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Does ESG affect stock market dependence? An empirical exploration of S&P 1200 companies shows the divergent nature of E–S–G pillars☆

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ABSTRACT

If ESG characteristics of companies attract loyal and resilient investors and customers, does ESG affect the stock-market connectedness during market upturns and downturns? The micro-level analysis uses the cross-quantilogram to measure quantile dependence between stocks in the S&P 1200 and the market with distinguishing factors of ESG scores. We employed the scores of seven major ESG data providers and their structural combination to capture the shared information. We found a systematic effect both on the level of multidimensional and unidimensional ESG scores. Moreover, we showed Governance scores create a counter-effect on the Environmental and Social pillars. In general, the high- and middle-ESG stocks tend to have lower dependence on the market during market downturns, with E and S scores pushing the dependence down and the G dimension pushing it up. Results suggest a lower distinguishing power of Environment and Social pillars and persistent Governance pillar power during moderate and upturn market times.

1. Introduction

Environmental, social, and governance (ESG) investing plays a crucial role in today's financial markets. The application of non-financial factors within the standard financial decision-making process is growing (Amel-Zadeh and Serafeim, 2018; Van Duuren et al., 2016), and the value of ESG integrated investments could reach $53 trillion by 2025 (Bloomberg, 2021). Sustainability became a necessity rather than an opportunity, and the Covid-19 pandemic fixed its position next to standard financial measures (Pástor and Vorsatz, 2020). Not only institutions but also retail investors and households focus on social responsibility now (Bauer et al., 2021). The main drivers of the growing investor demand are the societal pressure that shifts investors' preferences to utilize the social returns (Lagerkvist et al., 2020; Hartzmark and Sussman, 2019) or pushes them to fulfill their customers' or stakeholders' expectations (Amel-Zadeh and Serafeim, 2018) and regulatory (performance and disclosure) requirements (Renneboog et al., 2008; Ramelli et al., 2021), which, to certain extent, reflect the fight against climate change. As for the investors' view, hope for reduction of risks (Becchetti et al., 2015a) or the potential profit emerging from the new market paradigm play roles. Moreover, based on the standard portfolio theory, the restriction based on sustainability performance set on the market should lead to the penalization of returns (Pedersen et al., 2021). Although the question of sustainability's (or ESG's) effect on the risk-return profile of assets is widely researched, and many studies point to a positive relationship between sustainability and financial performance (Friede et al., 2015),

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no clear and concise answer has yet been given (Coqueret, 2021). The same opalescent situation prevails in the risk management area. Within the literature, ESG was found to be both risk reducing (Oikonomou et al., 2012; Drempetic et al., 2020; Khan et al., 2024) and risk enhancing, influencing implied volatility (Patel et al., 2021) or downside risks (Nofsinger et al., 2019).

To efficiently manage portfolio risks, knowledge of how ESG affects stock behavior in times of market upturns and downturns, as well as the dependence structure of assets, is needed. ESG investments are usually driven by more than financial performance (Bollen, 2007), which sheds light on the element of investor's loyalty. It was already shown that socially responsible investment (SRI) funds flows are less sensitive to past returns (Renneboog et al., 2011; Benson and Humphrey, 2008). Moreover, social responsibility lowers risks within the SRI cash flow volatility (Bollen, 2007), and firms with a high ESG profile are perceived by investors as more resilient (Roselle, 2016).

Nevertheless, the diversification properties focusing on the stocks' tail risk connectedness while considering ESG received growing attention only recently and still do not achieve coverage that would enable a proper answer. Assessing the connectedness between ESG indices and a set of influential macroeconomic and financial variables by applying the approach of Diebold and Yılmaz (2014), Umar et al. (2020) conclude that the portfolio diversification opportunities of ESG investments tend to diminish during market downturns. Czado et al. (2022) focused on the companies comprising the S&P index, applied vine copula models to capture cross-sectional dependence within ESG class indices based on the Refinitiv ESG data, and showed assets with moderate (middle-) ESG scores tend to show weaker dependence to the U.S. market compared to assets with extremely high or low ESG scores, and that the dependence becomes stronger in times of crisis. With a similar approach and results but focusing on risk dependence, Bax et al. (2023) looked on the individual E–S–G pillars and suggested that the E-pillar has a similar dependence as ESG in times of crisis, while in the case of high ESG class, the S-pillar provides strong risk dependence, and the G-pillar provides weak risk dependence. Pedini and Severini (2022) employed a cross-quantilogram approach to check safe haven and diversifier properties of ESG stock and bond indices and suggest ESG assets have a strong diversification potential. The micro-level research focusing on the relationship between individual stocks and the market is lagging behind, as the mainstream approach uses an individual ESG assessment of companies to build a portfolio that is later analyzed as a homogeneous unit.

The area of ESG data represents another research stream. Practitioners commonly use ESG data for red flagging and risk management (Van Duuren et al., 2016). According to Amel-Zadeh and Serafeim (2018), more than 63% of institutional investors use ESG information to manage investment performance. Aggregated ESG data provide an easy and fast assessment tool for assessment of a company's ESG position (Abramskiehn et al., 2015). ESG data represent a dynamically developing and growing market segment with various data providers, indicators, methodologies and thus severe heterogeneity (Chatterji et al., 2016; Semenova and Hassel, 2015; Dorfleitner et al., 2015). Data from one ESG provider should be critically assessed to provide comparable and valuable information (Sahin et al., 2022). Also, there is no clear definition of the three pillars and their measurement (Berg et al., 2022; Dimson et al., 2020). Filbeck et al. (2019) suggest disaggregating the ESG scores into E, S and G as an efficient way to deal with their different natures, as they found governance but not environmental scores positively rewarded by investors. Also, Badía et al. (2020), Cornell and Damodaran (2020) claim it is inappropriate to combine naturally different concepts into one aggregated score.

In this context, our study addresses the above two issues: ESG effect on assets' dependence properties and the ESG data heterogeneity critical view. In contrast to other papers, we focus our analysis directly on the individual stocks. We empirically analyze the stock market co-movements in extreme quantiles while accounting for their sustainability performance in various perspectives by employing the bi-variate cross-quantilogram by Han et al. (2016), which enables us to avoid any distributional or parametrical assumptions (Uddin et al., 2019; Baumöhl and Lyócsa, 2017) while being intuitive and easy to interpret. Moreover, to address the issue of unreliable ESG data, we used a unique data set and employed 20 various scores from seven major ESG data providers to cover the aggregate ESG level as well as separate E–S–G pillars. In addition, as Serafeim and Yoon (2022) suggest, the closer the scores between different providers, the higher the power to predict future ESG news. As proposed by Gyönyörová et al. (2021), we applied principal component analysis (PCA) to derive a structural combination of these scores on the aggregate and dimensional level, which reflects the value of shared information between all providers. In our empirical study for the period from 2015 to 2021, we show evidence for the ESG effects on the co-movement intensity between stocks in the S&P Global 1200 index and the market. We prove graphically and statistically significant differences between E–S–G scores effect with the Governance pillar having the opposite effect to the Environment and Social pillars. Aggregate ESG scores incorporate conceptual discrepancies and thus, in general, have the weakest differentiating effect. From the perspective of ESG classes, we suggest the middle class has interesting but often overlooked properties. The differentiation effect is strongest during market downturns, as the overall level of tail connectedness increases. We also found significant differences between providers' data that point to the core information of disclosure within the Governance pillar and an increased power of structurally shared information.

Our study has both practical and theoretical implications. We extend the literature by providing novel insights into the ongoing debate of sustainable investing by examining the micro-level relationships between ESG classes of stocks and the market. We provide market-wide findings on diversification and risk properties, addressing methodological and data limitations while emphasizing the significance of sub-scores and data quality. Our study contributes to the literature by uncovering unique insights into the co-movements of ESG classes and their implications for risk management in financial markets. From a practical point of view, we provide evidence for investors to improve their portfolio management by considering the distinct nature of E–S–G dimensions, the importance of their current market understanding and the diversification opportunities of ESG middle-class stocks. Regulators and policymakers should be aware of the uncertainty in ESG investing and help reduce blind use of ESG scores, enabling stakeholders to make informed decisions and promote sustainable investment practices.

We have organized the remainder of this paper as follows. Section 2 presents a theoretical framework for the relationship between ESG and financial risk. Section 3 shows the cross-quantilogram methodology and the description of the materials and necessary data transformations. Section 4 provides the results overview and discusses ESG and E–S–G score differentiation power, ESG classes, quantiles selection and provider–provider specifics. Finally, in Section 5, our conclusions, implications, limitations of our study and potential areas for future research are discussed.

2. Theoretical framework

The stakeholder theory offers the basic framework for the argumentation in favor of the negative relationship between Corporate Social Performance (CSP, in recent years gradually replaced with ESG, which jointly captures the corporate social responsibility actions and governance actions of a firm) and firm risks (Jensen, 2002). The value maximization approach based on the long-term company's financial performance should motivate managers to take into account all of the interests of the firm's stakeholders. High-CSP engagement acts as an insurance protection mechanism. In general, it reduces the probability of negative shock occurrence and lowers the volatility of performance measures (e.g. cash flow) in contrast to low-CSP engaged firms (Bouslah et al., 2013). Also, CSP contributes to damage mitigation and faster recovery after negative operational, environmental and social event occurrence (Godfrey, 2005; Godfrey et al., 2009; Klein and Dawar, 2004).

High CSP engagement reduces the litigation risk and strengthens the stakeholders' trust in the company, reducing agency and transaction costs (Becchetti et al., 2015b; Lins et al., 2017). Thus, high CSP reduces financial risk giving stable relationships with stakeholders, such as loyal customers, satisfied employees, lenders, government, and supportive community (McGuire et al., 1988; Hong and Kacperczyk, 2009; Bouslah et al., 2013). Good management theory (Waddock and Graves, 1997) also supports this view but focuses more on good corporate governance. Effective and clear CSR strategy and emphasizing stable relationships with the company's stakeholders signal a quality risk-management system and financial stability (Orlitzky and Benjamin, 2001; El Ghoul et al., 2011; Bouslah et al., 2013).

Besides, the investors' perspective plays its role. As non-financial criteria may drive investors, the high CSP may attract them and create a crisis-resistant loyalty amongst its investors base (Bollen, 2007; Lee and Faff, 2009). Moreover, the relative size of the investor base is considered another argument for lowering risks (Hong and Kacperczyk, 2009; El Ghoul et al., 2011). Heinkel et al. (2001) assume that a company's CSP may determine the attractiveness of stocks, which leads to higher risk for non-CSR stocks. High CSP indicates a transparent information environment and, thereby, reduces the company's idiosyncratic risk by boosting analysts, thus investors, attention (Liu et al., 2023).

On the other hand, several arguments exist proposing the positive relationship between high-CSP engagement and financial risk. The managerial opportunism theory deems CSR expenditures as unnecessary costs. High costs reduce resources, lead to over-investments and decrease the net worth of the company (Barnea and Rubin, 2010). Another issue is the different effects of sustainable practices across industries and the company's age (Peloza, 2006). Besides, CSR consists of various activities perceived differently by stakeholders and shareholders (Peloza and Shang, 2011).

In this paper, we build on this theoretical framework and explore the relationship between CSP (ESG) and financial risk from another perspective. Globalization and advanced technologies consistently integrate already highly intertwined financial markets across various asset classes, regions, and industries, making unexpected market events an immediate universal threat or opportunity. A stream of literature that focuses on the ESG and SRI specifics during crises suggests that SRI and ESG funds perform better (such as (Nofsinger and Varma, 2014) during the global financial crisis period or (Pástor and Vorsatz, 2020; Omura et al., 2021; Singh, 2020) during the period of the Covid-19 pandemic) and perform worse during economic downturns (Fiordelisi et al., 2020) or when controlling for other factors that have little or no hedging power (Demers et al., 2020; Mahmoud and Meyer, 2021; Demers et al., 2021; Folger-Laronde et al., 2022). Given the importance of portfolio diversification, we focus on the micro-level analysis of interconnections between stocks and the market. Moreover, the market dependency structure is influenced by market development, the openness of the economy, and financial or economic crises. We mainly focus on developed and opened markets, but we must incorporate the time dynamics within our research. In general, the stock market dependence intensifies during crisis periods due to contagion effects (Karanasos et al., 2016; Mokni and Mansouri, 2017). We can follow this presumption by employing the data covering the Covid-19 pandemic and exploring the effect of ESG on this relationship.

3. Methods and materials

We investigate the interdependence between stocks in the S&P 1200 Global index and the market represented by the values of this index by implementing the cross-quantilogram method of Han et al. (2016). The method is appealing because it measures the conditional dependence and directional predictability between pairs of variables at stationary levels for different quantiles (lower, middle, and upper) of the distributions. It provides a complete picture of the relationship between the variables under varying market conditions.

3.1. Cross-quantilogram

Given a specific sample of data, we consider a strictly stationary time series $x_{i,t}, t \in \mathbb{Z}, i = 1, 2$, where, in our context, $x_{1,t}$ represents the index S&P 1200 Global and $x_{2,t}$ represents each of the 1,220 S&P 1200 Global constituents. The density and distribution functions of series $x_{i,t}$ are labeled as f_i and F_i. The quantile of $x_{i,t}$ is given as $q_i\left(\alpha_i\right) = inf\left\{v : F_i(v) \geq \alpha_i\right\}$ for $\alpha_i \in (0,1)$, and the expressions of the two-dimensional series of quantiles are represented by $(q_1\left(\alpha_1\right) q_2\left(\alpha_2\right))^{\tau}$ for $\alpha \equiv (\alpha_1, \alpha_2)^{\tau}$. To measure and test for the directional predictability between $x_{1,t}$ and $x_{2,t}$ for different quantiles, Han et al. (2016) propose the cross-quantilogram for α-quantile with lag k as,

$$\rho_{\alpha}(k) = \frac{E\left[\Psi_{\alpha 1}(x_{1,t} - q_1(\alpha_1))\Psi_{\alpha 2}(x_{2,t-k} - q_2(\alpha_2))\right]}{\sqrt{E\left[\Psi^2_{\alpha 1}(x_{1,t} - q_1(\alpha_1))\right]}\sqrt{E\left[\Psi^2_{\alpha 2}(x_{2,t} - q_2(\alpha_2))\right]}} \tag{1}$$

where $k = 0, \pm 1, \pm 2, \ldots$, and $\Psi_a(\mu) \equiv 1\mu < 0 - a$, $1[]$ denotes the indicator function, and $1\left[x_{i,t} \leq_i \left(\alpha_i\right)\right]$ is the quantile exceeding process. According to Eq. (1), the cross-quantilogram measures the serial dependence between a pair of variables at different quantiles when $k = 1$, $\rho_{\alpha}(1)$ indicates the cross-dependence between the quantile $q_1(\alpha_1)$ of an index S&P 1200 Global $x_{1,t}$ at time t and the quantile $q_2\left(\alpha_2\right)$ of one of its constituents $x_{2,t}$ at time $t+1$. Therefore, this measures the one-day lead–lag effect between $x_{1,t}$ and $x_{2,t}$, and in the case of $\rho_{\alpha}(1) = 0$, there is no predictability from the quantile α_1 of index S&P 1200 to the quantile α_2 of its constituent, which means that $x_{2,t}$ is not dependent on the market represented by the S&P 1200. Contrary to this, $\rho_{\alpha}(1) \neq 0$ means that $x_{2,t}$ depends on the market conditions, that is, it follows its ups and downs to some extent. In Eq. (2), the cross-quantilogram of the sample counterpart is estimated as:

$$\hat{\rho}_{\alpha}(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\alpha 1}\left(x_{1,t} - q_1\left(\alpha_1\right)\right)\Psi_{\alpha 2}\left(x_{2,t-k} - \hat{q}_2\left(\alpha_2\right)\right)}{\sqrt{\sum_{t=k+1}^{T} \Psi^2_{\alpha 1}\left(x_{1,t} - \hat{q}_1\left(\alpha_1\right)\right)}\sqrt{\sum_{t=k+1}^{T} \Psi^2_{\alpha 2}\left(x_{2,t-k} - \hat{q}_2\left(\alpha_2\right)\right)}} \tag{2}$$

where $\hat{q}_i\left(\alpha_i\right)$ is the unconditional sample quantile.

3.2. Materials

We use daily data from 2015-01-01 to 2021-12-31 for log returns on the S&P Global 1200 index and all its constituent stocks separately (descriptive statistics shown in Table 1). We used 1,220 stocks in the full sample and ensured global coverage as the index covers 31 countries, all 11 industry sectors (GICS methodology) and approximately 70% of global stock-market capitalization.

We gathered the ESG data for these companies from seven major ESG data providers. We set the time period at 2016–2020 to include part of the Covid-19 pandemic while fighting the limited data accessibility. We gathered the data from three sources: (i) Bloomberg Terminal provided the majority of our ESG data, (ii) Yahoo Finance API provided the returns data, and (iii) the Thompson Reuters ESG data were obtained from Refinitiv. The majority of data was gathered during June and July 2022, except for the TR data set (collected in 2021) and the Sustainalytics data set, which was unavailable at Bloomberg due to a change in the methodology; we used the limited data set obtained in early 2021 (descriptive statistics shown in Table A.1).

The ESG ratings for each dimension E, S, and G, as well as the aggregate ESG ratings, were chosen for the research. Also, to address the ESG data heterogeneity issue (Avetisyan and Hockerts, 2017; Chatterji et al., 2016; Semenova and Hassel, 2015; Dorfleitner et al., 2015), we incorporated another ESG indicator that could embody the shared information between different data providers. The heterogeneity plays a significant role in the non-conclusive state of the ESG-financial performance relationship. Average ESG scores based on data from several ESG rating providers have been found to have the ability to predict future ESG news. However, this ability decreases the further away the ratings are from each other (Serafeim and Yoon, 2022). To this end, we were inspired by Gyönyörová et al. (2021), who proposed applying extracted factorial structures. Therefore, the new score represents the part of the information that all the data providers agree on. For this reason, it is not only a simple combination (such as that used by Serafeim and Yoon (2022)), but it can also be observed as a hidden but fairly objective ESG evaluation. Thus, the level of ESG data used can be seen according to three levels: aggregate ESG scores, individual E–S–G pillar scores, and synthetic cumulative ESG and dimensional E–S–G scores.

We employ principal component analysis (PCA) to construct the composite ESG rating together and separately for the E, S, and G dimensions. We standardized all inputs to have zero mean and unit variance before performing the PCA to account for the input data scale differences on a provider basis. We applied the same process on both the level of ESG ratings and on the E–S–G dimensions, leaving us with four brand-new scores. The descriptive statistics of our full ESG dataset can be seen in Table A.1 in the Appendix, showing the original scores discrepancies in scale and variability while still uncovering the majority of scores is, in summary, similar in the aggregated view. As an exception, the Bloomberg Governance score reports interesting distribution with a solid heavy right tail. Nevertheless, as the scores represent only a limited sample of the full ESG data coverage, the descriptives do not provide any controversial findings. The correlation matrix of synthetic and original scores in Table B.1 in the Appendix further clarifies the synthetic scores' accuracy. As an example of how the PCA works, the Sustainalytics scores for 2020, apart from their governance dimension, lost their representation power, which can be seen as a consequence of the complete methodological change in the score calculation in that year. For ISS Quality Score, the values are negative, as their methodology is based on the opposite evaluating scale. Besides, the Thompson Reuters dimensional scores have a minimal influence on the synthetic scores creation, which should be kept in mind for the following analyses. However, our preliminary results present that synthetic scores explain 50%–80% of the original data variance, suggesting the suitability of their use in further analyses. We use extracted principal components loadings on individual bases in the following process. The number of extracted cases is thus directly dependent on the coverage overlap and shrinks for some years, as can be seen in Table 2 and in the overall composition of our data set in the clean sample, as we used a pairwise method to treat the missing ESG data.

Table 1
Descriptive statistics of assets log returns.

Panel A: Descriptive Statistics of assets in S&P 1200					
	Mean	Median	SD	Min.	Max.
2015	0.0000	0.0007	0.0162	−0.3501	0.3084
2016	0.0004	0.0005	0.0197	−4.9081	4.8975
2017	0.0009	0.0009	0.0131	−0.3152	0.2637
2018	−0.0005	0.0005	0.0157	−0.6224	0.3711
2019	0.0008	0.0012	0.0148	−0.3969	0.2788
2020	0.0002	0.0006	0.0246	−4.6522	4.5936
2021	0.0006	0.0013	0.0168	−0.9248	0.3530
Panel B: Descriptive Statistics of index S&P 1200					
	Mean	Median	SD	Min.	Max.
2015	−0.0001	0.0000	0.0083	−0.0391	0.0234
2016	0.0002	0.0003	0.0080	−0.0514	0.0231
2017	0.0007	0.0003	0.0036	−0.0123	0.0159
2018	−0.0004	−0.0001	0.0080	−0.0317	0.0276
2019	0.0009	0.0010	0.0063	−0.0252	0.0259
2020	0.0005	0.0015	0.0178	−0.0998	0.0837
2021	0.0007	0.0009	0.0070	−0.0232	0.0211

Notes: SD denotes standard deviation, Min. and Max. the minimum and maximum observed values respectively. In Panel A, the reported values are find by first aggregating values for a given day across all 1220 stocks and next aggregating across time. For example, to arrive at the summary for year 2015, we followed the following steps. First, for each day we extracted the Log return for each stock. Second, we found the average, median, standard deviation, minimum and maximum for each day. Third, we took the mean, median, mean (for SD), minimum and maximum across time and those values are reported in the table.

Table 2
Selected ESG data set composition.

ESG data	Dimension	Available from	Domicile	2016	2017	2018	2019	2020
Bloomberg ESG Disclosure Score	ESG	2006	U.S.	1187	1193	1201	1203	1196
Bloomberg Environmental	E	2010	U.S.	1187	1193	1201	1203	1196
Bloomberg Social	S	2010	U.S.	1187	1193	1201	1203	1196
Bloomberg Governance	G	2010	U.S.	1187	1193	1201	1203	1196
RobecoSAM Total Sustainability Rank	ESG	2016	Switzerland	1213	1205	1197	1171	1145
RobecoSAM Environmental	E	2016	Switzerland	1213	1205	1197	1171	1145
RobecoSAM Social	S	2016	Switzerland	1213	1205	1197	1171	1145
RobecoSAM Economic	G	2016	Switzerland	1213	1213	1197	1171	1145
Sustainalytics ESG Rank	ESG	2014	Netherlands	1060	1058	1106	309	309
Sustainalytics Environmental	E	2014	Netherlands	1060	1058	1106	309	309
Sustainalytics Social	S	2014	Netherlands	1060	1058	1106	309	309
Sustainalytics Governance	G	2014	Netherlands	1060	1058	1106	309	309
Thompson Reuters ESG	ESG	2002	Canada	1065	1072	1077	1002	996
Thompson Reuters Environmental	E	2002	Canada	1043	1060	1069	991	989
Thompson Reuters Social	S	2002	Canada	1043	1060	1069	991	989
Thompson Reuters Governance	G	2002	Canada	1043	1060	1069	991	989
MSCI ESG Rating	ESG	1999	U.S.	1090	1090	1090	1090	1090
CDP Climate Change Performance Score	E	2013	U.K.	1007	777	749	815	1154
ISS Quality Score	G	2013	U.S.	1079	1084	1082	1109	1126
Synthetic structural ESG	ESG	–	–	889	882	916	248	245
Synthetic structural E	E	–	–	787	629	638	239	262
Synthetic structural S	S	–	–	910	919	962	266	262
Synthetic structural G	G	–	–	878	891	919	305	255

Notes: The table presents a basic description and the number of cases in our data set for each selected ESG or E–S–G score in the years 2016–2020. The ESG, E, S, and G variables in the four last lines represent the synthetic structural scores, which we extracted based on the methodology presented in Section 3.2. For this reason, they lack the "Availability since" and "Domicile" specifics.

In the next step, we transformed all 23 ESG-related indicators – 19 from ESG data providers and four synthetically made – from scales to classes. As most of the employed ESG data scores the company on the best-in-class approach, we do not account for industry specifics or regional affiliation, although we check the industry and region representation as a part of robustness checks. Thus, the stocks are repeatedly divided into quantiles based on every single used ESG score. Inspired by the approach of Chopra and Mehta (2022), who focused on the high and low quantiles of green bonds' E-scores (while ignoring the middle ones), we focus on the quantile (0.0–0.2; 0.4–0.5; 0.8–1.0), further named as low-, medium- and high-ESG stocks and ignore the rest. This way, we can check the proposed dependencies differentiation on the three mentioned levels without ignoring the middle ones, which may perform differently (Czado et al., 2022; Harjoto et al., 2017). We can account for the effect visibility level in case of disclosure data (Wen et al., 2022), keep the distance between explored groups, and continue to work with a sufficient number of observations in all sub-analyses. We then apply the cross-quantilogram approach to measure the co-movements of all chosen stocks and the market on a year-by-year basis as described in Section 3. To account for the time dynamics and proper time setting of ESG data, we run the analyses for ESG as a precedent, as a concurrent and as an antecedent to the financial data. For all analyses, we work with the same ESG data set from 2016–2020, but we shift the period for financial data. Because this approach leads us to a large number of results, we then aggregate them according to the original ESG classes (high-, medium- and low-ESG stocks) using their average and we calculate the unpaired t-test, also known as the independent samples t-test, to compare the means of two independent groups: the high-ESG and low-ESG stock groups in our case. The t statistic to test whether the means are different is calculated as given in Eq. (3), where $\bar{X}_{High}$ is mean of the quantilograms of high-ESG, $\bar{X}_{Low}$ is mean of the quantilograms of low-ESG, with the estimate of the variance s^2 of each of the group and the number of observation n.

$$t = \frac{\bar{X}_{High} - \bar{X}_{Low}}{\sqrt{\frac{s^2_{High}}{n_{High}} + \frac{s^2_{Low}}{n_{Low}}}} \tag{3}$$

The unpaired t-test allows us to assess whether a significant difference exists between the means of these two groups. It takes into consideration the variability within each group and the sample sizes. In the following figures, we present the p-value, which indicates the probability of obtaining the observed difference if the null hypothesis is true. A small p-value (typically below a predefined significance level, such as 0.05, although the exact level is left to the reader's discretion) suggests a significant difference between the means of the two groups.

4. Results and discussion

Because we focus on micro-level connectedness structure and our cross-quantilogram approach consists of many sub-analyses, we present them graphically in an aggregated form. Figs. 1, 2, 3, C.1 and C.2 present the results for quantile 0.1 (meaning the 10% of the worst trading days), while Figs. C.3–C.5 show the results for the quantile 0.9 (10% of the best trading days), both with a lag k = 0 (representing simultaneity). Each figure consists of several sub-analyses: on each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the y-axis, while three ESG group box plots for three different time settings are visualized on the x-axis. Over every ESG data time-setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other. This figure shows the heterogeneity of the group, its average connectedness with the market and whether the ESG scores can differentiate the co-movement strength between the explored groups.

At first, we explore the general patterns arising from the connectedness during market downturns (Figs. 1, 2, 3, C.1 and C.2). We describe the effect based on pillar affiliation. Then we add the perspective of a market upturn periods and an average market situation, followed by the summary of results based on provider affiliation. A discussion of the findings follows.

4.1. Results

Aggregated ESG scores, in general, have mixed and not very persuasive results. Most of the middle-ESG (Bloomberg, synthetic ESG) or high-ESG (RobecoSAM, MSCI) scored companies are less connected to the market than the low-ESG ones. Several interesting cases were explored: for Sustainalytics, no pattern was identified; for Thompson Reuters, 2020 is the only year when the middle-ESG class companies are significantly more strongly connected to the market than other classes. For MSCI, the pandemic year caused a shift from a previously unclear situation, but for the case of the financial data of 2021, the middle-ESG companies based on 2020 scores were the least connected to the market in 2021. In the case of Bloomberg in 2020, the middle-ESG companies showed the lowest connectedness to the market. Lastly, the synthetic ESG represents the most powerful indicator compared to other aggregated scores in the perspective of the best differentiation effect, with middle-ESG stocks showing the weakest co-movement with the market.

The overall effect of the Environment pillar can be described similarly to the aggregated ESG with significantly more robust results and prevailing effects of high-E stocks. All explored scores point to the lower co-movements of high-E stocks with the market with some variations: for CDP, the only significant year was 2019, and the middle-ESG stock connectedness was close to the connectedness of high-E stocks; Sustainalytics provides mixed results to some extent, and synthetic E also favored the middle-E companies, which had for several cases similarly weak co-movements as high-E stocks.

For the case of the Social pillar scores, the effect appears to remain somewhere between the Environmental scores and aggregate ESG scores. With the prevailing lowest connectedness for high-S stocks, the difference between S-class groups was more often insignificant. The results were mixed in the case of Sustainalytics (until 2018, the high-S stocks tended to be the most related to the market) and synthetic S (whose results have one of the lowest numbers of significant differences between classes in comparison to the providers' S-scores).

In contrast, in the case of the Governance pillar, the high-G followed by the middle-G stocks have the strongest co-movements with the market. Another important finding is that Bloomberg provides the most convincing results, and the synthetic G and

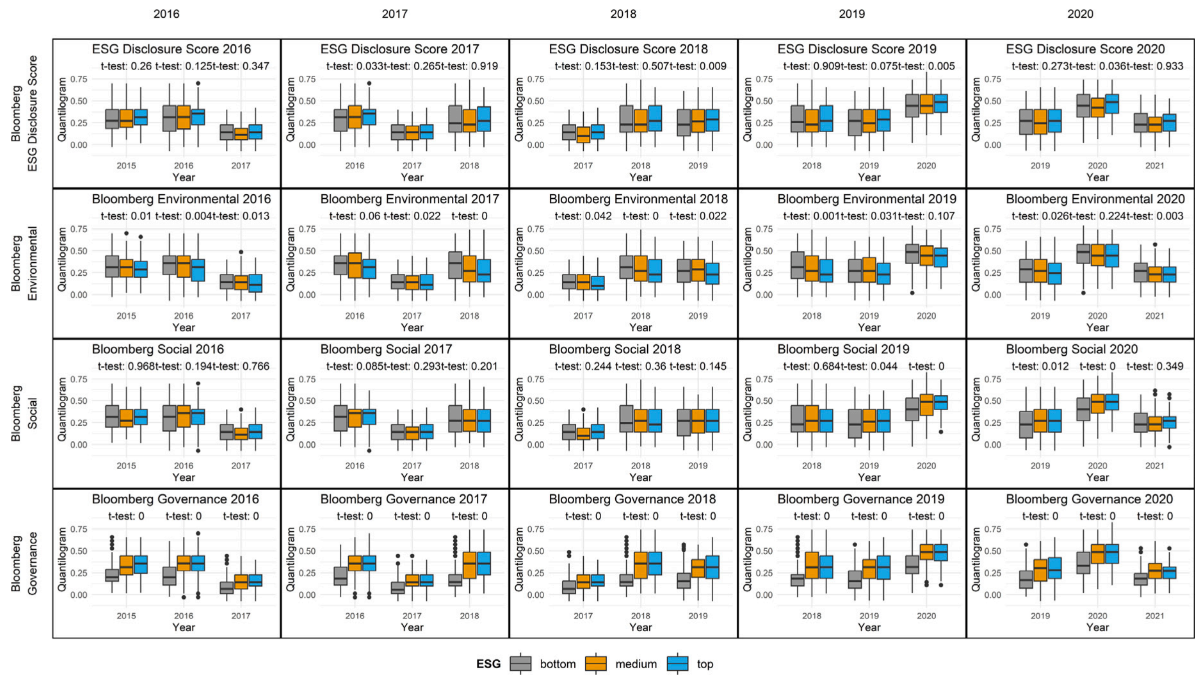

Fig. 1. The cross-quantilogram for quantile 0.1 output aggregation: Bloomberg data.
Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the worst trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of Bloomberg. On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data time-setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

Sustainalytics were one level higher in robustness than the other pillar scores. The effect was somewhat blurred for all other G-scores. RobecoSAM seemed to confirm this effect (middle- and high-G stocks were more related to the market), but statistically, the groups were not different. For ISS, the effect was only visible since 2018. Thompson Reuters data showed a significant difference only for 2019 and 2020 when middle-G stocks reported a stronger relationship with the market than the other groups.

Moving to the extreme right tail of the distribution, we observe similar results as for the left tail, with an expected overall lower level of connectedness and several specific differences. For the aggregate scores, mixed evidence was the major result among all providers. MSCI ESG again reported reinforcement during the Covid-19 years, when higher ESG meant lower co-movements than other groups. On the level of pillar scores, we saw the Environmental and Social scores also lost part of their power to differentiate between stocks and report similar results to aggregated scores (in the case of Sustainalytics, the results are almost interchangeable with the only exception for the Environment score in 2019 and 2020). If any pattern can be discerned, it is that a higher score points to lower co-movements. As for the Governance pillar, here we again found strong but opposite effects compared to other scores. Bloomberg and synthetic G achieved persuasive results, showing a pattern with high- and middle-class stocks having a stronger relationship with the market. Other providers' scores did not show significant results but still tend to the same relationship: ISS shows it for 2019 and 2020; RobecoSAM reports a counter-effect to other scores of the same provider; Thompson Reuters points to the middle-class having stronger co-movements with the market during the pandemic.

Focusing on the 0.5 quantile, we observed few differences. For Bloomberg Governance, Sustainalytics and RobecoSAM, the middle-class stocks show the strongest relationship with the market. Overall, this setting offered the most insignificant and mixed results.

From the provider's data power perspective, we observed much-expected result heterogeneity. Bloomberg Disclosure is, in general, a strong indicator on the pillar's level. Sustainalytics proved mixed results apart from the G-pillar. Thompson Reuters data were strongest in the E- and S-pillars; the G-pillar and aggregated ESG data were not very persuasive. RobecoSAM had overall low power to affect the group results: the best results were obtained for the E- and S-pillars and the worst for the G-pillar, which may be a consequence of a slightly different methodology (originally, this score had the name "RobecoSAM Economic" rather than "Governance"). MSCI ESG provided mixed evidence. ISS G-score and CDP E-score similarly reported some stronger years. Synthetic scores performed better on the level of G-scores and aggregated ESG but significantly worse when looking at the S-scores.

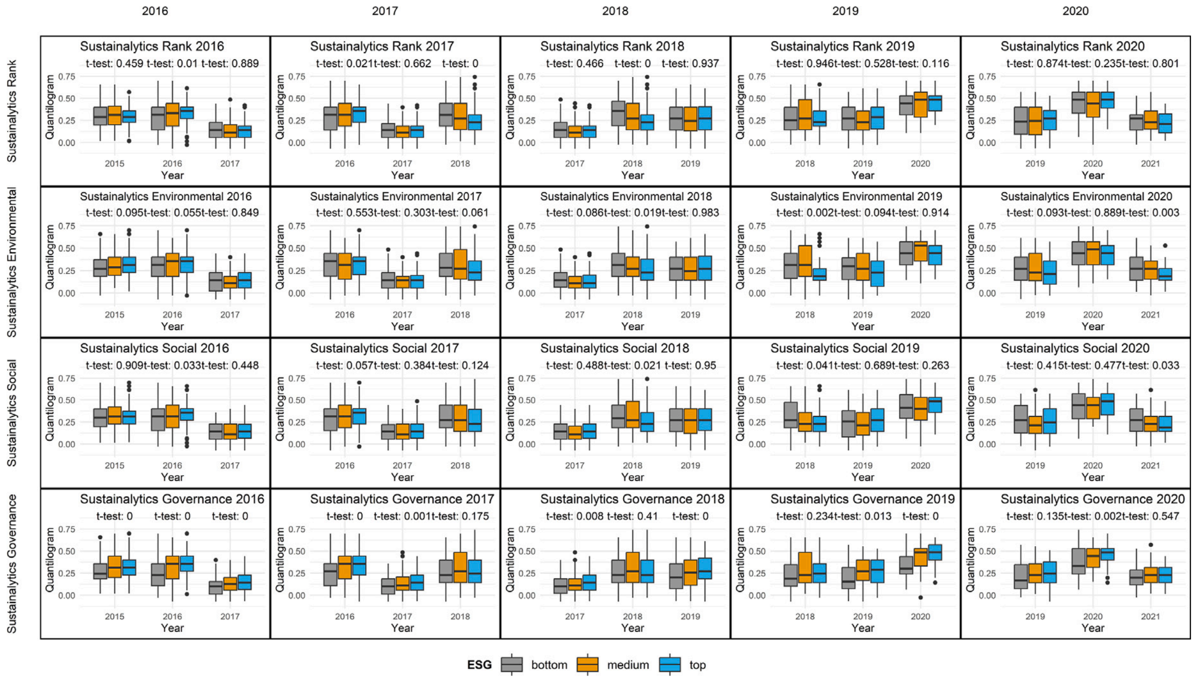

Fig. 2. The cross-quantilogram for quantile 0.1 output aggregation: Sustainalytics data.
Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the worst trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of Sustainalytics. On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data time-setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

4.2. Robustness checks

To ensure the results are robust, we ran the analysis in various settings. As described in Section 3, we focused on three of five ESG data quantiles. Throughout the checks, we also changed this setting to be more strict, focusing on the best, middle and worst deciles (0.0–0.1; 0.45–0.55; 0.9–1.0) with similar results to the original setting. We made another switch within the cross-quantilogram setting to check for a stricter version and run the analyses also for the 0.95 and 0.05 quantiles, and again, the results did not change significantly. In addition, we also tested the robustness of the results via the Granger causality test. The results in this test came out less significant based on t-test values than the results from our cross-quantilogram analysis, but despite the different methodology for measuring causality instead of dependence, these results do not contradict our findings. The question of ESG data time dynamics, that is, the insecurity of the date on which they were available to investors, was accounted for naturally by the proposed research design with three different ESG data time settings (leading, lagging or actual relationships).

Furthermore, following criticism of ESG data, we also checked other potentially influential factors. The most-cited factors in the debate on the heterogeneity of ESG data are the level of disclosure, regional and industrial affiliation and market capitalization (Clementino and Perkins, 2021; Drempetic et al., 2020; Gauthier and Wooldridge, 2018; Walter, 2019; Liang and Renneboog, 2017; Wanderley et al., 2008; Liu et al., 2024). We have done several analyses to control for industry-level and country-level omitted variable bias without finding significance, although we observed a slight trend of a growing proportion of European companies in higher ESG groups for MSCI, RobecoSAM and Sustainalytics data, and in the case of Bloomberg Governance DS, the shrinkage of Asian companies in middle and high ESG groups, what is in agreement with the observation of Badía et al. (2020). We present the regional and industrial distribution over all sub-samples and years in D. As we focused on the S&P 1200 index, which comprises only the world's largest companies, we consider companies in a fairly similar market capitalization position. In addition, the level of transparency is already included in the original set of analyses (represented by the Bloomberg Disclosure Score). The robustness of our findings to numerous alternative settings and checks suggests that the observed effect is worth thorough interpretation.

4.3. Discussion

As expected, the overall level of relationship with the market was higher during market downturns. Another expectation met is the ESG data heterogeneity, which cannot be seen as an evaluation of their quality. Moreover, our thorough analyses provided us with several important findings that we discuss further.

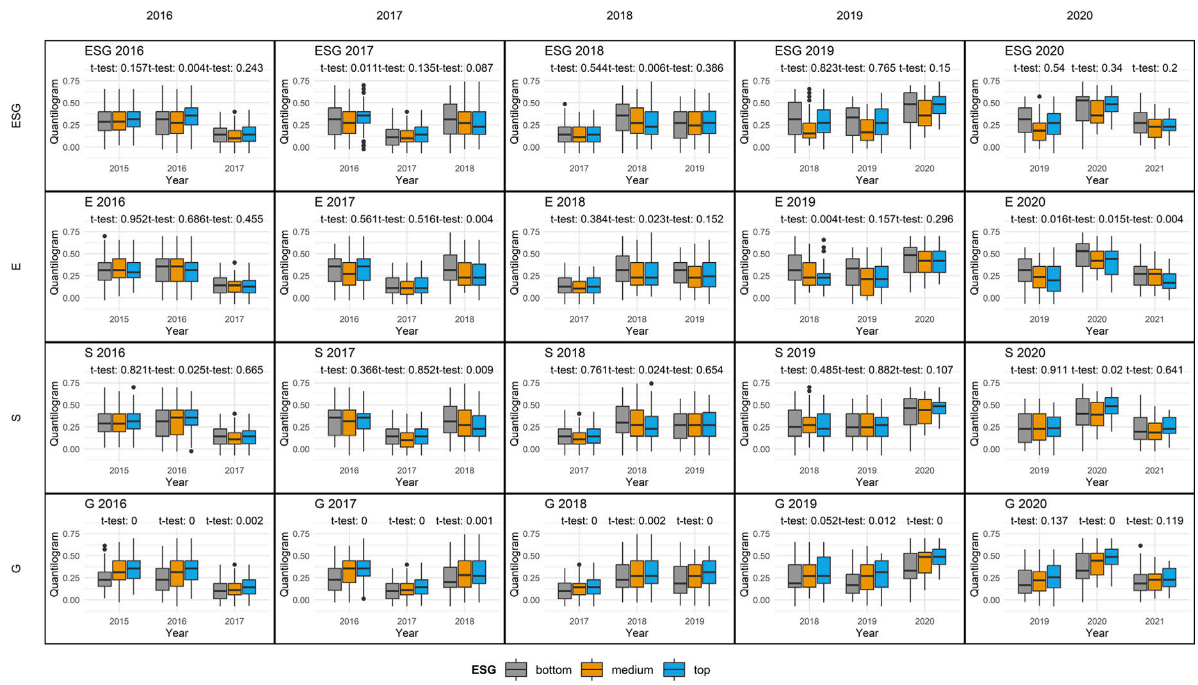

Fig. 3. The cross-quantilogram for quantile 0.1 output aggregation of synthetic structural scores.
Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the worst trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of synthetic structural scores (under the headings ESG, E, S, G). On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

First, separate pillar scores have significantly different effects both in comparison to the aggregate ESG score and within themselves. Unlike Khan et al. (2024), who found ESG pillars have consistently negative effects on market risks, our analysis points to pillars natural differences. Governance pillar scores tend to have the opposite and much stronger effect than Environment and Social pillar scores, and we can identify the strongest co-moved stocks with high (or at least middle) G-scores. On the other hand, Environmental and Social pillar data report the ability to mark stocks with a lower connection to the market with higher (or, in some cases, middle) scores. On the pillar basis, we thus agree with Díaz et al. (2021) who show that the Environmental and Social dimensions are the main drivers of the ESG impact when explaining portfolio returns. On the other hand, our results suggest different ESG effects compared to Bax et al. (2023), although we both point to the distinct nature of the Governance dimension. We suggest this counter-effect is based on structurally different concepts of these dimensions of sustainability. The Governance pillar naturally has more appeal to investors, who look for a company with growth potential, and the market identifies firms with better governance scores as value added (Filbeck et al., 2019). Corporate governance has been perceived the most important for institutional investors (Starks, 2009). In contrast, the Environmental and Social pillars tend to be connected with high costs and are thus being developed for high prices during market downturns (Al-Dah et al., 2018). (Filbeck et al., 2019) also pointed to the middle position of the Social dimension between the Environmental and Governance pillars, with the market viewing firms with strong environmental engagement less favorably. Investors who focus on these pillars may benefit more from the immaterial nature of ethical investment or believe in future rewards for such good behavior (Fu et al., 2019) and thus may not be very attentive to the short-term market development. Benuzzi et al. (2022) showed retail investors adopting sustainable perspective favors E-pillar, while those adopting a financial perspective perceive S-pillar the most relevant. We suggest these investors' loyalty may play a role in the extent of stock market connectedness. Aggregated ESG scores thus embody the combination of systematically different dimensions and, as confirmed with our results, for this reason, they lose some part of their differentiation power. However, ESG scores have shown a tendency to mark the weaker market-related stocks as middle- or high-ESG during market downturns, normal times and upturns. On the basis of this finding, we suggest that future studies discuss both individual and aggregated ESG scores, as investors may use the pillar scores differently to reach their various goals.

Second, our analyses revealed, for many cases within the E and S pillars, that the middle-class stocks tend to have the lowest dependence on the market during market crashes. This is, to a certain extent, in agreement with the results of Czado et al. (2022), who pointed to similar behavior using only Thompson Reuters Refinitiv scores for U.S. companies. They discussed the possible effect of middle-class invisibility, with high- and low-ESG (or E-S-G) stocks in the heart of the investors' focus (Amel-Zadeh and Serafeim, 2018), which makes them more sensitive to market movements. We confirmed that this phenomenon could appear within the data of multiple providers. A proper exploration of possible diversification opportunities should not be ignored in future literature.

Third, employing both the scores measuring the level of disclosure and synthetic structural scores based on the shared information between all explored data, we show that the level of disclosure may sometimes provide us with more robust information than the standard sustainability performance scores. As in the case of the Governance and Environment dimensions, the power of the Bloomberg Disclosure score and the synthetic score was of a similar extent for both the left and right tails of returns. We suggest the core information within this dimension is based on the level of a company's transparency. Moreover, as the synthetic scores reached a consistent significance over various settings within the Governance pillar, we suggest that this pillar is of higher consistency, and the shared information reflected in our structural combination is directly connected to a firm's financial potential, which is aligned with (Carnini Pulino et al., 2022)'s finding of a positive relationship between ESG disclosure and firm performance. On the other hand, the least power was gained in our synthetic score for the Social dimension and aggregated ESG score, what may again point to their structural ambiguity.

Fourth, the pandemic effect was mixed based on pillar and provider affiliation and no general rule, except for the jump in overall connectedness for all settings, can be drawn. Nevertheless, we can consider the pandemic as a strong factor within the effect exploration, as for many scores, the year 2020 meant a significant change in their power to differentiate between ESG-class groups. Moreover, even though our synthetic scores report some stability, they were also slightly affected by the unprecedented circumstances. Overall, our results do not suggest a dramatic change in investment behavior and point more to a temporal imbalance in the markets. This finding agrees with Pástor and Vorsatz (2020), who suggest investors were as focused on sustainability during the crisis as they were before the pandemic. Also, the prediction power to differentiate between class groups was low during the Covid-19 pandemic, with higher significance for E and S scores, which may suggest the attractiveness of these pillars during unexpected and extremely unusual events. In many cases, the power to differentiate strengthened for scores that could reflect the firm's behavior during the crisis (i.e., the score for 2020), but then, these scores' power again drops when looking at the year 2021 returns. We thus suggest the proper time-setting of ESG scores may play a crucial role in valid research.

5. Conclusion

Challenging geopolitical circumstances, climate change and threatening crises amplified the uncertainty in the financial markets. At the same time, the ESG-connected investments gained in interest and volume as an instrument of social and environmental justice, an (ethical) way to profit, or as a tool of risk management. Diversification opportunities arising from this new market paradigm are explored from many perspectives. Czado et al. (2022) suggest assets with moderate (middle-) ESG scores tend to show weaker dependence on the market compared with assets with extremely high or low ESG scores and that the dependence becomes stronger in times of crisis, but they only used Thompson Reuters data from the U.S. market. Moreover, Bax et al. (2023) suggested individual pillars may have different effects on risk dependence in times of crises and booms. Nevertheless, the question focused on micro-level relationships between various ESG classes of stocks and the market is not yet answered within academic literature.

The current paper thus extends the literature on the diversification and risk properties of stocks ESG classes (high-, middle-, and low-ESG rated stocks), as well as separate E–S–G pillar classes, by testing their co-movements with the market in extreme and middle quantiles using the bi-variate cross-quantilogram by Han et al. (2016). Also, it addresses the ongoing discussion on the ESG data quality and heterogeneity by applying the data of seven major providers and their synthetic structural combination proposed by Gyönyörová et al. (2021) to reflect the value of shared information between all providers on an aggregate and dimensional basis. Our empirical study for the period 2015–2021 shows evidence for the ESG effects on the co-movement intensity between stocks in the S&P 1200 index and the market from various perspectives.

Our paper reveals several important findings. Governance pillar scores tend to mark the strongest market-co-moved stocks with high (or at least middle) G-scores. This way, they form a very strong counter-effect compared to Environment and Social pillar scores, which deem the high (or middle) class groups as the least related to the market returns. The aggregated ESG scores represent the mix of E–S–G pillars to a certain extent and thus may have unpersuasive results. As mentioned here, the middle-class stocks may offer interesting patterns as proposed by Czado et al. (2022), and we consider them unjustifiably ignored. The level of disclosure may provide us with more robust information than the performance scores, and disclosure within the Governance score may be seen as the core of the shared yet influential information (making this score very similar to the synthetic G- score in results). Moreover, the synthetic structural scores pointed to the fact of the similar or different investments-important core information within pillars. Even though retail investors may perceive S-pillar as most relevant from a financial perspective (Benuzzi et al., 2022), our results point to its unstructured investment concept. On the other hand, G-pillar, and especially its core information, has a consistent and compelling relationship to stocks' behavior.

Moreover, considering that investors in the early months of the year have to use nothing but the previous year's data, we neither rejected nor accepted the power of ESG scores to predict future financial behavior (in terms of explored effect). Nevertheless, the two-side effect was usually visible (the effect was visible for two years with no persistent rule), pointing to the blurred nature of proper ESG data time setting. The issue of the Covid-19 pandemic is closely related to this question, and we may confirm its effect on the extent and sometimes even the direction of the explored relationship. Nonetheless, we agree with Pástor and Vorsatz (2020) on the temporal effect of the Covid-19 crisis. Overall, the power of ESG scores to differentiate between groups becomes stronger the worse the market performs.

Our findings align with previous literature, confirming higher stock-market relationships during market downturns (Karanasos et al., 2016; Mokni and Mansouri, 2017) and ESG-specific risk dynamics in the tail regions of return distribution (Bax et al., 2023;

Zhang et al., 2021; Górka and Kuziak, 2022; Pedini and Severini, 2022). However, our study goes beyond earlier research by addressing its methodological and data limitations.

Unlike previous studies that focused on indices, portfolios, or derivatives (Górka and Kuziak, 2022; Pedini and Severini, 2022; Zhang et al., 2021; Lashkaripour, 2023), we conduct a micro-level analysis of individual stocks. Additionally, compared to Czado et al. (2022) or Bax et al. (2023), we provide a global perspective by utilizing data with global coverage, covering the full scale of ESG classification. Our findings support the discussion of Bax et al. (2023), suggesting the "invisibility" effect, where middle-class stocks demonstrate the lowest dependence on the market. Nevertheless, compared to earlier research, our study not only focuses on the classification scale but also bases its design on using ESG data from several data providers; hence we offer robust and market-wide results. Moreover, as the discussion on the quality of ESG data is still unfinished, our synthetic scores cover this gap by focusing on the provider-to-provider agreed-on part of ESG information. Besides, by using ESG scores from seven data providers and investigating returns tail risk in different economic periods, we fill in several research gaps identified by Khan (2022), Landi and Sciarelli (2018), Brogi and Lagasio (2019).

Furthermore, we support and develop the suggestion of Zhang et al. (2021) and Díaz et al. (2021) by uncovering the nature of the distinct effects of separate pillar scores, with the Governance pillar demonstrating a stronger opposite effect. Our analysis challenges the notion of Lashkaripour (2023) that the composite ESG score represents green investment accurately and emphasizes the information losses resulting from dimensional aggregation. We discuss the connection between disclosure and standard sustainability performance scores, but in comparison to Carnini Pulino et al. (2022), we found this effect particularly within the Governance and Environment dimensions and with a significant connection between our synthetic scores within the Governance pillar and a firm's financial potential. Moreover, we observe a substantial ESG data heterogeneity and emphasize the structural ambiguity within aggregated ESG scores (similarly to Filbeck et al. (2019), Berg et al. (2022)), compared to existing literature, particularly for the Social dimension.

5.1. Theoretical and practical implications

The implications of our study's results are significant for policymakers, investors, and regulators alike. Our findings shed light on several important aspects contributing to understanding the relationship between ESG factors and the market. Based on our results, ESG scores offer diversification properties which can be used in systematic risk management. However, the divergence in pillar scores effects highlights the structural differences in the concepts of these sustainability dimensions. Governance-related factors, appealing to investors seeking growth potential, are perceived as value-added. In contrast, Environmental and Social factors associated with higher costs are developed for high prices during market downturns. These insights are particularly relevant for institutional investors who prioritize corporate governance. The "invisibility" effect of ESG middle-class stocks holds across multiple data providers, offering possible diversification opportunities for investors and emphasizing the importance of further exploration in future research.

Moreover, E and S scores results during the pandemic suggest the attractiveness of these pillars during unexpected and unusual events. Scores that reflect a firm's behavior during the crisis exhibit stronger differentiation, but this effect diminishes when examining returns in subsequent years. These findings highlight the importance of considering the appropriate time-setting of ESG scores for valid research as well as for investors and policymakers.

Besides, our study demonstrates that the level of disclosure can provide robust information comparable to standard sustainability performance scores. Our synthetic structural scores exhibit consistent significance within the Governance pillar but yield the least power for the Social dimension and aggregated ESG scores, suggesting potential structural ambiguity within these areas. Therefore, policymakers and regulators should consider the level of transparency and disclosure as a valuable source of information when evaluating sustainability performance. In addition, higher awareness of ESG dimensions' inconclusiveness points to the need for their complete understanding, particularly for the S-dimension, both on the level of investors and regulators. The proper definition would lead to stabilization and better predictability of the market environment.

Consequently, we suggest blind using ESG scores and using ESG as a general mark for sustainable investment leads to the reduction of their hedging and diversification opportunities. Thus, our findings contribute to a more nuanced understanding of the relationship between ESG and market outcomes, enabling stakeholders to make informed decisions and promote sustainable investment practices.

5.2. Limitations and future research

We applied the cross-quantilogram approach to companies comprising the S&P Global 1200 index, which is predominantly constituted of large-cap companies. Future research should extend the data set to establish a representation of mid-cap and small-cap companies. Also, we encourage future researchers to accompany the frequency domain issue and incorporate regional and industrial perspectives into analyses to provide a more complex view of the international diversification properties within the micro-level of ESG stocks. Thus, using other statistical techniques to examine the connectedness between ESG classes of stocks can be considered for future research. Another limitation of our study is the length of our ESG data series and the necessity to look separately on the yearly data. For future research, extending into the past and the present could produce more robust and valid information related to the effects of the global financial crisis and the Russia–Ukraine war. Moreover, a longer period and more granulated dataset would enable researchers to account for other effects, such as market sentiment in different time domains. The issue of proper ESG data timing also deserves thorough investigation, which may positively affect the wide range of academics and businesses that rely on this low-frequency data.

Table A.1
Descriptive statistics of ESG scores.

	Mean	Min.	Q 0.25	Median	Q 0.75	Max.
ESG Disclosure Score	50.7804	1.0764	42.4781	51.4335	59.2621	82.0139
ISS Quality Score	4.8086	1.0000	2.0000	4.0000	7.0000	10.0000
CDP Climate Change Perfor. Score	5.1406	0.0000	4.0000	6.0000	7.0000	8.0000
RobecoSAM Total Sustainability Rank	56.4863	0.0000	33.0000	58.0000	81.0000	100.0000
RobecoSAM Environmental	57.2750	0.0000	34.0000	59.0000	81.0000	100.0000
RobecoSAM Economic	56.3528	0.0000	33.0000	58.0000	81.0000	100.0000
RobecoSAM Social	54.3903	0.0000	29.0000	55.0000	81.0000	100.0000
Bloomberg Environmental	37.0389	0.0000	22.7726	37.8436	52.6427	87.2848
Bloomberg Social	30.9762	2.5695	20.1935	29.8670	40.9613	71.8561
Bloomberg Governance	84.1972	0.0000	80.6141	86.7249	91.2402	100.0000
Sustainalytics Rank	60.7330	0.0000	41.4634	65.2174	83.3234	100.0000
Sustainalytics Environmental	61.5102	0.0000	41.7582	66.0377	84.5361	100.0000
Sustainalytics Governance	59.8435	0.0000	38.7755	63.3803	83.7398	100.0000
Sustainalytics Social	60.2027	0.0000	39.7516	64.2857	83.6735	100.0000
Thomson Reuters ESG	64.5195	0.0000	54.5609	67.1360	77.1904	94.4673
Thomson Reuters E	59.2760	0.0000	42.9823	65.6331	80.4891	99.1625
Thomson Reuters S	65.7421	0.0000	52.1827	68.8246	82.1415	98.6277
Thomson Reuters G	62.2546	0.0000	48.3876	65.1207	78.1997	99.4496
MSCI ESG	5.1367	1.0000	4.0000	5.0000	6.0000	7.0000
ESG	0.0000	−2.9718	−0.6585	0.1127	0.7697	2.2096
G	0.0000	−4.0479	−0.6254	0.0750	0.7572	1.9654
E	0.0000	−3.4122	−0.6843	0.1338	0.7978	1.9502
S	0.0000	−2.5575	−0.7850	0.0637	0.8014	2.6442

Notes: Min. and Max. the minimum and maximum observed values respectively. Q 0.25 and Q 0.75 mean the 25th percentile and 75th percentile, respectively.

CRediT authorship contribution statement

Lucie Staněk Gyönyör: Conceptualization, Data curation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Matúš Horváth:** Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Descriptive statistics of ESG indicators

See Table A.1.

Appendix B. Correlation of synthetic ESG scores with their constituents

See Table B.1.

Appendix C. The cross-quantilogram for quantiles 0.1 and 0.9

See Figs. C.1–C.5.

Appendix D. ESG distribution by regions and industry sectors

See Figs. D.1–D.3.

Table B.1
Correlation of synthetic ESG scores with components.

Panel A: Correlation of synthetic ESG score with his components					
Scores	2016	2017	2018	2019	2020
Bloomberg ESG Disclosure Score	0.7939	0.7688	0.7513	0.6956	0.5755
RobecoSAM Total Sustainability Rank	0.8014	0.7831	0.7751	0.7391	0.7918
Sustainalytics Rank	0.8212	0.8051	0.7917	0.4940	−0.0063
Thomson Reuters ESG	0.8196	0.8004	0.7924	0.5900	0.6231
MSCI ESG	0.5409	0.5512	0.5454	0.6072	0.5972
Panel B: Correlation of synthetic E score with his components					
Scores	2016	2017	2018	2019	2020
CDP Climate Change Perfor. Score	0.8620	0.7663	0.7120	0.6740	0.8369
RobecoSAM Environmental	0.8631	0.8103	0.8215	0.8223	0.8171
Bloomberg Environmental	0.8000	0.6193	0.5694	0.5066	0.5415
Sustainalytics Environmental	0.8528	0.7315	0.7210	0.6125	0.0266
Thomson Reuters E	0.0460	−0.0007	−0.0633	−0.1658	−0.0375
Panel C: Correlation of synthetic S score with his components					
Scores	2016	2017	2018	2019	2020
RobecoSAM Social	0.8559	0.8437	0.8455	0.8040	0.7655
Bloomberg Social	0.8037	0.7733	0.7729	0.7310	0.5750
Sustainalytics Social	0.8490	0.8330	0.8232	0.6324	−0.1837
Thomson Reuters S	0.0297	0.0612	0.0177	−0.2309	−0.3399
Panel D: Correlation of synthetic G score with his components					
Scores	2016	2017	2018	2019	2020
ISS Quality Score	−0.5179	−0.4583	−0.5551	−0.4337	−0.5226
RobecoSAM Economic	0.7814	0.7657	0.7713	0.7262	0.7346
Bloomberg Governance	0.6349	0.6467	0.6303	0.4720	0.4634
Sustainalytics Governance	0.8193	0.8227	0.8009	0.7439	0.7106
Thomson Reuters G	0.0486	0.0159	0.0189	−0.0837	−0.2204

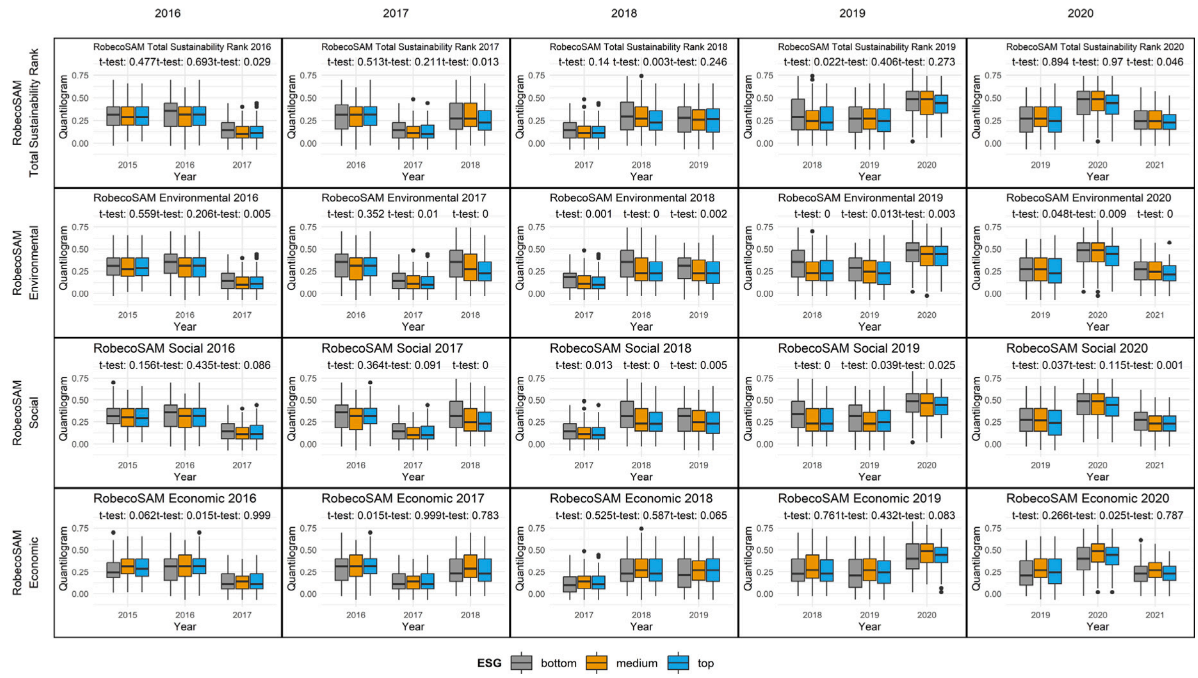

Fig. C.1. The cross-quantilogram for quantile 0.1 output aggregation: RobecoSAM.
Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the worst trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of RobecoSAM. On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data time-setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

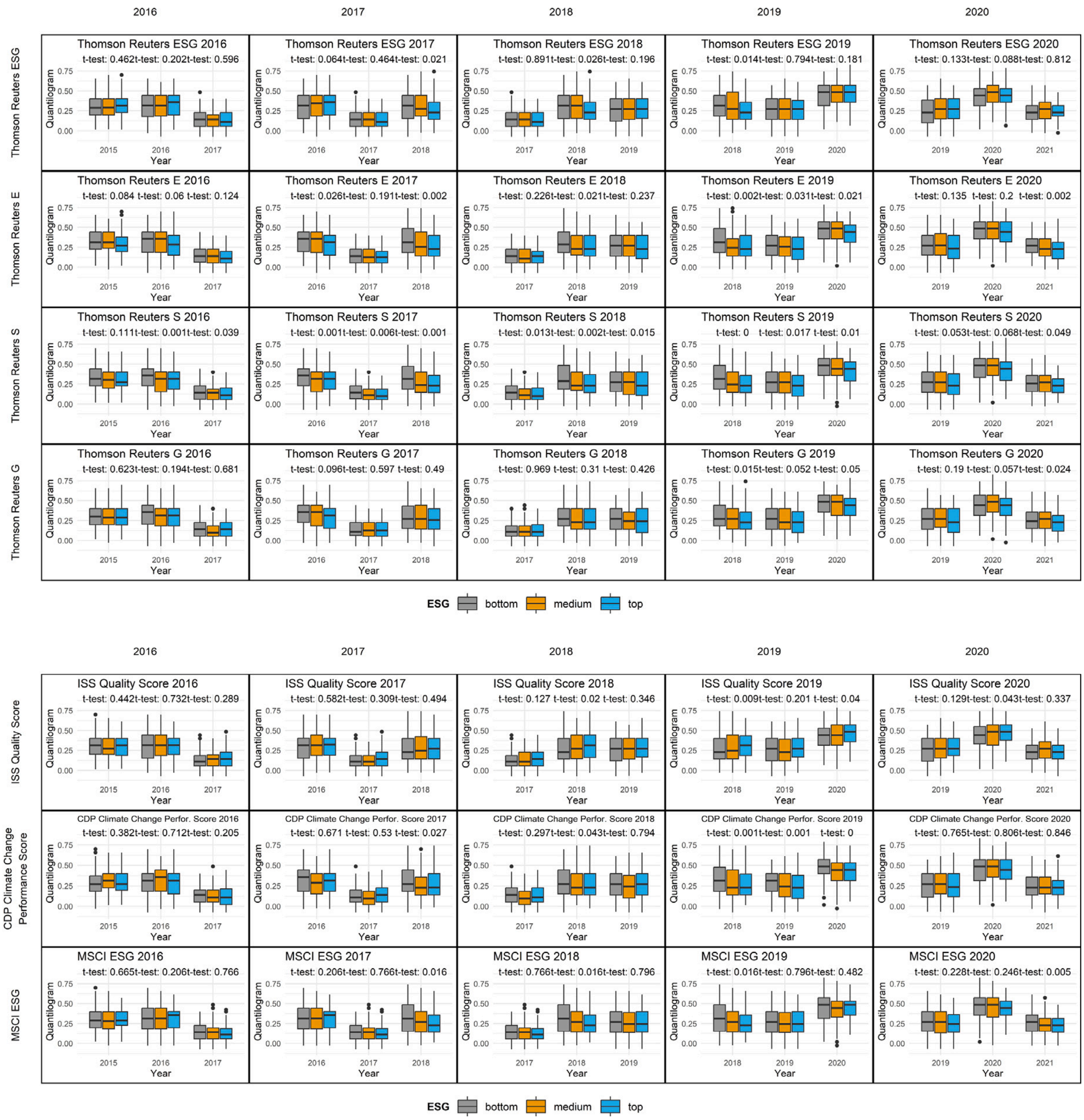

Fig. C.2. The cross-quantilogram for quantile 0.1 output aggregation: Thompson Reuters, ISS, CDP and MSCI data.
Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the worst trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of Thompson Reuters Refinitiv, CDP, ISS and MSCI data. On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data time-setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

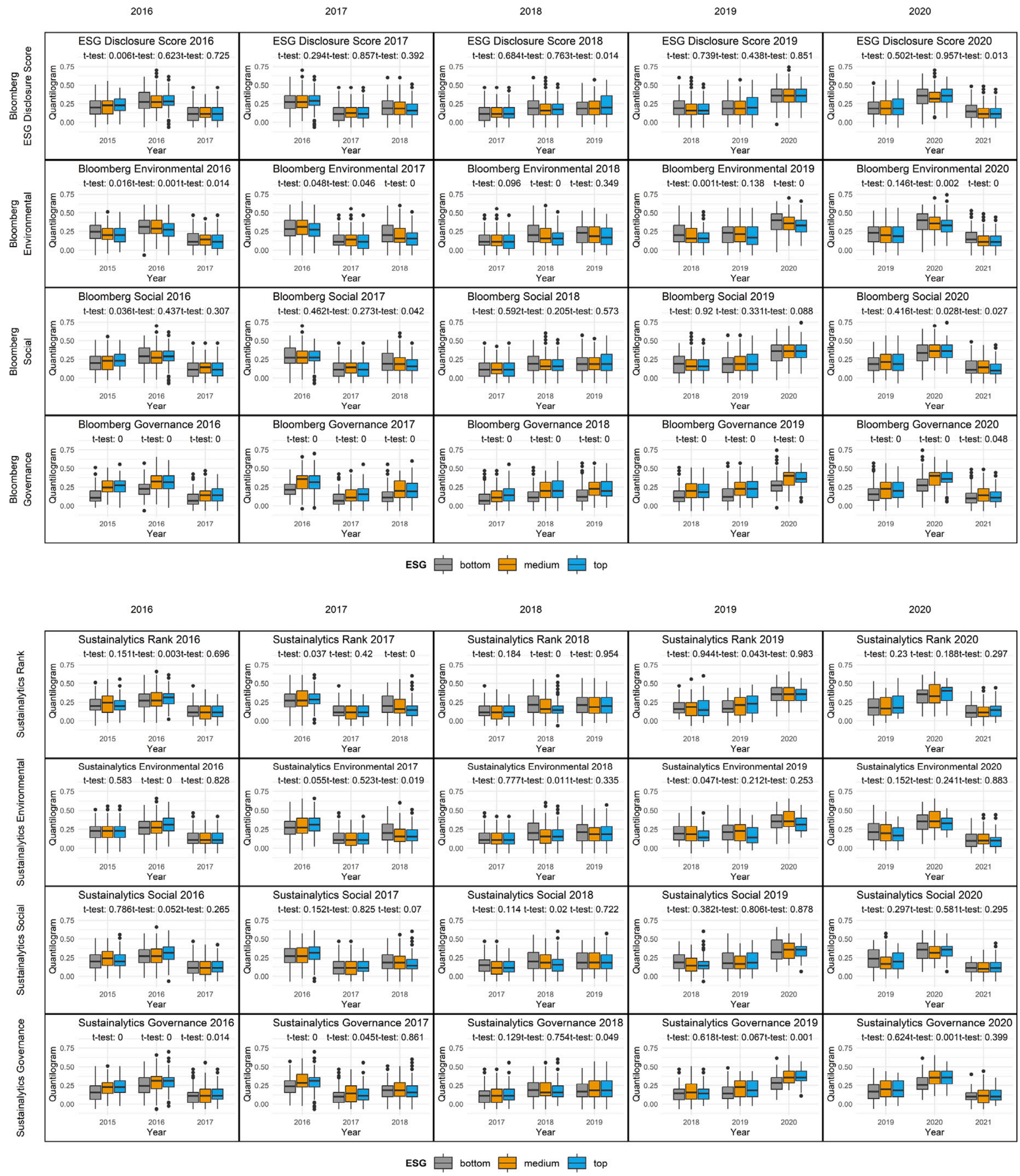

Fig. C.3. The cross-quantilogram for quantile 0.9 output aggregation: Bloomberg and Sustainalytics data.

Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the best trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of Bloomberg and Sustainalytics. On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

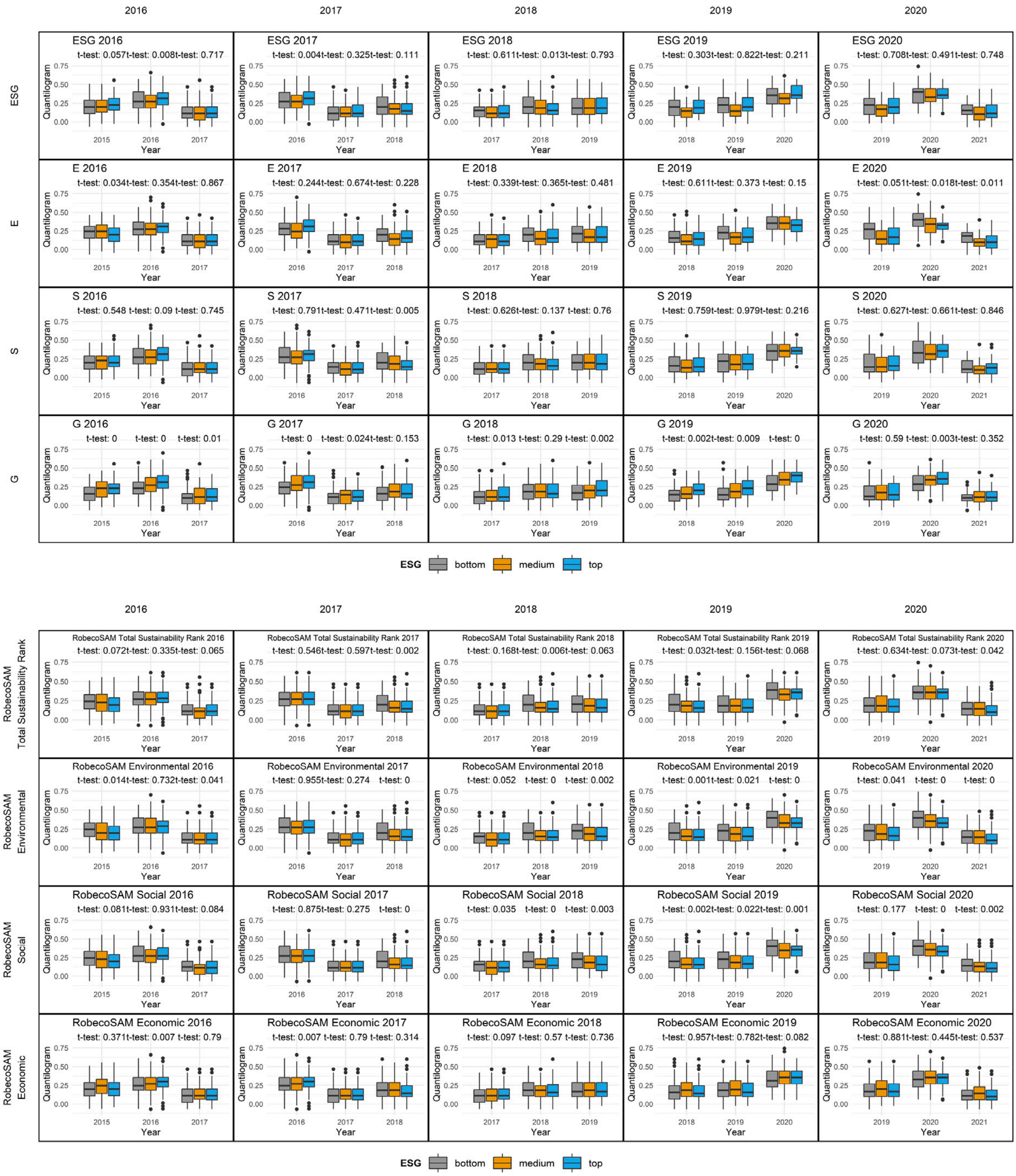

Fig. C.4. The cross-quantilogram for quantile 0.9 output aggregation: synthetic scores and RobecoSAM.

Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the best trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of synthetic structural scores and RobecoSAM. On each line, one separate ESG score is used to differentiate between stocks, and every column is a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data setting, a result of a t-test indicates whether the high-ESG and low-ESG groups differ significantly from each other.

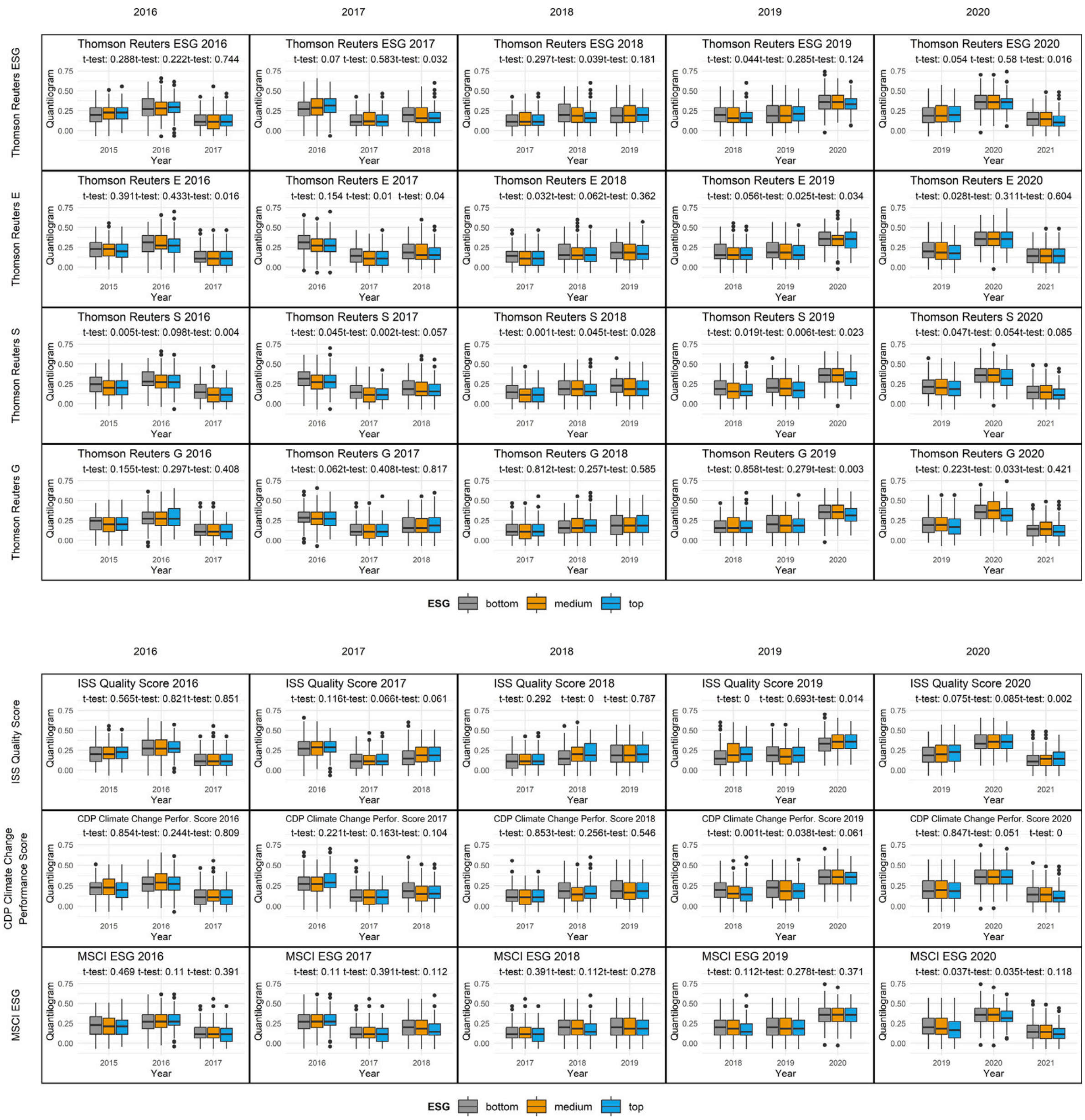

Fig. C.5. The cross-quantilogram for quantile 0.9 output aggregation: Thompson Reuters, ISS, CDP and MSCI data.
Notes: The figure presents the results of co-movement analyses between stocks and the market using the cross-quantilogram for the 10% of the best trading days with a lag k = 0 (representing simultaneity). This figure presents the ESG and E–S–G scores of the Thompson Reuters Refinitiv, CDP, ISS and MSCI data. On each line, one separate ESG score is used to differentiate between stocks, and every column shows a different year. Looking more in detail, the average co-movement power can be seen on the *y*-axis, while three ESG group box plots for three different time settings are visualized on the *x*-axis (e.g., for the 2016 column, the groups based on ESG data from the years 2015, 2016 and 2017 are shown). Over every ESG data setting, a result of a t-test indicates whether the high-ESG, middle-ESG and low-ESG groups differ significantly from each other.

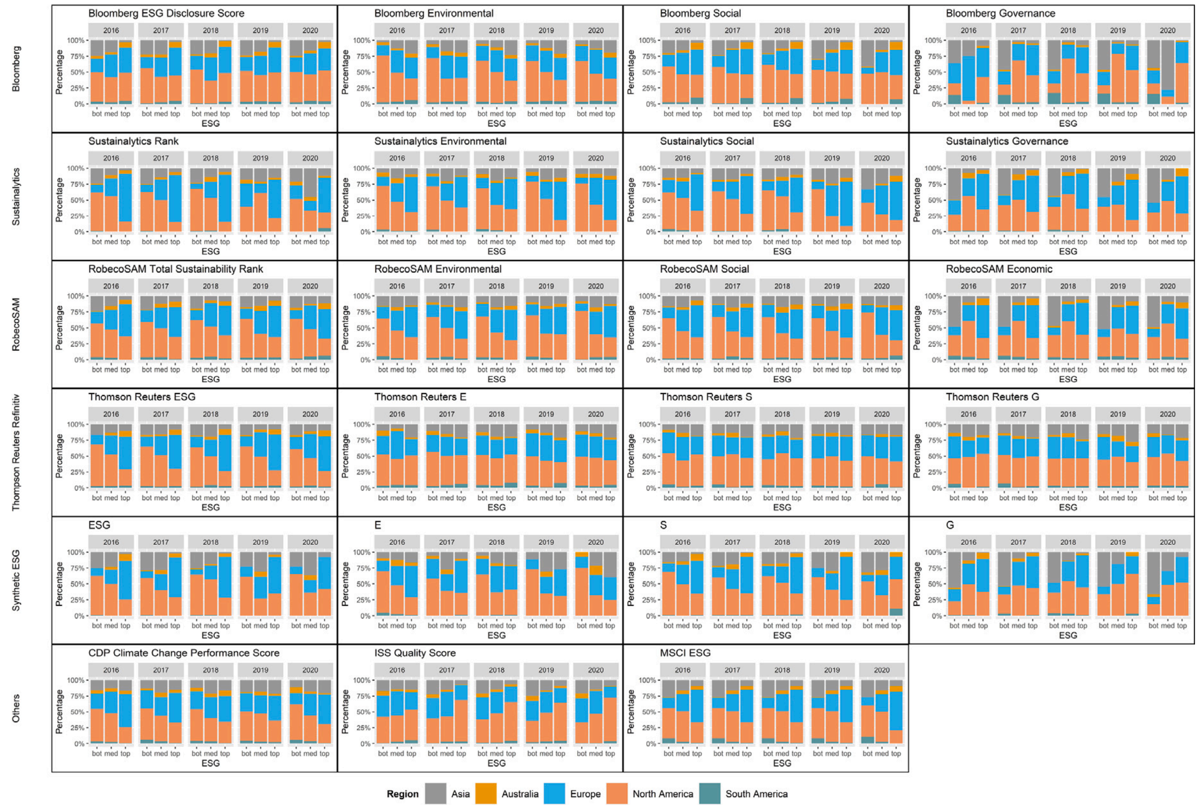

Fig. D.1. The companies' distribution over regions using all employed ESG scores and years.
Notes: The figure presents the distribution of companies over regions. The company's affiliation is based on its headquarter location.

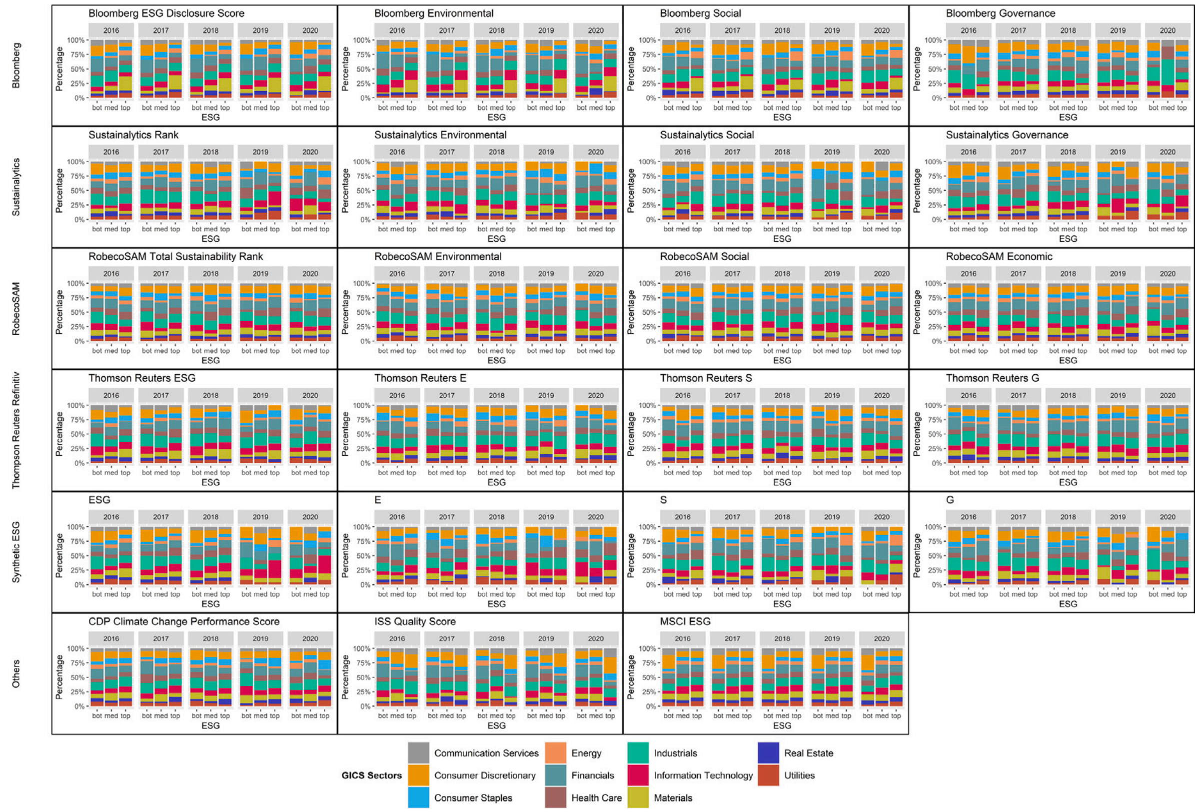

Fig. D.2. The companies' distribution over industries using all employed ESG scores and years.
Notes: The figure shows industries based on the GICS methodology.

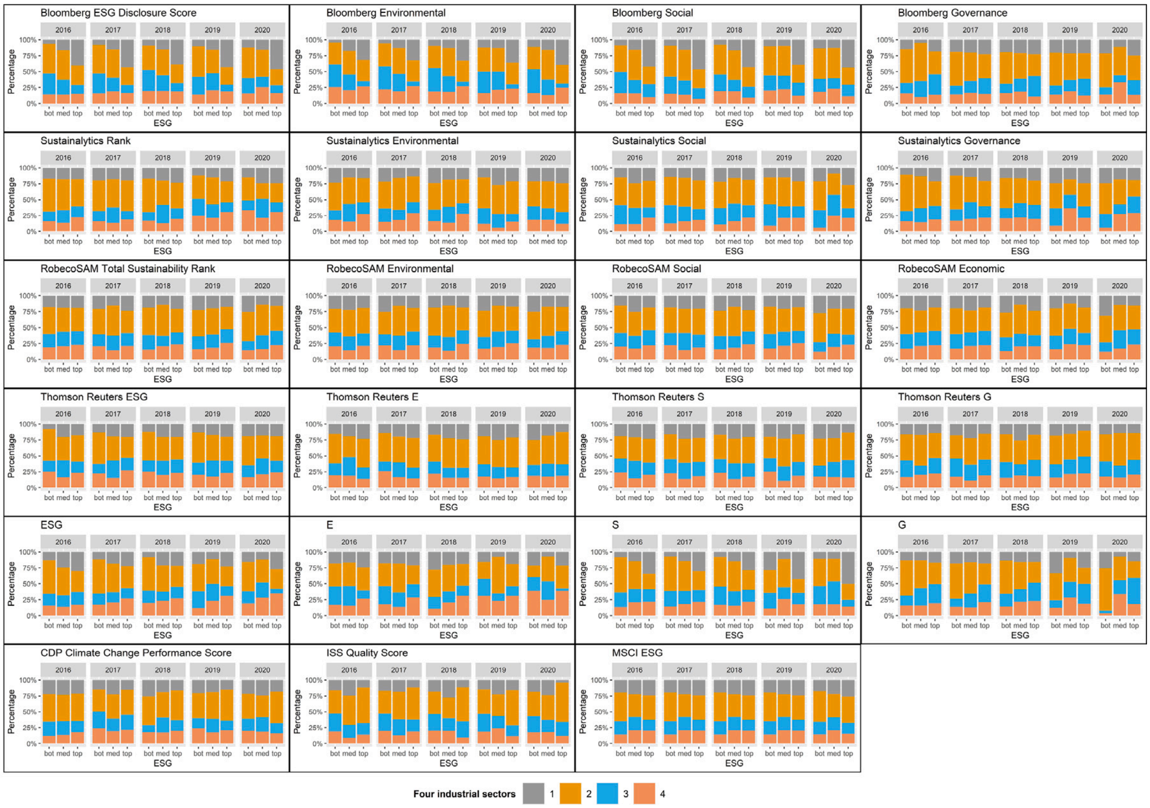

Fig. D.3. The companies' distribution over industries using all employed ESG scores and years.
Notes: The figure shows industries based on the four-sector model of the economy.

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