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

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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

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”? 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. Secondly, 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 treasury 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:

\[
\begin{align*}
    r_t & = \mu + \beta r_{t-1} + c r_{t-1}^{MSWI} + \epsilon_t \\
    \epsilon_t & \sim N(0_k, H_t)
\end{align*}
\]

where \( r_t \) is a \( k \times 1 \) vector of returns. \( \mu \) is a \( k \times 1 \) vector of intercept coefficients. \( \beta \) is a \( k \times k \) 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, \( \epsilon_t \) 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). 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 \( \hat{\beta} \), such that all eigenvalues of the \( \hat{\beta} \) matrix should be positive.

3.1.2. Conditional Variances

The conditional variance-covariance matrix of the error term \( \varepsilon_t \) is denoted by \( H_t \) such that:

\[
\varepsilon_t = H_t^{1/2} v_t
\]

\[
H_t = D_t^H R_t D_t^H
\]

\[
D_t^H = \text{diag}(h_{1,1}^{1/2}, h_{2,2}^{1/2}, ..., h_{k,k}^{1/2})
\]

\[
h_{t+1} = W + A\varepsilon_t^{(2)} + Bh_t
\]

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. \( v_t \) 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 \( H_{t,j} = R_{t,j} h_{t,j}^{1/2} h_{t,j}^{1/2} \), which is the well-known relation between covariance and correlation. \( W \) is a \( k \times 1 \) vector and \( A \) and \( B \) are \( k \times k \) 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:

\[
h_{t+1,j} = w_j + a_i \varepsilon_{t,j}^{(2)} + b_j h_{t,j}
\]

The conditional variances, \( h_{t,j} \) are stationary under the usual assumption that \( a_i + b_j < 1 \). Moreover, they are positive as long as \( w_j > 0, a_i \geq 0 \) and \( b_j \geq 0 \).

3.1.3. Conditional Correlations

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

\[
R_t = P_t Q_t P_t
\]

\[
P_t = \text{diag}(Q_t)^{-1/2}
\]

\[
Q_{t+1} = (1 - \delta_1 - \delta_2)\overline{Q} + \delta_1 v_t^* v_t^{*'} + \delta_2 Q_t
\]

\[
v_t^* = \text{diag}(Q_t)^{1/2} v_t.
\]

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 \( \overline{Q} \) with the sample covariance matrix of the \( v_t^* \) during estimation. The scalar parameters, \( \delta_1 \) and \( \delta_2 \), 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 \( R \):

\[
P = -D_K^{-1/2}KD_K^{-1/2}.
\]  

(5)

where \( K = R^{-1} \), and \( D_K = \text{diag}(K) \) 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:

\[
A = I + P = I - D_K^{-1/2}KD_K^{-1/2}
\]  

(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 \( r_i^t \) be \( k \times 1 \) the vector of the returns of stock \( i \). The system’s aggregated return, \( r_S^t \), therefore is given by:

\[
r_S^t = \sum_i r_i^t
\]

(7)

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

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

(8)

where \( h_{i,i} \) and \( v_{i,t} \) 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, \( \zeta_k \), have zero mean and have variance equal to \( \lambda_k \), such that:

\[
E(\zeta_k\zeta_l) = \begin{cases} 
\lambda_k, & \text{if } k = l \\
0, & \text{otherwise}
\end{cases}
\]

(9)

In fact, the \( \lambda_k \) 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 \( v_{i,t} \) as:

\[
v_{i,t} = \sum_k L_{ik} \zeta_k
\]

(10)

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

\[
R_t = \sum_k \sum_j L_{ik} L_{jl} E(\zeta_k\zeta_l) = \sum_k L_{ik}L_{jk}\lambda_k
\]

(11)

and the variance of the system becomes:

\[
\sigma_{t,S}^2 = \sum_i \sum_j \sum_k \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k
\]

(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 \( h_n = \frac{\omega_n}{\Omega} \) 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 \( h_n > H \):

\[
PCAS_{i,n} = \left. \frac{1}{2} \frac{\partial \sigma_{t,S}^2}{\partial \sigma_i^2} \right|_{h_n > H}
\]

(13)
The authors also discuss that by construction, systemic risk exposure is the same as the systemic risk contribution of stock \( i \):

\[
PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_S^2} \frac{\partial^2 \sigma_S^2}{\partial \sigma_i^2} \bigg|_{|h_n > H} = \sum_{k=1}^{n} \frac{\sigma_i^2}{\sigma_S^2} L_k^2 \lambda_k \bigg|_{|h_n > H}
\]

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 and for the Morgan and Stanley World Index (MSWI) from Yahoo Finance. For the constituents list, we made a formal request to SPGlobal. 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.

Our second data source was the S&P Global website. 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.

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 \(100 \times \log\left(\frac{P_t}{P_{t-1}}\right)\) 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).

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.

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.
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.

![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.](image1)

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.](image2)
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.](image)

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).
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. 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. 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. 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 | 0.0586 | ***  | 1.6423 | 0.1127 | ***  | 1.6603 | 0.0677 | ***  |
| Dt       | 0.0347 | 0.0894 | 0.0288 | 1.4331 | 0.2533 | 0.0347 | 1.0174 | 0.0189 | ***  |
| NetEC*logVol | -0.4329 | 0.0156 | ***  | -0.4449 | 0.0326 | ***  | -0.4335 | 0.0189 | ***  |
| logVol*Dt | 1.6016 | 0.3139 | ***  | 1.5794 | 0.6146 | **   | 1.7127 | 0.3897 | ***  |
| _cons    | -3.7423 | 0.4821 | ***  | -3.9077 | 1.0674 | ***  | -3.6757 | 0.5399 | ***  |

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.

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 | *** | 68.8956 | 8.6944 | *** |
| ESGrating| 0.0007 | 0.0004 | * | -0.0005 | 0.0008 | 0.0005 | * | 0.0009 | 0.0005 | * |
| logVol   | 1.6316 | 0.0568 | *** | 1.6710 | 0.1203 | *** | 1.6373 | 0.0677 | *** |
| NetEC*logVol | -0.1281 | 0.0204 | *** | -0.4501 | 0.0535 | *** | -0.4252 | 0.0242 | *** |
| Dt       | -0.4264 | 0.0204 | *** | -0.4501 | 0.0535 | *** | -0.4252 | 0.0242 | *** |
| 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 | 0.0000 | 0.0003 | 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
R² within 0.8896 0.8896 0.8896
R² between 0.8895 0.8729 0.8976
R² 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%. 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   | 76.7130 | 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 | 0.3077 | −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 | −0.0026 | 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 | ** | −0.0637 | 0.0265 | −0.0353 | 0.0351 | *** |
| 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 | 0.9948 | *** | −5.0623 | 1.6964 | −4.6851 | 0.6372 | *** |

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 |
| R²       | 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 | 0.0009 | | 0.0000 | 0.0003 |
| Esg_Soc  | −0.0001 | 0.0002 | | 0.0001 | | | 0.0000 | | |
| Esg_GovEcon | 0.0002 | 0.0003 | | −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 | | | −0.1165 | 0.4639 |
| _cons    | −0.1233 | 0.0645 | * | −0.1743 | 0.1054 | * | −0.1040 | 0.0803 |
| Pval_Ftest | 0.0000 | 0.0000 | 0.0000 |
| R²       | 0.9984 | 0.9984 | | 0.9984 |
| 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_Soc  | -0.0001 | 0.0003 | | -0.0013 | 0.0012 | | 0.0001 | 0.0003 |
| Esg_GovEcon | 0.0008 | 0.0004 | ** | 0.0013 | 0.0013 | | 0.0007 | 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 | 0.0025 | | 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 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| R²       | 0.9985 | 0.9983 | | 0.9986 | 0.9987 | | 0.9985 | 0.9986 |
| N        | 199 | 52 | 147 | 147 | 147 | 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                            | 88.4               |
| 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             |
| Clarient 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 | 0.0611  | 0.0645  | 13.708 | 79  |
| Banco Santander SA | Spain        | 0.0962 | 0.053   | 0.0829  | 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  | 0.0862  | 9.2565 | 46  |
| BASF SE       | Germany             | 0.0926 | 0.0569  | 0.0631  | 2.806  | 57  |
| 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  |
| Industriavarden AB A | Sweden    | 0.0886 | 0.0527  | 0.0597  | 1.3141 | 30  |
| Daimler AG    | Germany             | 0.0881 | 0.0337  | 0.0603  | 4.59   | 25  |
| ING Groep NV  | Netherlands          | 0.0877 | 0.0572  | 0.066   | 6.3443 | 52  |
| Porsche Automobil H. SE     | Germany             | 0.0873 | 0.0518  | 0.0599  | 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-Skan Skenskida 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  | 0.0635  | 1.7793 | 57  |
| 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     | 0.0903 | 0.0573  | 0.0637  | 2.5602 | 87  |
| BASF SE             | Germany     | 0.0924 | 0.0567  | 0.0632  | 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 Assurance   | Germany     | 0.0882 | 0.0534  | 0.0628  | 15.2751| 25  |
| Industriardenen 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  | 0.0626  | 7.1167 | 76  |
| Bayer Motoren Werke AG | Germany    | 0.0855 | 0.0548  | 0.0635  | 8.5389 | 80  |
| Credit Suisse Group AG | Switzerland  | 0.0853 | 0.0566  | 0.0646  | 9.406  | 65  |
| Royal Dutch Shell Plc | Netherlands | 0.0838 | 0.0502  | 0.0606  | 10.135 | 68  |
| TOTAL SA            | France      | 0.0832 | 0.0572  | 0.0599  | 3.9101 | 87  |
| 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 | 0.0394 | 0.0595  | 0.0627  | 13.5731| 90  |
| CNH Industrial NV   | United Kingdom | 0.0551 | 0.0534  | 0.0595  | 13.8615| 89  |
| Deutsche Telekom AG | Germany     | 0.0544 | 0.0556  | 0.0597  | 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  | 0.0674  | 1.1784 | 89  |
| Roche Hidge AG Ptg Gen. | Switzerland | 0.0435 | 0.0531  | 0.0595  | 0.7459 | 89  |
| AXA                 | France      | 0.0865 | 0.0569  | 0.0625  | 3.1292 | 88  |
| Energias de Portugal SA | Portugal | 0.0336 | 0.0551  | 0.0589  | 1.8833 | 88  |
| GlaxoSmithKline     | United Kingdom | 0.0344 | 0.0531  | 0.0592  | 1.2531 | 88  |
| Schneider Electric SE | France    | 0.0795 | 0.0572  | 0.0621  | 3.5495 | 88  |
| UPM-Kymmene Oyj     | Finland     | 0.0598 | 0.06   | 0.0633  | 4.1734 | 89  |
| 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  | 0.0611  | 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 | 0.0539  | 0.0607  | 1.2052 | 86  |
| Naturgy Energy Gr. SA | Spain   | 0.0449 | 0.0568  | 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 | 0.0351  | 0.0605  | 1.583  | 89  |
| Red Electrica Corp. SA | Spain        | 0.0389 | 0.0541  | 0.0591  | 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  |
| Energas de Portugal SA | Portugal     | 0.0313 | 0.0557  | 0.0601  | 1.9215 | 87  |
| GlaxoSmithKline    | United Kingdom   | 0.035  | 0.0536  | 0.0593  | 1.0876 | 87  |
| 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 | 0.0562  | 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   | 1.095  | 87  |
| Enagas SA          | Spain            | 0.0413 | 0.0537  | 0.0602  | 2.652  | 87  |
| Endesa SA          | Spain            | 0.0422 | 0.0534  | 0.0609  | 0.994  | 87  |
| Lanxess AG         | Germany          | 0.0716 | 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  | 1.5333 | 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 | 0.0527  | 0.0594  | 61.4814| 80  |
| 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  | 19.5252| 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  | 17.5384| 84  |
| Inter. Cons. A. Gr. SA | Spain         | 0.0522 | 0.0568  | 0.0619  | 16.8167| 32  |
| Mediobanca SpA     | Italy            | 0.0626 | 0.053   | 0.0589  | 15.1757| 53  |
| Telecom Italia SpA | Italy            | 0.0406 | 0.0501  | 0.0565  | 15.1757| 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.
| 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   |
| Uniball 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   | 42.6529   | 74   |
| Renault SA                    | France    | 0.0625 | 0.0549   | 0.0596   | 41.3718   | 45   |
| Melrose Industries Plc        | United Kingdom | 0.0477 | 0.05  | 0.0599   | 40.107   | 17   |
| Anglo American Inc            | United Kingdom | 0.0668 | 0.0537   | 0.0622   | 36.328    | 80   |
| Commerzbank AG                | Germany   | 0.0699 | 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| 0.0652 | 0.0532   | 0.0595   | 26.7761   | 41   |
| Deutsche Bank Germany         | Germany   | 0.0509 | 0.0534   | 0.06   | 25.4111   | 56   |
| GVC Holdings Plc              | United Kingdom | 0.0293 | 0.0539   | 0.059   | 23.5431   | 63   |
| ABN AMRO Group NV             | Netherlands| 0.0577 | 0.0504   | 0.0593   | 22.6387   | 83   |
| Byanair 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 systemic risk in descending order. Source: S&P Global ESG ratings and authors' calculations.

| 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   |
| SCS-Soc Gen Survell 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 & Sprunghi 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   | 0.0649   | 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 Survail 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  | 0.8396 | 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 | 0.0597  | 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 | 35  |
| 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.
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.

Figure A2. Cont.
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           | oo              |
| AAL.L   | Anglo American PLC           | 35,532                  | GB       | MNX           | oo              |
| ABBN.SW | ABB Ltd                      | 46,631                  | CH       | ELQ           | oo              |
| ABL.F   | Associated British Foods     | 24,306                  | GB       | FOA           | oo              |
| ABLR     | Anheuser Busch Inbev NV      | 123,000                 | BE       | BVG           | oo              |
| ABN.AS  | ABN AMRO Group NV            | 15,246                  | NL       | BNK           | oo              |
| AC.PA   | Accor                        | 11,274                  | FR       | TRT           | oo              |
| ACA.PA  | Credit Agricole SA           | 37,284                  | FR       | BNK           | oo              |
| ACS.MC  | ACS Actividades de           | 11,217                  | ES       | CON           | oo              |
|         | Construccion y Servicios SA  |                         |          |               |                 |
| 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           | oo              |
| AENA.MC | Aena SA                      | 25,575                  | ES       | TRA           | oo              |
| AGN.AS  | Aegon NV                     | 8523                    | NL       | INS           | oo              |
| AGS.BR  | Ageas                        | 10,430                  | BE       | INS           | oo              |
| AHT.L   | Ashfield Group               | 14,399                  | GB       | TCD           | oo              |
| ALPA    | L’Air Liquide S.A.           | 59,445                  | FR       | CHM           | oo              |
| AIR.PA  | Airbus SE                    | 101,000                 | FR       | ARO           | oo              |
| AKE.PA  | Arkema                       | 7242                    | FR       | CHM           | oo              |
| AKZA.AS | Akzo Nobel NV                | 20,643                  | NL       | CHM           | oo              |
| ALFA.ST | Alfa Laval AB                | 9,490                   | SE       | IEQ           | oo              |
| ALO.PA  | Alstom                       | 9,472                   | FR       | IEQ           | oo              |
| ALY.DE  | Allianz SE                   | 91,110                  | DE       | INS           | oo              |
| AMS.MC  | Amadeus IT Group SA          | 31,396                  | ES       | TSV           | o               |
| ASML.AS | ASML Holding NV              | 112,000                 | NL       | SEM           | oo              |
| ASSA.BT | Assa Abloy B                 | 22,025                  | SE       | BLD           | oo              |
| ATCO.AST| Atlas Copco AB A             | 29,893                  | SE       | IEQ           | oo              |
| ATL.MI  | Atlanta Spa                  | 17,153                  | IT       | TRA           | oo              |
| ATO.PA  | Atos SE                      | 8,115                   | FR       | TSV           | oo              |
| AVL     | Aviva                        | 19,478                  | GB       | INS           | oo              |
| AZN.L   | AstraZeneca PLC              | 118,000                 | GB       | DRG           | oo              |
| BA.L    | BAE Systems PLC              | 23,152                  | GB       | ARO           | oo              |
| BAER.SW | Julius Baer Group            | 10,284                  | CH       | FBN           | oo              |
| BALN.SW | Balloise Hldg Reg            | 7859                    | CH       | INS           | o               |
| BARCL    | Barclays                     | 36,376                  | GB       | BNK           | oo              |
| BAS.DE  | BASF SE                      | 61,859                  | DE       | CHM           | oo              |
| BATSL    | British American             | 94,014                  | GB       | TOB           | oo              |
| BAYN.DE  | Bayer AG                     | 67,099                  | DE       | DRG           | oo              |
| BBVA.MC  | Banco Bilbao Vizcaya         | 33,426                  | ES       | BNK           | oo              |
| Argentaria SA |

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 | 8981 | GB | HOM | ooo |
| B,E,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 | BKK | o |
| BKG.L | Berkeley Group Holdings Plc | 7860 | GB | HOM | ooo |
| BLD.L | British Land Co | 7108 | GB | REA | o |
| BMW.DE | Bayer Motoren Werke AG (BMW) | 44,029 | DE | AUT | o |
| BN.PA | danone | 50,625 | FR | FOA | ooo |
| BN.PA | BNP Paribas | 65,744 | FR | BKK | o |
| BNR.DE | Brenntag AG | 7490 | DE | TCD | ooo |
| BNZL.L | Bunzl | 8190 | GB | TCD | ooo |
| BOL.ST | Boliden AB | 6478 | SE | MNX | ooo |
| BPL | BP p.Lc | 120,000 | GB | OGX | ooo |
| BRBY.L | Burberry Group | 10,719 | GB | TEX | ooo |
| BT-A.L | BT Group | 22,669 | GB | TLS | ooo |
| BVR.LA | Bureau Veritas SA | 10,512 | FR | PRO | o |
| CA.PA | Carrefour SA | 12,068 | FR | FDR | o |
| CABK.MC | CaixaBank | 16,736 | ES | BKK | o |
| CAP.PA | Capgemini SE | 18,218 | FR | TSV | ooo |
| CARL-B.CO | Carlsberg AB | 15,807 | DK | BGG | ooo |
| CBK.DE | Commerzbank AG | 6909 | DE | BKK | o |
| CCL.L | Carnival Plc | 9321 | GB | TRT | o |
| CFR.SW | Richemont, Cie | 36,538 | CH | TEX | o |
| CHR.CO | Christian Hansen Holding A/S | 9341 | DK | LIF | o |
| CLN.SW | Clarient AG Reg | 6598 | CH | CHM | ooo |
| CNNX.MC | Cellnex Telecom S.A. | 14,784 | ES | TSL | o |
| CN.A.L | Centrica | 6152 | GB | MUW | ooo |
| CNH.LMI | CNH Industrial NV | 13,325 | IT | IEQ | o |
| COLO-B.CO | Coloplast AS B | 21,897 | DK | HEA | o |
| CON.DE | Continental AG | 23,952 | DE | ATX | ooo |
| CPG.L | Compass Group | 35,582 | GB | REX | o |
| CRDA.L | Croda Intl | 7981 | GB | CHM | ooo |
| CRH | CRH Plc | 28,198 | IE | COM | o |
| CS.PA | AXA | 60,928 | FR | INS | o |
| CSSG.SW | Credit Suisse Group AG | 30,826 | CH | FBN | o |
| DAL.DE | Daimler AG | 52,817 | DE | AUT | ooo |
| DANSKE.CO | Danske Bank A/S | 12,437 | DK | BKX | oo |
| DASY | Dassault Systemes SA | 38,532 | FR | SOF | ooo |
| DB | Deutsche Bank AG | 14,295 | DE | BKK | o |
| DB1.DE | Deutsche Boerse Group | 26,628 | DE | FBN | o |

**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 | o |
| DNB.O.L | DNB ASA | 26,283 | NO | BKK | o |
| 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 | o |
| DWN.L.E | Deutsche Wohnen AG BR | 13,100 | DE | REA | o |
| EBS.VI | Erste Group Bank AG | 14,424 | AT | BKK | o |
| EDN.PA | Edenred | 11,211 | FR | TSV | o |
| EDF.PA | Electricite de France | 30,290 | FR | ELC | o |
| EDPLS | Energias de Portugal SA | 11,931 | PT | ELC | o |
| EL.PA | EssilorLuxottica | 58,853 | FR | TEX | o |
| ELE.MC | Endesa SA | 25,187 | ES | ELC | o |
| ELISA.H.E | Elisa Corporation | 8190 | FI | TLS | o |
| ELUX.B.ST | Electrolux AB B | 6571 | SE | DHP | o |

**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. 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             |
| ENG.LPA| Engie                       | 34,731                  | FR       | MUW           | ooo             |
| ENI.MI | ENI SpA                      | 50,318                  | IT       | OGX           | ooo             |
| EOAN.DE| E.ON SE                     | 25,135                  | DE       | MUW           | ooo             |
| EONR.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                     | 6639                    | GB       | AIR           | ooo             |
| FCA.MI | Fiat Chrysler Automobiles   |                         |          |               |                 |
| 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             |
| FMD.DE | Fresenius Medical Care AG   | 20,239                  | 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           | ooo             |
| GALP.LS| Galp Energia SGPS SA        | 11,490                  | PT       | OGX           | ooo             |
| GBL.BR | Groupe Bruxelles Lambert    | 15,161                  | BE       | FBN           | oo              |
| GEBN.SW| Geberit AG Reg             | 18,517                  | CH       | BLD           | ooo             |
| GFC.PA | Gecina                      | 12,135                  | FR       | REA           | 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 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 | Gencore Plc                    | 40,569                  | GB       | MNX           | ooo             |
| GLPG.AS| Galapagos Genomics NV          | 12,060                  | BE       | BTC           | o               |
| GMAB.CO| Gennab AS                      | 12,880                  | DK       | BTC           | ooo             |
| GRF.MC | Grifols SA                     | 13,393                  | ES       | BTC           | ooo             |
| GSKL   | GlaxoSmithKline                | 113,000                 | GB       | DRG           | ooo             |
| GVC.L  | GVC Holdings PLC              | 6041                    | GB       | CNO           | oo              |
| HEL.DE | HeidelbergCement AG            | 12,889                  | DE       | COM           | ooo             |
| HEIA.AS| Heineken NV                    | 54,674                  | NL       | BVG           | ooo             |
| HEN3.DE| Henkel AG & Co. KGaA          | 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             |
| HLM.A.L| Halma                         | 9449                    | GB       | ITC           | ooo             |
| HM.B.ST| Hennes & Mauritz AB B         | 26,521                  | SE       | RTS           | ooo             |
| HNB1.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       | BKN           | oo              |
| IAG.L  | International Consolidated     | 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       | BKN           | 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  | 11,553                  | GB       | TRT           | ooo             |
| III.L    | 3I Group                 | 12,602                  | GB       | FBN           | oo              |
| INVIE-B.ST | Investor AB B           | 22,195                  | SE       | FBN           | oo              |
| IISMI    | 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             |
| KGPL     | Kingspan Group PLC       | 9888                    | IE       | BLD           | ooo             |
| KINV-B.ST | Kinnevik Investment AB B | 5280                    | SE       | 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 A14. Firms part V.

| Ticker   | Company                  | Market Cap in Billion $ | ISO Code | Industry Code | Model Inclusion |
|----------|--------------------------|-------------------------|----------|---------------|-----------------|
| KNIN.SW  | KUEHNE & NAGEL          | 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 Luftansa AG     | 7772                    | DE       | AIR           | ooo             |
| LHJ.SW   | LafargelHolcim Ltd       | 30,439                  | CH       | COM           | ooo             |
| LIPA     | Kleptierre               | 10,406                  | FR       | REA           | oo              |
| LSN.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           | oo              |
| LONN.SW  | Lonza AG                | 24,206                  | CH       | LIF           | oo              |
| LR.PA    | Legrand Promesses       | 19,234                  | FR       | ELQ           | ooo             |
| LSE.L    | London Stock Exchange PLC | 32,084                | GB       | FBN           | oo              |
| LXS.DE   | Lanxess AG               | 5231                    | DE       | CHM           | ooo             |
| MAERSK-A.CO | AP Moller-Maerk AS A     | 12,997                  | DK       | TRA           | o               |
| MB.MI    | Medibanca SpA            | 8648                    | IT       | BNK           | ooo             |
| MC.PA    | IVMH-Moet Vuitton        | 213,000                 | FR       | TIX           | oo              |
| MCRO.L   | Micro Focus International | 4561                | GB       | PRO           | ooo             |
| MKS.L    | Marks & Spencer Group   | 4920                    | GB       | FDR           | oo              |
| MLPA     | Michelin CGDE B Brown   | 19,645                  | FR       | ATX           | oo              |
| MNDL     | Mondi PLC                | 10,171                  | GB       | FRP           | oo              |
| MONC.MI  | Moncer SpA              | 10,336                  | IT       | TEX           | ooo             |
| MOW1.LOL | Mowi ASA                | 11,942                  | NO       | FOA           | oo              |
| MRK.DE   | MERCK KGaA              | 13,615                  | DE       | DRG           | ooo             |
| MRO.L    | Melrose Industries PLC   | 13,785                  | GB       | IEQ           | oo              |
| MRW.L    | Morrison (WM)           | 5650                    | GB       | FDR           | ooo             |

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### 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             |
| OCEO.L      | Oceano Group PLC               | 10,665                  | GB       | RTS           | o              |
| OMV.VI      | OMV AG                         | 16,369                  | AT       | OGX           | ooo             |
| OR.PA       | Orange                         | 147,000                 | FR       | COS           | ooo             |
| ORK.CO      | Orkla AS                       | 9034                    | NO       | FOA           | ooo             |
| PAF3.DE     | Porsche Automobil Holding SE   | 10,204                  | DE       | AUT           | oo              |
| PGHN.SW     | Partners Group Hldg            | 21,805                  | CH       | REA           | ooo             |
| PHA.AS      | Koninklijke Philips Electronics NV | 39,397                  | NL       | MTC           | ooo             |
| PINDOTA CO  | Pandora A/S                    | 3878                    | DK       | TEX           | ooo             |
| PROX.BR     | Proximus                       | 8626                    | BE       | ELQ           | ooo             |
| PRU.L       | Prudential PLC                 | 44,280                  | GB       | INS           | oooo            |
| FRYMI       | Prysmian SpA                   | 5762                    | IT       | ELQ           | ooo             |
| PSN.L       | Persimmon                      | 10,114                  | GB       | HOM           | ooo             |
| PSK.NL      | Pearson                        | 5876                    | GB       | PUB           | ooo             |
| PUBLPA      | 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                    | 9660                    | NL       | PRO           | oo              |
| RBL         | Reckitt Benekiser Group PLC    | 53,348                  | GB       | HOU           | ooo             |
| RDGA.L      | Royal Dutch Shell PLC          | 110,000                 | GB       | OGX           | ooo             |
| REE.MC      | Red Electrica                  | 9698                    | ES       | ELC           | ooo             |
| REL.L       | RELX PLC                       | 45,300                  | GB       | PRO           | ooo             |
| REP.MC      | Repsol SA                      | 22,271                  | ES       | OCG           | ooo             |
| RILPA       | Pernod-Ricard                  | 42,290                  | FR       | BVG           | ooo             |
| RIO.L       | Rio Tinto PLC                  | 67,920                  | GB       | MNX           | ooo             |
| RMS.PA      | Hermes Int'l                   | 70,330                  | FR       | TIX           | o              |
| RNO.PA      | Renault SA                     | 12,473                  | FR       | AUT           | ooo             |
| ROG.SW      | Roche Hldg AG                  | 203,000                 | CH       | DRG           | ooo             |
| RRL         | Rolls-Royce Holdings PLC       | 15,590                  | GB       | ARO           | ooo             |
| RSA.L       | RSA Insurance Group PLC        | 6861                    | GB       | INS           | ooo             |
| RTO.L       | Rentokil Initial                | 9636                    | GB       | ICS           | ooo             |
| RWE.DE      | RWE AG                         | 16,813                  | DE       | MUW           | ooo             |
| RYACIR      | Ryanair Holdings PLC           | 15,859                  | IE       | AIR           | ooo             |
| SAB.MC      | Banco de Sabadell SA           | 5840                    | ES       | BNK           | ooo             |
| SAEPA       | Safran SA                      | 56,334                  | FR       | ARO           | ooo             |
| SAMPO.HE    | Sampo Oyj A                    | 21,562                  | FI       | INS           | ooo             |
| SAN.MC      | Banco Santander SA             | 61,985                  | ES       | BNK           | 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 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       | IEG           | 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       | IEG           | ooo             |
| SCMN.SW     | Swisscom AG Reg                | 24,437                  | CH       | TLS           | ooo             |
| SCR.PA      | SCOR SE                        | 6980                    | FR       | INS           | ooo             |
| SDR.L       | Schroders PLC                  | 8905                    | GB       | FBN           | ooo             |
| SEB.AST     | SEB-Skand Enskilda Banken A    | 18,219                  | SE       | BNK           | ooo             |
| SECU.B.ST   | Securitas AB B                 | 5354                    | SE       | ICS           | ooo             |
| SESG.PA     | SES                            | 4705                    | LU       | PUB           | o              |
| SEVPA       | Suez SA                        | 8406                    | FR       | MUW           | ooo             |
| SGCL        | Sage Group                     | 9912                    | GB       | SOF           | ooo             |
| SGO.PA      | Saint-Gobain, Cie de          | 19,946                  | FR       | BLD           | ooo             |
| SGRD.L      | SEGREO PLC                     | 11,627                  | GB       | REA           | ooo             |
| SGSN.SW     | SGS-Soc Gen Survetel           | 18,624                  | CH       | PRO           | ooo             |
| SHIB.AST    | Svenska Handelsbanken A        | 18,699                  | SE       | BNK           | ooo             |
| SIE.DE      | Siemens AG                     | 99,059                  | DE       | IDD           | ooo             |
| SKIR        | Smurfit Kappa Group PLC        | 8096                    | IE       | CTR           | ooo             |
| SKA.BST     | SKANSKA AB-B                   | 8072                    | SE       | CON           | ooo             |
| SKF.BST     | SKF AB B                       | 7588                    | SE       | IEQ           | ooo             |
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              |
| SMDC.L  | DS Smith                             | 6209                    | GB       | CTR           | o               |
| SMIN.L  | Smiths Group                         | 7829                    | GB       | IDD           | ooo             |
| SN.L    | Smith & Nephew                       | 19,295                  | GB       | MTC           | ooo             |
| SOE.BR  | Solvay                               | 10,936                  | BE       | CHM           | ooo             |
| SOON.SW | Sonova Holding AG                    | 13,127                  | CH       | MTC           | o               |
| SPSN.SW | Swiss Prime Site AG                  | 7821                    | CH       | REA           | ooo             |
| SFN.L   | Spranex-Sanco Engineering            | 7724                    | GB       | IEQ           | ooo             |
| SREN.SW | Swiss Re Reg                         | 32,752                  | CH       | INS           | ooo             |
| SGR.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           | ooo             |
| STAM.MI | STMicroelectronics NV                 | 21,820                  | IT       | SEM           | ooo             |
| STMN.SW | Straumann AG Reg                     | 13,888                  | CH       | MTC           | o               |
| SUPA    | Schneider Electric SE                | 53,251                  | FR       | ELQ           | ooo             |
| SVTL    | Severn Trent                         | 7138                    | GB       | MUW           | ooo             |
| SWPA    | Sodexo                               | 15,578                  | FR       | REX           | o               |

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       | TOR           | ooo             |
| SYL.DE  | Symrise AG                           | 12,703                  | DE       | CHM           | ooo             |
| TATE.L  | Tate & Lyle                          | 4187                    | GB       | FOA           | ooo             |
| TEL.MC  | Telefonica SA                        | 32,331                  | ES       | TLS           | ooo             |
| TEL.OL  | Telenor ASA                          | 23,032                  | NO       | TLS           | ooo             |
| TEL2.B-ST| Tel2 AB B                            | 8621                    | SE       | TLS           | ooo             |
| TEMJ.AST| Telia Company AB                     | 16,151                  | SE       | TLS           | ooo             |
| TEMN.SW | Temenos Group AG                     | 10,213                  | CH       | SOF           | o               |
| TENS.MI | Tenaris SA                           | 11,864                  | IT       | OGX           | ooo             |
| TEP.PA  | Teleperformance                      | 12,735                  | FR       | PRO           | o               |
| TIT.MI  | Telecom Italia SpA                   | 8,459                   | 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             |
| UB.PA   | Ubisoft Entertainment SA             | 6939                    | FR       | IMS           | ooo             |
| UBSG.SW | UBS Group AG                         | 43,098                  | CH       | FBN           | ooo             |
| UCB.BR  | UCB SA                               | 13,790                  | BE       | DRG           | ooo             |
| UCG.MI  | Unicredit SpA Ord                    | 28,956                  | IT       | BNK           | ooo             |
| UGP.A   | 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           | ooo             |
| UPM.HE  | UPM-Kymmene Ostby                    | 16,448                  | FI       | FRP           | ooo             |
| URW.AS  | Unibail Rodamco Westfield            | 19,358                  | FR       | REA           | ooo             |
| UTDL.DE | United Internet AG Reg               | 6002                    | DE       | TLS           | ooo             |
| UUL.    | United Utilities Group Plc           | 7602                    | GB       | MUW           | ooo             |
| VIE.PA  | Veolia Environment                   | 13,332                  | FR       | MUW           | ooo             |
| VIF.PN.SW| Vifor Pharma Group                   | 10,567                  | CH       | DRG           | ooo             |
| VIV.PA  | Vivendi SA                           | 30,564                  | FR       | PUB           | ooo             |
| VNA.DE  | Vonovia SE                           | 26,029                  | DE       | REA           | ooo             |
| VOD.L   | Vodafone Group                       | 49,971                  | GB       | TLS           | ooo             |
| VOLV.BST| Volvo AB B                           | 24,537                  | SE       | AUT           | ooo             |
| VOW.DE  | Volkswagen AG                        | 51,124                  | DE       | AUT           | ooo             |
| VWS.CO  | Vestas Wind Systems AS               | 17,918                  | DK       | IEQ           | ooo             |
| WDL.DE  | Windancer AG                         | 13,275                  | DE       | FBN           | ooo             |
| WEIR.L  | Weir Group                           | 4631                    | GB       | IEQ           | ooo             |
| WKL.AS  | Wolters Kluver NV                    | 17,751                  | NL       | PRO           | ooo             |
| WPPL    | WPP Plc                              | 16,725                  | GB       | PUB           | ooo             |
| WRTY.1V | Warsells Oyj ABP                     | 5828                    | FI       | IEQ           | o               |
| WTB.L   | Whitbread                            | 8407                    | GB       | TRT           | ooo             |
| YAR.OL  | Yara International ASA               | 10,188                  | NO       | CHM           | ooo             |
| ZURIN .SW| Zurich Insurance Group AG             | 1011                    | GB       | INS           | 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 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 Code | Industry Code | Industry Code | Industry Code | Industry Code |
|---------------|---------------|---------------|---------------|---------------|---------------|
| AIR           | Airlines      | ITC           | Electronic Equipment, |
| ALU           | Aluminum      | LIF           | Life Sciences Tools |
| ARO           | Aerospace & Defense | MNX         | Metals & Mining |
| ATX           | Auto Components | PRO         | Professional Services |
| AUT           | Automobiles   | MTC           | Health Care Equipment |
| BLD           | Building Products | OGR         | Oil & Gas Refining |
| BNL           | Banks         | TC            | Supplies       |
| BTC           | Biotechnology | MUW           | Multi & Water Utilities |
| BUR           | Beverages     | JE            | Media, Movies |
| CMI           | Chemicals     | PAT           | & Marketing   |
| CNO           | Casinos & Gaming | OGX        | Oil & Gas Upstream |
| COM           | Construction Materials | PRO        | & Integrated |
| CON           | Construction & Engineering | PUB         | Facilities |
| COS           | Personal Products | REA         | Real Estate |
| CTR           | Containers & Packaging | REA         | & Entertainment |
| DHP           | Household Durables | REX         | Restaurants & Leisure |
| DRG           | Pharmaceuticals | REX           | Facilities |
| ELC           | Electric Utilities | RTS         | Retailing |
| ELQ           | Electrical Components & Equipment | SEM         | Semiconductors |
| FBN           | Diversified Financial Services & Capital Markets | SEM         | & Semiconductor |
| FDR           | Food & Staples Retailing | TCD         | Equipment |
| FNA           | Food Products | TCD           | Software     |
| FPA           | Paper & Forest Products | TCD         | Steel       |
| FRP           | Paper & Forest Products | TCD         | Trading Companies |
| GAS           | Gas Utilities | TCD           | & Distributors |
| HAE           | Health Care Providers & Services | TCD         | Textiles, Apparel |
| HEA           | Health Care Providers & Services | TCD         | & Luxury Goods |
| HOM           | Homebuilding | THQ           | Computers & Peripherals |
| HOU           | Household Products | TLS         | & Office Electronics |
| ICS           | Commercial Services & Supplies | TLS         | Telecommunication Services |
| IDD           | Industrial Conglomerates | TOB         | Tobacco |
| IEL           | Machinery & Electrical Equipment | TRA         | Transportation |
| IMS           | Interactive Media, Services & Home Entertainment | TRA         | Infrastructure |
| INS           | Insurance     | TSV           | Hotels, Resorts |
| INS           | Insurance     | TSV           | IT services |

Source: S&P Global and author.
| 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 (acceded on 5 October 2020).

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

9 https://www.spglobal.com/esg/scores/ (acceded 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 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.

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

13 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.

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

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