The Ripple Effect: ESG Decisions in Director Networks

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Abstract

We study the propagation of firms' Environmental, Social, and Governance (ESG) scores through director networks. Using detailed director-network data and a panel regression approach, we show that a firm's ESG ratings positively respond to those of its peer-director-connected firms. This transmission of ESG ratings through peer director networks differs from that through locality, industry, and interlocks. Firms are likelier 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 provides additional evidence of the causal nature of this effect across diverse ESG dimensions.

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1 Introduction

Substantial literature has studied why firms engage in ESG-related actions.[1] The prominent views are that firms spend time and resources on these activities because they accrue financial benefits (the *value* view) or because critical stakeholders and decision-makers care for them (the *values* view) (Starks, 2023). Of course, these are not excluding channels, and both types of forces probably shape firms' actions.

Despite these advances, the process by which firms' decision-makers form their views about the convenience of ESG activities (*value*) or shape their preferences for them (*values*) has gathered less attention. Among these decision-makers, board members likely play a key role, and the literature on board influences has provided substantial evidence that they do not operate in a vacuum and learn from peers' actions, experiences, and preferences (Chiu et al., 2013; Foucault and Fresard, 2014; Hong et al., 2004; Leary and Roberts, 2014). It is, therefore, natural to conjecture that these forces would also influence the decisions to engage in ESG-related actions. If this is so, targeting and influencing key firms can be an effective policy tool.

This paper examines the role of inter-firm connections through board members in the propagation of ESG practices. We construct a proximity measure that captures the extent to which the board members of one firm have previously served alongside those of another. Using this measure, we investigate whether a firm's ESG score is influenced by the ESG performance of other firms to which it is closely linked through past professional interactions among their directors. We use two different, complementary approaches to document the role of peers for ESG propagation: panel data regressions and a differences-in-differences strategy.

In our panel data analysis, we introduce a measure of a firm's exposure to the ESG performance of other firms, termed Peer ESG Exposure, calculated as the proximity-weighted average of the (lagged) ESG scores of all other firms. This measure combines historical ESG

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

scores of U.S. companies from LSEG Eikon with BoardEx network data at the individual director level. Using within-firm variation, we investigate whether a firm's ESG score is higher when it is more exposed to high-ESG firms, finding this to be the case across all ESG pillars (though the effect is not statistically significant for Governance). Additionally, Board Interlock ESG Exposure and Industry ESG Exposure are positively associated with a firm's ESG rating, but their effects are largely independent of that of the peers.

Aside from considering firm and year fixed-effects and other kinds of connections, to address endogeneity concerns further, we incorporate firm- and board-level time-varying controls and conduct instrumental variables regressions, concluding that the documented relationship is likely causal. Also, we show that ESG practices are influenced within the same category: exposure to environmental practices enhances environmental performance, social exposure boosts social practices, and governance exposure influences governance practices. This pillar-specific transmission highlights that ESG diffusion is targeted and not merely generic, mitigating concerns that the findings reflect broader characteristics correlated with aggregate ESG.

We explore three mechanisms behind the results that are linked to the motivations (value and values) for engaging in ESG practices: peer learning, social pressure, and strategic considerations. We show that the ESG actions of peers influence a firm's ESG practices more strongly when the peers have had superior financial performance, suggesting that firms are more likely to follow other firms' practices when they are perceived as generating value. Also, the propagation is stronger for the connections between the firms that come from past interactions with more influential board members (as measured by age and interconnectedness), suggesting that social pressure and the desire to conform to norms set by high-status actors can drive corporate behavior (values). Finally, ESG practices are more likely to propagate among direct competitors, where firms may use ESG as a differentiation strategy to enhance competitive advantage. On the contrary, we do not see this kind of propagation for firms down the supply chain. This is relevant because it rules out a merely mechanical effect resulting from the fact that in some cases the ESG score of a firm directly incorporates the actions of its suppliers (e.g., CO2 emissions).

Our second approach to examining the propagation of ESG practices through peer networks compares the responses of connected and unconnected firms to various ESG-related shocks affecting other firms but not themselves. For the environmental dimension (E), we analyze the impact of extreme weather events, such as major hurricanes, and significant environmental fines. For the social dimension (S), we consider high-profile scandals, such as sexual harassment cases, and extreme fines. Assuming that the timing of these events is uncorrelated with preexisting relationships among firms, comparing the ESG trajectories of firms connected to affected firms via director networks with those of unconnected firms provides further evidence for the causal nature of peer influence.

Consistent with our baseline panel data findings, we observe that firms connected through peer networks to shocked firms significantly increase their ESG ratings in the same dimension compared to unconnected firms. These results hold across different types of events and econometric specifications, further strengthening the causal interpretation. Together, our two complementary methodologies—panel data regressions and difference-in-differences analyses—demonstrate not only consistent directional effects but also comparable magnitudes of ESG responses.

This paper contributes to several strands of literature. In the ongoing Value vs. Values debate (Starks, 2023), we provide evidence that ESG-related decisions are influenced not only by financial considerations but also by the choices of peers, regardless of the specific context a firm faces. Our findings align with the values perspective, as they suggest that individuals embedded in networks tend to emulate those who share similar principles. At the same time, we also support the value perspective, demonstrating that ESG propagation is influenced by peers' performance and strategic considerations, highlighting the interplay between ethical principles and financial incentives.

Several papers have documented that firms socially connected through interactions among non-board members—such as workers, clients, suppliers, financiers, and analysts—exhibit common behavior.[2] We expand on this literature by examining connections through the board of directors, a particularly influential body in decision-making. Crucially, we can identify with certainty directors who have shared meaningful interactions in the same professional context.

Other authors have found evidence of commonality of other firms' behaviors at the local level (Kedia et al., 2015; Rind et al., 2022), through board interlocks (Chiu et al., 2013), or via industrial links (Grieser et al., 2022b). Limited evidence is available on ESG matters and each of its dimensions separately, particularly regarding the role of peers. Jiraporn et al., 2014, Husted et al., 2016, and Li and Wang, 2022 show that the corporate social responsibility engagement of neighboring firms impacts a firm's decisions on the same matter, while Liu and Wu, 2016 and Cao et al., 2019 show a similar result when looking at industry peers (competitors), and Dai et al., 2021a and Schiller, 2018 when focusing on customer/supplier relationships. Chen et al., 2020 also find these effects when defining peers based on common institutional ownership. We contribute to this literature by introducing a novel dimension of firms' linkages–the peer network, and showing that it significantly contributes to the diffusion of ESG actions, even after controlling for the type of linkages considered in the literature. Braun et al., 2022 provides evidence of this in the context of corporate misconduct. Our methodology based on exogenous events lends further support for a causal interpretation of the results in that literature.

The literature has identified several determinants of ESG practice adoption, both internal——such as board and firm characteristics (Ferrell et al., 2016)——and external, including the regulatory environment (Dyck et al., 2019), stakeholder pressure (Dai et al., 2021b, Hartzmark and Sussman, 2019), competitive forces (Gantchev et al., 2024), and cultural and social norms (Cronqvist and Yu, 2017, Liang and Renneboog, 2017). Our research adds to this understanding by demonstrating that these forces can influence other firms indirectly through

[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.

peer network connections, even when these firms do not face these pressures directly.

Methodologically, our use of both panel data regressions and difference-in-differences strategies contributes to the empirical literature by providing evidence of causal relationships in corporate finance research. By demonstrating consistent results across different methodologies, we strengthen the case for the influence of board network connections on firms' ESG practices.

Finally, we contribute to policy by suggesting that targeting and influencing key directors or firms—based on their directors' observable characteristics—can be an effective tool for ESG adoption.

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 examine connections through interlocking boards (Chiu et al., 2013) and geographic and industrial proximity (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 proximity 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. Two firms are considered connected at time t if their current board members have previously served together on any board—whether for one of the two firms or a third company. 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

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

where $i(t)$ and $j(t)$ denote the set of non-interlocked board members from firm i and j in year t, respectively, $\mathbb{1}$ 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: board professional experiences, board interlocks, geographic proximity, and industry. For each dimension, the exposure is measured as the weighted average of the peers' past ESG scores.

$$Exp^{p}_{i,t}(ESG) = \sum_{j} s^{p}_{i,j,t} \times \overline{ESG}_{j,t-1}, \tag{2}$$

where

$$s^{p}_{i,j,t} = \frac{w^{p}_{ijt}}{\sum_j w^{p}_{ijt}}, \quad p \in \{Inter, Brd, Loc, Ind\}, \tag{3}$$

$$\overline{ESG}_{j,t-1} = \frac{ESG_{j,t-1} + ESG_{j,t-2} + ESG_{j,t-3}}{3}. \tag{4}$$

We follow the same approach for each component of the overall ESG score: environmental (E), social (S), and governance (G). Using lagged peer ESG scores mitigates the reflection problem arising from the simultaneous influence between peers' and the focal firm's behaviors, complicating causal interpretation. Incorporating a three-year moving average reflects the gradual nature of ESG adoption, recognizing that such practices typically take time to implement. This temporal smoothing also reduces noise in annual ESG scores, providing a more stable and representative measure of peers' ESG commitment. We compute the weights $s^{p}_{i,j,t}$ by including all firms, regardless of whether they have an ESG score. This approach prevents overemphasizing rated firms in the weighting. [3]

[3] This is equivalent to imputing a score of zero to unrated firms. Alternatively, one could impute them the average score of the firm's industry, of similar firms, or its initial score once it becomes rated.

3 Data and Descriptive Statistics

3.1 Data sources

This paper uses data from three main 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 penalties related to environmental and social offenses. Second, we identify natural disasters linked to climate change using the Emergency Events Database (EM-DAT) and georeference 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.

3.2 Data consolidation

Our working dataset combines information from the sources described earlier. 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.[4]

Second, we retain only firms for which we 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 2,542 firms, corresponding to 20,517 firm-year observations.

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

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 19,748 firm-year observations for 2,416 unique firms.

Fourth, 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.[5] This step yields 15,372 firm-year observations for 1,594 unique firms.

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

3.3 Descriptive statistics

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 40.767 (standard deviation of 19.428), with pillar averages of 26.849 (E), 42.896 (S), and 49.265 (G). Variability, in terms of standard deviation, is highest in the Environmental pillar (27.497) and lowest in the Social pillar (21.174), reflecting firms' tendency to score higher and more consistently on Governance and Social dimensions. Median scores further emphasize this pattern: 18.947 (E), 39.602 (S), and 50.003 (G). Notably, 21.2% 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.[6]

Over time, ESG scores have trended upward, while dispersion has remained stable, except for the Environmental pillar, whose standard deviation increased from 6.364 in 2005 to 19.659

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

[6]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.

in 2022. Similarly, the number of firms with ESG ratings in LSEG grew from about 300 in 2005 to over 1,300 in 2022. In the Appendix, we compare firms with existing ESG scores to incoming firms, finding that the latter typically have lower scores.

Table 1 describes the network of board professional connections for 2020. Panel A shows a network of approximately 2,500 firms linked by 200,000 peer-director relationships, yielding a sparse density of 0.06. Panel B highlights significant firm-level heterogeneity: some firms are isolated, while others exhibit high centrality. The alpha measure, representing the average proportion of a firm's connections contributed by its neighbors, ranges from 0% to over 33.3%, with an average of 6.4%.

Panel A of Table 3 provides summary statistics for our main network exposure measures, firm fundamentals, and board characteristics. Panel B compares these statistics for firms with 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). They 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 correlations suggest that spillover mechanisms may play a role in disseminating ESG practices. These findings also highlight the need to control for firm characteristics in our econometric framework, whether parametrically or nonparametrically.

4 Panel Regression Analysis

We present our findings in three steps. First, we detail the baseline results. Second, we investigate the mechanisms underlying these results, focusing on peer learning, social pressure, and strategic considerations. Finally, we use IV estimates to demonstrate that the observed relationships are likely causal.

4.1 Baseline specification

We analyze ESG spillover effects using the following baseline specification:

$$
\begin{aligned}
y_{it} = \alpha_i + \alpha_t + \beta^{Brd} \underbrace{Exp_{it}^{Brd}(y)}_{\text{Peer Exposure}} + \beta^{Int} \underbrace{Exp_{it}^{Int}(y)}_{\text{Interlock Exposure}} + \beta^{Loc} \underbrace{Exp_{it}^{Loc}(y)}_{\text{Local Exposure}} + \beta^{Ind} \underbrace{Exp_{it}^{Ind}(y)}_{\text{Industry Exposure}} \\
+ \gamma \mathbf{Board}_{it} + \delta \mathbf{Firm}_{i,t-1} + \varepsilon_{it}
\end{aligned}
\tag{5}
$$

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. Firm and year fixed effects (α_i and α_t) control for unobserved heterogeneity across these dimensions.

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.[7]

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

[7] See the Appendix for detailed variable definitions.

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 5 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 specifications for the overall ESG score (Panel A) as well as for the environmental (Panel B) and social (Panel C) dimensions. For the governance score (Panel D), the board exposure coefficient is positive but not statistically significant, with a magnitude similar to that observed for other ESG scores. 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.

The pillar-specific influence of ESG practices—where one ESG pillar affects the same pillar in connected firms, rather than aggregate ESG influencing aggregate ESG—is significant for two reasons. First, it shows that ESG transmission is targeted and specific, not a generic process. Firms appear to prioritize adopting specific ESG components based on peer behaviors rather than broadly emulating overall ESG performance. Second, it reduces concerns that our findings merely reflect broader characteristics correlated with aggregate ESG scores. By demonstrating that specific pillars drive similar pillars in connected firms, we provide stronger evidence that ESG diffusion operates through targeted, substantive practices within each dimension.

In each panel, the coefficient magnitude 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 dimension has a distinct impact and that the effect of peer exposure does not merely reflect similarities among firms within the same industry, locality, or interlocked networks that attract directors with similar past experiences.

The coefficient magnitude further decreases when firm- and board-level time-varying controls are added in columns (8) and (9), underscoring the importance of controlling for these factors. However, the changes in coefficient size across specifications remain relatively modest, averaging around 25%.

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. These findings align with existing literature, which highlights these connections as key factors in explaining commonalities in firm behavior and the adoption of ESG practices.

The influence of shared director experiences on ESG scores is notable but generally weaker than that of direct interlocking directorates, except for social performance. This indicates that while ESG practices diffuse through directors' shared experiences across firms, direct board interlocks exert a stronger effect. In the full specifications with all control variables (column (9) of each panel), a one-standard-deviation increase in Peer ESG, E, S, and G exposures corresponds to increases of 0.46, 0.57, 0.62, and 0.31 points in ESG, E, S, and G scores, respectively. The corresponding figures for exposures through interlocks are 0.52, 0.9, 0.53, and 0.4, respectively.

Geographic proximity to firms with higher ESG exposure is positively associated with a firm's ESG score, although this effect is not statistically significant. By contrast, industry exposure has the strongest impact: a one-standard-deviation increase in sector-level ESG exposure corresponds to a 3.8 points increase in a firm's ESG score (20% of the standard-deviation of the variable).

To assess the economic significance of our results, we conduct two counterfactual analyses focusing on board exposure. First, we examine the first-order and total effects, including cascade effects, of a 1 standard deviation increase in ESG scores among currently connected peers. Second, we analyze the total effects if this ESG increase were limited to top central firms (those at the 75th percentile of the degree centrality distribution) and the resulting cascade effects on the broader peer network

A 1 standard deviation increase in peers' ESG scores is associated with a 3.5% standard deviation increase in the focal firm's ESG score. For the E and S pillars, this increase in peers' scores corresponds to 4.7% and 4.5% standard deviation increases in the focal firm's E and S scores, respectively. When accounting for second-order effects (network feedback), the impact rises to 14%, 19%, and 19% standard deviation increases for the ESG, E, and S scores, respectively.

If the 1 standard deviation increase occurs only among top central firms, the total impact on firms across the network averages 12.7%, 18.5%, and 19.4% standard deviation increases in ESG, E, and S scores, respectively.

The effect sizes we observe align with those reported in the literature. For instance, Dai et al., 2021a 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.

4.2 Instrumental variable approach

To address potential endogeneity concerns and bolster the causal interpretation of our findings, we use a shift-share instrument based on industry-level ESG trends. FollowingBorusyak 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 $p = \{Brd, Int, Loc\}$ 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, and S remain positive and statistically significant across both peer effects and interlock specifications. These results indicate that our panel specification is robust to potential biases, reinforcing the causal interpretation of our main findings.

4.3 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* (aligning with ethical standards or social norms). 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 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.

4.3.1 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.

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 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 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.

4.3.2 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 is 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 its connected firms. Specifically, we analyze the influence of the boards to which the firm is linked. We hypothesize that board exposure to ESG has a stronger effect when it originates from connections to firms with more influential boards. To evaluate this, we construct two sub-measures: $Exp_{it}^{Brd-HI}(y)$ for board exposure to firms with influential boards and

$Exp_{it}^{Brd-LI}(y)$ for connections to firms with less influential boards. The split is determined by the median of each influence indicator. We use two metrics to measure board influence: the average age of board members and their average number of connections to other firms (interconnectedness).

Table 7 presents the results. For overall ESG scores, the coefficient for peer 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 Social (S) and Governance (G) 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.

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

4.3.3 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., 2021a 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 peer ESG exposures based on their relationship type. We construct four sub-measures of peer 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 **??** provides details on how we extract vertical inter-industry 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 column (1), 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.

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 peer ESG exposure on a firm’s ESG decisions. However, the relevance of each mechanism varies depending on the type of linkage, ESG pillar, and specific firm characteristics.

In terms of economic magnitudes, the effect of peer ESG exposure is substantially amplified under certain conditions: it is 23.5% larger when connected firms have above-median ROA, 2.9 times greater when connected firms have highly interconnected boards, and 2.4 times greater when connected firms operate within the same industry (horizontal connections).

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 ESG outcomes of firms socially connected to impacted firms (the treatment group) compared to those unconnected and unaffected (the control group). 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.[8] Treated firms are socially

[8]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.

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 9 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:

$$y_{it} = \alpha_i + \alpha_t + \beta PostEvent_{it} + \varepsilon_{it} \tag{6}$$

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

In Equation (6), $PostEvent_{it}$ 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 (7) 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 models.

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 10 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 2 and 3.

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 3.748 and 2.744 points, respectively. Similarly, top S-related events and sexual harassment scandals increase treated firms' S scores by 2.566 and 1.785 points, respectively. The CS model suggests even larger effects, with extreme events 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, Peer 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.

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Figure 1: Peers network formation

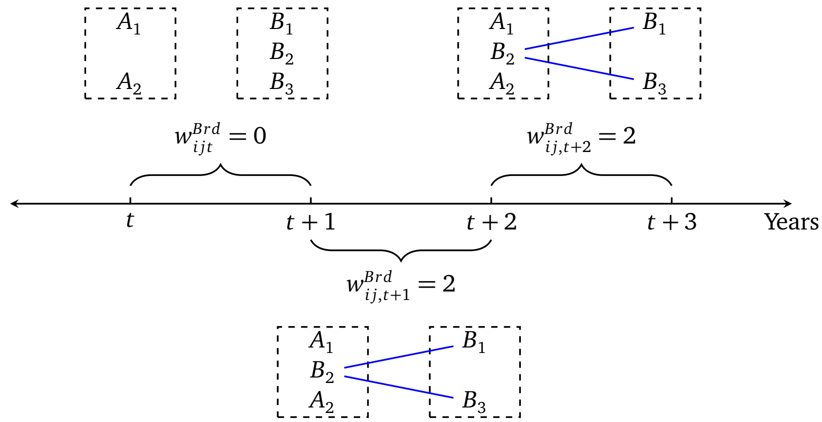

Table 1: Network statistics for 2020

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 centrality, clustering, and alpha summary 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
Alpha	0.064	0.152	0.005	0.017	0.333

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
Total	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	25.851	13.138	16.113	25.866	35.605		
$Exp^{Int}(y)$	21,461	22.090	19.247	0.000	19.834	35.952		
$Exp^{Loc}(y)$	21,461	20.219	12.147	9.508	20.585	29.715		
$Exp^{Ind}(y)$	21,461	21.634	11.416	11.292	22.438	30.738		
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	21.574	12.783	10,725	30.132	12.050	8.558	0.000
$Exp^{Int}(y)$	10,736	14.757	16.351	10,725	29.431	19.131	14.674	0.000
$Exp^{Loc}(y)$	10,736	19.695	12.169	10,725	20.744	12.103	1.049	0.000
$Exp^{Ind}(y)$	10,736	20.677	11.214	10,725	22.592	11.536	1.915	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									
$Exp^{Brd}(y)$	0.822***				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	0.791	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 5: Bartik IV regressions

	Peers				Interlocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ESG	E	S	G	ESG	E	S	G
$Exp^{Brd}(y)$	0.699***	1.269**	0.633**	0.602	0.457**	0.637**	0.620***	0.311
	(0.254)	(0.521)	(0.298)	(0.402)	(0.187)	(0.313)	(0.220)	(0.282)
$Exp^{Int}(y)$	0.516***	0.854***	0.534***	0.400*	0.484**	0.225	0.508**	0.518*
	(0.159)	(0.265)	(0.184)	(0.211)	(0.206)	(0.432)	(0.247)	(0.295)
$Exp^{Loc}(y)$	0.155	0.272	0.348	0.608	0.165	0.324	0.350	0.616
	(0.492)	(0.557)	(0.513)	(0.591)	(0.492)	(0.557)	(0.513)	(0.591)
$Exp^{Ind}(y)$	3.765***	5.524***	2.024***	2.430***	3.784***	5.691***	2.026***	2.460***
	(0.589)	(0.464)	(0.572)	(0.778)	(0.589)	(0.461)	(0.572)	(0.776)
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	0.048	0.062	0.023	0.022	0.048	0.062	0.023	0.023

Notes: This table shows the results of estimating instrumental variable regressions using shift-share instruments for 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) ESG	(2) E	(3) S	(4) G	(5) ESG	(6) E	(7) S	(8) G	(9) ESG	(10) E	(11) S	(12) G
$Exp^{Brd-HP}(y)$	0.286*	0.347	0.501***	0.084	0.295*	0.366	0.496***	0.102	0.335**	0.513**	0.323**	0.431**
	(0.157)	(0.255)	(0.185)	(0.211)	(0.157)	(0.257)	(0.185)	(0.209)	(0.141)	(0.216)	(0.157)	(0.189)
$Exp^{Brd-LP}(y)$	0.177	0.104	-0.012	0.542***	0.162	0.063	0.002	0.506***	0.218	-0.052	0.250	0.329
	(0.129)	(0.208)	(0.148)	(0.183)	(0.129)	(0.207)	(0.147)	(0.182)	(0.152)	(0.256)	(0.175)	(0.218)
$Exp^{Int}(y)$	0.517***	0.910***	0.534***	0.369*	0.517***	0.911***	0.533***	0.371*	0.507***	0.899***	0.522***	0.375*
	(0.159)	(0.262)	(0.185)	(0.211)	(0.159)	(0.262)	(0.185)	(0.211)	(0.159)	(0.262)	(0.185)	(0.210)
$Exp^{Loc}(y)$	0.167	0.317	0.353	0.605	0.166	0.317	0.354	0.603	0.159	0.321	0.361	0.587
	(0.491)	(0.555)	(0.513)	(0.590)	(0.491)	(0.556)	(0.513)	(0.590)	(0.490)	(0.554)	(0.513)	(0.590)
$Exp^{Ind}(y)$	3.760***	5.647***	2.021***	2.386***	3.762***	5.651***	2.020***	2.392***	3.747***	5.625***	2.006***	2.383***
	(0.590)	(0.460)	(0.573)	(0.777)	(0.590)	(0.460)	(0.573)	(0.777)	(0.590)	(0.460)	(0.572)	(0.776)
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	0.830	0.805	0.799	0.660	0.830	0.805	0.799	0.660	0.830	0.805	0.799	0.660

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 (M/B 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

	Board Age				Interconnectedness			
	(1) ESG	(2) E	(3) S	(4) G	(5) ESG	(6) E	(7) S	(8) G
$Exp^{Brd-HI}(y)$	0.306**	0.502**	0.269	0.228	0.371**	0.128	0.323*	0.373*
	(0.144)	(0.225)	(0.169)	(0.205)	(0.153)	(0.256)	(0.168)	(0.214)
$Exp^{Brd-LI}(y)$	0.189	-0.156	0.379**	0.382**	0.009	0.191	0.035	0.194
	(0.139)	(0.236)	(0.160)	(0.186)	(0.126)	(0.167)	(0.144)	(0.195)
$Exp^{Int}(y)$	0.511***	0.918***	0.515***	0.376*	0.514***	0.921***	0.530***	0.383*
	(0.159)	(0.262)	(0.185)	(0.210)	(0.159)	(0.262)	(0.185)	(0.211)
$Exp^{Loc}(y)$	0.166	0.319	0.357	0.601	0.170	0.319	0.368	0.601
	(0.491)	(0.556)	(0.513)	(0.590)	(0.490)	(0.556)	(0.512)	(0.589)
$Exp^{Ind}(y)$	3.761***	5.657***	2.003***	2.412***	3.775***	5.652***	2.033***	2.423***
	(0.591)	(0.461)	(0.573)	(0.777)	(0.590)	(0.460)	(0.573)	(0.777)
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	0.830	0.805	0.799	0.660	0.830	0.805	0.799	0.660

Notes: This table presents the results of estimating an extended baseline specification by distinguishing links with peer firms based on the degree of influence of their boards. Specifically, we differentiate between peers with influential boards and those with less influential boards. We consider two measures of board influence: their average age, and the average number of connections directors have to other firms. The split of connections is based on the median of each influence indicator, resulting in two new sub-measures: $Exp_{it}^{Brd-HI}(y)$ and $Exp_{it}^{Brd-LI}(y)$, which capture the peer exposure to ESG through the boards of influential and less influential peer firms, respectively. 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
$Exp^{Brd-Up}(y)$	0.152	0.208	0.038	0.142
	(0.149)	(0.233)	(0.167)	(0.228)
$Exp^{Brd-Down}(y)$	-0.057	-0.549**	0.051	0.090
	(0.147)	(0.231)	(0.183)	(0.211)
$Exp^{Brd-H}(y)$	0.379**	1.065***	0.257	0.448**
	(0.156)	(0.254)	(0.186)	(0.220)
$Exp^{Brd-UR}(y)$	0.130	0.161	0.114	0.024
	(0.110)	(0.190)	(0.126)	(0.158)
$Exp^{Int}(y)$	0.505***	0.878***	0.527***	0.371*
	(0.159)	(0.261)	(0.185)	(0.210)
$Exp^{Loc}(y)$	0.179	0.315	0.376	0.610
	(0.491)	(0.554)	(0.514)	(0.590)
$Exp^{Ind}(y)$	3.719***	5.378***	1.999***	2.378***
	(0.590)	(0.455)	(0.575)	(0.776)
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	0.830	0.805	0.799	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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Top E and S related offenses over time

	Top E-related offenses				Top S-related offenses			
	N° events	Mean penalty	SD	N° treated	N° events	Mean penalty	SD	N° treated
2005	15	195.5	357.2	281	5	426.6	565.2	166
2006	9	31.0	64.2	286	10	211.7	503.7	281
2007	11	476.1	1,397.1	244	6	41.3	37.0	292
2008	10	9.9	10.3	352	7	24.0	18.2	305
2009	12	27.9	43.1	359	10	87.0	99.0	375
2010	18	26.0	50.5	449	13	47.2	60.7	484
2011	13	78.1	180.4	414	8	50.7	38.9	408
2012	21	20.9	57.0	479	11	68.2	67.7	410
2013	21	94.5	227.0	500	14	232.4	576.7	454
2014	19	23.7	44.7	518	18	184.4	218.8	472
2015	21	307.7	1,124.0	740	26	93.1	152.1	786
2016	13	78.9	213.9	728	16	80.2	118.7	814
2017	11	44.0	87.6	764	14	45.7	71.2	845
2018	15	87.5	216.2	893	14	144.0	208.9	908
2019	5	6.8	3.9	351	12	565.2	1,414.4	854
Total	214	105.4	497.3	7,358	184	146.8	442.0	7,854

Notes: Amounts in millions of dollars.

Table 10: Difference-in-differences estimations

	Parametric TWFE				Non-parametric TWFE				Callaway-Sant'Anna			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	E	*E*	*S*	*S*	*E*	*E*	*S*	*S*	*E*	*E*	*S*	*S*
PostEvent	3.733***	2.747***	2.575***	1.792***								
	(0.809)	(0.727)	(0.529)	(0.525)								
$t-7$					-2.634	-3.866	0.851	-2.015	-0.560	1.101	-2.713*	-0.765
					(3.259)	(4.144)	(2.306)	(1.803)	(1.215)	(2.121)	(1.522)	(0.907)
$t-6$					-1.706	-6.386*	1.250	-1.875	0.353	-0.200	-0.001	0.929
					(2.966)	(3.397)	(1.960)	(1.646)	(0.933)	(1.899)	(1.386)	(0.941)
$t-5$					-2.767	-5.489*	0.466	-0.790	-0.930	0.102	-0.424	0.110
					(2.580)	(2.974)	(1.739)	(1.439)	(0.813)	(1.211)	(0.926)	(0.786)
$t-4$					-0.065	-4.746**	-0.879	-1.290	-0.025	1.932	0.316	0.459
					(2.090)	(2.302)	(1.338)	(1.131)	(0.889)	(1.324)	(0.983)	(0.772)
$t-3$					-2.419*	-6.381***	-2.025**	-2.322***	0.348	0.279	-0.128	-0.657
					(1.344)	(1.998)	(0.980)	(0.861)	(0.801)	(1.547)	(0.865)	(0.731)
$t-2$					-2.173**	-3.194***	-1.651***	-1.498***	0.479	-0.037	0.312	1.343**
					(0.933)	(1.051)	(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**	0.427	0.130	0.097	2.710***	1.880**	1.083**	0.284
					(0.542)	(0.537)	(0.432)	(0.363)	(0.499)	(0.752)	(0.505)	(0.444)
$t+1$					0.625	1.844***	0.879	0.230	3.864***	3.868***	2.901***	0.492
					(0.729)	(0.616)	(0.567)	(0.461)	(0.757)	(1.030)	(0.728)	(0.627)
$t+2$					2.704***	2.146***	2.202***	1.565***	7.274***	4.361***	5.379***	1.573**
					(0.864)	(0.654)	(0.615)	(0.580)	(1.199)	(1.213)	(0.929)	(0.787)
$t+3$					4.275***	3.274***	3.052***	2.442***	9.398***	6.791***	6.988***	2.502***
					(0.982)	(0.734)	(0.714)	(0.683)	(1.565)	(1.617)	(1.090)	(0.938)
$t+4$					5.398***	3.588***	3.385***	2.482***	10.775***	7.440***	7.512***	2.128**
					(1.099)	(0.804)	(0.827)	(0.777)	(1.980)	(1.800)	(1.360)	(1.083)
$t+5$					5.954***	3.908***	4.311***	2.965***	10.926***	8.560***	7.892***	2.309
					(1.262)	(0.920)	(0.940)	(0.898)	(2.491)	(2.073)	(1.826)	(1.421)
$t+6$					7.288***	4.722***	4.488***	3.602***	10.285***	8.681***	8.378***	3.126
					(1.400)	(1.150)	(1.053)	(1.041)	(3.056)	(3.316)	(2.222)	(2.051)
$t+7$					7.977***	5.264***	4.757***	4.070***	6.825*	10.003***	7.944***	3.339
					(1.543)	(1.218)	(1.170)	(1.176)	(3.830)	(3.129)	(2.636)	(2.418)
Observations	26,133	26,133	26,133	26,133	26,133	26,133	26,133	26,133				
Adjusted R^2	0.773	0.773	0.772	0.771	0.775	0.774	0.773	0.772				

Notes: Standard errors clustered at the firm level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: Difference-in-differences - Standard two-way fixed effects regression

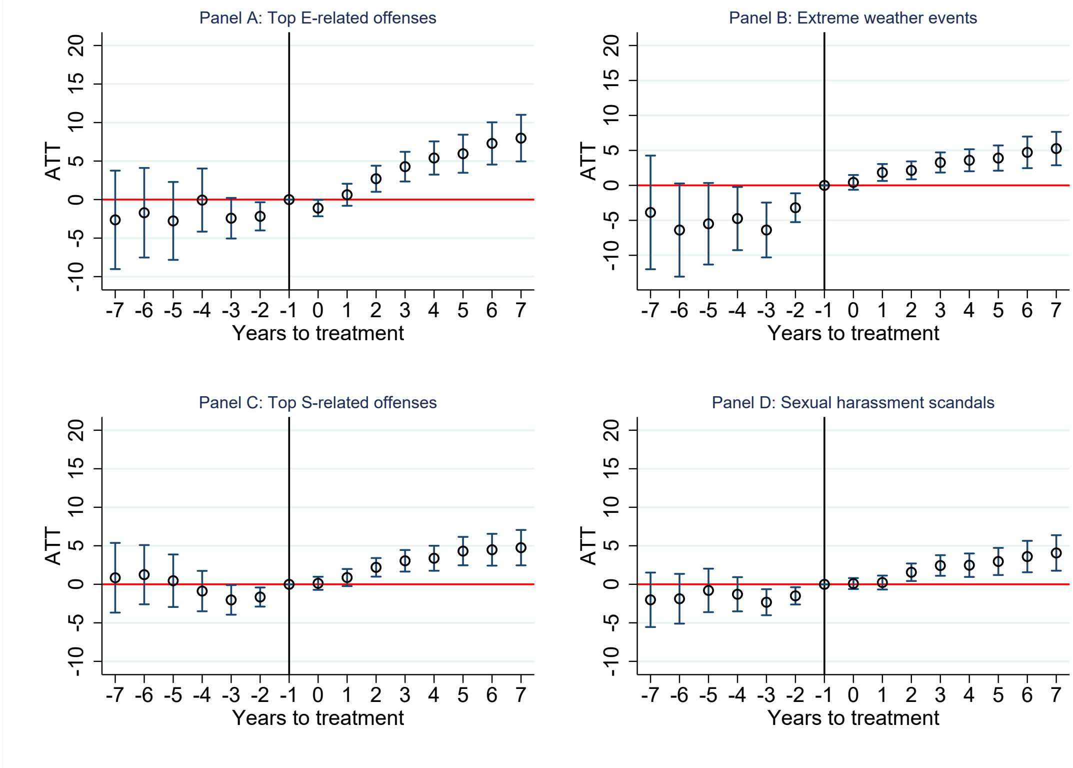

Figure 3: Difference-in-differences - Callaway and Sant'Anna