The Ripple Effect: ESG Decisions in Director Networks

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Abstract

We examine how ESG practices spread through director networks. Using firm-level ESG data and historical co-service ties among directors, we find that a firm's ESG score increases with the ESG performance of peer-connected firms. These effects are distinct from those due to geography, industry, or board interlocks that we also document. Firms are more likely to adopt ESG practices from peer-director firms that are financially successful or have influential boards, suggesting that value and values matter for ESG decisions. ESG adoption is also used strategically among competitors. A difference-in-differences approach leveraging exogenous ESG-related shocks provides further causal evidence. Our findings underscore the role of director networks in shaping ESG diffusion through both strategic and normative channels.

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1 Introduction

Substantial literature has studied why firms engage in ESG-related actions.[1] A central framing in this debate contrasts the *value* view—where ESG is pursued for financial or strategic benefits—with the *values* view, which emphasizes intrinsic motivations and normative pressures from stakeholders (Starks, 2023). These channels are not mutually exclusive, and both likely influence corporate behavior.

However, less attention has been paid to how decision-makers form these beliefs and preferences. In particular, little is known about how ESG norms and practices *spread* across firms via interpersonal or social mechanisms. Directors, as key decision-makers, are embedded in professional networks where they may learn from and be influenced by peers. Prior research documents peer effects in corporate behavior through various networks, including geographic proximity (Kedia et al., 2015; Rind et al., 2022), board interlocks (Chiu et al., 2013), and industry affiliation (Grieser et al., 2022b). Social influence has been shown to affect financial policy (Leary and Roberts, 2014), fraud (Dimmock et al., 2018), stock market participation (Hong et al., 2004), and other behaviors.

Several papers have documented that firms socially connected through interactions among non-board members—such as workers, clients, suppliers, financiers, and analysts—tend to exhibit common behavior.[2] However, professional ties among board members remain underexplored, despite the board being a particularly influential body in corporate decision-making.

This paper examines whether ESG behavior propagates through networks of prior professional connections among directors. We construct a proximity-weighted exposure measure based on whether directors of firm i have previously served on boards with directors from firm j. This captures enduring ties distinct from concurrent board interlocks or geographic proximity, and allows us to isolate a novel transmission channel. We then test whether firm

[1] See Gillan et al., 2021 and Starks, 2023 for two excellent recent reviews on the topic.

[2] See Leary and Roberts, 2014, Bustamante and Frésard, 2021, Cookson et al., 2022, Dimmock et al., 2018, Kuchler et al., 2022, and Gomes et al., 2023.

i's ESG performance is influenced by the ESG practices of firms to which it is connected in this network.

Our identification strategy combines three approaches: panel data regressions with firm and year fixed effects, an instrumental variables approach using Bartik-style instruments, and a difference-in-differences design based on plausibly exogenous ESG-related events. In our panel specification, we find that a one standard deviation increase in the ESG score of peer-connected firms is associated with a 3.5% standard deviation increase in the focal firm's ESG score. The effects are present across all three ESG pillars—Environmental, Social, and Governance. Importantly, we find that exposure to each specific pillar has an effect on that same pillar's adoption, consistent with targeted learning or norm transmission rather than general trends.

To reinforce the causal interpretation, we implement a difference-in-differences strategy exploiting a set of salient ESG shocks that are arguably exogenous to the focal firm but affect its connected peers. For the Environmental dimension (E), we examine both extreme weather events (e.g., major hurricanes) and high-fine environmental violations. For the Social dimension (S), we consider large-scale labor violations and high-profile sexual harassment scandals. These shocks produce significant responses in the ESG behavior of peer-connected firms relative to observationally similar but unconnected firms, consistent with a causal peer effect.

An analysis of potential mechanisms suggests that both *value*-driven and *values*-driven channels are at play. Peer effects are stronger when peer firms are financially successful (Leary and Roberts, 2014), consistent with strategic learning. Effects are also more pronounced when connections involve influential directors, suggesting a role for social norms and conformity. Moreover, propagation is stronger among direct competitors (Cao et al., 2019; Liu and Wu, 2016) than along supply chains, implying ESG may serve as a strategic differentiator. In contrast, we do not observe such propagation through supply chain relationships (Dai et al., 2021; Schiller, 2018), helping rule out mechanical scoring artifacts.

This paper contributes to three strands of the literature. First, we add to the understanding of ESG adoption by providing empirical evidence that both *value*-based (strategic and financial) and *values*-based (normative and social) forces influence firm behavior and propagate through social connections (Gillan et al., 2021; Starks, 2023).

Second, we document a novel channel of peer influence: past co-service ties among board members. Unlike board interlocks (Chiu et al., 2013), which reflect current shared membership, our measure captures prior professional ties—connections where we can be confident that directors interacted meaningfully and at a level relevant for strategic decisions. This complements existing work on the influence of social networks on financial policy and behavior (Dimmock et al., 2018; Hong et al., 2004; Leary and Roberts, 2014) and extends the literature on peer effects through other channels such as industry (Grieser et al., 2022b), geography (Kedia et al., 2015; Rind et al., 2022), and non-board stakeholders (Bustamante and Frésard, 2021; Cookson et al., 2022; Gomes et al., 2023; Kuchler et al., 2022).

Third, we contribute to the ESG peer effects literature (Cao et al., 2019; Chen et al., 2020; Dai et al., 2021; Husted et al., 2016; Jiraporn et al., 2014; Li and Wang, 2022; Liu and Wu, 2016; Schiller, 2018) by showing that director networks are a distinct and significant transmission mechanism, even after controlling for traditional linkages such as geography, industry, supply chains, and ownership. Our use of multiple identification strategies—including instrumental variables and difference-in-differences based on exogenous ESG-related events—reinforces the causal interpretation of our findings.

By identifying and quantifying the role of director networks in shaping ESG adoption, this paper provides new insight into how ESG norms diffuse in the corporate world. These findings also have direct policy relevance: targeting firms or individuals who hold central positions in these networks—through subsidies, training, or public recognition—can amplify ESG diffusion and accelerate adoption at scale. A network-based approach to ESG policy can therefore complement traditional regulation by leveraging social dynamics to shape firm behavior.

This paper is organized as follows: Section 2 explains how we measure a firm's exposure to the ESG action of its peers across several networks and introduces our measure of professional board exposure. Section 3 describes the various data sources used to construct our network exposure measures and capture ESG actions. Section 4 presents the results of our empirical analysis, including our baseline regressions, instrumental variables, robustness analysis, and mechanisms. Section 5 reports the outcome of our differences-in-differences estimation of the effect of shocks to E and S. Section 6 concludes.

2 Measuring Network ESG Exposure

Firms are interconnected in various ways that can facilitate the spread of ESG practices. Consistent with the literature, we first construct measures of connections through interlocking boards (Chiu et al., 2013), geographic proximity (John et al., 2011; Kedia et al., 2015), and industrial similarity (Grieser et al., 2022a, 2022b; Parsons et al., 2018).

For interlocking boards, firms i and j are considered connected at time t if they share at least one director, with the connection intensity w_{ijt}^{Inter} measured by the number of shared directors. Geographic proximity is defined by headquarters located in the same metropolitan statistical area (MSA). Industrial similarity is based on firms sharing the same TRBC industry group code. In these two cases, connection intensity is either zero or one.

Beyond these traditional connections, we propose a novel measure of board connections based on shared professional experience. This measure considers that two firms are connected at time t if their current board members have previously served together on any board. To measure connection intensity, we count the number of such shared board members, excluding direct interlocks, and scale each connection by the total years of shared professional experience. This measure thus captures the cumulative years of shared board service between members of the two firms.

Formally, our intensity of board professional connection between firms i and j in year t, w_{ijt}^{Brd}, corresponds to

$$w_{ijt}^{Brd} = \sum_{(p,q)\in i(t)\times j(t)} \mathbb{1}(p \text{ overlaps with } q) \times \Delta_{pqt}, \tag{1}$$

where $i(t)$ and $j(t)$ denote the set of non-interlocked board members from firm i and j in year t, respectively, $\mathbb{1}(\cdot)$ is an indicator function that takes the value of 1 if director p from firm i has served as a board member with director q from firm j before year t, and Δ_{pqt} is the number of years that directors p and q overlapped until year t (inclusive).

Figure 1 depicts how w_{ijt}^{Brd} works. In year t, two recently formed firms, A and B, have boards composed of directors A_i $(i = 1, 2)$ and B_j $(j = 1, 2, 3)$. At this point, w_{ijt}^{Brd} equals zero since no board members shared a common history before the year t. Then, at $t+1$, board member B_2 moves from firm B to A, making $w_{ij,t+1}^{Brd}$ equal to two since she served as a director with board members B_1 and B_3 for one year. Finally, in year $t+2$, $w_{ij,t+2}^{Brd}$ remains equal to two given that no changes in board composition occurred. Since B_2 shared the board with B_1 and B_3 for only one year, Δ_{pqt} remains equal to one at $t+1$ and $t+2$.

Using our bilateral connection measures, we construct summary metrics to capture a firm's exposure to its peers' ESG practices across four dimensions p: board professional experiences, interlocks, geographic proximity, and industry. The exposure is the connections-weighted average of the peers' ESG scores for each dimension.

$$Exp_{it}^{p}(ESG) = \sum_{j=1}^{N} s_{ijt}^{p} \times ESG_{jt}, \tag{2}$$

where

$$s_{ijt}^{p} = \frac{w_{ijt}^{p}}{\sum_{j=1}^{N} w_{ijt}^{p}}, \quad p \in \{Brd, Inter, Loc, Ind\} \tag{3}$$

We follow the same approach for each component of the overall ESG score: environmental (E), social (S), and governance (G). Appendix A provides a more detailed explanation on how the exposure variables are computed.

We compute the weights s_{ijt}^{p} including all firms, regardless of whether they are rated. This avoids disproportionately emphasizing rated firms in the exposure calculation—equivalent to imputing a score of zero to unrated firms. Without this adjustment, the exposure index would be biased toward rated peers. As robustness, we also explore alternative imputations, such as assigning unrated firms their industry average or initial rating upon coverage (see Appendix C). Results remain robust under these specifications, though the effect weakens for the Governance pillar.

3 Data and Descriptive Statistics

This paper uses data from three primary sources. First, we retrieve historical ESG scores and financial characteristics for U.S. companies from LSEG Eikon. Second, we construct board features and firm-level social networks using individual-level BoardEx network files. Third, we identify firms' locations using tools from the U.S. Census Bureau, including the U.S. Census Bureau Geocoder and Core-Based Statistical Area (CBSA) layers.

For the difference-in-differences estimations, we draw on three additional data sources. First, we use Violation Tracker data, from Good Jobs First, to track top environmental and social offenses penalties. Second, we identify natural disasters linked to climate change using the Emergency Events Database (EM-DAT) and geo-reference them with the Geocoded Disasters (GDIS) Dataset. Lastly, we include data from Borelli-Kjaer et al., 2021 to pinpoint corporate

sexual harassment scandals in the U.S.

Our working dataset combines information from the sources described above. The merging process follows these steps:

First, we begin with all US-domiciled firms with an LSEG ESG rating, yielding 25,224 firm-year observations from 2005 to 2022, covering 3,099 unique firms.[3]

Second, we retain only firms for which we can retrieve key financial controls from Eikon, including Analyst Coverage, B/M Ratio, Total Assets, Leverage, ROA, Stock Return, and Tobin's Q. This step narrows the sample to 3,079 firms, corresponding to 24,788 firm-year observations.

Third, we process director-level data from BoardEx to compute six board features at the firm-year level: board achievements, age, diversity, graduate education, independence, size, and interlocking. We merge these features with our dataset, resulting in 22,976 firm-year observations for 2,806 unique firms.

Finally, we use the U.S. Census Bureau Geocoder to convert firms' headquarters addresses into geographic coordinates, enabling us to identify their Metropolitan Statistical Area (MSA). We use the 2017 Core-Based Statistical Area (CBSA) layer from the U.S. Census Bureau's TIGER system.[4] Altogether, this yields a panel dataset comprising 21,461 firm-year observations for 2,584 unique firms.

Finally, we compute various ESG exposure measures based on different network connections, as detailed in Section 2.

Table 1 describes the network of board professional connections in 2020. Panel A reveals a large and economically meaningful network: nearly 2,500 firms are connected through close to 200,000 peer-director ties, resulting in a density of 0.06. While 6% may seem low

[3] We identify firms using the six-character CUSIP code (CUSIP-6).

[4] TIGER stands for "Topologically Integrated Geographic Encoding and Referencing," the U.S. Census Bureau's geographic spatial data system.

in absolute terms, it is substantial given the size of the network and the fact that ties are defined by historical co-service rather than concurrent board interlocks. This indicates a rich and complex web of past professional interactions that may serve as a conduit for influence.

Panel B highlights pronounced heterogeneity at the firm level: while some firms are isolated, others are highly central within the network, suggesting variation in their potential to diffuse or absorb ESG practices. This heterogeneity in connectedness is crucial for our identification strategy and simulation exercises, as it allows us to exploit variation in peer exposure to isolate network-driven ESG propagation.

Table 2 provides time-series descriptive statistics for the overall ESG score and its three pillars (Environmental, Social, and Governance) in our working sample. The average ESG score is 40.8 (standard deviation of 19.4), with pillar averages of 26.8 (E), 42.9 (S), and 49.3 (G). Variability, in terms of standard deviation, is highest in the Environmental pillar (27.5) and lowest in the Social pillar (21.2), reflecting firms' tendency to score higher and more consistently on Governance and Social dimensions. Median scores further emphasize this pattern: 18.9 (E), 39.6 (S), and 50.0 (G). Notably, 26.5% of US firms have an Environmental pillar score of zero due to limited public disclosures, as LSEG assigns a default value of zero in the absence of relevant data.[5]

Over time, ESG scores have trended upward, while dispersion has remained stable, except for the Environmental pillar, whose standard deviation increased from 22.9 in 2005 to 27.6 in 2022. Similarly, the number of firms with ESG ratings in LSEG grew from 377 in 2005 to 2,147 in 2022. In the Appendix D, each year, we compare firms with existing ESG scores to incoming firms, finding that the latter typically have lower scores.

Panel A of Table 3 provides summary statistics for our main network exposure measures, firm fundamentals, and board characteristics.[6] Panel B compares these statistics for firms with

[5] As of September 2024, 683 out of 3,325 U.S. firms have zero scores in all Environmental subcategories, including Emissions, Environmental Innovation, and Resource Use.

[6] See Appendix A for a detailed description of each of the variables.

below- and above-median ESG scores. Firms with higher ESG scores tend to have greater exposure to firms with high ESG ratings across the four networks (professional connections, board interlocks, location, and industry). These correlations suggest that spillover mechanisms may play a role in disseminating ESG practices. Nevertheless, high-ESG firms are also larger and exhibit more advanced board features, including higher achievements, greater female participation, better educational attainment, increased independence, and more interlocking directorates. These findings highlight the need to control for firm characteristics in our econometric framework.

4 Panel Regression Analysis

In what follows, we present the findings of the panel regression analysis. We first document the baseline results and quantify the economic magnitude of the propagation effects. The, we present IV results to strengthen the causal interpretation of the results and other robustness exercises. Finally, we investigate three likely mechanisms that could explain these relationships.

4.1 Baseline specification

We analyze ESG spillover effects using the following baseline specification:

$$y_{it} = \alpha_i + \alpha_t + \beta^{Brd} \underbrace{Exp_{it}^{Brd}(y)}_{\text{Board exposure}} + \beta^{Int} \underbrace{Exp_{it}^{Int}(y)}_{\text{Interlock Exposure}} + \beta^{Loc} \underbrace{Exp_{it}^{Loc}(y)}_{\text{Local Exposure}} + \beta^{Ind} \underbrace{Exp_{it}^{Ind}(y)}_{\text{Industry Exposure}} + \gamma \mathbf{Board}_{it} + \delta \mathbf{Firm}_{i,t-1} + \varepsilon_{it} \quad (4)$$

where the dependent variable y_{it} represents the ESG score of firm i in year t, including

the overall ESG score and its E, S, and G pillars. Our main independent variable of interest, $Exp_{it}^{Brd}(y)$, measures ESG exposure through professional board networks. The variables $Exp_{it}^{Int}(y)$, $Exp_{it}^{Loc}(y)$, and $Exp_{it}^{Ind}(y)$ capture ESG exposures through interlocking boards, geographic proximity, and industry, respectively.

The vector $\mathbf{Board}_{it}$ includes firm i's board characteristics in year t, such as achievements, age, diversity, graduate education, independence, interlocking, and size. The vector $\mathbf{Firm}_{i,t-1}$ includes financial characteristics from year $t-1$, including analyst coverage, book-to-market ratio, size, leverage, ROA, stock annual return, and Tobin's Q.

We cluster standard errors at the firm level to account for within-firm serial correlation. To facilitate interpretation, we standardize the four exposure measures so that each coefficient represents the impact of a one standard deviation change in the corresponding exposure measure on a firm's ESG score.

Our panel regression approach relies on within-firm, time-varying variation for identification. By including firm and time fixed effects, we address potential biases stemming from unobservable firm characteristics that may influence both exposures and ESG indices, as long as these characteristics remain relatively stable over time. To further mitigate concerns, we control for the key time-varying factors identified in the literature, including a comprehensive set of firm-level financial and board attributes. This detailed control framework enhances the robustness of our results by accounting for potential changes in firm characteristics over time.

Table 4 presents the results of estimating Equation (4) for the overall ESG score (Panel A) and its three components (Panels B to D). Columns (1) to (4) in each panel show specifications with each exposure measure included separately, while columns (5) to (7) progressively incorporate all four exposure measures. Columns (8) and (9) add financial and board-level controls, respectively.

The coefficient for board exposure is positive and statistically significant across all specifica-

tions for the overall ESG score (Panel A), as well as for the environmental (Panel B), social (Panel C), and governance (Panel D) dimensions. These results support the notion that firms more closely connected through board linkages to higher ESG-scoring firms also tend to have higher ESG scores.

In each panel, the magnitude of the board exposure coefficient is only slightly larger when each exposure measure is considered in isolation compared to when all measures are included jointly (compare column (1) to column (7)). This small change suggests that each exposure dimension has a distinct impact and that the effect of board exposure does not merely reflect similarities among firms within the same industry, locality, or interlocked networks that attract directors with similar past experiences.

The board exposure coefficient also decreases when time-varying controls are added at the firm and board level in columns (8) and (9), underscoring the importance of controlling for these factors. However, the sign and significance of the board exposure coefficient remain unchanged.

The coefficients for interlock and industry exposures are positive, indicating that firms connected through interlocks or operating in industries with higher ESG-scoring peers tend to have higher ESG scores themselves. Similarly, geographic proximity to firms with higher ESG levels is positively associated with a firm's own ESG score. This aligns with existing literature (Parsons et al., 2018), which highlights these connections as key factors in explaining commonalities in firm behavior and the adoption of ESG practices. However, this effect becomes statistically nonsignificant when the other exposure measures are also included in the regression, underscoring the importance of taking into account the diverse ways in which firms are related to each other, which could explain why they behave similarly.

Notice that the influence of shared director experiences on ESG scores is quantitatively comparable to the effect of direct board interlocks. This is somewhat surprising, as interlocks involve active, simultaneous service and facilitate immediate information sharing and coor-

dination, which are often seen as powerful channels of influence. However, two factors may help explain the similarity in magnitudes.

First, the board experience measure aggregates diverse and often long-standing connections—capturing not just the presence of ties, but their depth and accumulated exposure—whereas interlock exposure is defined by the count of currently overlapping directors. It is plausible that the marginal influence of each additional interlocked director exhibits diminishing returns, as additional ties may bring redundant information or reinforce existing ESG orientations rather than introduce new ones.

Second, past professional ties may be particularly effective at diffusing behavioral norms and decision-making heuristics, consistent with the idea of the "strength of weak ties" (Granovetter, 1973). These weaker but more diverse connections can facilitate broader and potentially more persistent transmission of practices, as directors internalize ESG approaches encountered in previous appointments and carry them across firms over time.

Geographic proximity, by itself, does not predict a firm's ESG score once other channels are controlled for. Local clusters group together firms from very different industries, so it is possible that industry-specific ESG pressures may offset one another and any positive spillovers may be diminished. In sharp contrast, industry exposure delivers the strongest peer effect: a one-standard-deviation rise in the average ESG score of a firm's own sector lifts its own score by 4.16 points—roughly 21 percent of the score's overall standard deviation. Because firms in the same industry face the same regulations, investor benchmarks and competitive yardsticks, their ESG moves are highly visible and readily emulated, making the industry channel far more potent than simple geographic proximity.

We now construct pillar-specific peer-exposure measures by weighting only the E, S or G scores of connected firms, and we re-estimate the model using the matching pillar as the dependent variable. The striking result (in panels B to D) is that each pillar's exposure correlates positively with the corresponding pillar in the focal firm: environmental exposure boosts

the firm's own E score, social exposure raises its S score, and governance exposure lifts its G score, all at conventional levels of statistical significance.

This finding is important for two reasons. First, it shows that directors do not merely import a generic "ESG mindset"; they appear to internalise and propagate very specific practices—carbon targets, employee policies, board structures—depending on what they observed in their peers. Second, it rules out a simple mechanical explanation in which a firm would increase all pillars simultaneously once it becomes more sustainability-minded.

Admittedly, pillar exposures are naturally correlated with a broader, common ESG dimension. In Table 10 of Appendix B, we decompose each pillar into a (common) ESG component and an orthogonal pillar-specific component. The pillar-specific effects survive this decomposition (although not significantly so in the case of G), confirming that what we are picking up is truly letter-by-letter transmission, not merely spillover from an overall ESG trend.

4.2 Simulating Network Multipliers and the Economic Magnitude of ESG Spillovers

To further interpret the estimated network effects, we conduct simulation exercises that exploit the matrix representation of the model described in Equation (4) (see Appendix E). This approach allows us to decompose the total peer influence into direct (first-order) and indirect (higher-order) effects, and to analyze the propagation of ESG shocks through the board network.[7]

While the original method was developed in a spatial context—where agents are embedded in physical space and proximity governs the strength of interactions—we adapt it to our setting by interpreting the peer network as a form of *social space*. In this framework, firms that are more closely connected via board ties are considered "socially proximate," analogous to

[7] For example, see Grieser et al., 2022b for an application to the product-market network.

physical proximity in geographic models. Just as spatial econometric models capture the attenuation of influence with distance, our model assumes that higher-order effects are stronger when transmitted through tightly connected paths in the board network.

In particular, we conduct two exercises using this framework. First, we evaluate the contributions of first-order (direct) and higher-order (indirect) effects to the total peer influence implied by the estimated model. This allows us to quantify the extent to which firms are influenced not just by their immediate connections, but also by the broader network structure. In this exercise, we assume that all firms exogenously increase their ESG score by one standard deviation and compute the resulting direct and indirect increases in ESG scores across the network.

Second, we simulate a set of counterfactual scenarios in which only firms at different percentiles of the degree centrality distribution receive an exogenous ESG improvement. Specifically, for each targeted percentile, the corresponding firms are assigned a one standard deviation increase in ESG score as the initial shock, while all other firms receive no shock. We then compute the resulting increase in ESG scores of all firms to assess how the intervention propagates through the network and affects untreated firms.

The exercise shows that a one standard deviation increase in peers' ESG scores is associated with a 3.5% standard deviation increase in the focal firm's ESG score.[8] For the E and S pillars, this increase in peers' scores corresponds to 4.3% and 4.5% standard deviation increases in the focal firm's E and S scores, respectively. When accounting for higher-order effects (network feedback), the impact rises to 3.6% , 4.5% , and 4.7% standard deviation increases in the ESG, E, and S scores, respectively. These results show that most propagation is immediate and occurs directly through direct peers. The fact that second-order paths add little, is still informative: it indicates that ESG practices do travel beyond a firm's first-degree network but decay quickly with social distance, consistent with imitation or information that loses salience as it diffuses. On average, the additional propagation through peers of peers,

[8]The back-of-the-envelope calculation is given by: β^{Brd} /(SD of $Exp^{Brd}(ESG)$) = (0.467/13.479) ≈ 3.5%.

and so on, contributes marginally to the overall effect.

The effect sizes we observe align with those reported in the literature. For instance, Dai et al., 2021 find that a one standard deviation increase in a customer's corporate social responsibility (CSR) score leads to a 17.5% standard deviation increase in the firm's CSR score. Similarly, Dyck et al., 2019 show that a one standard deviation increase in institutional ownership raises a firm's environmental performance by 6.7% of a standard deviation, while Chen et al., 2020 report that a comparable increase in shareholder monitoring intensity results in a 17% standard deviation higher CSR score. Finally, Husted et al., 2016 find that a one standard deviation increase in local CSR density among firms in the same area boosts a firm's CSR score by 7% of a standard deviation.

Exogenous increases in the ESG scores of the most connected firms disproportionately affect the broader network. Figure 2 shows the total impact of counterfactual shocks to the ESG scores of firms above various percentiles of board network centrality. The x-axis indicates the centrality cutoff—for example, 10 refers to shocks applied only to the top 10% most central firms. The above-mentioned computed size of the effect corresponds to the case when the cutoff is equal to 100, that is, when all firms are shocked. The figure displays two estimates: the average total effect and the average effect per shocked firm (i.e. the normalized effect). While the total effect increases with the share of shocked firms, it does so at a decreasing rate, indicating that much of the overall impact originates from the most connected firms. This is confirmed by the steep, nonlinear decline in the per-firm effect as the cutoff expands: shocking only the top 10% yields an average per-firm effect of 11.3%, which falls to 6.3% when the top 50% are shocked.

Finally, it is important to note that the impact of these targeted shocks is heterogeneous across firms, as they are not all equally connected to the firms where the shock originates. As a result, the total impact varies depending on a firm's position in the network. For example, Figure 3 shows a histogram of the total impact, given a one standard deviation shock in ESG score to the top 25% most central firms. Although the average effect is about 2.0% standard

deviations, firms in the top decile of the impact distribution see their scores increase by more than 2.7% standard deviations.

4.3 Instrumental variable approach

Although the estimates of the baseline panel are rich in fixed effects and controls, they could still be biased if unobserved shocks simultaneously shape the firm's ESG score and the scores of its peers. To strengthen a causal interpretation, we instrument peer exposure with exogenous, industry-level ESG trends—an approach that isolates variation unrelated to firm-specific or local factors. Following Borusyak et al., 2022 and Borusyak et al., 2024, this approach assumes that industry-wide dynamics impact a firm's ESG performance independently of firm-specific or local factors. By instrumenting a firm's ESG score with the industry ESG average and incorporating it into our exposure measures (except for industry exposure), we isolate variation driven by broader industry trends, effectively controlling for idiosyncratic firm-level shocks.

Specifically, we construct our instrument as $z_{it}^{p} = \sum_j s_{ijt}^{p} \overline{ESG}_{jt}^{Ind(j)}$, where s_{ijt}^{p} are the weights associated with the network $p = \{Brd, Int\}$ and $\overline{ESG}_{jt}^{Ind(j)}$ represents the average ESG score of the industry in which firm j operates.

Table 5 presents the results of the instrumental variable approach, which align with those from the baseline specification. The coefficients for ESG, E, S, and G remain positive and statistically significant, confirming the robustness our results to potential biases and reinforcing the causal interpretation of our main findings.

4.4 Robustness

In Appendix C, we conduct robustness checks to ensure our findings are not driven by specific choices in constructing the ESG exposure variables.

First, we examine whether our results depend on the timing and smoothing of peer exposure. In Table 12, we re-estimate the baseline model by replacing each firm's contemporaneous peer ESG score with a lagged three-year moving average of the peers' past ESG scores. This simple transformation serves two purposes: (i) filter out year-to-year noise in ratings, and (ii) pushes the information set further into the past, mitigating the standard 'reflection' concern that my ESG today could influence the ESG of my peers this year. The coefficients remain virtually unchanged, confirming that the peer effects we document reflect durable, forward-looking influences rather than short-lived co-movements.

We use LSEG ratings as our main data source because they offer the longest, methodologically consistent panel available for U.S. firms back to the early 2000s and align seamlessly with our identifiers in BoardEx and Eikon. This choice maximizes sample size, ensures uniform 0–100 scales for the three pillars, and facilitates replication by readers who have access to standard financial-research platforms. However, in Table 13 in Appendix C, we assess the sensitivity of our results to the choice of the ESG data provider by reconstructing the four exposure measures -board, interlock, local and industry - using MSCI ESG scores instead of our baseline source. All key coefficients remain of the same sign and similar magnitude. The peer effects we document therefore do not hinge on LSEG's ESG taxonomy; they reflect a broader phenomenon that survives when ESG is measured by a second, widely used vendor.

4.5 Mechanisms

Our analysis reveals a positive correlation between a firm's ESG ratings and those of its peer-connected firms. To better understand this relationship, we examine three mechanisms that could drive the spread of ESG practices through these networks. These mechanisms are tied to the motivations for firms to engage in ESG practices. As outlined by Starks, 2023, such engagement can stem from two primary drivers: the pursuit of *value* (enhancing financial performance) or adherence to *values* (conforming with social standards). The mechanisms

explored in this section—peer learning, social pressure, and strategic considerations—are closely linked to these motivations.

First, in terms of peer learning, directors may observe how ESG practices impact peer firms' performance and adopt similar practices when they perceive financial benefits. This aligns with the motivation to pursue *value*.

Second, under social influence, influential figures within director networks (such as board members serving at firms with higher centrality) can establish norms around ESG practices, pressuring firms to conform. This mechanism reflects the pursuit of *values*, as firms may adopt ESG practices to align with ethical standards or social expectations within their network, even when direct financial benefits are uncertain.

Finally, the relationship between a firm's ESG index and that of its peers may be driven by strategic considerations. Among competitors, firms might adopt ESG practices as a differentiation strategy to gain a competitive advantage, aligning with the pursuit of *value* (Albuquerque et al., 2019). In vertical supplier-customer relationships, a firm's ESG performance is often influenced by upstream partners in the production chain. Consequently, changes in a firm's ESG score—whether motivated by *value* or *values*—may prompt related firms to adjust their ESG practices as well.

4.5.1 Learning about value

The effectiveness of ESG practices in enhancing firm value remains a topic of active debate. Some studies, such as Albuquerque et al., 2020 and Lins et al., 2017, argue that ESG engagement can reduce risk and enhance value, particularly during periods of market turbulence. However, other research, including Di Giuli and Kostovetsky, 2014 and Buchanan et al., 2018, highlights that the benefits of ESG practices are not universally clear and may even detract from firm value under certain conditions (Braun et al., 2025).

Given this uncertainty, it is reasonable to expect firms to look to the experiences of others when deciding whether to engage in ESG practices. The concept of peer learning is well-established, with evidence showing that firms often draw on the financial decisions of their peers. For instance, Leary and Roberts, 2014 demonstrate that a firm's capital structure decisions are influenced by the actions of similar firms within its industry or peer group. These peer effects are particularly strong in situations of information asymmetry, aligning with information-based theories of learning.

To examine this dimension, we analyze whether the positive link between a firm's ESG score and that of its board-connected peers is stronger when these peers exhibit greater financial performance. We differentiate peers with positive industry-adjusted financial performance over the past three years from those with non-positive performance, creating two sub-measures: $Exp_{it}^{Brd-HP}(y)$ capturing exposure to ESG through high-performance peers, and and $Exp_{it}^{Brd-LP}(y)$, capturing exposure through low-performance peers. We use return on assets (ROA), return on equity (ROE), and the market-to-book ratio (M/B Ratio) as performance metrics.

Table 6 shows that the ESG practices of financially high-performing peers significantly influence a firm's own ESG decisions. The coefficient for board exposure to high-performing peers is positive and significant, indicating a strong alignment with the practices of successful peers. In contrast, the relationship is weaker and less significant for board linkages to low-performing peers. This pattern suggests a learning mechanism, where firms interpret the ESG actions of successful peers as indicative of value creation, driving their own ESG strategies. This effect is consistent across the overall ESG score and also (though not always significantly so) its environmental and social components, supporting the 'learning about value' hypothesis.

Interestingly, the opposite result emerges for the governance component, particularly when considering ROA and ROE. Firms may view strong governance practices as potential constraints on managerial discretion, aligning instead with less stringent governance practices of

low-performing peers to avoid such limitations. Alternatively, firms might intentionally adopt governance practices that differ from high-performing peers to attract a distinct investor base or signal a unique approach to value creation.

4.5.2 Social influence and values

High-status individuals within corporate networks play a critical role in shaping organizational behavior by creating and enforcing social norms. Prominent directors and business leaders are often perceived as possessing superior expertise and decision-making abilities, prompting others in their network to follow their lead (Lord et al., 1984). This dynamic stems from cognitive biases linking status with competence and the influence of social proof, where behaviors endorsed by influential figures are viewed as more legitimate and socially acceptable(Cialdini, 2006, Cialdini, 2007). Consequently, high-status individuals wield significant power in establishing norms that others feel compelled to adopt, even when financial benefits are not immediately apparent.

This mechanism could be particularly relevant to the adoption of Environmental, Social, and Governance (ESG) practices. Influential figures within director networks can foster a normative environment that pressures firms to align with the network's ethical standards and social expectations. DiMaggio and Powell, 1983 's concept of institutional isomorphism explains how firms, seeking legitimacy and social acceptance, adopt ESG practices to conform to these norms. Empirical evidence supports this perspective, showing that firms are more likely to engage in ESG initiatives when their leaders hold higher relative status within civil society (Ioannou and Serafeim, 2014). This social pressure serves as a powerful force, driving firms to align with broader societal values, even when the direct financial benefits are not immediately evident.

To test the hypothesis that social influence drives the transmission of ESG practices between firms, we examine whether a focal firm's ESG adoption is moderated by the characteristics

of the board members of its connected peer firms. Specifically, we hypothesize that a focal firm's peer influence is stronger when the connection occurs through allegedly influential board members.

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We consider two complementary approaches to test this hypothesis. The first approach focuses on the *aggregate influence* of the peer firm's board, regardless of the specific individuals mediating the connection. That is, a peer firm is considered *influential* if its board, as a whole, is classified as influential—even if the focal firm is not connected to it through an influential director. The corresponding sub-measures are defined as follows: $Exp_{it}^{Brd-HI}(y)$ denotes exposure to peer firms with influential boards, and $Exp_{it}^{Brd-LI}(y)$ denotes exposure to peer firms with less influential boards.

Specifically, a board is classified as *influential* if it meets at least one of two criteria: (i) the average age of its board members is above the sample median, or (ii) the firm's degree centrality within the peer network is above the sample median.

The second approach shifts the focus to peer firms with which the focal firm is directly connected through allegedly *influential* board members. To evaluate this, we construct two sub-measures: $Exp_{it}^{Brd-HI}(y)$, which captures exposure to peer firms connected via influential board members, and $Exp_{it}^{Brd\text{-}LI}(y)$, which captures exposure to peer firms connected via less influential board members. In this case, a peer firm is classified as *influential* if the focal firm is connected to it through at least one *influential* director.

Similarly, we identify influential directors using two indicators: (i) the director's age, and (ii) the director's degree centrality within the director-level peer network. We compute the

sample median for each indicator and classify a director as influential if their value on either indicator exceeds this threshold. This distinction allows us to test whether peer effects in ESG adoption are more pronounced when the influence stems from more senior or better-connected directors.

Table 7 presents the results based on firm-level board influence (Panel A) and board member-level influence (Panel B).

In Panel A, we see that, for overall ESG scores, the coefficient for board exposure is positive and significant for professional connections to more influential boards, as measured by both board age and degree of interconnectedness. In contrast, the coefficient for professional connections to less influential boards, while positive, is smaller and statistically insignificant.

Examining the ESG components reveals heterogeneity. For the Environmental (E) score, board age has the strongest impact, suggesting that older, more established boards may prioritize environmental initiatives due to historical experience or a greater alignment with long-term sustainability concerns. In contrast, the degree of interconnectedness plays a more significant role for Governance (and, to some extent Social) scores. Highly connected boards may promote the spread of social and governance practices by sharing insights and setting network-wide standards, as these dimensions often rely on shared norms and collective buy-in.

The results in Panel B confirm the previous findings, particularly when influence is measured with the centrality of the connected director. Overall, these findings support the hypothesis that social influence significantly contributes to the diffusion of ESG practices. The greater ESG adoption observed among firms connected to influential boards underscores the role of social pressure and the drive to conform to norms set by high-status actors. However, the observed heterogeneity across components indicates that no single mechanism explains how peer board characteristics influence the transmission of ESG practices across networks.

4.5.3 Strategic considerations

Firms increasingly view ESG performance as a way to differentiate themselves and attract customers, investors, and employees who prioritize sustainability and ethical practices, leading to increased market share, brand value, and financial performance (Porter and Kramer, 2006). Consequently, ESG-related actions by one firm can create a competitive advantage, prompting others in the same industry to follow suit. Liu and Wu, 2016 show that a firm's CSR behavior is positively influenced by the CSR levels of its competitors, while Cao et al., 2019 find that implementing a CSR proposal during shareholder meetings encourages peer firms to adopt similar practices. Albuquerque et al., 2019 further model CSR as an investment for product differentiation.

Vertical relationships also drive common ESG behavior. Dai et al., 2021 document that socially responsible corporate customers influence suppliers to adopt similar strategies. Similarly, Schiller, 2018 find that customer E&S policies positively affect supplier behavior, especially when customers have greater bargaining power or suppliers operate in regions with weaker ESG standards. Moreover, certain ESG dimensions, such as Scope 2 and 3 emissions, are directly linked to supplier performance.

This literature highlights the importance of examining how supply chain relationships affect ESG practice propagation. To investigate, we differentiate board ESG exposures based on their relationship type. We construct four sub-measures of board ESG exposure: $Exp_{it}^{Brd-Up}(y)$ for upstream (supplier) relationships, $Exp_{it}^{Brd-Down}(y)$ for downstream (customer) relationships, $Exp_{it}^{Brd-H}(y)$ for industry competitors, and $Exp_{it}^{Brd-UR}(y)$ for unrelated firms.

We identify upstream and downstream inter-industry relationships using input-output matrices (Make and Use) for the U.S. economy from the U.S. Bureau of Labor Statistics for 2020. Appendix F provides details on how we extract the relationships from these matrices.

Table 8 presents the results of our analysis, highlighting a nuanced relationship between ESG

peer effects and the type of firm linkages. In the third row of the table we document that the coefficient for horizontal board connections—firms operating within the same industry—is positive, significant, and the largest among the sub-measures. This suggests that ESG practices propagate most effectively among direct competitors, where firms may use ESG as a differentiation strategy to gain a competitive edge. This aligns with the literature on ESG-driven competition, supporting the notion of a "race to the top", where firms improve ESG practices to outpace competitors, prompting rapid imitation through peer networks.

In contrast, coefficients for unrelated and upstream (supplier) linkages are not statistically significant, indicating that ESG behaviors are less likely to spread among non-competing firms or those loosely connected in the supply chain. Notably, the lack of significance for vertical relationships—particularly downstream linkages—suggests that mechanically integrated supplier-related ESG factors (e.g., CO2 emissions) in ESG scores do not drive the observed effects [9].

Examining the ESG components across columns, horizontal relationships consistently exhibit the largest coefficients, though the one for the Social (S) pillar is not statistically significant. Environmental (E) and Governance (G) practices often have industry-specific implications, such as emissions standards or board structures, making their propagation within the same industry more likely as competitors adopt similar practices to neutralize competitive advantages. By contrast, Social (S) practices address broader societal concerns, such as labor and community engagement, which transcend industry boundaries and are less influenced by horizontal relationships.

Overall, our findings support the three proposed mechanisms—peer learning, social influence, and strategic considerations—that drive the impact of board ESG exposure on a firm's ESG decisions. However, the relevance of each mechanism varies depending on the type of

[9] An exception arises when focusing on the Environmental (E) component, where the coefficient on downstream connections is negative and statistically significant. This result is hard to interpret: it may partly reflect that firms with environmentally conscious downstream partners might face less pressure to improve their own environmental practices.

linkage, ESG pillar, and specific firm characteristics.

In terms of economic magnitudes, the effect of board ESG exposure is substantially amplified under certain conditions: it is 1.5 times greater when connected firms have above-median ROA when compared to those with lower than median ROA, 5.8 times greater when they have highly interconnected boards versus when they don't, and 2.2 times greater when they operate within the same industry (horizontal connections) relative to unrelated firms.

5 Difference in Differences

Our baseline specification, which employs a panel dataset with fixed effects and a comprehensive set of controls, effectively identifies peer effects and decomposes their influence across different dimensions under relatively mild assumptions. Moreover, our instrumental variable (IV) results reinforce the causal interpretation of these findings. To complement this analysis, we now use a staggered Difference-in-Differences (DID) approach to further isolate the causal impact of ESG spillover effects.

5.0.1 Quasi-experimental design

This approach leverages differential responses to shocks affecting peer-connected firms within a staggered Difference-in-Differences (DID) framework. We analyze the ESG outcomes of firms that are socially connected to impacted firms (the treatment group), compared to those that are unconnected and unaffected (the control group). Specifically, a firm is considered treated if it is socially connected to at least one impacted firm. The key identification assumption is that the timing of the shocks is uncorrelated with firms' pre-existing social connections.

We consider four types of shocks. The first two involve significant environmental and social offenses recorded in the Violation Tracker File. We focus on environment-related offenses

and stakeholder-related offenses (e.g., competition violations, consumer protection breaches, and employment offenses) with penalties above the 95th percentile. Treated firms are those socially connected to the offending firm, while control firms are the remainder.

The other two shocks include extreme weather events and corporate sexual harassment scandalss, which we consider as shocks to E and S, respectively. For environmental shocks, we analyze catastrophic Climatological, Hydrological, and Meteorological disasters in the U.S. after 2005, identified using the Emergency Events Database (EM-DAT) and georeferenced to the MSA-year level with the Geocoded Disasters (GDIS) Dataset.[10] Treated firms are socially connected to those within affected MSAs, while the control group consists of unconnected firms outside affected MSAs. For social shocks, we focus on highly publicized corporate sexual harassment scandals documented by Borelli-Kjaer et al., 2021 in our sample after 2005. As with the other shocks, treated firms are socially connected to implicated firms, and control firms are unconnected.

Table **??** provides the distribution of these events over time and related summary statistics.

5.0.2 Difference-in-differences estimations

We first analyze the impact of these events on treated firms using standard two-way fixed-effects (TWFE) regressions with parametric and non-parametric models:

$$y_{it} = \alpha_i + \alpha_t + \beta \times PostEvent_{it} + \varepsilon_{it} \tag{5}$$

$$y_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{-1} \mu_k + \sum_{k=1}^{7} \mu_k + \varepsilon_{it} \tag{6}$$

where α_i and α_t denote firm and year fixed effects, respectively.

[10]The GDIS Dataset is a geocoded extension of the EM-DAT database, encompassing spatial geometry and GIS data for over 39,000 disaster locations worldwide from 1960 to 2018.

In Equation (5), $PostEvent_{it}$ takes a value of 1 after the event for treated firms and 0 otherwise, with β capturing the change in ESG scores of treated firms compared to the yet-to-be-treated and never-treated firms, conditional on firm and year fixed effects. Equation (6) uses μ_k, an indicator for year k relative to the event, with $\mu_{-1} = 0$ for normalization. These indicator variables are always 0 for firms that are never treated. Standard errors are clustered at the firm level in both specifications when using top environmental and social-related offenses and sexual harassment scandals as sources of exogenous variation. In the case of extreme weather events, standard errors are clustered at both the firm and MSA-year levels.

Recognizing recent critiques of TWFE estimators when units are treated at different times (Athey and Imbens, 2022; Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021), we also estimate the average treatment effect on the treated (ATT) using the Callaway-Sant'Anna (CS) estimator Callaway and Sant'Anna, 2021, designed to address these limitations.

Table 9 summarizes the results. Columns 1–4 show the parametric TWFE results, columns 5–8 report non-parametric TWFE estimates, and columns 9–12 present CS estimator results. Across models, treated firms experience significant increases in ESG scores following peer firms' extreme E- or S-related penalties. The non-parametric TWFE and CS results further indicate that the effects materialize post-event, with coefficients positive and statistically significant starting the year after the shock. Pre-event coefficients are mostly insignificant, supporting the parallel trends assumption, as confirmed visually in Figures 4 and 5.

These exercises are encouraging for several reasons. First, they provide strong support for the causal interpretation of our findings. Using peer connections at the board level as treatment assignment consistently yields positive and significant effects across different types of shocks. Responses vary by dimension—for example, E-related shocks prompt different adjustments than S-related ones, reflecting distinct firm capabilities—yet the overall pattern of ESG spillovers remains consistent. Second, the responses are specific to the nature of the shock. Shocks targeting E trigger adjustments in E-related practices among connected firms

without significant spillovers to unrelated areas such as S or G. This precision highlights the targeted nature of ESG spillovers driven by peer influence.

The parametric model estimates indicate that top E-related events and extreme weather shocks increase treated firms' E scores by approximately 3.7 and 1.9 points, respectively. Similarly, top S-related events and sexual harassment scandals increase treated firms' S scores by 2.6 and 1.8 points, respectively. The CS model suggests even larger effects, with environmental related shocks leading to increases of around 10 points in the E score. Responses to S-related shocks are also significant, though smaller for sexual harassment scandals. These magnitudes must be interpreted with caution, however, since they capture the response to extreme events and not the average relationship reported in our panel regression approach.

The effects appear highly persistent. Treatment effects grow until around year five, stabilize, and do not decline thereafter. This pattern suggests enduring changes in ESG practices prompted by extreme events, reinforcing the durability of these peer-driven ESG spillovers.

6 Conclusions

Our research examines how peer networks, particularly through the shared experiences of board members, shape the adoption and spread of ESG (Environmental, Social, and Governance) practices. By introducing a novel measure, board ESG exposure, which tracks board member connections to firms with strong ESG ratings, we demonstrate that firms are more likely to engage in ESG activities when connected to peers with higher ESG scores. These peer effects are distinct from traditional forms of influence, such as board interlocks, geographic proximity, or industry relationships, highlighting the unique role that social and professional networks play in driving corporate ESG behavior. To ensure the robustness of our findings, we address potential endogeneity concerns through several strategies that support a causal interpretation of the documented effects.

Our findings reveal several important insights. First, firms with board linkages to peers with high ESG scores and superior financial performance or influential boards tend to adopt stronger ESG practices. This suggests that, in making ESG decisions, firms are influenced not only by financial outcomes (the value-driven view) but also by social pressures and a desire to conform to norms established by high-status actors (the values-driven view). Second, ESG practices are more likely to spread through board connections with direct competitors, indicating that firms may adopt ESG initiatives as a competitive differentiation strategy in their markets. This competitive dynamic fosters a "race to the top," where firms improve their ESG practices to outpace rivals, encouraging others to follow suit.

A key policy implication of our research is that targeting influential directors from successful firms can act as a powerful catalyst for broader ESG adoption. Regulators and policymakers could leverage the centrality of these individuals within social and professional networks to promote sustainable practices more effectively. By focusing on a few key firms that are central to these networks, they can trigger a ripple effect, inspiring peer firms to adopt similar ESG practices. This network-driven approach has the potential to significantly amplify the impact of ESG policies, creating widespread change through the influence of a strategically targeted few.

References

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. *The Review of Corporate Finance Studies*, *9*(3), 593–621.

Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, *65*(10), 4451–4469.

Athey, S., & Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, *226*, 62–79.

Borelli-Kjaer, M., Moehl Schack, L., & Nielsson, U. (2021). #MeToo: Sexual harassment and company value. *Journal of Corporate Finance*, *67*, 101875.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs (D. Krueger, Ed.). *The Review of Economic Studies*, *89*(1), 181–213.

Borusyak, K., Hull, P., & Jaravel, X. (2024). Design-based identification with formula instruments: A review. *The Econometrics Journal*.

Braun, M., Marcet, F., & Raddatz, C. (2025). How do esg firms invest? *International Review of Financial Analysis*, *97*, 103863.

Buchanan, B., Cao, C. X., & Chen, C. (2018). Corporate social responsibility, firm value, and influential institutional ownership. *Journal of Corporate Finance*, *52*, 73–95.

Bustamante, M. C., & Frésard, L. (2021). Does firm investment respond to peers' investment? *Management Science*, *67*(8), 4703–4724.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Cao, J., Liang, H., & Zhan, X. (2019). Peer effects of corporate social responsibility. *Management Science*, *65*(12), 5487–5503.

Chaisemartin, C. D., & D'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*, 2964–96.

Chen, T., Dong, H., & Lin, C. (2020). Institutional shareholders and corporate social responsibility. *Journal of Financial Economics*, *135*(2), 483–504.

Chiu, P.-C., Teoh, S. H., & Tian, F. (2013). Board interlocks and earnings management contagion. *The Accounting Review*, *88*(3), 915–944.

Cialdini, R. B. (2006, December). *Influence: The psychology of persuasion* (Revised edition). Harper Business.

Cialdini, R. B. (2007). Descriptive social norms as underappreciated sources of social control. *Psychometrika*, *72*(2), 263–268.

Cookson, J. A., Engelberg, J. E., & Mullins, W. (2022). Echo chambers. *The Review of Financial Studies*, *36*(2), 450–500.

Dai, R., Liang, H., & Ng, L. (2021). Socially responsible corporate customers. *Journal of Financial Economics*, *142*(2), 598–626.

Di Giuli, A., & Kostovetsky, L. (2014). Are red or blue companies more likely to go green? politics and corporate social responsibility. *Journal of Financial Economics*, *111*(1), 158–180.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147.

Dimmock, S. G., Gerken, W. C., & Graham, N. P. (2018). Is fraud contagious? coworker influence on misconduct by financial advisors. *The Journal of Finance*, *73*(3), 1417–1450.

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics*, *131*(3), 693–714.

Gillan, S. L., Koch, A., & Starks, L. T. (2021). Firms and social responsibility: A review of esg and CSR research in corporate finance. *Journal of Corporate Finance*, *66*, 101889.

Gomes, A., Gopalan, R., Leary, M. T., & Marcet, F. (2023). Analyst coverage networks and corporate financial policies. *Management Science*.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*, 254–277.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Grieser, W., Hadlock, C., LeSage, J., & Zekhnini, M. (2022a). Network effects in corporate financial policies. *Journal of Financial Economics*, *144*(1), 247–272.

Grieser, W., Maturana, G., Spyridopoulos, I., & Truffa, S. (2022b). Agglomeration, knowledge spillovers, and corporate investment. *Journal of Corporate Finance*, *77*, 102289.

Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. *The Journal of Finance*, *59*(1), 137–163.

Husted, B. W., Jamali, D., & Saffar, W. (2016). Near and dear? the role of location in CSR engagement. *Strategic Management Journal*, *37*(10), 2050–2070.

Ioannou, I., & Serafeim, G. (2014). The impact of corporate social responsibility on investment recommendations: Analysts' perceptions and shifting institutional logics: Csr and investment recommendations. *Strategic Management Journal*, *36*(7), 1053–1081.

Jiraporn, P., Jiraporn, N., Boeprasert, A., & Chang, K. (2014). Does corporate social responsibility (CSR) improve credit ratings? evidence from geographic identification. *Financial Management*, *43*(3), 505–531.

John, K., Knyazeva, A., & Knyazeva, D. (2011). Does geography matter? firm location and corporate payout policy. *Journal of Financial Economics*, *101*(3), 533–551.

Kedia, S., Koh, K., & Rajgopal, S. (2015). Evidence on contagion in earnings management. *The Accounting Review*, *90*(6), 2337–2373.

Kuchler, T., Russel, D., & Stroebel, J. (2022). JUE insight: The geographic spread of COVID-19 correlates with the structure of social networks as measured by facebook. *Journal of Urban Economics*, *127*, 103314.

Leary, M. T., & Roberts, M. R. (2014). Do peer firms affect corporate financial policy? *The Journal of Finance*, *69*(1), 139–178.

Li, C., & Wang, X. (2022). Local peer effects of corporate social responsibility. *Journal of Corporate Finance*, *73*, 102187.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, *72*(4), 1785–1824.

Liu, S., & Wu, D. (2016). Competing by conducting good deeds: The peer effect of corporate social responsibility. *Finance Research Letters*, *16*, 47–54.

Lord, R. G., Foti, R. J., & De Vader, C. L. (1984). A test of leadership categorization theory: Internal structure, information processing, and leadership perceptions. *Organizational Behavior and Human Performance*, *34*(3), 343–378.

Parsons, C. A., Sulaeman, J., & Titman, S. (2018). The geography of financial misconduct. *The Journal of Finance*, *73*(5), 2087–2137.

Porter, M., & Kramer, M. (2006). Strategy society: The link between competitive advantage and corporate social responsibility. *Harvard Business Review*, *84*(12), 78–92.

Rind, A. A., Abbassi, W., Allaya, M., & Hammouda, A. (2022). Local peers and firm misconduct: The role of sustainability and competition. *Economic Modelling*, *116*, 106000.

Schiller, C. M. (2018). Global supply-chain networks and corporate social responsibility. *SSRN*.

Starks, L. T. (2023). Presidential address: Sustainable finance and ESG issues — value versus values. *The Journal of Finance*, *78*(4), 1837–1872.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*, 175–199.

Figure 1: Peers network formation

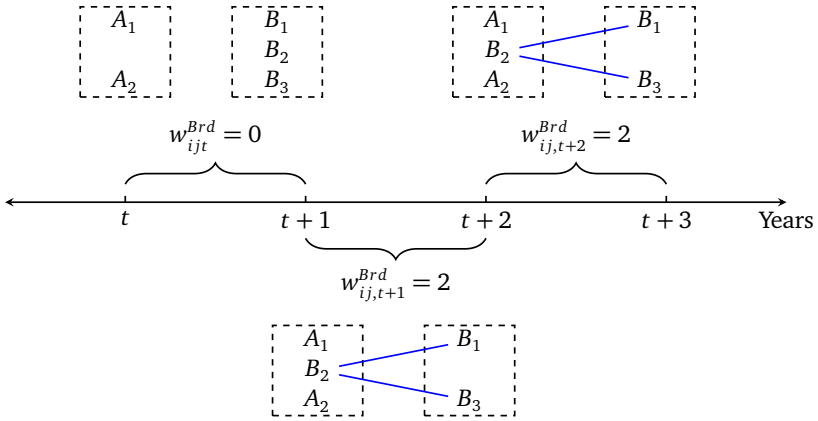


Table 1: Network statistics for 2020

Panel A: General characteristics of the peers network	
Number of firms	2,488
Number of links	195,371
Density	0.06

Panel B: Firm-level network statistics

Measure	Mean	SD	p5	p50	p95
Degree	157.051	3915.871	3.000	60.000	217.000
Eigenvector	0.015	0.024	0.001	0.010	0.043

Table 2: ESG over time

	ESG						*E*					*S*					*G*				
	N	Mean	SD	p25	p50	p75	Mean	SD	p25	p50	p75	Mean	SD	p25	p50	p75	Mean	SD	p25	p50	p75
2005	377	34.137	16.930	21.483	30.462	43.925	18.410	22.914	0.000	6.364	27.209	35.862	20.002	20.608	31.585	48.684	47.560	21.608	29.432	47.210	65.386
2006	391	35.773	17.011	22.616	33.615	45.769	19.724	23.411	0.000	10.870	30.886	38.039	20.362	22.696	34.695	50.041	47.882	20.957	31.246	47.955	63.742
2007	428	40.023	17.966	25.877	38.248	51.731	27.899	26.415	0.571	21.960	47.575	43.538	19.745	28.529	41.024	57.072	47.303	21.771	30.578	46.042	64.655
2008	533	40.511	19.529	24.746	37.152	54.346	29.504	27.148	2.667	22.668	51.114	43.202	20.598	27.519	39.686	56.927	47.969	22.997	29.776	47.426	66.566
2009	598	40.711	20.574	24.915	36.557	55.575	30.393	28.227	2.634	21.883	53.613	42.792	21.228	27.295	37.901	58.500	48.440	23.766	28.671	48.381	68.023
2010	622	42.274	20.053	27.017	38.423	57.233	33.171	28.112	6.131	26.391	56.434	44.229	21.256	28.360	40.169	59.520	49.254	22.777	31.894	47.691	67.149
2011	645	43.518	20.231	27.104	40.812	58.671	34.908	28.231	9.119	30.552	58.724	45.566	21.320	29.418	42.167	60.808	49.526	22.731	31.647	50.440	68.492
2012	664	43.908	19.877	27.788	42.014	59.743	35.956	27.984	12.461	31.366	59.829	45.855	21.076	29.888	42.455	61.271	49.414	22.639	31.772	50.575	66.745
2013	672	44.143	19.871	28.916	42.643	59.732	35.898	27.859	11.610	32.407	60.288	46.268	21.281	30.273	42.707	62.694	49.592	22.765	31.285	50.198	68.163
2014	676	44.593	19.415	29.880	43.203	58.886	36.499	27.815	12.493	32.846	61.311	46.639	20.819	30.388	43.484	62.092	49.552	22.604	31.851	49.839	67.740
2015	1,057	40.850	19.294	26.070	38.047	53.613	29.427	27.212	3.555	20.077	49.790	42.429	20.683	26.468	39.137	57.357	49.792	22.391	30.913	50.804	67.853
2016	1,509	38.707	18.559	24.504	34.558	50.503	25.148	26.060	0.000	20.743	41.283	40.540	20.131	25.199	36.711	52.951	49.029	21.872	32.486	49.594	66.859
2017	1,959	37.510	18.718	23.667	33.431	49.048	23.039	25.381	0.000	16.983	36.167	39.300	20.847	23.948	35.664	51.824	48.685	22.112	31.438	49.203	66.383
2018	2,096	38.196	19.144	23.580	34.421	50.127	20.950	26.926	0.000	6.234	37.790	39.793	21.078	23.766	35.842	53.369	48.598	22.332	31.126	50.070	66.680
2019	2,253	39.864	19.092	24.832	36.620	52.859	23.671	27.412	0.000	10.968	42.900	41.692	21.215	25.167	38.149	56.153	49.005	22.042	32.092	49.669	66.332
2020	2,371	41.453	19.461	26.041	38.572	55.502	25.450	27.654	0.000	14.581	46.536	43.917	21.264	26.983	40.517	59.279	49.548	22.450	30.902	50.257	67.371
2021	2,463	42.894	19.697	26.959	40.167	58.147	27.562	27.852	1.411	18.950	49.335	45.635	21.382	28.617	43.147	61.565	50.119	22.757	32.166	51.188	68.719
2022	2,147	43.215	19.625	27.214	41.062	59.019	28.062	27.632	1.846	19.659	49.985	45.697	21.334	28.037	44.113	61.571	50.513	22.456	32.521	51.855	68.738
Whole sample	21,461	40.767	19.428	25.483	37.501	54.640	26.849	27.497	0.000	18.947	47.462	42.896	21.174	26.360	39.602	57.779	49.265	22.398	31.469	50.003	67.245

Notes: This table presents time-series descriptive statistics for the main outcome variables of our working sample used in the paper: the ESG score and the scores for the Environmental (E), Social (S), and Governance (G) pillars.

Table 3: Firm-level characteristics across firms' ESG tendency

	N	Mean	SD	p25	p50	p75		
Panel A: Full sample ($y = ESG$)								
$Exp^{Brd}(y)$	21,461	28.542	13.479	18.945	28.949	38.614		
$Exp^{Int}(y)$	21,461	24.445	20.419	3.412	22.883	39.530		
$Exp^{Loc}(y)$	21,461	23.366	12.898	12.007	24.958	33.609		
$Exp^{Ind}(y)$	21,461	24.961	11.830	14.777	27.558	33.921		
Analyst Coverage	21,461	1.989	1.098	1.386	2.197	2.890		
B/M Ratio	21,461	0.494	0.482	0.207	0.401	0.683		
Firm Size	21,461	21.941	1.961	20.762	21.981	23.189		
Leverage	21,461	28.792	28.886	5.582	23.531	42.161		
ROA	21,461	0.059	20.662	0.603	3.154	7.644		
Stock Return	21,461	16.689	61.510	-12.508	9.151	32.552		
Tobin's Q	21,461	2.281	2.184	1.127	1.560	2.499		
Board Achievements	21,461	41.927	23.418	25.000	41.667	58.333		
Board Age	21,461	63.186	4.511	60.500	63.200	65.846		
Board Diversity	21,461	17.032	12.945	9.091	16.667	25.000		
Board Grad. Education	21,461	37.939	21.560	22.222	37.500	50.000		
Board Independence	21,461	81.878	13.261	75.000	85.714	90.000		
Board Interlocking	21,461	38.683	26.144	16.667	37.500	57.143		
Board Size	21,461	8.147	2.515	7.000	8.000	10.000		
	Below median y-score ($D(y) = 0$)			Above median y-score ($D(y) = 1$)			Diff.	
	N	Mean	SD	N	Mean	SD	Δ Mean	p-value
Panel B: Subsamples ($y = ESG$)								
$Exp^{Brd}(y)$	10,736	24.203	13.419	10,725	32.884	12.067	8.681	0.000
$Exp^{Int}(y)$	10,736	16.822	17.876	10,725	32.075	19.952	15.253	0.000
$Exp^{Loc}(y)$	10,736	22.845	12.980	10,725	23.887	12.794	1.041	0.000
$Exp^{Ind}(y)$	10,736	24.040	11.686	10,725	25.883	11.902	1.843	0.000
Analyst Coverage	10,736	1.609	1.063	10,725	2.369	0.997	0.760	0.000
B/M Ratio	10,736	0.520	0.515	10,725	0.469	0.445	-0.052	0.000
Firm Size	10,736	21.060	1.788	10,725	22.822	1.716	1.762	0.000
Leverage	10,736	27.604	32.724	10,725	29.982	24.390	2.379	0.000
ROA	10,736	-3.918	26.670	10,725	4.040	10.517	7.958	0.000
Stock Return	10,736	19.083	73.676	10,725	14.292	46.108	-4.791	0.000
Tobin's Q	10,736	2.408	2.512	10,725	2.155	1.788	-0.253	0.000
Board Achievements	10,736	34.910	22.168	10,725	48.952	22.512	14.043	0.000
Board Age	10,736	63.133	5.113	10,725	63.239	3.815	0.106	0.085
Board Diversity	10,736	12.627	12.323	10,725	21.442	12.018	8.815	0.000
Board Grad. Education	10,736	33.361	22.002	10,725	42.522	20.091	9.161	0.000
Board Independence	10,736	78.279	14.835	10,725	85.481	10.278	7.203	0.000
Board Interlocking	10,736	32.677	26.721	10,725	44.695	24.099	12.018	0.000
Board Size	10,736	7.443	2.548	10,725	8.852	2.273	1.409	0.000

Notes: Panel A shows descriptive statistics for the main firm-level characteristics of the entire working sample. Panel B provides descriptive statistics for two subsamples split according to the dummy variable $D(y)$, which takes the value 1 if a firm's ESG score is above the median ESG score of the entire sample (and zero otherwise). The left-hand columns display summary statistics for firm-year observations with $D(y) = 0$, while the right-hand columns display summary statistics for firm-year observations with $D(y) = 1$. The column labeled 'Diff.' reports the estimated coefficients from regressing each variable on $D(y)$. Robust standard errors are used to calculate p-values, which are reported in the final column.

Table 4: Multivariate analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: ESG score									
$Exp^{Brd}(y)$	0.882***				0.827***	0.826***	0.715***	0.600***	0.467***
	(0.182)				(0.180)	(0.180)	(0.177)	(0.174)	(0.172)
$Exp^{Int}(y)$		0.769***			0.732***	0.731***	0.683***	0.601***	0.462***
		(0.156)			(0.154)	(0.154)	(0.151)	(0.147)	(0.145)
$Exp^{Loc}(y)$			0.131			0.065	-0.106	-0.145	-0.255
			(0.408)			(0.403)	(0.392)	(0.384)	(0.381)
$Exp^{Ind}(y)$				4.752***			4.640***	4.273***	4.160***
				(0.535)			(0.529)	(0.509)	(0.491)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.821	0.822	0.821	0.824	0.822	0.822	0.825	0.828	0.831
Panel B: E score									
$Exp^{Brd}(y)$	1.766***				1.619***	1.595***	0.787***	0.666**	0.550**
	(0.315)				(0.311)	(0.310)	(0.273)	(0.269)	(0.270)
$Exp^{Int}(y)$		1.378***			1.262***	1.248***	0.940***	0.845***	0.710***
		(0.258)			(0.256)	(0.256)	(0.234)	(0.226)	(0.224)
$Exp^{Loc}(y)$			1.289**			1.175**	0.164	0.370	0.323
			(0.508)			(0.500)	(0.452)	(0.438)	(0.431)
$Exp^{Ind}(y)$				10.558***			10.356***	10.506***	10.423***
				(0.502)			(0.503)	(0.492)	(0.486)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.792	0.792	0.792	0.813	0.793	0.793	0.813	0.818	0.819
Panel C: S score									
$Exp^{Brd}(y)$	1.021***				0.969***	0.960***	0.840***	0.721***	0.637***
	(0.206)				(0.204)	(0.204)	(0.203)	(0.200)	(0.201)
$Exp^{Int}(y)$		0.747***			0.705***	0.698***	0.637***	0.563***	0.472***
		(0.174)			(0.173)	(0.173)	(0.171)	(0.168)	(0.170)
$Exp^{Loc}(y)$			0.599			0.493	0.218	0.127	0.107
			(0.441)			(0.437)	(0.429)	(0.423)	(0.423)
$Exp^{Ind}(y)$				4.235***			4.084***	3.669***	3.620***
				(0.501)			(0.498)	(0.487)	(0.481)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.795	0.795	0.794	0.797	0.795	0.795	0.798	0.800	0.801
Panel D: G score									
$Exp^{Brd}(y)$	0.834***				0.810***	0.802***	0.672***	0.593**	0.458*
	(0.257)				(0.256)	(0.256)	(0.254)	(0.253)	(0.249)
$Exp^{Int}(y)$		0.702***			0.685***	0.682***	0.635***	0.570***	0.412**
		(0.204)			(0.203)	(0.203)	(0.200)	(0.199)	(0.196)
$Exp^{Loc}(y)$			0.584			0.526	0.442	0.404	0.227
			(0.485)			(0.483)	(0.481)	(0.482)	(0.476)
$Exp^{Ind}(y)$				3.645***			3.485***	3.255***	3.200***
				(0.692)			(0.690)	(0.689)	(0.675)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.652	0.652	0.651	0.653	0.652	0.652	0.654	0.655	0.660

Notes: This table presents the results of a series of regressions that examine the impact of exposure to ESG measures on ESG scores. The financial controls include lagged values of analyst coverage, B/M ratio, firm size, leverage, stock return, and Tobin's Q. The board controls consist of current values for board achievements, board age, board diversity, board graduate education, board independence, board interlocking, and board size. We detail how we construct each variable in the Internet Appendix. Panels A, B, C, and D present the estimated coefficients for ESG, E, S, and G, respectively. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: Total effect by shocked percentile

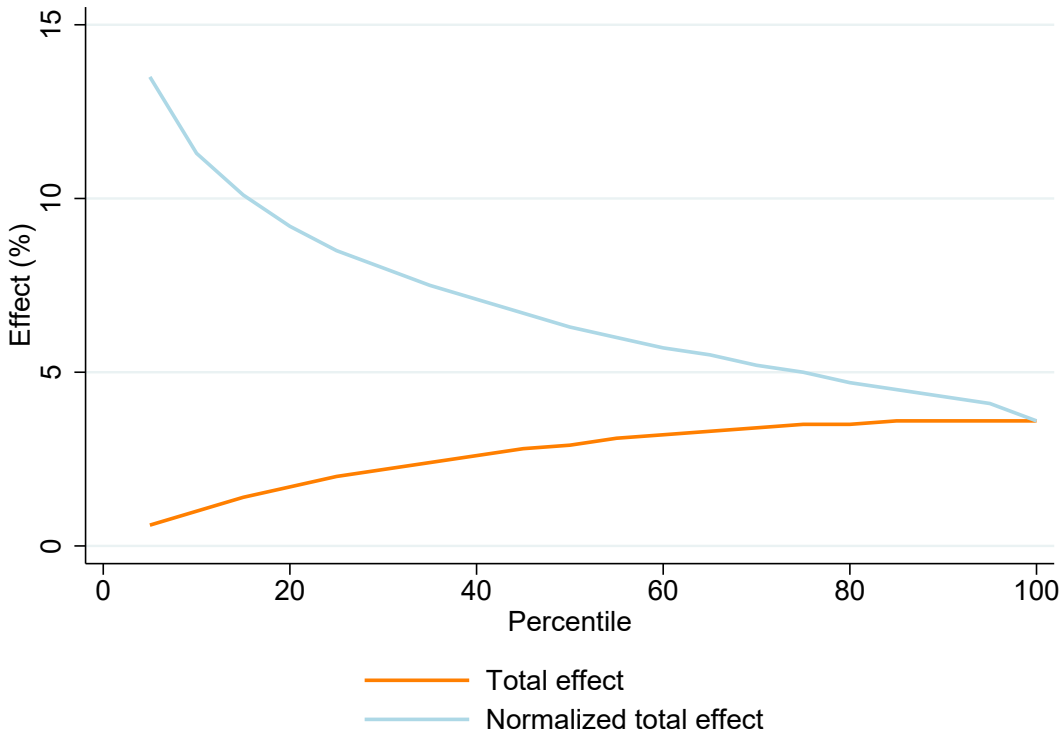


Figure 3: Distribution of total impact from a 1SD shock to the top 25% most central firms

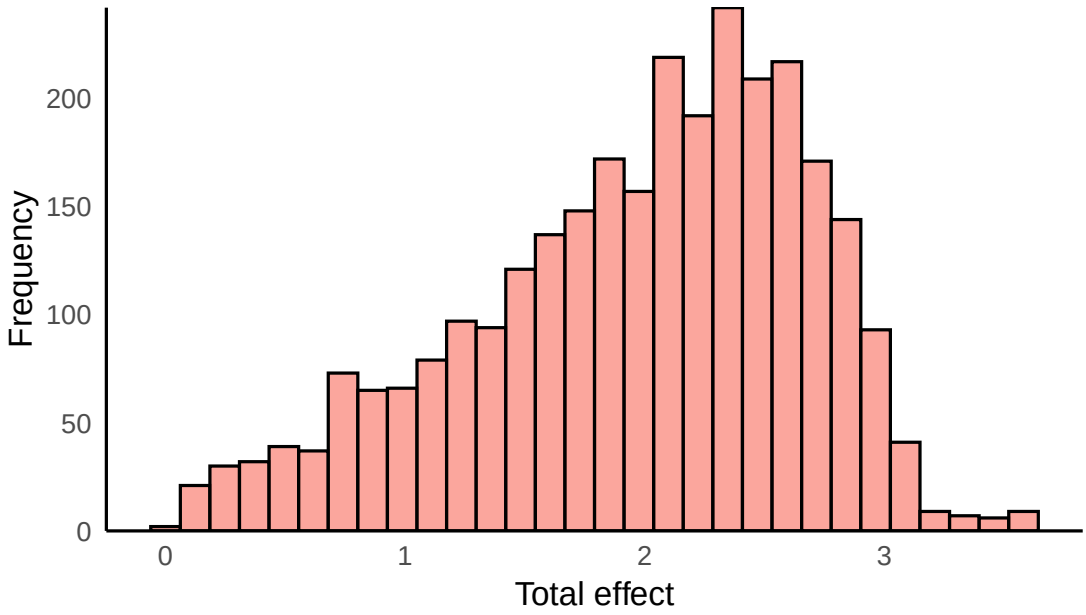


Table 5: Instrumental variables regressions

	Board exposure			
	(1)	(2)	(3)	(4)
	ESG	E	S	G
$Exp^{Brd}(y)$	0.730***	1.683***	0.675**	0.675*
	(0.236)	(0.467)	(0.277)	(0.367)
$Exp^{Int}(y)$	0.453***	0.641***	0.471***	0.409**
	(0.145)	(0.226)	(0.169)	(0.196)
$Exp^{Loc}(y)$	-0.263	0.292	0.105	0.217
	(0.381)	(0.431)	(0.423)	(0.476)
$Exp^{Ind}(y)$	4.141***	10.286***	3.618***	3.173***
	(0.491)	(0.487)	(0.481)	(0.675)
Firm controls	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461
Adjusted R^2	0.053	0.131	0.031	0.025

Notes: This table shows the results of instrumental variable regressions using shift-share instruments to instrument for Board exposures and Interlocks exposures. The Bartik-like instruments are constructed by replacing, in the exposure formula, the ESG score of the neighboring firm by the industry mean ESG score of the industry in which the neighboring firm operates. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: High and low performance

	ROA				ROE				M/B Ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ESG	*E*	*S*	*G*	*ESG*	*E*	*S*	*G*	*ESG*	*E*	*S*	*G*
$Exp^{Brd-HP}(y)$	0.260*	0.217	0.405**	0.176	0.297**	0.275	0.421**	0.196	0.348***	0.264	0.295**	0.451**
	(0.144)	(0.223)	(0.170)	(0.195)	(0.145)	(0.226)	(0.171)	(0.191)	(0.131)	(0.191)	(0.145)	(0.179)
$Exp^{Brd-LP}(y)$	0.169	0.076	0.078	0.468***	0.139	0.016	0.079	0.459***	0.213	0.178	0.259	0.406**
	(0.123)	(0.189)	(0.142)	(0.174)	(0.123)	(0.187)	(0.142)	(0.174)	(0.142)	(0.218)	(0.165)	(0.196)
$Exp^{Int}(y)$	0.452***	0.725***	0.467***	0.384*	0.454***	0.726***	0.468***	0.384*	0.442***	0.713***	0.459***	0.380*
	(0.146)	(0.225)	(0.171)	(0.196)	(0.146)	(0.225)	(0.171)	(0.196)	(0.145)	(0.225)	(0.171)	(0.195)
$Exp^{Loc}(y)$	-0.251	0.332	0.124	0.217	-0.251	0.332	0.124	0.215	-0.255	0.328	0.118	0.201
	(0.380)	(0.432)	(0.422)	(0.476)	(0.380)	(0.432)	(0.422)	(0.475)	(0.380)	(0.431)	(0.423)	(0.475)
$Exp^{Ind}(y)$	4.155***	10.463***	3.628***	3.156***	4.156***	10.467***	3.628***	3.156***	4.149***	10.441***	3.629***	3.143***
	(0.492)	(0.486)	(0.482)	(0.674)	(0.492)	(0.486)	(0.482)	(0.674)	(0.491)	(0.485)	(0.481)	(0.674)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.831	0.819	0.801	0.660	0.831	0.819	0.801	0.660	0.831	0.819	0.801	0.661

Notes: This table shows the results of estimating an augmented baseline specification by distinguishing links with peer firms based on their financial performance. Specifically, we differentiate between peers that had positive industry-adjusted financial performance in the past three years and those with non-positive financial performance. We then compute two new sub-measures: $Exp_{it}^{Brd-HP}(y)$ and $Exp_{it}^{Brd-LP}(y)$, which capture the peer exposure to ESG through high-performance and low-performance peer firms, respectively. Performance is measured using return on assets (ROA), return on equity (ROE), and Market-to-Book Ratio. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Degree of influence of peers

Panel A: Firm level board influence								
	Board Age				Peer Centrality			
	(1) ESG	(2) E	(3) S	(4) G	(5) ESG	(6) E	(7) S	(8) G
$Exp^{Brd-HI}(y)$	0.311**	0.232	0.268*	0.509***	0.341**	0.202	0.411**	0.539**
	(0.130)	(0.200)	(0.153)	(0.186)	(0.148)	(0.232)	(0.178)	(0.211)
$Exp^{Brd-LI}(y)$	0.217	0.128	0.416***	0.281	0.019	0.437***	0.040	-0.166
	(0.135)	(0.214)	(0.152)	(0.178)	(0.120)	(0.149)	(0.136)	(0.179)
$Exp^{Int}(y)$	0.445***	0.718***	0.450***	0.383*	0.467***	0.720***	0.479***	0.413**
	(0.145)	(0.225)	(0.171)	(0.195)	(0.145)	(0.224)	(0.170)	(0.196)
$Exp^{Loc}(y)$	-0.249	0.329	0.118	0.221	-0.246	0.323	0.122	0.239
	(0.380)	(0.432)	(0.422)	(0.475)	(0.381)	(0.431)	(0.422)	(0.476)
$Exp^{Ind}(y)$	4.149***	10.450***	3.617***	3.142***	4.171***	10.373***	3.638***	3.211***
	(0.492)	(0.485)	(0.481)	(0.674)	(0.492)	(0.487)	(0.482)	(0.675)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.831	0.819	0.801	0.661	0.831	0.819	0.801	0.660
Panel B: Board member influence								
	Board Age				Peer Centrality			
	(1) ESG	(2) E	(3) S	(4) G	(5) ESG	(6) E	(7) S	(8) G
$Exp^{Brd-HI}(y)$	0.236	0.338	0.418**	0.338	0.449***	0.459*	0.579***	0.545**
	(0.148)	(0.229)	(0.178)	(0.210)	(0.161)	(0.255)	(0.190)	(0.221)
$Exp^{Brd-LI}(y)$	0.324**	0.245	0.347**	0.324	0.078	0.172	0.045	0.051
	(0.139)	(0.208)	(0.161)	(0.200)	(0.095)	(0.135)	(0.110)	(0.143)
$Exp^{Int}(y)$	0.445***	0.701***	0.451***	0.394**	0.460***	0.712***	0.473***	0.408**
	(0.145)	(0.224)	(0.170)	(0.196)	(0.145)	(0.224)	(0.170)	(0.196)
$Exp^{Loc}(y)$	-0.251	0.328	0.113	0.233	-0.254	0.317	0.112	0.228
	(0.381)	(0.431)	(0.422)	(0.476)	(0.381)	(0.431)	(0.423)	(0.476)
$Exp^{Ind}(y)$	4.157***	10.428***	3.618***	3.187***	4.160***	10.416***	3.623***	3.191***
	(0.491)	(0.486)	(0.482)	(0.674)	(0.491)	(0.485)	(0.481)	(0.674)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.831	0.819	0.801	0.660	0.831	0.819	0.801	0.660

Notes: Panel A presents results from an extended version of the baseline specification, in which the original measure of peer board exposure is decomposed into two components: $Exp_{it}^{Brd-HI}(y)$ and $Exp_{it}^{Brd-LI}(y)$. These variables capture the ESG exposure of peer firms with, respectively, more influential boards and less influential boards. Board influence is determined based on firm-level characteristics. Specifically, a board is classified as *influential* if the firm's board satisfies at least one of two criteria: (i) the average age of its board members is above the median and (ii) the firm's degree centrality within the peer network is above the median. Firms meeting at least one of these conditions are classified as having influential boards. In Panel B, board influence is determined based on the characteristics of individual directors. Specifically, a board is classified as *influential* if it includes at least one *influential* director. We identify influential directors using two indicators: (i) the director's age and (ii) the director's degree centrality within the peer network at the director level. For each indicator, we compute the sample median, and classify a director as influential if their value on either indicator exceeds this threshold. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Upstream, downstream, horizontal and unrelated connections

	(1) ESG	(2) E	(3) S	(4) G
$Exp^{Brd-Up}(y)$	0.078	0.058	0.054	0.123
	(0.145)	(0.209)	(0.162)	(0.215)
$Exp^{Brd-Down}(y)$	-0.016	-0.410*	0.041	0.213
	(0.140)	(0.211)	(0.171)	(0.196)
$Exp^{Brd-H}(y)$	0.328**	0.966***	0.133	0.446**
	(0.146)	(0.233)	(0.171)	(0.208)
$Exp^{Brd-UR}(y)$	0.151	0.251	0.174	0.017
	(0.104)	(0.179)	(0.116)	(0.155)
$Exp^{Int}(y)$	0.452***	0.703***	0.477***	0.381*
	(0.146)	(0.224)	(0.171)	(0.195)
$Exp^{Loc}(y)$	-0.236	0.336	0.135	0.235
	(0.381)	(0.431)	(0.424)	(0.476)
$Exp^{Ind}(y)$	4.110***	10.157***	3.621***	3.130***
	(0.492)	(0.485)	(0.484)	(0.673)
Firm controls	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461
Adjusted R^2	0.831	0.820	0.801	0.660

Notes: This table presents the results of estimating an augmented baseline specification by distinguishing links with peer firms based on four types of relationships: suppliers (upstream), customers (downstream), industry peers (horizontal), and firms that are neither upstream, downstream, nor horizontally related (unrelated). These distinctions allow us to compute the following sub-measures: $Exp_{it}^{Brd-Up}(y)$ for upstream positioned peer firms, $Exp_{it}^{Brd-Down}(y)$ for downstream positioned peer firms, $Exp_{it}^{Brd-H}(y)$ for horizontally positioned peer firms, and $Exp_{it}^{Brd-UR}(y)$ for unrelated peer firms. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Top *E*-related offenses					Top *S*		
	N° events	Mean penalty	SD	N° treated	N° not-yet treated	N° events	Mean penalty	
2005	15	195.5	357.2	281	399	5	426.6	
2006	9	31.0	64.2	286	133	10	211.7	
2007	11	476.1	1,397.1	244	94	6	41.3	
2008	10	9.9	10.3	352	117	7	24.0	
2009	12	27.9	43.1	359	113	10	87.0	
2010	18	26.0	50.5	449	110	13	47.2	
2011	13	78.1	180.4	414	99	8	50.7	
2012	21	20.9	57.0	479	77	11	68.2	
2013	21	94.5	227.0	500	60	14	232.4	
2014	19	23.7	44.7	518	55	18	184.4	
2015	21	307.7	1,124.0	740	123	26	93.1	
2016	13	78.9	213.9	728	159	16	80.2	
2017	11	44.0	87.6	764	161	14	45.7	
2018	15	87.5	216.2	893	125	14	144.0	
2019	5	6.8	3.9	351	34	12	565.2	1

Table 9: Difference-in-differences estimations

	Parametric TWFE				Non-parametric TWFE				Callaway-Sant'Anna			
	(1) Top E	(2) EWE	(3) Top S	(4) SH Scandal	(5) Top E	(6) EWE	(7) Top S	(8) SH Scandal	(9) Top E	(10) EWE	(11) Top S	(12) SH Scandal
$PostEvent$	3.733***	1.857**	2.575***	1.792***								
	(0.809)	(0.722)	(0.529)	(0.525)								
$t-7$					-2.634	-3.900	0.851	-2.015	-0.560	1.101	-2.713*	-0.765
					(3.259)	(4.372)	(2.306)	(1.803)	(1.215)	(2.121)	(1.522)	(0.907)
$t-6$					-1.706	-5.821	1.250	-1.875	0.353	-0.200	-0.001	0.929
					(2.966)	(3.653)	(1.960)	(1.646)	(0.933)	(1.899)	(1.386)	(0.941)
$t-5$					-2.767	-4.698	0.466	-0.790	-0.930	0.102	-0.424	0.110
					(2.580)	(3.052)	(1.739)	(1.439)	(0.813)	(1.211)	(0.926)	(0.786)
$t-4$					-0.065	-5.419**	-0.879	-1.290	-0.025	1.932	0.316	0.459
					(2.090)	(2.333)	(1.338)	(1.131)	(0.889)	(1.324)	(0.983)	(0.772)
$t-3$					-2.419*	-6.747***	-2.025**	-2.322***	0.348	0.279	-0.128	-0.657
					(1.344)	(1.896)	(0.980)	(0.861)	(0.801)	(1.547)	(0.865)	(0.731)
$t-2$					-2.173**	-3.418***	-1.651***	-1.498***	0.479	-0.037	0.312	1.343**
					(0.933)	(1.047)	(0.632)	(0.571)	(0.602)	(1.448)	(0.748)	(0.676)
$t-1$									0.985	2.526*	1.075*	0.884
									(0.615)	(1.338)	(0.628)	(0.561)
t					-1.103**	0.359	0.130	0.097	2.710***	1.880**	1.083**	0.284
					(0.542)	(0.651)	(0.432)	(0.363)	(0.499)	(0.752)	(0.505)	(0.444)
$t+1$					0.625	1.508*	0.879	0.230	3.864***	3.868***	2.901***	0.492
					(0.729)	(0.769)	(0.567)	(0.461)	(0.757)	(1.030)	(0.728)	(0.627)
$t+2$					2.704***	1.823**	2.202***	1.565***	7.274***	4.361***	5.379***	1.573**
					(0.864)	(0.841)	(0.615)	(0.580)	(1.199)	(1.213)	(0.929)	(0.787)
$t+3$					4.275***	2.743***	3.052***	2.442***	9.398***	6.791***	6.988***	2.502***
					(0.982)	(0.865)	(0.714)	(0.683)	(1.565)	(1.617)	(1.090)	(0.938)
$t+4$					5.398***	3.266***	3.385***	2.482***	10.775***	7.440***	7.512***	2.128**
					(1.099)	(0.919)	(0.827)	(0.777)	(1.980)	(1.800)	(1.360)	(1.083)
$t+5$					5.954***	4.044***	4.311***	2.965***	10.926***	8.560***	7.892***	2.309
					(1.262)	(1.096)	(0.940)	(0.898)	(2.491)	(2.073)	(1.826)	(1.421)
$t+6$					7.288***	4.268***	4.488***	3.602***	10.285***	8.681***	8.378***	3.126
					(1.400)	(1.310)	(1.053)	(1.041)	(3.056)	(3.316)	(2.222)	(2.051)
$t+7$					7.977***	4.864***	4.757***	4.070***	6.825*	10.003***	7.944***	3.339
					(1.543)	(1.382)	(1.170)	(1.176)	(3.830)	(3.129)	(2.636)	(2.418)
Observations	26,133	19,474	26,133	26,133	26,133	19,474	26,133	26,133	26,133	19,474	26,133	26,133
Adjusted R^2	0.773	0.776	0.772	0.771	0.775	0.777	0.773	0.772				

Notes: Standard errors clustered at the firm level. In the case of extreme weather events (EWE) standard errors are clusteres at the firm and MSA-year level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Difference-in-differences - Standard two-way fixed effects regression

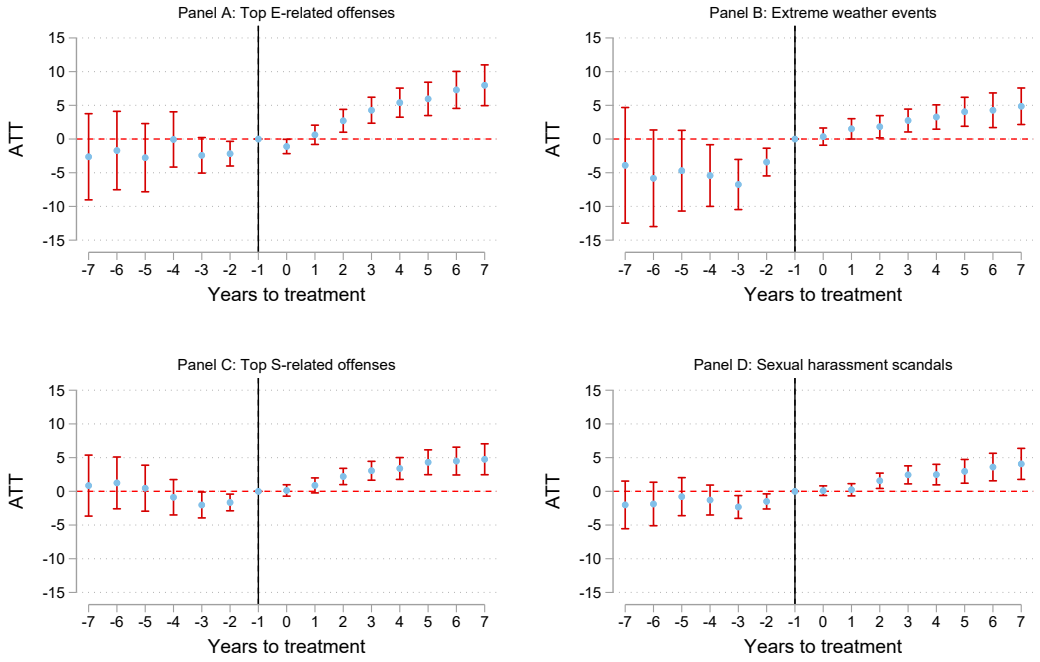
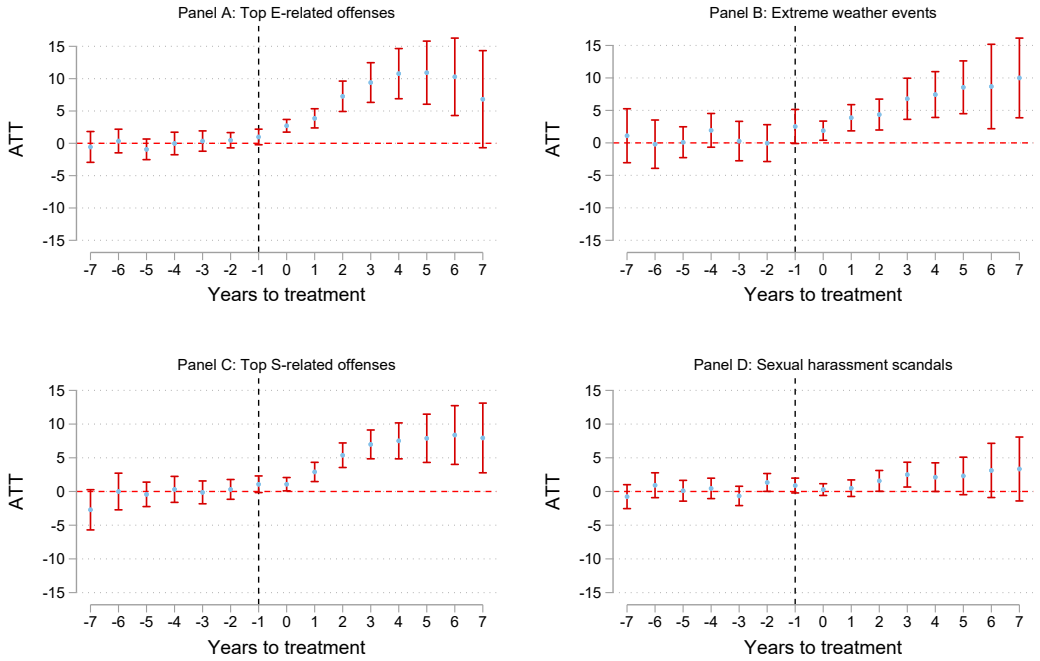


Figure 5: Difference-in-differences - Callaway and Sant'Anna



Appendix for
The Ripple Effect: ESG Decisions in Director Networks

A Variable definitions

Most of the definitions for the financial variables are considered standard in the literature. The items in parentheses refer to the corresponding field name in Refinitiv Eikon, while a star in parentheses means that the variable was to be computed from other variables. Throughout the paper, we use lagged financial variables. BoardEx Individual Profiles database is used to compute board variables.

Exposure Variables

Each year t, we construct four measures of exposure to ESG at the firm-level. All of these measures are constructed as follows:

$$Exp^{p}_{it}(y) = \sum_{j=1}^{N} s^{p}_{ijt} \times y_{jt},$$

such that

$$s^{p}_{ijt} = \frac{w^{p}_{ijt}}{\sum_{j=1}^{N} w^{p}_{ijt}}, \quad p \in \{Brd, Inter, Loc, Ind\},$$

where y_{jt} is the y-score of peer firm j in year t, and w^{p}_{ijt} are the elements of network p's proximity matrix.

For the baseline specification, we simply use y_{jt} to assess peers ESG. However, for the robustness checks, we also explore alternative measures of peers' ESG. In particular, we use:

$$\overline{y}_{jt} = \frac{y_{j,t-1} + y_{j,t-2} + y_{j,t-3}}{3},$$

which corresponds to the three-year lagged moving average of peer j's y-score.

The weights w_{ijt}^{p} of each exposure are given by:

> ***Peer Exposure*** $(p = Brd)$: $w_{ijt}^{Brd} = \sum_{(p,q)\in i(t)\times j(t)|p\neq q} \mathbb{1}(p\ knows\ q) \times \Delta_{pqt}$, $i(t)$ denotes the set of board members from firm i in year t, $j(t)$ represents the set of board members from firm j in year t, $\mathbb{1}$ is an indicator function that takes the value of 1 if director p in firm i has served as board member with director q in firm j prior to year t, and Δ_{pqt} is the overlapping number of years between directors p and q until year t (inclusive) arising from their historical overlap in boards through their careers as firm directors. Firms that are not socially connected, according to our data, are assigned a value of zero.
>
> ***Interlock Exposure*** $(p = Inter)$: w_{ijt}^{Int} is the number of interlocking board members between focal firm i and focal firm j in year t. Firms that are not interlocking, according to our data, are assigned a value of zero.
>
> ***Local Exposure*** $(p = Loc)$: w_{ijt}^{Loc} is an indicator function taking the value of one if firm j's headquarter is located in the same MSA of focal firm i's headquarter, and zero otherwise. Firms that are located alone in an MSA, according to our data, are assigned a value of zero.
>
> ***Industry Exposure*** $(p = Ind)$: w_{ijt}^{Ind} is an indicator function taking the value of one if firm j operates in the same industry of focal firm i, and zero otherwise. Firms that operate alone in an industry, according to our data, are assigned a value of zero.

When constructing board sub-exposures, we compute them as follows:

$$Exp_{it}^{Brd-G}(y) = \sum_{j=1}^{N} s_{ijt}^{Brd-G} \times y_{jt},$$

such that

$$s_{ijt}^{Brd-G} = \frac{w_{ijt}^{Brd} \times \mathbb{1}\{jt \in G\}}{\sum_{j=1}^{N} w_{ijt}^{Brd} \times \mathbb{1}\{jt \in G\}},$$

where set G comprises allegedly influential firms, and $\mathbb{1}\{jt \in G\}$ is a dummy variable equal to 1 if firm-year jt belongs to set G, and 0 otherwise.

Financial Variables

> ***Analyst Coverage***: natural logarithm of one plus number of analysts covering the firm (`TR.NumberOfAnalysts`).

B/M Ratio: ratio between book value of total equity (`TR.TotalEquity`) and company market capitalization (`TR.CompanyMarketCap`), winsorized at the [1,99] percentiles by year.

Firm Size: natural logarithm of the total assets of the company (`TR.TotalAssetsReported`).

Leverage: ratio between total debt (`TR.TotalDebtOutstanding`) and lagged total assets (`TR.TotalAssetsReported`), multiplied by 100.

ROA: return on assets (`TR.ROATotalAssetsPercent`), winsorized at the [1,99] percentiles by year.

ROE: ratio between net income after taxes (`TR.NetIncomeAfterTaxes`) and average total assets $\left(\frac{\texttt{TR.TotalAssetsReported}+\text{lagged }\texttt{TR.TotalAssetsReported}}{2}\right)$, multiplied by 100 and winsorized at the [1,99] percentiles by year.

Stock Return: ratio [closing price of stock (`TR.PriceClose`) - lagged closing price of stock]/lagged closing price of stock, multiplied by 100.

Tobin's Q: ratio [total assets (`TR.TotalAssetsReported`) - total equity (`TR.TotalEquity`) + market capitalization (`TR.CompanyMarketCap`)]/total assets (`TR.TotalAssetsReported`), winsorized at the [1,99] percentiles by year.

Board Variables

Board Achievements: proportion of the firm's year-t board members who accomplished an academic or professional "achievement" before year t.

Board Age: average age of the firm's year-t board members.

Board Diversity: proportion of women on the firm's year-t board.

Board Grad. Education: proportion of the firm's year-t board members who received a graduate degree before year t.

Board Independence: proportion of the firm's year-t board members who are classified as "independent" in year t (i.e. their `rolename` field contains the word "independent" on it).

Board Interlocking: proportion of the firm's year-t board members who participate in more than one board in year t.

Board Size: firm's number of board members in year t.

B Cross propagation

Table 10: ESG cross propagation

	(1)	(2)	(3)	(4)	(5)
Panel A: E score					
$Exp^{Brd}(ESG)$	0.922***	0.917***	0.906***	0.914***	0.853***
	(0.302)	(0.302)	(0.301)	(0.301)	(0.268)
$Exp^{Brd}(y)$		1.208***	1.193***	1.146***	0.286***
		(0.127)	(0.126)	(0.126)	(0.100)
$Exp^{Int}(y)$			0.231*	0.222	0.038
			(0.135)	(0.135)	(0.124)
$Exp^{Loc}(y)$				0.630***	0.265**
				(0.136)	(0.106)
$Exp^{Ind}(y)$					4.127***
					(0.126)
Firm controls	Yes	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.798	0.799	0.800	0.800	0.821
Panel B: S score					
$Exp^{Brd}(ESG)$	0.575***	0.576***	0.570***	0.569***	0.571***
	(0.203)	(0.203)	(0.203)	(0.203)	(0.202)
$Exp^{Brd}(y)$		0.217**	0.210**	0.202**	0.108
		(0.089)	(0.089)	(0.088)	(0.087)
$Exp^{Int}(y)$			0.115	0.111	0.065
			(0.101)	(0.101)	(0.101)
$Exp^{Loc}(y)$				0.129	0.123
				(0.120)	(0.122)
$Exp^{Ind}(y)$					0.996***
					(0.130)
Firm controls	Yes	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.799	0.799	0.799	0.799	0.801
Panel C: G score					
$Exp^{Brd}(ESG)$	0.370	0.378	0.380	0.382	0.382
	(0.284)	(0.283)	(0.284)	(0.283)	(0.284)
$Exp^{Brd}(y)$		0.279**	0.276**	0.263**	0.251**
		(0.118)	(0.117)	(0.118)	(0.118)
$Exp^{Int}(y)$			0.045	0.040	0.035
			(0.113)	(0.113)	(0.113)
$Exp^{Loc}(y)$				0.179*	0.178*
				(0.108)	(0.108)
$Exp^{Ind}(y)$					0.161
					(0.127)
Firm controls	Yes	Yes	Yes	Yes	Yes
Board controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.659	0.659	0.659	0.659	0.659

Notes: This table presents regression results examining the propagation that stems from a broad ESG dimension that is common across pillars or operates through pillar-specific actions. To do this, we regress each pillar score on the overall ESG exposure and an orthogonalized pillar-specific exposure measure. Specifically, to isolate pillar-specific variation from the common ESG component, we follow a two-step procedure. In the first step, we regress each ESG pillar score on the overall ESG score, controlling for firm and year fixed effects: $y_{it} = \alpha_i + \alpha_t + \beta \times ESG_{it} + \varepsilon^{y}_{it}$, where $y_{it} \in \{E_{it}, S_{it}, G_{it}\}$. Thus, the residual from this regression captures the specific component of each pillar after partialling out the common ESG component. We use these residuals to construct orthogonalized exposure measures for each pillar. In the second step, we estimate: $y_{it} = \alpha_i + \alpha_t + \theta \times \text{Exp}^{\text{Brd}}_{it}(ESG) + \phi \times Exp^{Brd,\perp}_{it}(y) + \mathbf{X}'_{it}\gamma + \varepsilon_{it}$, where $Exp^{Brd}_{it}(ESG)$ denotes exposure to the overall ESG score through board connections, and $Exp^{Brd,\perp}_{it}(y)$ denotes the orthogonalized exposure based on the residualized pillar scores. Column (1) includes only the overall ESG exposure and controls, while subsequent columns sequentially add orthogonalized exposures. Financial controls include lagged values of analyst coverage, book-to-market ratio, firm size, leverage, stock return, and Tobin's Q. Board controls include current values for board achievements, age, diversity, graduate education, independence, interlocking, and size. All regressions include firm and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Further Robustness

Table 11: Alternative imputation methods

	Industry mean				Last observation carried backward			
	(1) ESG	(2) E	(3) S	(4) G	(5) ESG	(6) E	(7) S	(8) G
$Exp^{Brd}(y)$	0.407**	0.704***	0.601***	0.317	0.411**	0.618**	0.622***	0.300
	(0.161)	(0.257)	(0.189)	(0.242)	(0.170)	(0.271)	(0.201)	(0.242)
$Exp^{Int}(y)$	0.432***	0.707***	0.435***	0.390*	0.461***	0.783***	0.479***	0.377*
	(0.144)	(0.220)	(0.167)	(0.201)	(0.149)	(0.233)	(0.172)	(0.207)
$Exp^{Loc}(y)$	-0.512	0.518	0.167	0.259	-0.700	0.615	-0.398	0.308
	(0.399)	(0.410)	(0.467)	(0.464)	(0.582)	(0.527)	(0.593)	(0.612)
$Exp^{Ind}(y)$	2.896***	9.348***	2.991***	4.012***	5.084***	11.165***	5.356***	3.606***
	(0.275)	(0.434)	(0.292)	(0.389)	(0.514)	(0.451)	(0.574)	(0.762)
Observations	21461	21461	21461	21461	21461	21461	21461	21461

Notes: This table presents the results of baseline regressions, where the exposure measure is constructed by imputing scores for firms with missing ESG data. The left columns assign the industry mean to firms with missing scores, or zero if the industry mean is not available. The right columns replace each missing value with the most recent previously available value, or zero otherwise. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: LSEG - Lagged peer ESG values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: ESG score									
$Exp^{Brd}(y)$	0.822***				0.764***	0.761***	0.685***	0.587***	0.455**
	(0.196)				(0.194)	(0.194)	(0.192)	(0.188)	(0.186)
$Exp^{Int}(y)$		0.826***			0.794***	0.792***	0.761***	0.683***	0.524***
		(0.169)			(0.168)	(0.168)	(0.166)	(0.161)	(0.158)
$Exp^{Loc}(y)$			0.378			0.305	0.149	0.212	0.163
			(0.519)			(0.514)	(0.511)	(0.495)	(0.491)
$Exp^{Ind}(y)$				4.333***			4.216***	3.927***	3.782***
				(0.632)			(0.628)	(0.604)	(0.589)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.821	0.822	0.821	0.823	0.822	0.822	0.824	0.827	0.830
Panel B: E score									
$Exp^{Brd}(y)$	1.439***				1.271***	1.251***	0.738**	0.689**	0.567*
	(0.333)				(0.329)	(0.329)	(0.314)	(0.309)	(0.308)
$Exp^{Int}(y)$		1.451***			1.352***	1.343***	1.094***	1.029***	0.900***
		(0.282)			(0.280)	(0.281)	(0.272)	(0.264)	(0.261)
$Exp^{Loc}(y)$			0.834			0.683	-0.040	0.316	0.304
			(0.599)			(0.595)	(0.588)	(0.566)	(0.556)
$Exp^{Ind}(y)$				5.667***			5.422***	5.660***	5.619***
				(0.468)			(0.476)	(0.465)	(0.461)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.792	0.792	0.792	0.798	0.793	0.793	0.798	0.803	0.805
Panel C: S score									
$Exp^{Brd}(y)$	0.970***				0.918***	0.905***	0.841***	0.711***	0.618***
	(0.224)				(0.222)	(0.222)	(0.222)	(0.218)	(0.220)
$Exp^{Int}(y)$		0.798***			0.763***	0.754***	0.726***	0.638***	0.534***
		(0.187)			(0.186)	(0.186)	(0.185)	(0.183)	(0.184)
$Exp^{Loc}(y)$			0.776			0.643	0.388	0.326	0.348
			(0.529)			(0.523)	(0.521)	(0.513)	(0.513)
$Exp^{Ind}(y)$				2.787***			2.611***	2.111***	2.025***
				(0.585)			(0.583)	(0.573)	(0.572)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.795	0.795	0.794	0.795	0.795	0.795	0.796	0.799	0.799
Panel D: G score									
$Exp^{Brd}(y)$	0.628**				0.611**	0.604**	0.512*	0.441	0.312
	(0.289)				(0.289)	(0.288)	(0.287)	(0.285)	(0.281)
$Exp^{Int}(y)$		0.702***			0.693***	0.689***	0.658***	0.598***	0.402*
		(0.220)			(0.219)	(0.219)	(0.217)	(0.215)	(0.211)
$Exp^{Loc}(y)$			0.778			0.737	0.693	0.746	0.618
			(0.598)			(0.597)	(0.595)	(0.596)	(0.590)
$Exp^{Ind}(y)$				2.816***			2.673***	2.570***	2.468***
				(0.803)			(0.800)	(0.796)	(0.776)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461	21,461
Adjusted R^2	0.652	0.652	0.651	0.652	0.652	0.652	0.653	0.654	0.660

Notes: This table presents the results of a series of regressions that examine the impact of exposure to ESG measures on ESG scores. The financial controls include lagged values of analyst coverage, B/M ratio, firm size, leverage, stock return, and Tobin's Q. The board controls consist of current values for board achievements, board age, board diversity, board graduate education, board independence, board interlocking, and board size. We detail how we construct each variable in the Internet Appendix. Panels A, B, C, and D present the estimated coefficients for ESG, E, S, and G, respectively. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: MSCI ESG scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: ESG score									
$Exp^{Brd}(y)$	0.474***				0.463***	0.462***	0.366***	0.363***	0.352***
	(0.136)				(0.135)	(0.135)	(0.133)	(0.132)	(0.131)
$Exp^{Int}(y)$		0.349***			0.341***	0.340***	0.263***	0.261***	0.241**
		(0.104)			(0.104)	(0.103)	(0.102)	(0.101)	(0.101)
$Exp^{Loc}(y)$			0.093			0.057	-0.330	-0.323	-0.334
			(0.328)			(0.326)	(0.302)	(0.301)	(0.296)
$Exp^{Ind}(y)$				4.499***			4.490***	4.512***	4.529***
				(0.356)			(0.358)	(0.361)	(0.361)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925
Adjusted R^2	0.625	0.625	0.624	0.642	0.625	0.625	0.642	0.643	0.644
Panel B: E score									
$Exp^{Brd}(y)$	0.783***				0.761***	0.747***	0.432*	0.424*	0.403*
	(0.259)				(0.257)	(0.259)	(0.232)	(0.231)	(0.231)
$Exp^{Int}(y)$		0.535**			0.517**	0.508**	0.243	0.241	0.222
		(0.218)			(0.217)	(0.218)	(0.201)	(0.200)	(0.200)
$Exp^{Loc}(y)$			0.558			0.485	-0.650	-0.659	-0.668
			(0.510)			(0.511)	(0.456)	(0.456)	(0.454)
$Exp^{Ind}(y)$				9.792***			9.813***	9.790***	9.819***
				(0.522)			(0.532)	(0.536)	(0.537)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925
Adjusted R^2	0.727	0.727	0.727	0.756	0.727	0.727	0.756	0.756	0.756
Panel C: S score									
$Exp^{Brd}(y)$	0.746***				0.727***	0.729***	0.461**	0.458**	0.465**
	(0.221)				(0.220)	(0.220)	(0.206)	(0.206)	(0.206)
$Exp^{Int}(y)$		0.649***			0.637***	0.638***	0.422**	0.431**	0.444***
		(0.177)			(0.177)	(0.177)	(0.169)	(0.168)	(0.169)
$Exp^{Loc}(y)$			-0.031			-0.091	-0.523	-0.489	-0.490
			(0.421)			(0.420)	(0.414)	(0.413)	(0.413)
$Exp^{Ind}(y)$				7.367***			7.318***	7.337***	7.345***
				(0.534)			(0.534)	(0.534)	(0.535)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925
Adjusted R^2	0.566	0.566	0.565	0.594	0.566	0.566	0.595	0.596	0.596
Panel D: G score									
$Exp^{Brd}(y)$	1.288***				1.280***	1.268***	1.066***	1.062***	1.050***
	(0.301)				(0.302)	(0.302)	(0.296)	(0.295)	(0.293)
$Exp^{Int}(y)$		0.486**			0.472**	0.466**	0.391*	0.377*	0.368*
		(0.212)			(0.211)	(0.211)	(0.207)	(0.207)	(0.207)
$Exp^{Loc}(y)$			0.484			0.384	-0.197	-0.199	-0.203
			(0.498)			(0.496)	(0.454)	(0.454)	(0.447)
$Exp^{Ind}(y)$				6.967***			6.893***	6.879***	6.898***
				(0.491)			(0.495)	(0.495)	(0.493)
Firm controls	No	No	No	No	No	No	No	Yes	Yes
Board controls	No	No	No	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925	18,925
Adjusted R^2	0.424	0.423	0.423	0.444	0.424	0.424	0.445	0.446	0.449

Notes: This table presents the results of a series of regressions that examine the impact of exposure to ESG measures on ESG scores. The financial controls include lagged values of analyst coverage, B/M ratio, firm size, leverage, stock return, and Tobin's Q. The board controls consist of current values for board achievements, board age, board diversity, board graduate education, board independence, board interlocking, and board size. We detail how we construct each variable in the Internet Appendix. Panels A, B, C, and D present the estimated coefficients for ESG, E, S, and G, respectively. Standard errors clustered at the firm level are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Rated vs. incoming firms

Table 14: Difference in ESG scores between rated and incoming firms

	Rated firms			Incoming firms			Average difference	
	N	Mean	SD	N	Mean	SD	Diff.	p-value
2005	336	33.391	16.921	41	40.248	15.921	3.603	0.126
2006	390	35.821	17.006	1	16.770	0	-14.523	0.005
2007	401	40.589	18.016	27	31.617	15.140	-10.436	0.000
2008	426	43.677	19.608	107	27.905	13.105	-14.708	0.000
2009	533	42.562	20.720	65	25.536	10.845	-14.653	0.000
2010	605	42.671	20.078	17	28.141	13.063	-13.229	0.000
2011	640	43.667	20.207	5	24.416	14.422	-15.771	0.000
2012	663	43.935	19.880	1	26.139	0	-18.347	0.004
2013	671	44.176	19.867	1	21.841	0	-12.667	0.006
2014	665	44.977	19.292	11	21.419	11.449	-18.486	0.000
2015	682	47.959	19.159	375	27.921	11.089	-19.193	0.000
2016	1,091	43.403	18.944	418	26.452	9.960	-16.403	0.000
2017	1,601	40.996	18.416	358	21.920	10.170	-19.165	0.000
2018	2,048	38.529	19.183	48	24.015	9.925	-14.856	0.000
2019	2,199	40.357	19.017	54	19.795	8.322	-17.569	0.000
2020	2,315	41.929	19.383	56	21.769	10.428	-17.975	0.000
2021	2,438	43.123	19.631	25	20.546	12.014	-11.761	0.000
2022	2,141	43.222	19.623	6	40.864	22.062	-18.963	0.000
Total	19,845	41.990	19.431	1,616	25.758	11.507	-15.230	0.000

Notes: This table reports descriptive statistics for two samples. The left-hand columns (Rated firms) show statistics for firms that already had a non-missing ESG score in the previous year $t-1$, and still have a non-missing ESG score in year t. The middle columns (Incoming firms) show statistics for firms that did not have an available ESG score in year $t-1$ but do in year t. The right-hand columns show the average difference in means between these two groups by presenting the beta coefficient estimate and its p-value from regressing, for each year t, the following specification: $ESG_i = \alpha + \beta \times IncomingFirm_i + \varepsilon_i$, where $IncomingFirm_i$ is a dummy variable equal to 1 if firm i is an incoming firm, and 0 if it is an already rated firm.

E First and higher order network effects

The panel model described in Equation (4) can be represented in matrix form as:

$$\mathbf{y}_t = \beta^{\text{Brd}}\mathbf{S}_t^{\text{Brd}}\mathbf{y}_t + \beta^{\text{Int}}\mathbf{S}_t^{\text{Int}}\mathbf{y}_t + \beta^{\text{Loc}}\mathbf{S}_t^{\text{Loc}}\mathbf{y}_t + \beta^{\text{Ind}}\mathbf{S}_t^{\text{Ind}}\mathbf{y}_t + \vartheta\mathbf{X}_t + \boldsymbol{\varepsilon}_t \tag{7}$$

where $\mathbf{y}_t = (y_{1,t}, \ldots, y_{n,t})'$ is a vector of ESG scores at time t, and $\mathbf{S}_t^p$ is a matrix of bilateral proximity measures for the network $p \in \{\text{Brd}, \text{Int}, \text{Loc}, \text{Ind}\}$, with (i, j) elements defined as in Equation (3). $\mathbf{X}_t$ is a matrix whose columns contain the fixed effects and control variables described in Equation (4). The parameters $\beta^{\text{Brd}}, \beta^{\text{Int}}, \beta^{\text{Loc}}$, and β^{Ind} are the same as in Equation (4), and ϑ is a vector of coefficients corresponding to the control variables in $\mathbf{X}_t$.

This equation has a structural representation:

$$\mathbf{y}_t = \left(I - \beta^{\text{Brd}}\mathbf{S}_t^{\text{Brd}} - \beta^{\text{Int}}\mathbf{S}_t^{\text{Int}} - \beta^{\text{Loc}}\mathbf{S}_t^{\text{Loc}} - \beta^{\text{Ind}}\mathbf{S}_t^{\text{Ind}}\right)^{-1}(\vartheta\mathbf{X}_t + \boldsymbol{\varepsilon}_t) \tag{8}$$

which relates changes in $\mathbf{y}_t$ to changes in the exogenous variables $\mathbf{X}_t$ or to shocks to each firm's ESG scores, $\boldsymbol{\varepsilon}_t$. Using this expression, we can compute the overall effect of a shock to the ESG score of a particular firm or group of firms on all other firms. We can also compute counterfactual effects assuming only one network is operating. For instance, if only the board connection network is active, the effects of a shock vector $\boldsymbol{\varepsilon}_t$ are given by:

$$\mathbf{y}_t = \left(I - \beta^{\text{Brd}}\mathbf{S}_t^{\text{Brd}}\right)^{-1}\boldsymbol{\varepsilon}_t \tag{9}$$

This expression captures how a shock to one or more firms propagates through the network via both direct and indirect linkages. The matrix inverse $(I - \hat{\beta}^{\text{Brd}}\mathbf{S}^{\text{Brd}})^{-1}$ summarizes the cumulative multiplier effects from all orders of peer interactions.

Additionally, the polynomial expansion of this expression can be used to decompose the first- and higher-order effects of a shock vector:

$$\mathbf{y}_t = \sum_{j=0}^{\infty}\left(\beta^{\text{Brd}}\mathbf{S}^{\text{Brd}}\right)^j\boldsymbol{\varepsilon}_t \tag{10}$$

where each term in the sum corresponds to a "round" of effects. While all these rounds occur simultaneously in the network, this representation allows us to distinguish the direct effect from the effects resulting from within-network propagation.

However, to focus on the effects excluding the initial shock, we define the net change as $\Delta\mathbf{y}_t = \mathbf{y}_t - \boldsymbol{\varepsilon}_t$, which can be written as:

$$\Delta \mathbf{y}_t = \sum_{j=1}^{\infty} \left(\beta^{\text{Brd}} \mathbf{S}^{\text{Brd}}\right)^j \boldsymbol{\varepsilon}_t = \left[\left(I - \beta^{\text{Brd}} \mathbf{S}_t^{\text{Brd}}\right)^{-1} - I\right] \boldsymbol{\varepsilon}_t \tag{11}$$

Thus, the first-order effect is given by the first term of the sum, $\beta^{\text{Brd}} \mathbf{S}^{\text{Brd}} \boldsymbol{\varepsilon}_t$, and the total effect is given by the full matrix expression above.

F Identifying upstream and downstream relationships

There are two basic IO matrices: make and use

- The use matrix entries $U_{i,j}$ contain the value (real and nominal) of commodity row i used as an input in industry column j. It also includes a VA row. This matrix can be represented in share of inputs form by dividing each entry in a column by the sum of inputs $U_j = \sum_{i \neq VA} U_{i,j}$ (excluding VA sectors): $u_{i,j} = U_{i,j}/U_j$. In this way, $u_{i,j}$ is the share of industry j firms' inputs represented by good i.
- The make matrix represents the production of goods by industry. This is because good i is not only produced by industry i. Each entry $M_{i,j}$ represents the amount of column good j produced by firms in row industry i. Dividing each entry by the sum across rows $M_j = \sum_i M_{i,j}$, one gets the share of good j total production corresponding to firms in industry i: $m_{i,j} = M_{i,j}/M_j$
- We aim to compute $s_{i,j}$ the share of industry i's inputs represented by goods produced by industry j. Using the previous notation, this share will correspond to:

$$s_{i,j} = \sum_k u_{k,i} \times m_{j,k}$$

- This process could be simplified by transposing the shares matrices. Let $\tilde{u} = u'$ and $\tilde{m} = m'$, such that $\tilde{u}_{i,j}$ is the share of industry i's inputs represented by good j, and $\tilde{m}_{i,j}$ is the share of good i total production represented by firms in industry j. By doing this transformation,

$$s_{i,j} = \sum_k \tilde{u}_{i,k} \times \tilde{m}_{k,j}$$

  Which can be directly expressed in matrix form as:

$$s = \tilde{u} \times \tilde{s}$$

- With this matrix, we can define IO relations among industries by considering that industry j is upstream to industry i if $s_{i,j} > s_{j,i}$

For practical purposes, we use a single year (2020) instead of using time series variation. These matrices are quite stable, and changes in IO relations are not the paper's main point.