings and authors' calculations.

Table A18. Countries.

ISO Code	Country	ISO Code	Country	ISO Code	Country
AT	Austria	FI	Finland	NL	Netherlands
BE	Belgium	FR	France	NO	Norway
CH	Switzerland	GB	United Kingdom	PT	Portugal
DE	Germany	IE	Ireland	SE	Sweden
DK	Denmark	IT	Italy		
ES	Spain	LU	Luxembourg		

Source: S&P Global and author.

Table A19. Industries.

Industry Code	Industry	Industry Code	Industry
AIR	Airlines	ITC	Electronic Equipment,
ALU	Aluminum		Instruments &
ARO	Aerospace & Defense		Components
ATX	Auto Components	LIF	Life Sciences Tools
AUT	Automobiles		& Services
BLD	Building Products	MNX	Metals & Mining
BNK	Banks	MTC	Health Care Equipment
BTC	Biotechnology		& Supplies
BVG	Beverages	MUW	Multi & Water Utilities
CHM	Chemicals	OGR	Oil & Gas Refining
CMT	Communications Equipment		& Marketing
CNO	Casinos & Gaming	OGX	Oil & Gas Upstream
COM	Construction Materials		& Integrated
CON	Construction & Engineering	PRO	Professional Services
COS	Personal Products	PUB	Media, Movies
CTR	Containers & Packaging		& Entertainment
DHP	Household Durables	REA	Real Estate
DRG	Pharmaceuticals	REX	Restaurants & Leisure
ELC	Electric Utilities		Facilities
ELQ	Electrical Components	RTS	Retailing
	& Equipment	SEM	Semiconductors
FBN	Diversified Financial Services		& Semiconductor
	& Capital Markets		Equipment
FDR	Food & Staples Retailing	SOF	Software
FOA	Food Products	STL	Steel
FRP	Paper & Forest Products	TCD	Trading Companies
GAS	Gas Utilities		& Distributors
HEA	Health Care Providers	TEX	Textiles, Apparel
	& Services		& Luxury Goods
HOM	Homebuilding	THQ	Computers & Peripherals
HOU	Household Products		& Office Electronics
ICS	Commercial Services	TLS	Telecommunication
	& Supplies		Services
IDD	Industrial Conglomerates	TOB	Tobacco
IEQ	Machinery & Electrical	TRA	Transportation
	Equipment		& Transportation
IMS	Interactive Media, Services		Infrastructure
	& Home Entertainment	TRT	Hotels, Resorts
INS	Insurance		& Cruise Lines
		TSV	IT services

Source: S&P Global and author.

Table A20. Sectors.

Sector -> Industry	Num of Firms	Sector -> Industry	Num of Firms
Communication Services	**22**	**Industrials**	**69**
Interactive Media, Services & Home Entertainment	1	Aerospace & Defense	7
Media, Movies & Entertainment	7	Airlines	4
Telecommunication Services	14	Building Products	4
Consumer Discretionary	**35**	Commercial Services & Supplies	3
Auto Components	3	Construction & Engineering	6
Automobiles	9	Electrical Components & Equipment	5
Casinos & Gaming	2	Industrial Conglomerates	4
Homebuilding	3	Machinery and Electrical Equipment	14
Hotels, Resorts & Cruise Lines	5	Professional Services	11
Household Durables	1	Trading Companies & Distributors	5
Restaurants & Leisure Facilities	2	Transportation and Transportation Infrastructure	6
Textiles, Apparel & Luxury Goods	10	**Information Technology**	**16**
Consumer Staples	**31**	Communications Equipment	2
Beverages	5	Computers & Peripherals and Office Electronics	1
Food & Staples Retailing	6	Electronic Equipment, Instruments & Components	2
Food Products	8	IT services	4
Household Products	2	Semiconductors & Semiconductor Equipment	3
Personal Products	3	Software	4
Retailing	4	**Materials**	**31**
Tobacco	3	Aluminum	1
Energy	**10**	Chemicals	15
Oil & Gas Refining & Marketing	1	Construction Materials	3
Oil & Gas Upstream & Integrated	9	Containers & Packaging	2
Financials	**62**	Metals & Mining	5
Banks	27	Paper & Forest Products	4
Diversified Financial Services and Capital Markets	16	Steel	1
Insurance	19	**Real Estate**	**11**
Health Care	**23**	Real Estate	11
Biotechnology	3	**Utilities**	**21**
Health Care Equipment & Supplies	4	Electric Utilities	9
Health Care Providers & Services	2	Gas Utilities	3
Life Sciences Tools & Services	3	Multi and Water Utilities	9
Pharmaceuticals	11		
		Total number of stocks	331

Notes: The sector names are indicated in bold font, while the industries that constitute these sectors are listed under with a regular font. Source: S&P Global and author.

Notes

[1] "Too big to fail" is a concept that became famous with the systemic risk research. If a firm is too big to fail, then its collapse would cause a cascading catastrophic effect on the economy. To prevent this, the governments should consider intervening.

[2] For meta-analyses please see Friede et al. (2015), Clark et al. (2015), Revelli and Viviani (2015).

[3] 40 points is not arbitrarily chosen. The distribution of the ESG ratings, given in Figure 3a, is bimodal with about 40 points difference between the modes.

[4] We assumed a VAR model of order 1 for simplicity. VAR order could be chosen based on AIC criterion, although typically low orders are preferred. Similarly, Anufriev and Panchenko (2015) and Chiang et al. (2007) use ARMA(1,1) and AR(1) models for simplicity, respectively. Bauwens et al. (2006) note that it is typical that one uses a simple model for conditional mean before applying a multivariate GARCH model.

[5] Given the number of series in consideration including an unobservable factor *a la* Eratalay and Vladimirov (2020) would not be feasible due to the number of parameters to estimate.

[6] S&P Dow Jones Indices.

[7] https://www.spglobal.com/spdji/en/indices/equity/sp-europe-350/#overview (accesed on 5 October 2020).

[8] On average 0.4% of the returns were identified as outliers.

[9] https://www.spglobal.com/esg/scores/ (accesed on 25 March 2021).

[10] The ESG metrics that different institutions offer weigh these subcategories differently. It is important to obtain ESG ratings data from a reputable source. Berg et al. (2019) point towards the divergence of the ESG metrics provided by different institutions.

[11] https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Europe (accesed on 19 October 2021).

[12] Similar networks were analysed in detail in Cortés Ángel and Eratalay (2021), with the difference that an initial cut-off was used in that study to define a sparse network. In our work, this is not necessary since we are not focusing on finding resilient relationships over time.

[13] Data source: https://sdw.ecb.europa.eu/reports.do?node=1000003285 (accesed on 12 October 2021).

[14] Wirecard AG's declaration of insolvency did not cause a cascading effect. This is in support of our model that systemic risk contribution and exposure of a firm should be thought of together with the network centrality of that firm.

[15] Given the log-linear relation, we can calculate the exact impact of Δ increase in the regressor x on the dependent variable as $100 * [exp(\hat{\beta}\Delta x) - 1]$. See Chapter 6.2 of Wooldridge (2015) for details.

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