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Book

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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 paper we explore whether maintaining higher ESG ratings would reduce 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, (3) Covid-19 augmented the partial effects of volatility, centrality measures and some financial performance ratios. When considering only the Covid-19 period, we found that social and governance factors have statistically significant impacts on systemic risk.

Keywords: systemic risk, network centrality, sustainable, ESG, volatility, principal components, Covid-19.

JEL Classification: C32, C33, C58, Q56.

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1 Introduction

Since the 2008 financial crisis, there has been ever-growing interest in understanding the systemic risk concept. The term itself refers to the probability or the risk of a large number of financial institutions defaulting simultaneously (Lehar, 2005). Many central banks and other institutions, such as the Systemic Risk Council formed in 2012 and the Systemic Risk Centre created in 2013, look into measuring systemic risk locally and globally. There has been an extensive amount of research on the topic. SRISK of Brownlees and Engle (2017) and CoVaR of Adrian and Brunnermeier (2011b) are two of the many prominent works in the literature, while survey papers such as De Bandt and Hartmann (2000), Benoit et al. (2017) 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"?[3] For example the works of Billio et al. (2012) and Adrian and Brunnermeier (2011b) among many others look into the systemic risk contribution and exposure of firms. One interesting line of research that extends from here is to analyse 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. Cerqueti et al. (2020) mentions that ESG investment could help reduce systemic risk and if firms comply with ESG requirements they would be less vulnerable to systemic shocks. His argument is that the firms with higher ESG ratings have less problems with their stakeholders, possibly due to more transparent governance. Second, he mentions that ESG-related investments rely on the longer term; therefore, the investors of ESG assets are not likely to sell off even in crisis periods. Lastly, he states that ESG related assets are not yet commonly preferred; therefore, they are less vulnerable to shocks. Leterme and Nguyen (2020) found some evidence that ESG factors can be considered a systemic risk factor. 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 some others found a positive relationship.[4].

In this paper we aim to study 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 under the Covid-19 situation. If

[3]"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.

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

a firm's stock is central, has high volatility and this firm is performing poorly financially, it is likely that this firm is threatening the financial system it is in, or being threatened by a shock from this financial system, and even more so 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 paper 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 paper 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 paper 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 relating 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.[5] 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 found that while the "social" factor in ESG ratings is positively related to systemic risk contribution and exposure, the "governance" factor was negatively affecting 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.

[5] 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.

The paper is structured as follows. Section 2 gives a literature review on systemic risk and sustainability. Section 3 discusses the econometric model to extract the partial correlations. Section 4 explains network construction and centralities. Section 5 describes how the systemic risk measures are computed. Section 6 presents the data. Section 7 discusses the results of the OLS and panel data regressions. Section 8 concludes.

2 Literature Review

2.1 Systemic Risk

The global financial crisis that occurred in 2007-2008 has 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 has large coverage of different industries. There are other papers that have used stock markets for systemic risk analysis. For example Liu et al. (2020) analyses stock market indices of 43 countries to represent global financial markets, while Zhao et al. (2019) analysed the systemic risk of the Chinese stock market and Eratalay and Vladimirov (2020) focused on the Russian stock market.

There are a lot of papers that have proposed methods of measuring systemic risk. To start with, Gray et al. (2007) uses the risk-adjusted balance sheet and Contingent Claims Analysis method to gauge the asset-liabilities mismatches between sovereign, corporate, household and financial sectors, and through stress-testing depicts systemic instability due to an external factor. Tarashev et al. (2010) used a game-theoretic model, the Shapley value method, where the risk contributed by a bank is measured using the aggregate of the marginal contributions of the banking system. Additionally, Adrian and Brunnermeier (2011a) defined 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) applied the absorption ratio to asset prices to gauge the systemic risk in the US stock market, and Acharya et al. (2017) not only measured the systemic risk but also proposed an optimal taxation policy to manage it.

Some papers went further to distinguish the systemic risk contribution and exposure of firms. Billio et al. (2012) used 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 paper, since it is straightforward and easily applicable using stock return shocks derived from our econometric model. Another paper which discusses systemic risk contribution and exposure separately is by Tobias and Brunnermeier (2016), who base their methodology on value-at-risk.

For further reading we recommend Bougheas and Kirman (2015), who 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 on the uncertainty of our future, due to all 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, seeking to be 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, as well as thermal coal generators) 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, are characteristics that are taken into account to obtain ESG certification (See Drempetic et al. (2020), Dorfleitner et al. (2015), Friede et al. (2015), 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) discusses 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 reducing 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 are 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). There are also meta-analyses which argue in favour of ESG investing. Based on 2000 previous studies, Friede et al. (2015) documents that there is evidence that ESG investing has a positive impact on financial performance. Clark et al. (2015) analyses 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.

From the systemic risk perspective, Cerqueti et al. (2020) shows that ESG investments could help reduce systemic risk and the funds that follow ESG requirements would be less vulnerable to systemic shocks. Boubaker et al. (2020) suggests that firms with higher ESG ratings have lower financial distress risk and are less likely to crash. Giese et al. (2019) mentions that the ESG factor could mitigate tail risk and there may be a long-term ESG risk premium.

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. By network connectedness analysis using a wavelet method and a multivariate vector autoregression model, Reboredo et al. (2020) found that green bonds are significantly affected by corporate and treasure bond spillovers, although their transmission is unnoticeable besides the high connectivity among them in Europe and USA. Friede et al. (2015) notes 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.

Given this diverging view on whether higher ESG ratings could be beneficial for firms in terms of mitigating systemic risk or not, our paper 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 paper is similar to that of Cerqueti et al. (2020) 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 this subsection, we explain the econometric methodology, from which we derive the dynamic volatility and correlation estimates.

3.1.1 Conditional returns

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

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

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

Our approach differs here from Eratalay and Vladimirov (2020), as we consider an observable common factor, namely r_t^{MSWI}, which is the returns from the Morgan Stanley World Index (MSWI).[6] Considering MSWI allows us to take into account the common trends in the world that may affect all the stocks in a similar manner. As Barigozzi and Brownlees (2019) states, the consideration of a common factor is essential. If ignored, it could yield a spuriously connected network. The typical stationarity restrictions apply on the coefficients β, such that all eigenvalues of the β matrix should be positive.

3.1.2 Conditional variances

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

[6] 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.

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

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

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

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

3.1.3 Conditional correlations

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

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

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

For the estimation of this model, we follow the three-step estimation procedure discussed in Eratalay and Vladimirov (2020), which is consistent and asymptotically normal (See Bollerslev and Wooldridge (1992), Carnero and Eratalay (2014)).

3.2 Partial correlation network

Following Anufriev and Panchenko (2015) and Eratalay and Vladimirov (2020), we use 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 use partial correlations to isolate the correlation between two specific series eliminating the indirect effect of other series, obtaining the true relationship between every two series. The matrix of partial correlations, P, can be obtained using the correlation matrix R:

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

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

In the model we are constructing, the cDCC-GARCH approach from Section 3.2 provides us with the time varying conditional correlations. Therefore, we are able to construct a partial correlation network for each day in the time interval of our data. This gives us a dynamic network which takes each firm's stock as a node. The strength of the connections between these nodes are obtained using the adjacency matrix, which is 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 are also symmetrical. Consequently, this network's connections are bi-directional, meaning that there is no causal relationship. The adjacency matrix is defined as:

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

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

In our paper, 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 therefore 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, we cannot; therefore, we considered the absolute values of the partial correlations. More details can be found in Eratalay and Vladimirov (2020), Cortés Ángel and Eratalay (2021).

3.3 Systemic risk measure

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

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

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

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

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

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

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

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

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

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

and the variance of the system becomes:

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

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

$h_n > H$:

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

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

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

In our paper, 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 is as follows. First, we apply the econometric model to the stock returns and obtain volatilities and dynamic conditional correlations. Then from the volatilities and correlations we derive the systemic risk measures. From the conditional correlations, we derive the partial correlations which help 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 are used as regressors in fixed effects regressions, where the dependent variable is the systemic risk measures.

4 Data

4.1 Data sources

For this paper we collected the data from three sources. We collected the historical stock market data for the constituents of the S&P Europe 350 index[7] and for the Morgan and Stanley World Index (MSWI) from Yahoo Finance. For the constituents list, we made a formal request to SPGlobal[8]. 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 05.01.2016 - 15.09.2020 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 consider is given in Tables 19-26 in the appendix. After pre-treating the data, we had 1,202 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

[7]SP Dow Jones Indices

[8]https://www.spglobal.com/spdji/en/indices/equity/sp-europe-350/#overview

the outliers, we set the parameters of the Hampel filter such that the probability of observing an outlier is very small.[9]

Our second data source is the S&P Global website[10]. 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 and economic for 2020. Unfortunately, for some of the constituent stocks, the ESG data was not provided. We were able to collect the data for 308 stocks.[11]

Finally, our third data-set is 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 is annual and for years 2016-2020. The stock market performance of the firms not only depend 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 was available for only 200 of the constituent stocks. We summarize the description of these three panels in the 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 was from our samples as explained in Section 5.2. Source: authors' calculations.

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

[10] https://www.spglobal.com/esg/scores/

[11] 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.

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 21/02/2020 with a vertical dashed grid line, which is when a cluster of cases occurred in Lombardy, Italy.[12] 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 7.2.

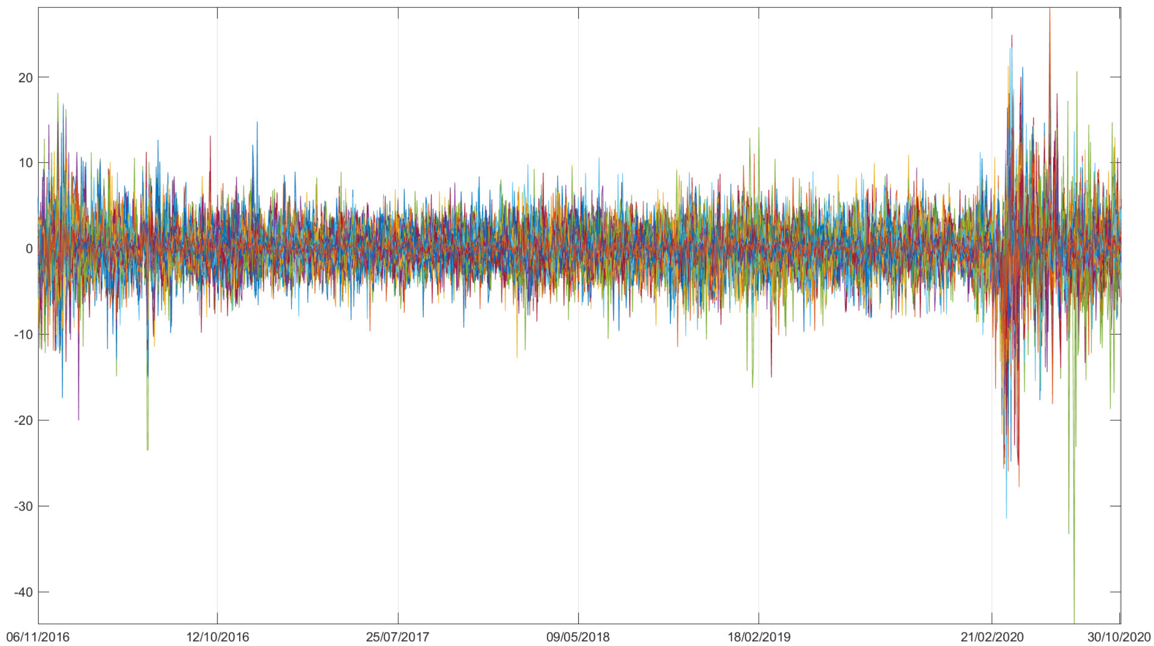


Figure 1: Returns of the S&P Europe 350 stocks

Notes: This figure plots the returns of the stocks in the dataset, which contains 331 stocks from S&P 350 Europe. Period: 05.01.2016 - 15.09.2020. 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 are 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 1

[12]https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Europe

and 3, but exceeding 3 for some series. For most stocks the returns are negatively skewed, and in some cases exceeding the conventional threshold of unit skewness indicating that the return distribution is highly skewed, implying that there are many negative extreme returns. We also observe that the kurtosis is very high for all the stocks, much above the kurtosis of normal distribution. This means that the sample distribution of the stock returns are leptokurtic and this is one of the stylized facts about financial time series data (Ghysels et al., 1996).

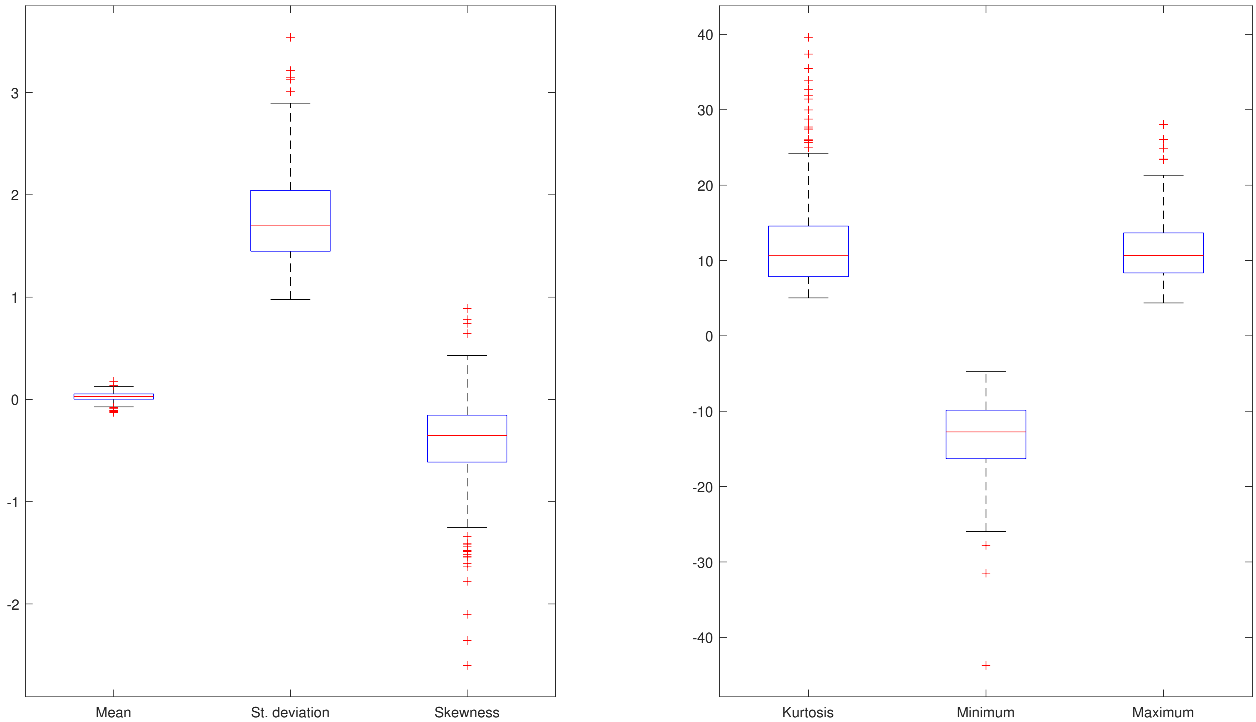
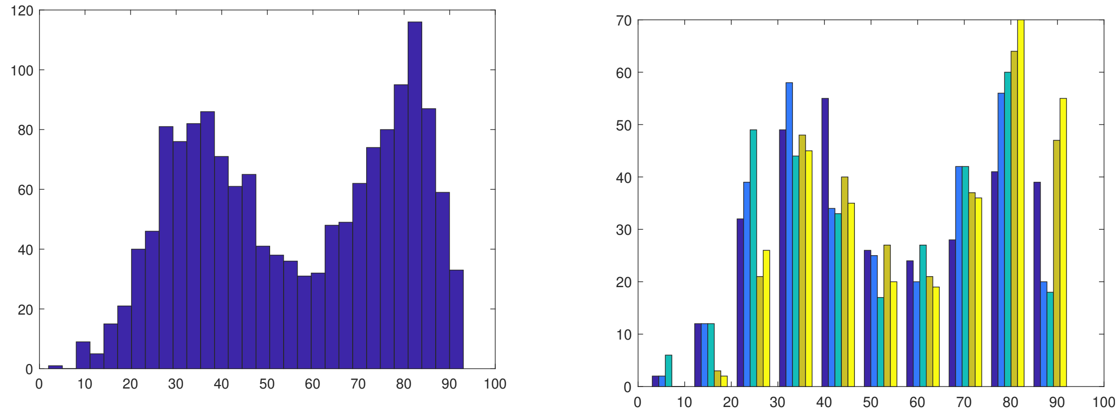


Figure 2: Box plots of basic descriptive statistics for S&P Europe 350 stocks

Notes: 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: 05.01.2016 - 15.09.2020. Source: authors' calculations.

We now discuss the ESG-ratings data. In Figure 3 we present the histograms of (a) merged ESG-ratings and (b) yearly ESG-ratings. When we look at the figure 3a we see that the distribution is bimodal and the difference between the modes is about 40-50 points. The figure 3b shows that the trend in ESG-ratings over the years is different around 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.



(a) Merged

(b) Per year

Figure 3: Histograms of merged and yearly ESG-ratings

Notes: 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: 05.01.2016 - 15.09.2020. 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 was 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.

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 7.

In Table 10 in the appendix 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, German, France and Switzerland have many firms in the S&P Europe

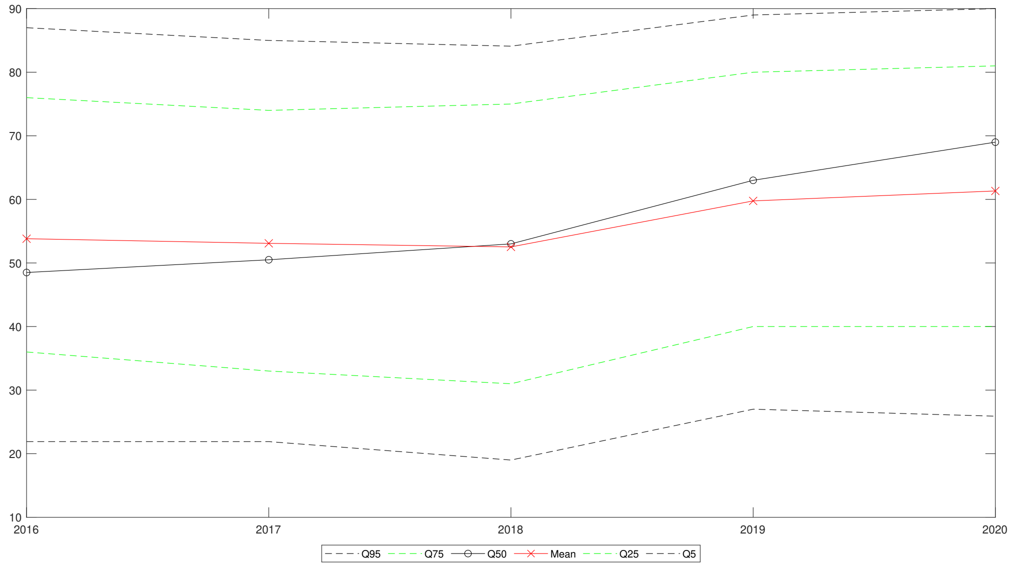


Figure 4: Quantiles and mean of ESG ratings over time

Notes: 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: 05.01.2016 - 15.09.2020. Source: authors' calculations.

Table 2: Average overall ESG rating by country over 2016-2020

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 over 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.

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 7. 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, (3) 199 of those 307 for which firm-level financial performance ratios were 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 9 in the appendix, 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 the industries such as banking, diversified financial services, machinery and electrical equipment, chemicals and insurance. In terms of countries, there are more 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 part, 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 were positive.

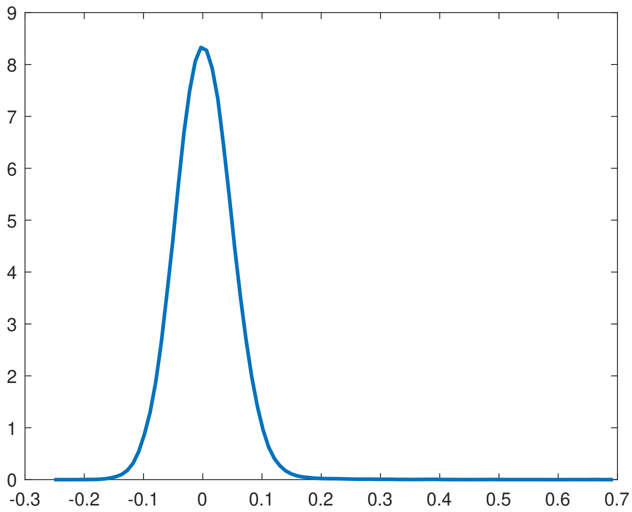


Figure 5: Kernel density estimate of all the partial correlations

Notes: 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: 05.01.2016 - 15.09.2020. Source: authors' calculations.

Considering all positive and negative partial correlations, we calculate the normalized number of edges over time in Figure 6, which suggests that the normalized number of edges stayed more or less the same over time. In Figure 7 we see that the maximum eigenvalues reach an all time high just after the first news of Covid-19 patients and deaths appear 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 paper, 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.[13] We calculate 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

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

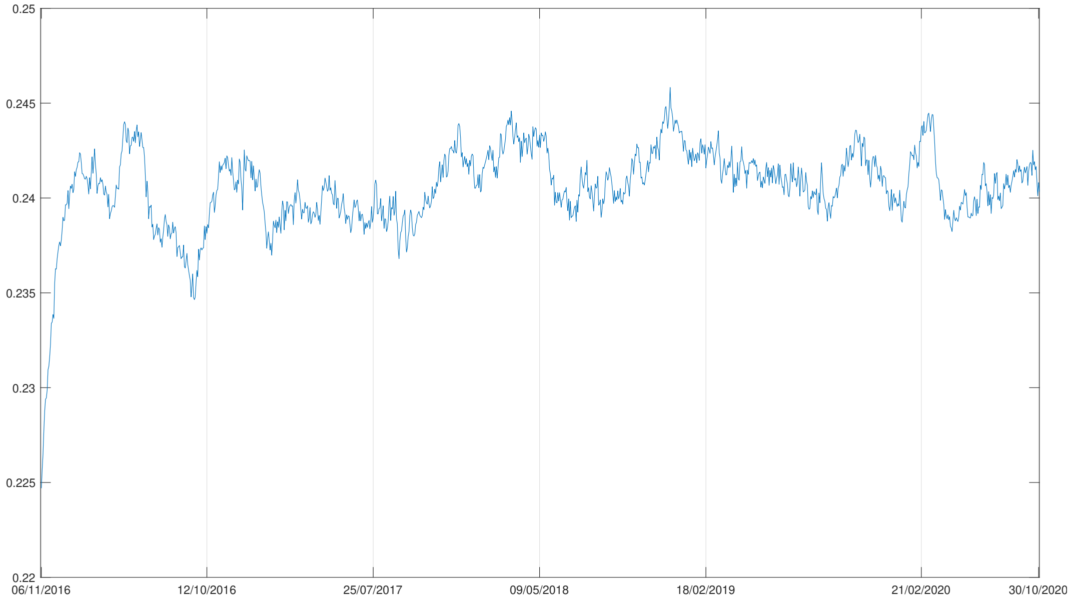


Figure 6: Normalized number of edges over time

Notes: This figure shows the normalized number of edges in the dynamic networks of the stocks in the S&P 350 Europe stock index during the data period 05.01.2016 - 15.09.2020. The normalization is done using the maximum number of possible edges. Source: authors' calculations.

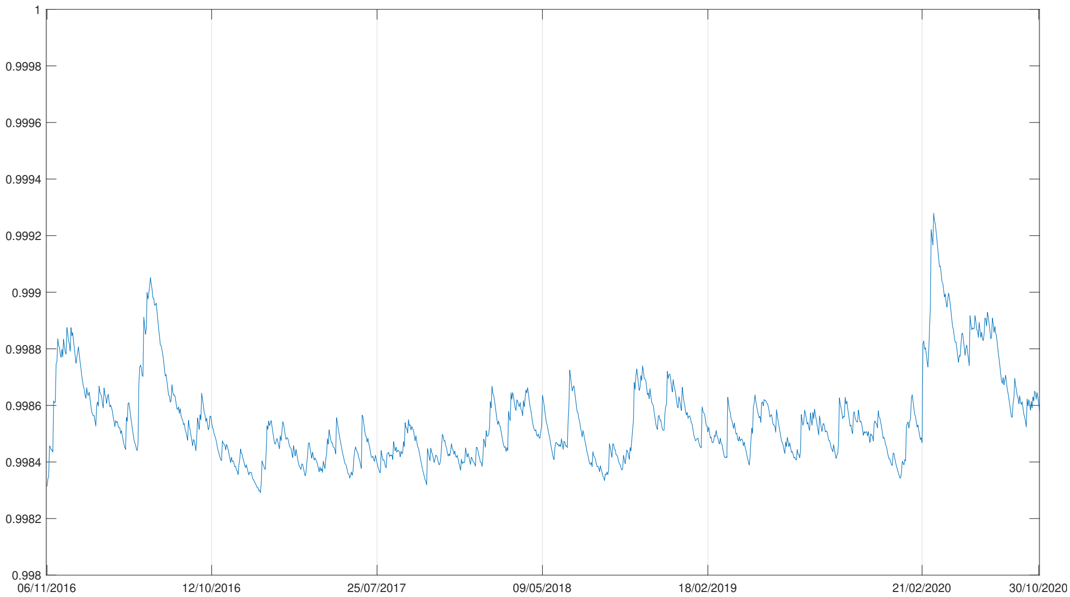


Figure 7: Maximum eigenvalues over time

Notes: This figure shows the maximum eigenvalue of the adjacency matrices in the dynamic networks of the stocks in the S&P 350 Europe stock index during the data period 05.01.2016 - 15.09.2020. Source: authors' calculations.

the nodes, it has a higher closeness centrality. Therefore, if the node has a high closeness centrality, then 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 neigbouring 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 consider the absolute value of the closeness centrality.

In tables 11 and 12 in the appendix, 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 Financials 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 was obtained from the Statistical Data Warehouse of the European Central Bank.[14] 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.

[14]Data source: https://sdw.ecb.europa.eu/reports.do?node=1000003285

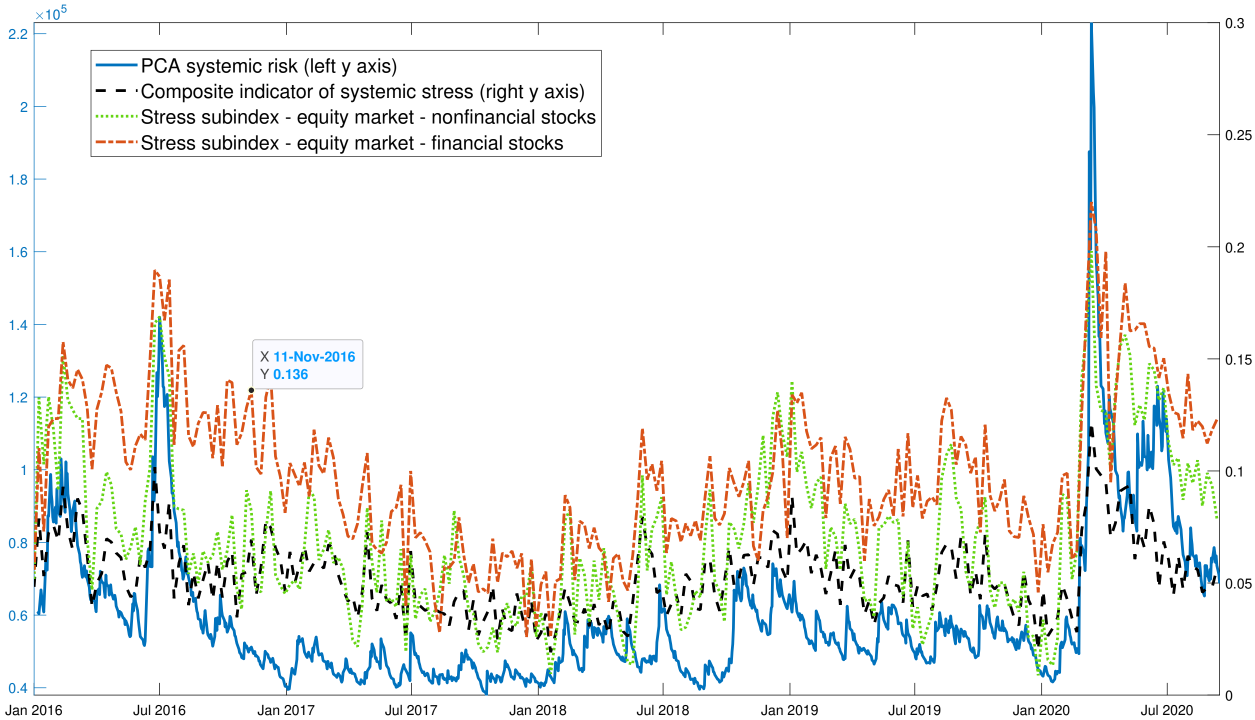


Figure 8: PCA systemic risk of S&P Europe 350 stocks versus the Composite Indicator of Systemic Stress of the ESRB

Notes: 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 are 0.6474, 0.7790, 0.7477. The data period was 05.01.2016 - 15.09.2020. 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 more clearly in early March 2020.

Tables 15 and 16 in the appendix 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 is calculated as about 9 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 data set. According to tables 15 and 16, 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 17 and 18 in the appendix show 25 firms for which the systemic risk was the lowest in 2016-2019 and 2020, respectively. We could 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 eliminated 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 10 in the appendix. 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 some 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 6.2.

The dependent variable in all these regressions is the natural logarithm of the systemic risk. Since it had 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 closeness centrality, logarithm of volatility, and the dummy variable that takes the value 1 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 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) are relatively higher in Table 2, we performed the same regressions using sub-samples with respect to geographical location.

In Table 3 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 3: Fixed effects estimation results, only using the stock market and network data

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

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

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

In Table 4 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. We also notice the same way that the partial effects of centralities and volatility increased in 2020.

Table 4: Fixed effects estimation results, using the stock market, network and ESG ratings data

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

Notes: For this regression, the yearly average of systemic risk, network characteristics, volatilities and ESG ratings are used. Cross section size is 307. The stock ticker was used as panel id for the fixed effect 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.

What is more in these results is that the ESG rating is negatively linked to systemic risk. The coefficient is significant at 10% and is small in magnitude. However, if we consider the approximately 40 point difference between the two modes in the histogram of Figure 3a, we can calculate that a 40-point increase in ESG ratings would decrease systemic risk contribution and exposure by 2.90%.[15] This means that firms with higher ESG ratings are benefitting 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 had no significant impact on systemic risk for southern European countries. For stocks from northern European countries it had a higher impact, which would imply 3.41% decline in systemic risk contribution and exposure for a 40-point increase in ESG ratings.

In Table 5, we further include the financial ratios of the firms to the regression. As we said before, due to lack of data, we end up with 199 stocks among which there are less banks and insurance firms. As before, the coefficients of centrality measures are positive. In addition, we found 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 would imply 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.

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

Table 5: Fixed effects estimation results using the stock market, network, ESG ratings and firm level financial data

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

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

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 had 307 stocks and it 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. The results call for further research considering different industries, which we consider in Section 5.3.3.

5.3.2 OLS regressions for 2020

As explained in Section 6.2., we were able to collect data for the subcategories of the ESG ratings for the 199 firms in our smallest panel in 2020. To have a fair comparison, we run 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 for calculating the standard errors.

Using the 330 stocks of the first panel, we found similar results as in the fixed effects regression that the centralities and volatility significantly affect the systemic risk contribution and exposure. We present these results in Table 6. 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 have ESG rating data available, we found similar coefficients in Table 7. Interestingly, in these regressions we found that ESG subcategories did not have an affect on the dependent variable. When we move on to include the financial performance ratios to the OLS regressions in Table 8, we see that eigenvector centrality and volatility regressors are significant, while in the sub-samples the former is not significant.

Table 8 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 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 6: OLS estimation results only using the stock market and network data for 2020

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

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

Table 7: OLS estimation results using the stock market, network and ESG ratings data for 2020

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

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

Table 8: OLS estimation results using the stock market, network, ESG ratings and firm level financial data for 2020

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

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

5.3.3 Further regressions

In Table 9 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 29 in the appendix. As Hox et al. (2017) mentions, when a panel data has less than 50 groups and less than 5 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 9. That 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 were as in Table 4, we find significant coefficients for ESG ratings for Energy, Financials 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

Table 9: 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. 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.

helped reduce the systemic risk contribution and exposure. In 2020, this beneficial impact of ESG rating is slightly offset for Consumer Discretionary and Information Technology sectors, while it is increased for the Real Estate sector. When we consider the panel of 199 stocks, where the regressors were as in Table 5, 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%.

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 7.5. 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) suggests that for each regressor, one should have 10-20 observations per regressor, while Green (1991) suggests to have at least 50+8*p number observations where p is the number of regressors. In these regressions we had 7 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. We do not present the results of these regressions to save space.

6 Conclusions

In this paper we explore 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 05.01.2016 - 15.09.2020, and yearly ESG ratings and firm performance ratios for these firms. We employ an interdisciplinary approach that connects 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 principal components method we derived the systemic risk contribution and exposure measures. Subsequently, we obtain dynamic partial correlations using Gaussian graphical modelling and construct the daily partial correlation networks of stocks, which provided us with the network centralities. Finally, we employ panel data and OLS regressions, where the systemic risk contribution and exposure of each firm is the dependent variable and the volatility estimates, network centralities, ESG ratings and firm performance ratios are the regressors. We also consider a dummy variable for the year 2020 to keep 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 are benefitting 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. Interpreting these results could suggest that investors might see social investments as risky, but value how the firms are governed.

The findings of this paper 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 the 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.

7 APPENDICES

Appendix: Tables and Figures

Table 10: 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 servces	89.4
CNH Industrial NV	United Kingdom	Machinery and Electrical Equipment	88.8
Red Electrica Corporacion SA	Spain	Electric utilities	88.8
Energias de Portugal SA	Portugal	Electric utilities	88.6
Iberdrola SA	Spain	Electric utilities	88.2
Roche Hldgs AG Ptg Genus	Switzerland	Pharmaceuticals	88.2
Banco Santander SA	Spain	Banks	87.2
UPM-Kymmene Oyj	Finland	Paper and forest products	87.2
Allianz SE	Germany	Insurance	87
Enagas SA	Spain	Gas utilities	86.8
Enel SpA	Italy	Electric utilities	86.6
GlaxoSmithKline	United Kingdom	Pharmaceuticals	86.2
Telecom Italia SpA	Italy	Telecommunication servces	86.2
Diageo Plc	United Kingdom	Beverages	86
Endesa SA	Spain	Electric utilities	85.4
Deutsche Telekom AG	Germany	Telecommunication servces	85.2
Koninklijke Philips Electronics NV	Netherlands	Health Care Equipment & Supplies	84.6
Naturgy Energy Group SA	Spain	Gas utilities	84.6
UBS Group AG	Switzerland	Diversified Financial Services and Capital Markets	84.6
Clariant AG Reg	Switzerland	Chemicals	84.4
Lanxess AG	Germany	Chemicals	84.4
Schneider Electric SE	France	Electrical Components and Equipment	84.2
Adidas AG	Germany	Textiles, Apparel & Luxury Goods	84
CaixaBank	Spain	Banks	84

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

Table 11: Centralities for 2016-2019, before Covid-19, by net eigenvector centrality

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

Notes: This table provides the net and absolute eigenvector centralities and absolute 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 12: Centralities in 2020, during Covid-19, by net eigenvector centrality

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

Notes: This table provides the net and absolute eigenvector centralities and absolute 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 13: Centralities for 2016-2019, before Covid-19, by ESG rating

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

Notes: This table provides the net and absolute eigenvector centralities and absolute 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 14: Centralities in 2020, during Covid-19, by ESG rating

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

Notes: This table provides the net and absolute eigenvector centralities and absolute 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 15: Centralities for 2016-2019, before Covid-19, by systemic risk: most risky

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

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

Table 16: Centralities in 2020, during Covid-19, by systemic risk: most risky

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

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

Table 17: Centralities for 2016-2019, before Covid-19, by systemic risk: least risky

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

Notes: This table provides the net and absolute eigenvector centralities and absolute 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 18: Centralities in 2020, during Covid-19, by systemic risk: least risky

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

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

(a) 330 firms - industries

(b) 330 firms - countries

(c) 307 firms - industries

(d) 307 firms - countries

(e) 199 firms - industries

(f) 199 firms - countries

Figure 9: Word clouds to visualize the industries and countries of the firms in our data set. In our data set 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.

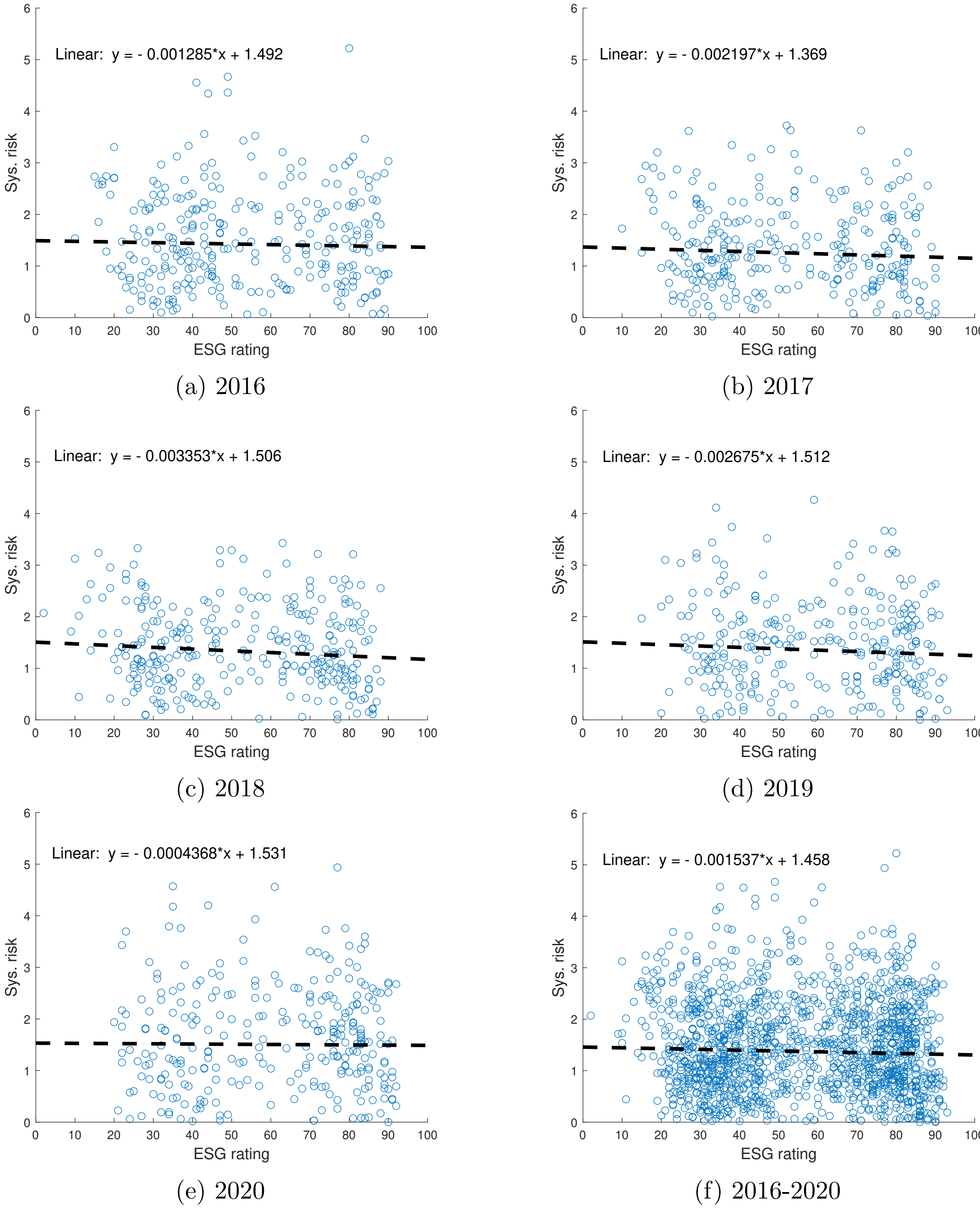


Figure 10: Scatter plots of average systemic risk per year versus the ESG ratings in that year.

Tables related to stock data

Table 19: *Firms part I*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
1COV.DE	Covestro AG	7585 350000	DE	CHM	ooo
AAL.L	Anglo American PLC	35532 325635	GB	MNX	ooo
ABBN.SW	ABB Ltd	46631 121398	CH	ELQ	oo
ABF.L	Associated British Foods	24306 770982	GB	FOA	ooo
ABI.BR	Anheuser Busch Inbev NV	123000 000000	BE	BVG	ooo
ABN.AS	ABN AMRO Group NV	15246 800000	NL	BNK	oo
AC.PA	Accor	11274 420500	FR	TRT	ooo
ACA.PA	Credit Agricole SA	37284 605325	FR	BNK	oo
ACS.MC	ACS Actividades de Construccion y Servicios SA	11217 807250	ES	CON	ooo
AD.AS	Ahold Delhaize NV	26391 148875	NL	FDR	oo
ADP.PA	ADP Promesses	17427 032100	FR	PRO	o
ADS.DE	Adidas AG	58080 556800	DE	TEX	ooo
AENA.MC	Aena SA	25575 000000	ES	TRA	ooo
AGN.AS	Aegon NV	8523 000416	NL	INS	oo
AGS.BR	AGEAS	10450 342320	BE	INS	oo
AHT.L	Ashtead Group	14359 138055	GB	TCD	ooo
AI.PA	L'Air Liquide S.A.	59445 121800	FR	CHM	ooo
AIR.PA	Airbus SE	101000 000000	FR	ARO	ooo
AKE.PA	Arkema	7242 750700	FR	CHM	ooo
AKZA.AS	Akzo Nobel NV	20643 260000	NL	CHM	ooo
ALFA.ST	Alfa Laval AB	9490 388121	SE	IEQ	ooo
ALO.PA	Alstom	9472 357920	FR	IEQ	ooo
ALV.DE	Allianz SE	91110 583200	DE	INS	oo
AMS.MC	Amadeus IT Group SA	31396 310400	ES	TSV	ooo
ASML.AS	ASML Holding NV	112000 000000	NL	SEM	ooo
ASSA-B.ST	Assa Abloy B	22025 237708	SE	BLD	oo
ATCO-A.ST	Atlas Copco AB A	29893 459353	SE	IEQ	oo
ATL.MI	Atlantia SpA	17153 267670	IT	TRA	ooo
ATO.PA	AtoS SE	8115 372400	FR	TSV	ooo
AV.L	Aviva	19478 435620	GB	INS	oo
AZN.L	AstraZeneca PLC	118000 000000	GB	DRG	ooo
BA.L	BAE Systems PLC	23152 520936	GB	ARO	ooo
BAER.SW	Julius Baer Group	10284 124741	CH	FBN	oo
BALN.SW	Baloise Hldg Reg	7859 340301	CH	INS	o
BARC.L	Barclays	36376 018151	GB	BNK	oo
BAS.DE	BASF SE	61859 560650	DE	CHM	ooo
BATS.L	British American	94014 870214	GB	TOB	oo
BAYN.DE	Bayer AG	67899 111120	DE	DRG	oo
BBVA.MC	Banco Bilbao Vizcaya Argentaria SA	33226 080921	ES	BNK	oo

Notes: The last column indicates in which panels a stock is 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 20: *Firms part II*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
BDEV.L	Barratt Developments Tobacco PLC	8981 456822	GB	HOM	ooo
BEI.DE	Beiersdorf AG	26875 800000	DE	COS	ooo
BHP.L	BHP Group Plc	44349 528279	GB	MNX	ooo
BIRG.IR	Bank of Ireland Group	5270 162938	IE	BNK	oo
BKG.L	Berkeley Group Holdings Plc	7860 684449	GB	HOM	ooo
BLND.L	British Land Co	7108 239101	GB	REA	oo
BMW.DE	Bayer Motoren Werke AG (BMW)	44029 914300	DE	AUT	oo
BN.PA	danone	50625 564500	FR	FOA	ooo
BNP.PA	BNP Paribas	65744 980290	FR	BNK	oo
BNR.DE	Brenntag AG	7490 160000	DE	TCD	ooo
BNZL.L	Bunzl	8190 216743	GB	TCD	ooo
BOL.ST	Boliden AB	6478 950144	SE	MNX	ooo
BP.L	BP p.l.c	120000 000000	GB	OGX	ooo
BRBY.L	Burberry Group	10719 812115	GB	TEX	ooo
BT-A.L	BT Group	22669 956904	GB	TLS	ooo
BVI.PA	Bureau Veritas SA	10512 101140	FR	PRO	oo
CA.PA	Carrefour SA	12068 626700	FR	FDR	oo
CABK.MC	CaixaBank	16736 063524	ES	BNK	oo
CAP.PA	Capgemini SE	18218 316600	FR	TSV	ooo
CARL-B.CO	Carlsberg AS B	15807 271025	DK	BVG	ooo
CBK.DE	Commerzbank AG	6909 259086	DE	BNK	oo
CCL.L	Carnival Plc	9321 627486	GB	TRT	oo
CFR.SW	Richemont, Cie Financiere A Br	36538 864514	CH	TEX	oo
CHR.CO	Christian Hansen Holding A/S	9341 145735	DK	LIF	oo
CLN.SW	Clariant AG Reg	6598 424555	CH	CHM	ooo
CLNX.MC	Cellnex Telecom S.A.	14784 996990	ES	TLS	o
CNA.L	Centrica	6152 218228	GB	MUW	ooo
CNHI.MI	CNH Industrial NV	13325 257110	IT	IEQ	oo
COLO-B.CO	Coloplast AS B	21897 018624	DK	HEA	ooo
CON.DE	Continental AG	23052 691560	DE	ATX	ooo
CPG.L	Compass Group	35582 324369	GB	REX	ooo
CRDA.L	Croda Intl	7981 408595	GB	CHM	ooo
CRH	CRH Plc	28198 133760	IE	COM	ooo
CS.PA	AXA	60928 360380	FR	INS	oo
CSGN.SW	Credit Suisse Group AG	30826 778129	CH	FBN	oo
DAI.DE	Daimler AG	52817 852690	DE	AUT	ooo
DANSKE.CO	Danske Bank A/S	12437 947310	DK	BNK	oo
DASTY	Dassault Systemes SA	38532 098400	FR	SOF	ooo
DB	Deutsche Bank AG	14295 868841	DE	BNK	oo
DB1.DE	Deutsche Boerse AG	26628 500000	DE	FBN	oo

Notes: The last column indicates in which panels a stock is 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 21: *Firms part III*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
DCC.L	DCC	7836 826228	IE	IDD	ooo
DG.PA	Vinci	59918 562000	FR	CON	ooo
DGE.L	Diageo Plc	97310 307888	GB	BVG	ooo
DLG.L	Direct Line Insurance Group	5078 020620	GB	INS	oo
DNB.OL	DNB ASA	26283 427706	NO	BNK	oo
DPW.DE	Deutsche Post AG	41805 942250	DE	TRA	ooo
DSM.AS	Koninklijke DSM NV	21063 442500	NL	CHM	ooo
DSV.CO	Dsv Panalpina A/s	24146 014608	DK	TRA	ooo
DTE.DE	Deutsche Telekom AG	69374 457630	DE	TLS	oo
DWNI.DE	Deutsche Wohnen AG BR	13100 456100	DE	REA	oo
EBS.VI	Erste Group Bank AG	14424 088000	AT	BNK	oo
EDEN.PA	Edenred	11211 750500	FR	TSV	ooo
EDF.PA	Electricite de France	30290 030160	FR	ELC	ooo
EDP.LS	Energias de Portugal SA	11931 027360	PT	ELC	oo
EL.PA	EssilorLuxottica	58853 004000	FR	TEX	ooo
ELE.MC	Endesa SA	25187 710080	ES	ELC	ooo
ELISA.HE	Elisa Corporation	8190 669000	FI	TLS	ooo
ELUX-B.ST	Electrolux AB B	6571 380437	SE	DHP	oo
EN.PA	Bouygues	14072 723040	FR	CON	ooo
ENEL.MI	Enel SpA	71827 885376	IT	ELC	ooo
ENG.MC	Enagas SA	5428 811160	ES	GAS	ooo
ENGI.PA	Engie	34731 072000	FR	MUW	ooo
ENI.MI	ENI SpA	50318 925510	IT	OGX	ooo
EOAN.DE	E.ON SE	25155 922156	DE	MUW	ooo
EQNR.OL	Equinor ASA	59422 071034	NO	OGX	ooo
ERIC-B.ST	Ericsson L.M. Telefonaktie B	23660 551313	SE	CMT	ooo
EXO.MI	EXOR NV	16648 280000	IT	FBN	oo
EXPN.L	Experian Plc	29221 182071	GB	PRO	oo
EZJ.L	Easyjet	6659 805941	GB	AIR	ooo
FCA.MI	Fiat Chrysler Automobiles NV	20446 042518	IT	AUT	o
FER.MC	Ferrovial SA	19942 211340	ES	CON	ooo
FERG.L	Ferguson PLC	18780 339920	GB	TCD	ooo
FGR.PA	Eiffage	9996 000000	FR	CON	ooo
FLTR.L	Flutter Entertainment plc	8465 277150	IE	CNO	ooo
FME.DE	Fresenius Medical Care AG	20259 086320	DE	HEA	ooo
FORTUM.HE	Fortum Oyj	19544 074000	FI	ELC	ooo
FP.PA	TOTAL SA	131000 000000	FR	OGX	ooo
FR.PA	Valeo	7546 346730	FR	ATX	ooo
G.MI	Assicurazioni Generali SpA	28638 458095	IT	INS	oo
G1A.DE	GEA AG	5320 904160	DE	IEQ	oo
GALP.LS	Galp Energia SGPS SA	11490 447900	PT	OGX	ooo
GBLB.BR	Groupe Bruxelles Lambert	15161 197680	BE	FBN	oo
GEBN.SW	Geberit AG Reg	18517 002581	CH	BLD	ooo
GFC.PA	Gecina	12155 614800	FR	REA	oo

Notes: The last column indicates in which panels a stock is 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 22: *Firms part IV*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
GFS.L	G4S Plc	3997 388193	GB	ICS	ooo
GIVN.SW	Givaudan AG	25757 519041	CH	DRG	ooo
GLE.PA	Societe Generale	26292 438995	FR	INS	oo
GLEN.L	Glencore Plc	40569 355368	GB	MNX	ooo
GLPG.AS	Galapagos Genomics NV	12060 395500	BE	BTC	o
GMAB.CO	Genmab AS	12880 438320	DK	BTC	ooo
GRF.MC	Grifols SA	13393 265900	ES	BTC	ooo
GSK.L	GlaxoSmithKline	113000 000000	GB	DRG	ooo
GVC.L	GVC Holdings PLC	6041 813756	GB	CNO	oo
HEI.DE	HeidelbergCement AG	12889 103360	DE	COM	ooo
HEIA.AS	Heineken NV	54674 204760	NL	BVG	ooo
HEN3.DE	Henkel AG & Co. KGaA Nvtg - Pref	16426 628600	DE	HOU	ooo
HEXA-B.ST	Hexagon AB	17520 937593	SE	ITC	ooo
HL.L	Hargreaves Lansdown Plc	10846 590177	GB	FBN	ooo
HLMA.L	Halma	9449 553980	GB	ITC	ooo
HM-B.ST	Hennes & Mauritz AB B	26521 955023	SE	RTS	ooo
HNR1.DE	Hannover Ruck SE	20778 863100	DE	INS	oo
HO.PA	Thales	19586 946600	FR	ARO	ooo
HSBA.L	HSBC Holdings Plc	144000 000000	GB	BNK	oo
IAG.L	International Consolidated Airlines Group SA	14713 577672	GB	AIR	oo
IMB.L	Imperial Brands PLC	22548 389450	GB	TOB	ooo
IMI.L	IMI	3988 017359	GB	PRO	o
INDU-A.ST	Industrivarden AB A	5938 978289	SE	FBN	oo
INF.L	Informa PLC	12676 181930	GB	PUB	ooo
INGA.AS	ING Groep NV	41645 321728	NL	BNK	oo
IBE.MC	Iberdrola SA	58403 820960	ES	ELC	ooo
IFX.DE	Infineon Technologies AG	25391 338590	DE	SEM	ooo
IHG.L	InterContinental Hotels Group PLC	11553 634759	GB	TRT	ooo
III.L	3I Group	12602 800553	GB	FBN	oo
INVE-B.ST	Investor AB B	22195 627041	SE	FBN	oo
ISP.MI	Intesa SanPaolo	41114 341692	IT	BNK	oo
ITRK.L	Intertek Group PLC	11119 592874	GB	PRO	ooo
ITV.L	ITV PLC	7183 377677	GB	PUB	ooo
ITX.MC	Inditex SA	98018 642500	ES	RTS	o
JMAT.L	Johnson, Matthey	7043 813456	GB	CHM	ooo
KBC.BR	KBC Group NV	27961 807020	BE	BNK	oo
KER.PA	Kering	73803 668400	FR	TEX	ooo
KGP.L	Kingspan Group PLC	9888 392250	IE	BLD	ooo
KINV-B.ST	Kinnevik Investment AB B	5280 737098	SE	FBN	oo
KNEBV.HE	Kone Corp B	26178 851480	FI	IEQ	oo

Notes: The last column indicates in which panels a stock is 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 23: *Firms part V*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
KNIN.SW	KUEHNE & NAGEL INTL AG-REG	18023 105439	CH	TRA	ooo
KPN.AS	Koninklijke KPN NV	11057 682564	NL	TLS	oo
KYGA.L	Kerry Group A	19531 935500	IE	FOA	ooo
LAND.L	Land Securities Group PLC	8789 760224	GB	REA	oo
LDO.MI	Leonardo S.p.a.	6041 667500	IT	ARO	ooo
LEG.DE	LEG Immobilien AG	7237 880150	DE	REA	o
LGEN.L	Legal & General Group	21154 473153	GB	BNK	oo
LHA.DE	Deutsche Lufthansa AG	7772 662140	DE	AIR	ooo
LHN.SW	LafargeHolcim Ltd	30439 194891	CH	COM	ooo
LI.PA	Klepierre	10406 302400	FR	REA	oo
LISN.SW	Lindt & Sprungli AG Reg	10701 218854	CH	FOA	oo
LLOY.L	Lloyds Banking Group PLC	51831 247152	GB	BNK	oo
LOGN.SW	Logitech International SA	7301 174195	CH	THQ	ooo
LONN.SW	Lonza AG	24206 078639	CH	LIF	oo
LR.PA	Legrand Promesses	19234 418240	FR	ELQ	oo
LSE.L	London Stock Exchange PLC	32084 185501	GB	FBN	oo
LXS.DE	Lanxess AG	5231 139360	DE	CHM	ooo
MAERSK-A.CO	AP Moller - Maersk AS A	12997 745612	DK	TRA	o
MB.MI	Mediobanca SpA	8648 440290	IT	BNK	oo
MC.PA	LVMH-Moet Vuitton	211000 000000	FR	TEX	ooo
MCRO.L	Micro Focus International	4561 232100	GB	PRO	ooo
MKS.L	Marks & Spencer Group	4920 181628	GB	FDR	oo
ML.PA	Michelin CGDE B Brown	19645 200600	FR	ATX	oo
MNDI.L	Mondi PLC	10171 043700	GB	FRP	ooo
MONC.MI	Moncler SpA	10336 016430	IT	TEX	ooo
MOWI.OL	Mowi ASA	11942 557638	NO	FOA	ooo
MRK.DE	MERCK KGaA	13615 644700	DE	DRG	ooo
MRO.L	Melrose Industries PLC	13785 236033	GB	IEQ	ooo
MRW.L	Morrison (WM) Supermarkets	5650 440187	GB	FDR	ooo
MT.AS	ArcelorMittal Inc	15888 392784	LU	STL	ooo
MTX.DE	MTU Aero Engines AG	13239 200000	DE	ARO	ooo
MUV2.DE	Munich Re AG	37955 634000	DE	INS	o
NDA-FI.HE	Nordea Bank Abp	29111 104460	FI	BNK	oo
NESN.SW	Nestle SA Reg	287000 000000	CH	FOA	ooo
NESTE.HE	Neste Oyj	23860 956240	FI	OGR	ooo
NG.L	National Grid PLC	41881 362823	GB	MUW	ooo
NHY.OL	Norsk Hydro AS	6848 706583	NO	ALU	ooo
NN.AS	NN Group N.V.	11619 063920	NL	INS	oo
NOKIA.HE	Nokia OYJ	18561 447072	FI	CMT	ooo
NOVN.SW	Novartis AG Reg	216000 000000	CH	DRG	ooo
NOVO-B.CO	Novo Nordisk AS B	96373 738885	DK	DRG	oo

Notes: The last column indicates in which panels a stock is 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 24: *Firms part VI*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
NTGY.MC	Naturgy Energy Group SA	22044 332800	ES	GAS	ooo
NXT.L	Next	11049 786129	GB	RTS	ooo
NZYM-B.CO	Novozymes AS B	10350 570630	DK	CHM	ooo
OCDO.L	Ocado Group PLC	10685 197490	GB	RTS	o
OMV.VI	OMV AG	16389 831840	AT	OGX	ooo
OR.PA	L'Oreal	147000 000000	FR	COS	ooo
ORA.PA	Orange	34750 589760	FR	TLS	ooo
ORK.OL	Orkla AS	9034 708498	NO	FOA	ooo
PAH3.DE	Porsche Automobil Holding SE	10204 250000	DE	AUT	oo
PGHN.SW	Partners Group Hldg	21805 141471	CH	REA	ooo
PHIA.AS	Koninklijke Philips Electronics NV	39397 568000	NL	MTC	ooo
PNDORA.CO	Pandora A/S	3878 179176	DK	TEX	ooo
PROX.BR	Proximus	8626 398000	BE	ELQ	ooo
PRU.L	Prudential PLC	44280 510043	GB	INS	oo
PRY.MI	Prysmian SpA	5762 414560	IT	ELQ	ooo
PSN.L	Persimmon	10114 746939	GB	HOM	ooo
PSON.L	Pearson	5876 761866	GB	PUB	ooo
PUB.PA	Publicis Groupe	9701 292840	FR	PUB	ooo
QIA.DE	QIAGEN NV	6913 384360	DE	LIF	ooo
RACE.MI	Ferrari NV	28681 211700	IT	AUT	ooo
RAND.AS	Randstad NV	9960 451280	NL	PRO	oo
RB.L	Reckitt Benckiser Group PLC	53348 811760	GB	HOU	ooo
RDSA.L	Royal Dutch Shell PLC	110000 000000	GB	OGX	ooo
REE.MC	Red Electrica Corporacion SA	9698 859000	ES	ELC	ooo
REL.L	RELX PLC	45300 422373	GB	PRO	ooo
REP.MC	Repsol SA	22271 158630	ES	OGX	ooo
RI.PA	Pernod-Ricard	42290 573400	FR	BVG	ooo
RIO.L	Rio Tinto PLC	67920 021937	GB	MNX	ooo
RMS.PA	Hermes Intl	70330 067800	FR	TEX	o
RNO.PA	Renault SA	12473 553960	FR	AUT	oo
ROG.SW	Roche Hldgs AG Ptg Genus	203000 000000	CH	DRG	ooo
RR.L	Rolls-Royce Holdings PLC	15590 884245	GB	ARO	ooo
RSA.L	RSA Insurance Group PLC	6861 117604	GB	INS	oo
RTO.L	Rentokil Initial	9836 210575	GB	ICS	ooo
RWE.DE	RWE AG	16813 303100	DE	MUW	oo
RY4C.IR	Ryanair Holdings PLC	15859 007780	IE	AIR	ooo
SAB.MC	Banco de Sabadell SA	5840 797040	ES	BNK	oo
SAF.PA	Safran SA	56314 955050	FR	ARO	ooo
SAMPO.HE	Sampo Oyj A	21562 054320	FI	INS	oo
SAN.MC	Banco Santander SA	61985 568950	ES	BNK	oo

Notes: The last column indicates in which panels a stock is 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 25: *Firms part VII*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
SAN.PA	Sanofi-Aventis	113000 000000	FR	DRG	ooo
SAND.ST	Sandvik AB	21857 965979	SE	IEQ	ooo
SAP.DE	SAP SE	148000 000000	DE	SOF	ooo
SBRY.L	Sainsbury (J)	6008 030226	GB	FDR	ooo
SCA-B.ST	SCA - B shares	5774 424878	SE	FRP	o
SCHN.SW	Schindler-Hldg AG Reg	14642 544020	CH	IEQ	ooo
SCMN.SW	Swisscom AG Reg	24437 307425	CH	TLS	oo
SCR.PA	SCOR SE	6980 326800	FR	INS	oo
SDR.L	Schroders PLC	8905 494694	GB	FBN	oo
SEB-A.ST	SEB-Skand Enskilda Banken A	18219 828720	SE	BNK	oo
SECU-B.ST	Securitas AB B	5354 462712	SE	ICS	oo
SESG.PA	SES	4793 225000	LU	PUB	o
SEV.PA	Suez SA	8406 050055	FR	MUW	ooo
SGE.L	Sage Group	9912 283546	GB	SOF	ooo
SGO.PA	Saint-Gobain, Cie de	19940 789500	FR	BLD	oo
SGRO.L	SEGRO PLC	11627 787008	GB	REA	oo
SGSN.SW	SGS-Soc Gen Surveil Hldg Reg	18624 735178	CH	PRO	ooo
SHB-A.ST	Svenska Handelsbanken A	18699 691239	SE	BNK	oo
SIE.DE	Siemens AG	99059 000000	DE	IDD	ooo
SK3.IR	Smurfit Kappa Group PLC	8096 425980	IE	CTR	ooo
SKA-B.ST	SKANSKA AB-B	8072 421673	SE	CON	ooo
SKF-B.ST	SKF AB B	7588 180375	SE	IEQ	oo
SLA.L	Standard Life Aberdeen	9100 512935	GB	FBN	oo
SLHN.SW	Swiss Life Reg	15019 669587	CH	INS	oo
SMDS.L	DS Smith	6209 762969	GB	CTR	o
SMIN.L	Smiths Group	7829 724427	GB	IDD	ooo
SN.L	Smith & Nephew	19295 676774	GB	MTC	ooo
SOLB.BR	Solvay	10936 990800	BE	CHM	ooo
SOON.SW	Sonova Holding AG	13127 267443	CH	MTC	ooo
SPSN.SW	Swiss Prime Site AG	7821 016722	CH	REA	ooo
SPX.L	Spirax-Sarco Engineering	7724 540020	GB	IEQ	ooo
SREN.SW	Swiss Re Reg	32752 395869	CH	INS	oo
SRG.MI	Snam SpA	15908 224926	IT	GAS	ooo
SSE.L	Scottish & Southern Energy	17583 650712	GB	ELC	o
STAN.L	Standard Chartered	26909 227396	GB	BNK	oo
STERV.HE	Stora Enso OYJ R	7939 610420	FI	FRP	ooo
STJ.L	St James's Place	7280 987158	GB	FBN	oo
STM.MI	STMicroelectronics NV	21820 346430	IT	SEM	ooo
STMN.SW	Straumann AG Reg	13888 578547	CH	MTC	o
SU.PA	Schneider Electric SE	53251 444500	FR	ELQ	ooo
SVT.L	Severn Trent	7138 539011	GB	MUW	ooo
SW.PA	Sodexo	15578 620750	FR	REX	ooo

Notes: The last column indicates in which panels a stock is 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 26: *Firms part VII*

Ticker	Company	Market Cap	ISO Code	Industry Code	Model Inclusion
SWED-A.ST	Swedbank AB	15047 719773	SE	BNK	oo
SWMA.ST	Swedish Match AB	7821 532927	SE	TOB	ooo
SY1.DE	Symrise AG	12703 052600	DE	CHM	ooo
TATE.L	Tate & Lyle	4187 414119	GB	FOA	ooo
TEF.MC	Telefonica SA	32331 405964	ES	TLS	ooo
TEL.OL	Telenor ASA	23032 664468	NO	TLS	ooo
TEL2-B.ST	Tele2 AB B	8621 912671	SE	TLS	oo
TELIA.ST	Telia Company AB	16151 169427	SE	TLS	ooo
TEMN.SW	Temenos Group AG	10213 002525	CH	SOF	o
TEN.MI	Tenaris SA	11864 396850	IT	OGX	ooo
TEP.PA	Teleperformance	12735 509400	FR	PRO	o
TIT.MI	Telecom Italia SpA	8459 017637	IT	TLS	ooo
TKA.DE	ThyssenKrupp AG	7495 285280	DE	IDD	ooo
TPK.L	Travis Perkins	4730 642257	GB	TCD	ooo
TRN.MI	Terna SpA	11913 412186	IT	ELC	o
TSCO.L	Tesco	29294 351743	GB	FDR	ooo
TUI1.DE	TUI AG	6612 159756	DE	TRT	ooo
UBI.PA	Ubisoft Entertainment SA	6939 327040	FR	IMS	o
UBSG.SW	UBS Group AG	43098 836809	CH	FBN	oo
UCB.BR	UCB SA	13790 475400	BE	DRG	ooo
UCG.MI	Unicredit SpA Ord	28956 662280	IT	BNK	oo
UG.PA	Peugeot SA	19272 836400	FR	AUT	o
UHR.SW	Swatch Group AG-B	7663 132882	CH	TEX	ooo
UMI.BR	Umicore	10683 904000	BE	CHM	ooo
UNA.AS	Unilever NV	79136 415440	NL	COS	oo
UPM.HE	UPM-Kymmene Oyj	16448 725590	FI	FRP	ooo
URW.AS	Unibail Rodamco Westfield	19358 644050	FR	REA	oo
UTDI.DE	United Internet AG Reg	6002 400000	DE	TLS	ooo
UU.L	United Utilities Group Plc	7602 365565	GB	MUW	ooo
VIE.PA	Veolia Environnement	13332 180420	FR	MUW	ooo
VIFN.SW	Vifor Pharma Group	10567 085500	CH	DRG	ooo
VIV.PA	Vivendi SA	30564 528280	FR	PUB	oo
VNA.DE	Vonovia SE	26029 152000	DE	REA	oo
VOD.L	Vodafone Group	49971 317452	GB	TLS	ooo
VOLV-B.ST	Volvo AB B	24537 431397	SE	AUT	oo
VOW.DE	Volkswagen AG	51124 342500	DE	AUT	ooo
VWS.CO	Vestas Wind Systems AS	17918 957786	DK	IEQ	ooo
WDI.DE	Wirecard AG	13275 282500	DE	FBN	
WEIR.L	Weir Group	4631 300556	GB	IEQ	ooo
WKL.AS	Wolters Kluwer NV	17751 500320	NL	PRO	oo
WPP.L	WPP Plc	16725 083182	GB	PUB	ooo
WRT1V.HE	Wartsila Oyj ABP	5828 501100	FI	IEQ	o
WTB.L	Whitbread	8407 368452	GB	TRT	oo
YAR.OL	Yara International ASA	10188 092051	NO	CHM	ooo
ZURN.SW	Zurich Insurance Group AG	55011 937615	CH	INS	oo

Notes: The last column indicates in which panels a stock is 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 27: *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 28: *Industries*

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

Source: S&P Global and author.

Table 29: *Sectors*

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

Source: S&P Global and author.

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KOKKUVÕTE

ESG-reitingute mõju Euroopa usaldusväärsete ja tuntud ettevõtete süsteemsele riskile

Käesolevas artiklis uurime, kas kõrgemate vastutustundliku rahastamise reitingutega (ESG, Environmental, Social, Governance – vastavalt keskkond, sotsiaalsed aspektid, juhtimine) reitingute säilitamine vähendaks ettevõtete panust süsteemsesse riski ja süsteemsele riskile avatust. Selleks analüüsime S&P Europe 350 indeksit moodustavate aktsiate süsteemse riski näitajaid perioodil jaanuar 2016 kuni september 2020, mis katab osaliselt ka Covid-19 perioodi. Nende aktsiate tulususte šokkide osaliste korrelatsioonide andmetest tuvastamiseks kasutame VAR-MGARCH mudelit. Seejärel arvutame süsteemse riski näitajad peakomponentide meetodi abil. Konkreetse ettevõtte süsteemse riski näitajad sõltuvad ettevõtte aktsia tootluse volatiilsusest ning ka ettevõtte aktsia tähtsusest ja suhtelisest kaugusest teiste ettevõtete suhtes aktsiate võrgustikus. Seetõttu konstrueerime osakorrelatsiooni võrgustiku, et eraldada andmetest kaks tsentraalsuse mõõdikut, need on omavektori tsentraalsuse ja lähedus kõigile (closeness centrality) näitajad. Süsteemne risk võib olla seotud ka ettevõtte enda finantstulemustega, seega võtame arvesse ka ettevõtte tasandi finantstulemusnäitajaid, milleks on lühiajalise võlgnevuse kattekordaja, kasumimarginaalid ja maksevõime suhtarvud. Lõpuks võtame arvesse andmestikus olevate ettevõtete iga-aastaseid ESG-reitinguid. Regressioonianalüüsis kasutame ettevõtete fikseeritud efekte. Meie tulemused näitavad, et (1) aktsia tootluse volatiilsus ja selle tsentraalsuse näitajad aktsiavõrgustikus on peamised süsteemse riski allikad; (2) kõrgema ESG reitinguga ettevõtetel on kuni 7,3% väiksem süsteemse riski panus ja süsteemsele riskile avatust võrreldes madalama ESG-reitinguga ettevõtetega; (3) Covid-19 suurendas volatiilsuse, ESG-reitingute, tsentraalsuse näitajate ja finantstulemusnäitajate osamõjusid. Arvestades analüüsis ainult Covid-19 perioodi, leidsime, et ESG reitingute sotsiaalsetel aspektidel ja juhtimise teguritel on süsteemsele riskile statistiliselt oluline mõju.