The Social Geography of Misconduct

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Abstract

We construct social and physical proximity measures between pairs of firms, using the professional trajectory of board members and geographic data. A firm's tendency to engage in corporate misconduct and earnings management increases with its social proximity to firms exhibiting similar past behavior. The effect is stronger when the link involves board members that are more influential. It is also higher when the conduct is less likely to be detected and when the neighboring firms were not heavily penalized when caught. Results are not driven by the endogenous matching between firms and directors and are independent of that of local norms.
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1 Introduction

Corporate misconduct seems to be pervasive (Graham et al. [2005], Dyck et al. [2021]). It hurts trust in people and organizations, ultimately dampening economic efficiency (Arrow [1974], Arrow [2010]).[1] It can take several forms, such as mistreatment of employees, environmental regulation violations, financial fraud or earnings management, and represents an extreme departure from the standards that society and financiers increasingly expect from firms. These types of conduct are hard to deter because of the difficulty of detecting and punishing them. Regulation and market discipline help but are not sufficient (Dyck et al. [2010]). Ethical norms regarding what is acceptable and what is not can also play a role (Parsons et al. [2018]).[2] What your peers *do* may also affect how you behave regarding these issues. This paper explores the relevance of peer effects by looking at whether the chance of a firm misbehaving is affected by the behavior of other firms that are close to it.

We use data at the director-firm level to develop a measure of social proximity that intends to capture the effect of peers beyond conventional proxies (e.g. industry- or geographical-related measures). In particular, we rely on the professional background of board members to assess the extent to which they have interacted with each other by measuring the time that they have concurrently served as directors at a given institution in the past. This allows us to compute a firm-to-firm pairwise social distance. We also use the specific location of firms' headquarters (geographic coordinates) to measure the bilateral distances between firms, as another proxy for local peer interactions.

A firm's tendency to engage in future corporate misconduct (CM) as well as in earnings management (EM) is positively affected by its geographical and social proximity to firms with a high rate of past misconduct. Firms that are one standard deviation closer in terms of social connections to a firm engaged in misconduct —equivalent to

[1] "Now trust has a very important pragmatic value, if nothing else. Trust is an important lubricant of a social system. It is extremely efficient; it saves a lot of trouble to have a fair degree of reliance on other people's word."

[2] The effects of social interactions must be interpreted with caution as they can be easily confounded with other possible unobserved factors, e.g. local social norms.

six more years of board overlap —are 14 percent more likely to commit CM, while its measure of EM is 0.6 standard deviations higher. Likewise, geographical exposure with misconduct commensurate to being 450 miles closer to a firm engaged in CM is associated with an increase of 17 percent in the probability of also behaving that way and a 0.16 standard deviations increase in the extent to which a firm manages its reported earnings. These effects are independent to those of being part of the same industry or locality (e.g. state or metropolitan area), for which we also provide evidence. Thus, our results are consistent with both social interactions and local norms being relevant determinants of the misconduct phenomena.

Recent studies show that some behavioral patterns cluster geographically mainly due to a regional context. For instance, in a seminal work, Glaeser et al. [1996] argues that local social norms can account for the persistent cross-sectional differences in crime rates. More recently, Parsons et al. [2018] use different misbehavior measures to proxy for local social norms and show that local customs can play an important role in explaining the observed regional differences in corporate financial misconduct.

Disentangling the role of social interactions from local social norms in influencing corporate (mis)behavior remains a lingering challenge for several reasons. First, local social norms are hard to measure accurately in non-controlled environments.[3] This is especially the case when using broad geographic areas such as cities and states. Secondly, corporate misconduct could cluster within different groups of firms. Thus, some types of conduct that could be attributed to geographical factors related to norms may just be a manifestation of the fact that firms with similar characteristics or in the same industry tend to locate close to each other. Lastly, geographical and social clusters can also be endogenously co-determined. Indeed, workers may sort into places because of their social networks, and concurrently their social networks might be an emergent feature of local interactions (the reflection problem, Manski [1993]).

The panel structure of our data helps in overcoming some of the challenges we pose

[3] For instance, Camerer and Fehr [2004] have measured social norms using experimental games in laboratory settings.

above. It allows us to construct time-varying measures of exposure to misconduct and look at their impact on a firm's *future* behavior. We do this also controlling for many potential confounding effects thanks to the fact that local norms and corporate culture change slowly over time. Our boards-induced network reveals that the social network we exploit captures information beyond geographical factors. In our sample, a significant fraction of a firm's boards-induced connecting neighbors reside in a geographically distant location.[4] Moreover, this aspect of the social network appears stronger among central (high-degree) and therefore more influential firms in the network.[5] This suggests that if there exists additional diffusion of (mal)practices along the social network, this does not necessarily takes place across firms with similar characteristics.

We also approach the issue of the sorting that may take place between firms and board members by exploiting our director-level data to estimate a structural matching model, therefore correcting for potential endogeneities. In particular, we estimate a two-sided matching model (à la Sørensen [2007]) which intends to account for potential director-firm sorting on various unobservable characteristics.[6] We find that, while matching does exist, our results are neither driven nor biased by this type of sorting.

The importance of the board-induced social network in diffusing misconduct depends on the characteristics of the peers considered. Specifically, the marginal effect of the "social-proximity" measure to misconduct on a firm's tendency to misbehave tends to be larger when we focus on allegedly more influential board members, i.e. board members exhibiting above-median levels of multiple board participation or business achievements to construct the social network. The role of social interaction also differs across firms: spillovers appear to be stronger when the expected cost of committing misconduct is smaller. In general, the effect of social proximity to misconduct on firms' future misbehavior is higher when firms are small, provide less information about ESG matters, and

[4]Figure 2 (D) shows that more than half of a firm's socially connecting neighbors have their headquarters located in regions outside a 500-mile radius.

[5]Figure 2 (E) shows that for high-degree firms, there is less dispersion in the fraction of socially-connected neighboring firms belonging to distant locations.

[6]Specifically, we exploit the characteristics of other directors in the market to separately identify and estimate the influence of firms' characteristics and the extent of sorting on a firm's tendency to commit misconduct.

when are not covered by many analysts. Furthermore, we find that the peer effects are weaker when the misconducting neighbor was heavily penalized for its conduct. These results suggest a mechanism in which board members learn from the conduct of prominent directors that are close to them and decide whether to follow their actions based on their own likelihood of being caught and the penalties they could face.

This paper contributes to several strands of the corporate finance and accounting literature. In finance, recent studies document that corporate decisions —such as, investment prospects (Fracassi [2016]), compensation structures (Geletkanycz et al. [2001]), and M&A deals parties (Shue [2013]) —, are more similar if the key decision-makers (e.g. board members) are part of the same social network. This literature has also shown that social interactions play a role in asset management (Cohen et al. [2008]), and household finance choices (Brown et al. [2008], Kuchler and Stroebel [2020]). Yet, it has been documented that social interactions can also lead to undesirable corporate behavior, in particular when they involve top-level corporate members. For instance, Fracassi and Tate [2012] show that social linkages between CEOs and board members can lead to decreased monitoring, ultimately lowering firm's value. Similarly, Hwang and Kim [2009] document that CEOs are paid more when they and the directors are more connected, while Nguyen [2012] shows that these linkages make the board less effective in getting rid of poorly performing CEOs. Our paper contributes to this strand of the literature by exploring which types of board members are most relevant to explaining misconduct spillovers. We find that the marginal effect of the "social-proximity" measure to misconduct on a firm's tendency to misbehave, tends to increase as we focus on the allegedly more influential board members. Furthermore, by incorporating measures of geographical distance, we try to disentangle social network effects from potentially confounding local social norms.

The paper also relates to the recent emerging literature on the role of geography in corporate decision making (e.g. Leary and Roberts [2014], Fracassi [2016]). In particular, we relate to a strand of the literature looking at how regional factors can influence corporate decisions. For example, Dougal et al. [2015] show that corporate investment depends on regional externalities outside of industry relationships; Almazan et al. [2010] show that agglomerated firms have more acquisition opportunities; and, Engelberg et al. [2018] show that geography facilitates knowledge spillovers between information intermediaries. We contribute to this research by focusing on corporate misconduct, and disentangling the role of local factors, from confounding social interactions.

There is extensive literature in accounting, economics, and finance showing a direct relationship between personal ethics, and corporate behavior. For instance, Griffin et al. [2013] show that corporate behavior depends on individual traits in multiple settings. This literature shows evidence on how managerial traits affect firms in different dimensions (Bertrand and Schoar [2003]) like managerial indiscretions (Cline et al. [2018]), personal risk-taking (Cain and McKeon [2016]), frugality and misconduct record (Davidson et al. [2015], Egan et al. [2019]), the propensity to corrupt (Mironov [2015]), military service (Benmelech and Frydman [2015]), optimism and managerial risk-aversion (Graham et al. [2013]), personal mortgage leverage (Cronqvist et al. [2012]), and early-life experiences (Malmendier et al. [2011]). Overall, it is well documented that certain managerial features are important determinants of firm's behavior.

There is parallel literature analyzing how situational features like corporate culture affects corporate behavior. In particular, Guiso et al. [2015] and Biggerstaff et al. [2015] show the importance of corporate culture and how it interacts with local norms (Dyck et al. [2010], DeBacker et al. [2015], and Parsons et al. [2018]).

Finally, it is important to understand the role of peer effects in diffusing corporate misbehavior. In that regard, Dimmock et al. [2018] show that coworkers influence matters in regard to an individual's propensity to commit financial misconduct, and Grieser et al. [2021] use a peer network approach to estimate peer effects in corporate financial policies.

We add to this literature by focusing on a high stakes setting, boards, to show that there are peer effects in financial misconduct for board members and that these peer effects are independent of director's personal traits, and situational features such as local social norms and corporate culture.

This paper is organized as follows. Section 2 presents the data. Section 3 describes the methodology and the selection model, Section 4 presents the main results, and finally, section 5 concludes.

2 Data

2.1 Misconduct

2.1.1 Corporate Misconduct

We identify corporate misconduct (CM) events from the Violation Tracker file provided by Good Jobs First.[7] This database covers nonviolent criminal offenses related to banking, consumer and labor protection, false claims, environmental offenses, price-fixing and, bribery, among others.[8] Table 1 shows the CM used in our baseline analysis, where most of the CM considered relates to “workplace safety or health violence”, “railroad safety”, “environmental offenses”, “wage and hour”, “aviation safety”, and “labor relations” violations. The cases considered in this file correspond to claims resolved by more than 40 federal regulatory agencies of the U.S. Department of Justice between 2000 and 2018.

In our Compustat sample, for each year t, a firm i is classified as “committing CM” (i.e. $\text{M\_Event(CM)}_{it} = 1$) if it exhibits a penalty paid over that year on this data set. Table 2, panels (A) and (C) reports some time-series descriptive statistics of the CM measure considered. Time-series descriptive statistics are provided both for about the entire Compustat sample considered in our study (42,453 firm-year observations) and for the sample used over the conditional panel data analysis we conduct (11,790 firm-year observations). As the conditional analysis focuses on the effect of each independent variable on CM at the firm level (within analysis), it requires each firm to exhibit variability along the dependent variable, i.e. the CM classification dummy. A firm that presents an invariant CM classification dummy over the period studied is excluded from this analysis. In both samples, the average CM rate shows a positive trend. This may be a reflection of either more stringent regulatory enforcement or an increase in firms’ corporate misconduct.[9] We include time fixed effects to insulate our results from the presence of this

[7] See Li and Raghunandan [2019], Marinescu et al. [2020], Heese and Pérez-Cavazos [2019], Stubben and Welch [2020], Raghunandan [2019].

[8] https://www.goodjobsfirst.org/violation-tracker.

[9] Apart from very few exceptions, the database covers the same set of regulatory agencies since 2000.

trend.

The measure of corporate misconduct classifies firms as misbehaving only if they have been discovered and fined. Of course, we know that much of the time these types of conduct go undetected. For instance, Dyck et al. [2021] recently showed that only one third of corporate frauds are actually detected. Thus, our CM measure is in many cases classifying firms as not having committed misconduct when actually they were (false negatives). This error makes it more difficult to identify any peer effects in our setting. CM will not only measure actual misconduct but also pick up any change in the efficiency with which the authorities prosecute misbehavior. It also focuses on a subset of types of conduct that are probably more salient and/or easy to prosecute, complicating the generalization of the results. Furthermore, this reduces our sample since our methodology focuses only on those firms that have at least one misconduct case. Lastly, CM is a discrete variable that classifies firms as either misbehaving or not, when we know that behavior is rarely that clear cut. Of course, the main advantage of the measure is that we are certain that the behavior took place, i.e. that there are no false positives (if we are to believe the courts). Notwithstanding, given the nature of the CM measure, an advantage is that it is possible to inquire into the firm's dynamic learning process from being fined.

2.1.2 Earnings Management

We complement the CM indicator with an index of the extent to which the company is engaging in earnings management (EM). There is a large body of literature documenting that many firms engage regularly in the management of their accounting figures. Dyck et al. [2021], for instance, estimate that as many as 43% of corporations misrepresent their financial reports. Although this is a misrepresentation, EM is not always illegal nor easily detected. As such, the measure is less subject to the type II error described above. It can also be measured for a larger number of firms and does not restrict us to analyzing only those firms that have at least one case of misconduct. It can also be measured as a continuous index, which allows to analyze the intensive margin. Of course, it is also possible that we are incurring a type I error and this is why the two measures complement each other.

In this study, we employ the absolute value of the modified Jones [1991] model to proxy for financial reporting quality, i.e. earnings management. As in previous research studying earnings management,[10] we use the absolute value of discretionary accruals since we do not have a priori directional expectation regarding the management's motivation for incurring this type of (mis)behavior. To operationalize this measure, we estimate —for each industry-year (SIC two digits, conditional on having at least 20 firm-years) —a cross-sectional variant of the model proposed by Jones [1991] using Compustat data.

As is pinpointed by Chiu et al. [2013], consider actions that are publicly visible and verified easily by others at their occurrence may lead to weaker inferences about causality from contagion. Paraphrasing Chiu et al. [2013], there is no need for a social network for the misconduct spread. On the contrary, our EM measure leads to stronger inferences about causality from social peer effects. Said in game theory's jargon, EM is private information.

Panels (B) and (C) of Table 2 show how the average EM measure has varied over time. While the CM measure has increased, EM has been relatively stable apart from the big spike around the time of the financial crisis. Looking at this alternative measure of misconduct further reassures us that we are not just picking changes over time in the way CM is constructed, which may affect firms with these behaviors differently from others without it. Panel (D) shows the entire distribution of EM across firms in different moments in time, confirming that the distribution is more or less stable.

2.2 Social Network

We aim to compute a measure of the exposure of each firm to misconduct based on the proximity to other firms engaging in that behavior. We think of proximity as a proxy for

[10] Recent works using this measure: Johnson et al. [2002], Ashbaugh-Skaife et al. [2008], Warfield et al. [1995], Cornett et al. [2008], Klein [2002], Frankel et al. [2002], Balsam et al. [2003], Chandar et al. [2012], Ebrahim [2007], Chung and Kallapur [2003], Cao et al. [2016], DeFond et al. [2017].

the extent of social interaction. We compute two proxies for proximity: one based on the overlap of board members in different firms (i.e. the social network) and one based on the geographical distance between firms' headquarter (physical proximity).

To build firms' board-induced social network, we use BoardEx/Individual Networks file, which compiles a full employment history and complete profiles of directors and senior managers working in around 18,000 companies worldwide. We focus on the employment history of directors, which includes their experience in any board position.[11] The final "network" data set used in our study comprises the job records of 175,549 board members (i.e. about 15 billions of bilateral distances at the board level).

As a first step in our analysis, we use the board members' job history data set to construct a network of board-to-board connections. We do this for each year in our sample. Table 3 reports the descriptive statistics, at the board-level, of the boards' social network. We use the year 2017 to illustrate the characteristics of this network. Table 3 Panel (A) shows that the typical director has been part of the same board with 15.8 current directors in the past.[12]

However, these averages mask a wide dispersion across the number and the extent of those board connections. According to Table 3 Panel (B), the number of connections ranges from 1 to more than 50. The typical duration of a connection, that is, the number of years in which the two directors shared the same board, is 4.3 years. Again, the duration varies significantly, in some cases exceeding 10 years. Thus, there is ample variation in one of the key elements that will help identify the effect of the exposure to other firm's misconduct on one's own behavior.

Board-to-board connections also vary along board characteristics. Table 3 Panel (A) shows that relative to young directors (lower than median age), older ones exhibit approximately 5 more connections, stemming from a professional overlap that lasts 2-years longer. This result highlights the importance of controlling for other features of

[11] That is, from BoardEx, we focus on those individuals' historical positions exhibiting a "Board Position Indicator" field different from "No".

[12] Notice that the current directors can be part of the same or a different firm currently.

board members because the size of the network can be correlated with them. Interestingly, Table 3 also shows that the connections to other boards tend to be larger in number (but slightly weaker in terms of the link length), for boards whose directors have an above-median level of achievement and involvement in other activities, when they have a higher fraction of female members, and there is at least one director with a graduate degree.[13] We will later use these varying board characteristics to measure the likely influence that a board has on a firm's decision making.

In Section 2.4, we exploit these connections between board members to uncover the implied connections among firms. In particular, we aggregate the board-to-board connections to the firm-level in order to build a time-varying-proximity matrix among organizations. Next, in Section 2.4.3, we utilize the time-varying-proximity matrix to build our main variable of interest: a firm-level measure of exposure to misconduct induced by the board's social network.

2.3 Physical Network

In order to construct firms' physical network, we utilize the US Census Geocoder, which allows us to transform firms' headquarters addresses from Compustat into approximate geographic coordinates. In Section 2.4, we utilize this network to compute the implied physical proximity matrix across firms, which we later use to build a firm-level geographic measure of exposure to misconduct.

2.4 Variable Description

2.4.1 Social Proximity

We start with boards' social network described in Section 2.2, which we use to uncover the implied links among organizations. In particular, for each year t, we construct a firm-level "social" proximity matrix ($\{C_{ijt}^{\text{Brd}}\}_{i,j=1}^{N}$) among the N firms in our sample. We proceed by aggregating the connections between the directors of firms i and j arising

[13] Appendix A provides details of the variable construction.

from historical past overlaps through their board experience. Directors' connections are weighted by the corresponding overlapping number of years to capture the extent to which the two directors have interacted.

Table 4 Panel (A) shows some features of the aggregated firm-by-firm links. On average, each "socially" connected firm will be connected to another firm by 1.6 members of its board. In fact, Table 4 Panel (A), sixth column, shows that each of these connected board members will establish on average 2.5 connections to board members at the connecting firms; where each of these connections will correspond to a professional overlap in the past that on average, lasted 4.4 years. Interestingly, Panel (A) shows that firm-by-firm proximity appears to be stronger in terms of number of board connections, the more similar the connecting firms are. For example, firms in the same industry, or state, or in the same half of the B/M, size, and age cross-sectional distribution, show more links among their board members.

Table 4 Panel (B), columns 1-5, report features of the resulting network of firms. On average, each firm is connected to about 67 firms in the sample. Yet, the number of connecting firms varies widely in the cross-section, in some cases reaching more than 97. The data also seem to suggest that firms connect to other firms with similar *fundamentals* as the number of connecting firms tend to increase among firms in the same half of the B/M, size and age cross-sectional distribution.

The literature has relied on current board interlocks to identify networks of firms (e.g. Chiu et al. [2013], Brown and Drake [2014], Bizjak et al. [2009]). Our measure of firms' social proximity complements the ones used before because it captures links even in the absence of current boards interlocks. This is material since, as Table 4 Panel (B) column 6-10 show, the number of connecting firms drops by a third when we only consider contemporaneous/current board-to-board connections.

It is worth mentioning that the firm-level network that results from the network of boards produces connections that go beyond the links implied by standard grouping methods that rely on industry classification or geographical location. Indeed, Table 4

Panel (B) shows that a large fraction of a firm's connecting firms do not belong to the same industry and their headquarters reside in a different state to the firm's headquarters location.

To illustrate the distinct features of board-induced social proximity among firms, Figure 1 plots the closest set of firms to Apple Inc. based on its board-induced social proximity score for two years in our sample. As shown by Figure 1, the board-induced social proximity index captures information beyond that implicit in any geographic-based proximity measure. Moreover, the proximity measures implied by boards' social links varies importantly over time. For example, for Apple Inc., while Chevron Corp. and Northrop Grumman corresponded to its closest and second closest "neighbours" in 2011, respectively, neither of these firms were part of Apple Inc.'s 2017 top-5 social-based closest neighbours. This time-series dimension is very useful to identify the impact of these links on misconduct, while at the same time controlling for time-invariant firm characteristics.

Figure 2 illustrates other salient features of firms' social network. Figure 2 (A) shows an important cross-firm variation in the network concentration: a small share of firms appear highly concentrated (high levels of node degree). Figure 2 (B) shows a negative relationship between a firm's degree and local clustering, which suggests that a high level of local clustering may facilitate firms' interactions, even among less concentrated firms.[14] Moreover, Figure 2 (C) shows that, on average, firms also tend to be more connected with other firms that are similar to them in terms of their relevance (captured by the degree) in the board-induced network. Figure 2 (D)-(E) suggest that the board-induced connections among firms, although related, are not just a manifestation of their geographic closeness. This is consistent with Figure 1. Figure 2, panels (D) and (E) illustrate that a relevant fraction of a firm's board-induced links corresponds to geographically distant firms. For example, for the median firm, about 50% of its socially-connected neighbours reside more than 800 miles away from the location of the firm's current headquarters —roughly the

[14] Local clustering of a network's node measures the extent of control of the node over flows between its immediate neighbors/vertex.

length of Texas from north to south.

2.4.2 Physical Proximity

We use geographical coordinates and the Haversine distance (Sinnott [1984], Boeh and Beamish [2012]) to compute the geographic distance between two firms' headquarters. Next, we define the physical proximity matrix between firms i and j, ($\{C_{ij}^{\text{Geo}}\}_{i,j=1}^{N}$), as the inverse of the geographic distance. In this case, contrary to the social proximity matrix, the physical proximity matrix does not vary over time.

2.4.3 Exposure to Misconduct

Using both proximity matrices described previously, for each year t, we proceed to construct firm-level measures of exposure to misconduct. In particular, for each year t, a firm i's board-induced (geographic) exposure to misconduct is computed by value-weighting —using C_{ijt}^{Brd} (C_{ij}^{Geo}) as weights —the connecting firms' past misconduct measures, $\mathbf{M}_{jt}$. Where neighbouring firms' misconduct $\mathbf{M}_{jt}$, $j \neq i \in \{1, ..., N\}$, is defined based on their misconduct measures observed over the time-window $[t-3, t-1]$.[15]

In the case of CM events described in Section 2.1.1, $\mathbf{M}_{jt}$ will be an indicator taking the value of one if the neighboring firm j has a case of misconduct over the time-window, and zero otherwise. In the case of the EM measure described in Section 2.1.2, $\mathbf{M}_{jt}$ will be the average EM measure that the neighboring firm j exhibits over the time-window.

Then, at time t, we compute firm i's exposure to misconduct M_Exp_{it}^{ℓ} implied by the board's social network ($\ell =$"Brd") and physical network ($\ell =$"Geo") as,

$$\begin{aligned} \text{M\_Exp}_{it}^{\text{Brd}} &= \left[\sum_{j\neq i}^{N} \mathbf{M}_{jt} \times C_{ijt}^{\text{Brd}}\right] \Big/ \sum_{j\neq i}^{N} C_{ijt}^{\text{Brd}} \\ \text{M\_Exp}_{it}^{\text{Geo}} &= \left[\sum_{j\neq i}^{N} \mathbf{M}_{jt} \times C_{ij}^{\text{Geo}}\right] \Big/ \sum_{j\neq i}^{N} C_{ij}^{\text{Geo}} \end{aligned} \tag{1}$$

[15]The inclusion of multiple past years allows us to reduce the potential problem of endogeneity in our main results.

Table 5 contains time-series descriptive statistics for both measures of exposure to misconduct. Table 5 Panel (A) shows that the average social and physical misconduct exposure M_Exp^{ℓ}_{it} for CM has a positive trend. On the other hand, 5 Panel (B) shows that the average social and physical misconduct exposure M_Exp^{ℓ}_{it} for EM has been relatively stable. Comparing these time-patterns with those of Sections 2.1.1 and 2.1.2, it is established that there is a positive correlation over time between the misconduct measures and their exposure measure counterparts, both the social and physical ones. Table 6 shows cross-section descriptive statistics for each misconduct exposure measure. Table 6 Panel (A) shows a sizable cross-sectional variation of the misconduct exposures M_Exp^{ℓ}_{it} when they are compared across the CM events described in Section 2.1.1. As a preview of the main results, it can already be seen that the CM-based misconduct exposure measure appears to be larger among those firms currently committing CM (i.e. those exhibiting $\text{M\_Event(CM)}_{it} = 1$ according to Section 2.1.1). Similarly, Table 6 Panel (B) shows that M_Exp^{ℓ}_{it}—when they are based on the EM measure (see Section 2.1.2) —also tend to be larger among those firms exhibiting an EM index above the median. In all cases, the differences are large and statistically significant.

This preliminary evidence motivates our multivariate analysis on the study of misconduct spillover along firms' social and physical networks.

2.4.4 Industry Exposure and Local Norms

Following Parsons et al. [2018], for completeness, we would like to control and assess the role of industry exposure to misconduct in explaining misconduct. We additionally construct a measure to assess the role of industry peer effects,

$$\text{M\_Exp}^{\text{Ind}}_{it} = \Big[\sum_{j\neq i}^{N} \mathbf{M}_{jt} \times \mathbf{1}_{ijt}\Big] \Big/ \sum_{j\neq i}^{N} \mathbf{1}_{ijt} \tag{2}$$

where $\mathbf{1}_{ij}$ is an indicator function taking the value of one if the firm $j \neq i$ operates in the same industry of firm i, and zero otherwise.

Initially, our baseline results consider as the local area (or geographic unit) the state where the firm's headquarters are located. As long as these norms are persistent over time, then using fixed effects by state should capture their influence.

Later, in section 4.2.6, we inquire more deeply into the effects of considering the state as the local area. Our baseline results are robust to other geographic unit definitions such as metropolitan statistical areas (MSAs) and to the distance to its centroid.

Notice that Parsons et al. [2018] use as geographic units "economic areas" (EAs), as defined by the U.S. Bureau of Labour Statistics. They also mention that EAs are typically larger than MSAs and are designed to capture regions within which workers commute. Some examples of EAs given by them are Washington DC-Columbia-Baltimore, Fort Worth-Arlington-Dallas, and San Francisco-Oakland-San Jose.

3 Methodology

This section describes the analysis undertaken to study misconduct spillovers along firms' physical and board-induced social networks. Our goal is to exploit the cross-firm variation of our measures of exposure to misconduct, M_Exp^{ℓ}_{it}, to see whether these exposures are related to the two firm-level misconduct variables, that is, CM and EM.

Our panel-data sample starts with the universe of firm-year observations in the Compustat Annual file from 2005-2018, which corresponds to 42,453 firm-year observations (i.e. about 1 billion of bilateral distances at the firm level). We exclude firms for which we cannot compute the full set of control variables included in the multivariate analysis described below. We consider two measures of misconduct to test our hypothesis regarding misconduct spillovers. CM has the advantage that an illegal action was committed, as far as the courts and regulators are concerned. However, it includes only the actions for which the company was prosecuted and fined. EM does not require any legal action to be conducted but reflects one particular type of misbehavior -the management of accounts- and is probably measured with more noise.

The two measures are complementary, yet they to capture distinct misconduct phenomena. Indeed, at the aggregate level, Table 2 Panel (C) shows that while the aggregate CM rate has persistently increased since 2005, the EM measure has remained stable since the last financial crisis. Moreover, in the cross-section, Table 6 shows that not all firm characteristics are related to each measure in the same way.

Interestingly and despite their alleged distinct nature, both CM and EM variables are positively related to our main measures of misconduct exposure M_Exp^{ℓ}_{it}, with $\ell \in \{\text{Geo}, \text{Brd}\}$ as it is shown in Table 6. This result suggests that the board-induced and physical network can serve as a potential channel through which corporate misbehavior could be spreading.

As seen in Table 6, other characteristics of the firm are also correlated with misconduct. Thus, these univariate results are only indicative and must be taken with caution.

For this reason, in Table 7, we study the misconduct spillover hypothesis through the lens of several multivariate regression models. Table 7 reports estimates of the following model across several specifications,

$$
\begin{aligned}
\text{M\_Measure}_{it} = \alpha + \text{Fixed\_Effects} + \gamma \times \text{Firm\_Characteristics}_{i,t-1} \\
+ \underbrace{\beta_{\text{Brd}} \times \text{M\_Exp}_{it}^{\text{Brd}}}_{\text{Social Peer Effects}} + \underbrace{\beta_{\text{Geo}} \times \text{M\_Exp}_{it}^{\text{Geo}}}_{\text{Physical Peer Effects}} + \underbrace{\beta_{\text{Ind}} \times \text{M\_Exp}_{it}^{\text{Ind}}}_{\text{Industry Peer Effects}} + \varepsilon_{it}
\end{aligned}
\tag{3}
$$

where the dependent variable M_Measure_{it} is an indicator variable in the case of the CM measure taking the value of one if the firm i is involved in a CM event in year t (according to Section 2.1.1), and 0 otherwise. In the case of EM, the dependent variable, M_Measure_{it} will denote the earnings management measure computed as explained in Section 2.1.2. The independent variables $\text{M\_Exp}_{it}^{\text{Brd}}$ and $\text{M\_Exp}_{it}^{\text{Geo}}$ correspond to our main exposure to the misconduct variables described in Section 2.4.3. The vector $\text{Firm\_Characteristics}_{i,t-1}$ includes the firm i's size, age, ROA, cash holdings, market leverage, and B/M, among other controls (including information about the characteristics of the board) as of the fiscal year-end before the misconduct variable's record. We also account for a battery of fixed effects (at the firm-, industry-, and state-level) to reduce the potential problem of omitted variables and endogeneity. Importantly, since local social norms and corporate culture change slowly over time, the empirical strategy using location and firm-fixed effects can absorb part of these confounding influences.

The model is estimated with a panel conditional logit model in the case of CM. We first rely on the within firm variation of the data and therefore ask, among the firms that have misbehaved, when they did do so. We also estimate pooled-data coefficients. In the case of EM we estimate a panel linear fixed effects model that also relies on the within firm variation of the data. Standard errors are robust to heteroskedasticity.

To further investigate the board-induced network's ability to diffuse misbehavior among firms, and using model (3), we also explore the effect of several refinements to the definition of the social network. In particular, we construct our primary misconduct exposure variable $\text{M\_Exp}_{it}^{\text{Brd}}$ by concentrating on those board-to-board links generated by the allegedly more influential board members. This is inspired by the preliminary results in Table 3 which show that board-to-board links appear to be more prominent among boards exhibiting an above-median age, level of achievements, and involvement in other activities as well as graduate education. Our objective is to pin down the channel through which board members' connections have an impact on firms' choices to engage in misconduct.

3.1 Selection Model

Our battery of controls and fixed effects, and documentation of the ancillary implications of the hypothesis ease concerns about the relationship being the result of other processes not being considered. Yet, there is a particular source of endogeneity that stems from a potential multidimensional matching problem. We consider it formally to make sure that our effect is not explained away by matching. This also allows us to quantify the extent of selection and compare it to that of social relations. Quantifying the role of social and geographical networks in affecting firms misbehavior requires understanding the mechanism through which board members and firms endogenously match based on their observable and unobservable characteristics. For instance, in the same way that board members may end up appealing to certain firms due to (observable) characteristics such as education, age, and gender, firms may also prefer some (unobservable) board members' traits such as honesty. Similarly, board members sort into firms (company boards) conditional on geographical features and other firms' unobservable characteristics that might be highly attractive to potential board members. Consequently, board members might induce misbehavior in their firms because they are already dishonest, independent of the level of misbehavior occurring in their surrounding environment. In this context, if more dishonest board members sort into specific types of firms, then disentangling the effects of sorting and firms' network influence becomes a challenging task: that is, sorting may create an endogeneity problem. In our analysis, we address this concern through the lens of a structural model based on a two-sided matching model (Sørensen [2007]) that exploits directors' characteristics in the market to separately identify and estimate the influence of firm characteristics, and sorting.

Our two-sided matching model can exploit the characteristics of other directors in the market to separately identify and estimate the influence of firm characteristics, and sorting.[16]

The model has two parts. The first part consists of an outcome equation that specifies which firm each person would choose to take a directorship in (within a state). Given sorting, if we were to estimate this equation alone, we would have an endogeneity problem. Thus the second part of the model controls for sorting. This model is a generalization of the discrete choice models, allowing for interactions among the choices made by different directors. The matching model controls the sorting and selection of the observed job decisions and eliminates the bias in the estimation of the outcome equation. Appendix B describes the main characteristics of the model implemented.

[16]The decision of where to work also depends on where other directors decided to work. However, directors' misbehavior is independent of other directors' characteristics (this is an identifying assumption). Thus other board members' features present a source of exogenous variation. This exogenous variation is similar to an instrumental variable, and the model uses it to identify influence and sorting.

4 Results

In this section, we use the empirical methodology described in Section 3 to show that both the physical and social networks have an effect on individual firms' future tendency to misbehave. In our analysis, we document a pervasive positive effect of firms' misconduct on their connecting neighbors' future misconduct rates. This result remains economically and statistically significant along two types of misconduct definitions (see Section 2.1.1 and 2.1.2) and after several robustness tests. In what follows, we start to motivate our analysis by describing key features of the board-induced social network that later we link to firms' misconduct rates. We use this link to inspire the construction of our measure of exposure to misconduct, which we exploit extensively in a multivariate panel regression analysis.

4.1 Boards' Social Network Description

In this section we explore the extent to which our firm-level board-induced social network exhibits properties that can facilitate the diffusion of information. First, we start by analyzing the distribution of firms' connections in the board-induced social graph. In fact, Figure 2 (A) shows firms' distribution of the number of other firms linked to it (the degree measure). To make the analysis clearer, Figure 2 (A) plots the log of a node's degree against the log of the frequency of nodes with that degree in firms' board-induced social graph. The resulting distribution of the degree measure exhibits thicker tails and a larger dispersion compared to the Poisson distribution coming out of a randomly generated graph with a similar average degree that tends to drop more sharply. As is the case in other economic networks that have been studied (e.g. Bailey et al. [2018]), the majority of nodes of the firm-level board-induced social network have a low degree, yet, a small number of nodes exhibit a sizable degree.

To explore the connectivity structure along firms' neighborhood in the boards-induced social network, Figure 2 (B) plots firms' local clustering versus firms' degree. The local clustering coefficient of firm i measures, across all its connecting/neighboring firms, the proportion of firm pairs connected to each other. To some extent it is important to understand this feature, since high levels of local clustering may help to sustain social interaction and the diffusion of (mis)behavior. Figure 2 (B) shows that less extensive networks (exhibiting a lower degree) tend to be more clustered on average. This suggests that even if a firm connects to few other nodes in the network (i.e. low degree), its social neighborhood can still play an important role in diffusing information given the high level of connectivity among its connecting firms.

To complement the analysis presented in Table 4 Panel (B), Figure 2 (C) explores further similarities along connected firms in the network. Figure 2 (C) shows that firms tend to be connected, on average, to other firms that are similar to them in terms of their network degree. In particular, Figure 2 (C) illustrates a "degree correlation" feature that captures the tendency of high-degree nodes to be connected to other high-degree nodes. In our sample, the correlation between a firm's degree and the average degree of its connecting firms is above 70 percent. Also, the data show that until firms have substantially more than 3 times the average degree, their average connecting firm has more connecting firms than they do.

Lastly, Figure 2 (D) extends the analysis in Table 4 Panel (B) by addressing a potential concern regarding the geographic concentration of the board-induced social network links. The Figure shows the percentiles of the cumulative distribution of connecting firms with headquarters ranging up to 1000 miles. Interestingly, Figure 2 (D) illustrates that a large fraction of the board-induced links corresponds to connections to geographically distant firms.

Thus, physical and social proximity are not the same. This pattern in the data allows us to exploit the information contained in the firm-level board-induced network to explore its role in misconduct diffusion as a channel that is independent of that of a network based on physical links, which, by its nature, will weigh heavily on firms that are geographically close.

4.2 Firms' Networks and Misconduct Tendency

Parsons et al. [2018] document that firms' misconduct tends to cluster geographically, with most of its cross-sectional heterogeneity explained by a local factor, which they argue corresponds to social norms. In this section, we add to this previous understanding by showing that an economically significant part of firms' misconduct tendency can also be attributed to firms' characteristics beyond geographical features. In particular, we highlight the importance of other ties that play a crucial role in spreading malpractices among linked firms. We hypothesize that one important channel of misconduct diffusion is related to the linkages created by the interaction of board members with directors in other firms. In particular, we propose and analyze the implications of a firm-level measure that captures this "social" proximity to misbehaving neighbors.

4.2.1 Univariate Analysis

Table 6 contains the summary statistics of our main misconduct exposure variables by distinct levels of misconduct. Higher levels of misconduct are related to several other firm characteristics. Panel (A) shows that CM rates increase as firms become larger, older, more operationally efficient, and prone to exhibit higher levels of ESG disclosure, as well as analyst coverage. In terms of the board features, CM rates increase as board members are more involved in other activities, have greater achievements, and participate in multiple boards. Board members' average age, education, expertise, and female participation are also positively related to CM.

Panel (B) shows that the EM measure tends to decrease as firms become larger, older, and prone to exhibit higher levels of ESG disclosure and analyst coverage. In terms of board features, the EM measure decreases as board members appear to be involved in other activities, achievements, and multiple boards. Board members' average age, expertise, and female participation also reduce the EM level.

It is worth noting that even though several firm characteristics appear to have an opposite effect on firms' misconduct depending on its source (CM and EM), the proposed measures of exposure to misconduct have an unequivocal reinforcing effect on firms' misconduct independent of its origin. Yet, given the significance differences across misconduct groups of several firm characteristics, in the next section we undertake a multivariate panel data analysis that controls for these differences.

4.2.2 Multivariate Analysis: Baseline Results

Table 7 presents the main results of the paper; it provides the estimated coefficients of equation (3). In general, we find that both social peer effects and geographical distance matter for explaining corporate misbehavior. As can be seen, both measures of misbehavior exposure proposed in (1) have a positive and generally statistically significant relationship with the future tendency to commit misconduct. These relationships are robust to the addition of several time-varying firm and board-specific controls. As can be seen, the effects of social and geographical factors are largely independent of one another.

The industry peer effect measure defined in (2) has a positive and significant relationship with the future tendency to commit EM, which is consistent with Parsons et al. [2018] who find that the local culture matters for financial misconduct. This is not generally the case for CM, which covers a broader set of misconduct types beyond just the misrepresentation of financial figures, where we find positive but not significant effects[17]. The inclusion of industry exposure to misconduct does not result in a material change to the magnitude of the effects of the geographical and social proximity measures.

Table 7, columns (1)-(8), report the results obtained in regard to explaining CM. In particular, both measures of misconduct exposure appear to have an unequivocal positive effect on predicting future CM rates. The marginal effect reported in Table 7 column (7) indicates that a 1 SD increase in a firm's geographical exposure to misconduct,[18] is associated with an increase in the firm's probability of committing misconduct of

[17] Parsons et al. [2018] focus on financial misconduct only.

[18] According to Table 6, Panel (A) column (4); the cross-firm SD of $\text{M\_Exp}^{\text{Geo}}$ is 0.201 for those firms not committing CM. To interpret the marginal effect of $\text{M\_Exp}^{\text{Geo}}$ in Table 7, we make the SD of the variable equal to 0.201.

13.25%.[19] Similarly, the marginal effect in column (7) shows that a 1 SD increase in a firm's social exposure to misconduct,[20] is associated with an increase in the firm's probability of committing misconduct of 3.67%.[21]

These effects are comparable to the estimates previously documented in the literature. In particular, Parsons et al. [2018] show that a 1% increase in the (contemporaneous) financial misconduct rates of a firm's local non-industry peers leads to an increase, on average, in firm-level financial misconduct of about 10% of its mean.[22]

Below we provide a few examples to convey the economic magnitude of these effects. For instance, a reduction of 44 miles in the distance to other firms committing misconduct (1 SD, intensive margin)[23] —which increases $\text{M\_Exp}^{\text{Geo}}$ by 0.01 units —would result in a 0.66% higher probability of committing misconduct.[24] That is, being located 450 miles closer to other firms that commit misconduct (roughly the distance between Boston and Washington, and slightly more that that between Los Angeles and San Francisco) is associated with an almost 0.9 percentage point ($0.089 \times 0.01 \times 10$) increase in the probability of misconduct. A 1 SD increase in the average number of firms committing misconduct

[19] Table 2, Panel (A), All firms, column (3); shows that the average CM rate for the entire sample is about 0.135. Then, we have that $0.089 \times 0.201/0.135 \approx 13.25\%$.

[20] According to Table 6, Panel (A), column (4); the cross-firm SD of $\text{M\_Exp}^{\text{Brd}}$ is 0.099 for those firms not committing CM. To interpret the marginal effect of $\text{M\_Exp}^{\text{Brd}}$ in Table 7, we make the SD of the variable equal to 0.099.

[21] This result comes from $0.05 \times 0.099/0.135 \approx 3.67\%$.

[22] Parsons et al. [2018] report an estimated coefficient for the main explanatory variable (Table 10) of ≈ 9.8, which implies that after a 1% increase in this main variable, the odds ratio of an average firm committing financial misconduct will increase by $e^{0.098} - 1 \approx 10.3\%$. Since the baseline average firm-level financial misconduct rate is 1.46%, this increase in the odds ratio will translate to an average firm-level financial misconduct rate of about 1.61% (= 1.46% + 15bps.). That is, an increase in the firm probability of misconduct of $\approx 10\%$ of its mean.

[23] Intensive margin: this equivalence is motivated by expressing the change in the exposure variable $(\overline{\text{M\_Exp}^{\star}} - \overline{\text{M\_Exp}})$ as a function of a perturbation ($\Delta > 1$) to the misbehaving firms' connecting distance C_{ij}. Omitting the time subscript,

$$\overline{\text{M\_Exp}^{\star}} = \frac{1}{N} \sum_{i}^{N} \frac{\sum_j^N C_{ij} M_j \mathbf{1}_{\{M_j > \widehat{M}\}} \Delta + \sum_j^N C_{ij} M_j \left(1 - \mathbf{1}_{\{M_j > \widehat{M}\}}\right)}{\sum_j^N C_{ij} \mathbf{1}_{\{M_j > \widehat{M}\}} \Delta + \sum_j^N C_{ij} \left(1 - \mathbf{1}_{\{M_j > \widehat{M}\}}\right)}$$

where $\widehat{M}$ is set to 0 and to the highest cross-sectional decile for the economic interpretation of the coefficient estimates of the CM and EM the regression, respectively.

[24] Equally, this result comes from $0.089 \times 0.01/0.135 \approx 0.66\%$.

(extensive margin)[25] —which increases $\text{M\_Exp}^{\text{Geo}}$ by 0.012 units —[26] is associated with an increase in the probability of committing misconduct of 7.9%.[27]

Similarly, for CM, one can think of the effect of moving one connecting director of a firm to a misconducting company (intensive margin). Such a move —which is associated with an increase of $\text{M\_Exp}^{\text{Brd}}$ of 0.0625 units —[28] would result in a 2.31% higher probability of committing misconduct.[29] Also, a 1 SD increase in the average number of socially-connecting companies committing misconduct (extensive margin) —which augments $\text{M\_Exp}^{\text{Brd}}$ by 0.205 units —,[30] results in an increase in the probability of committing misconduct of 7.59%.[31]

Table 7, columns (9)-(14), report the results obtained for the case of EM. Analogous to our results for CM, the measures of geographical and social exposure exhibit a positive effect on predicting the degree of future EM. Column (14) indicates that, on average, a 1 SD increase in a firm's geographical exposure to misconduct,[32] is related to a 5.4% higher degree of earnings management.[33] Similarly, the marginal effect of the board-induced exposure to misconduct reported shows that a 1 SD increase in a firm's social exposure to misconduct,[34] is associated with a 4.42% higher measure of EM.[35]

Again, a reduction of 44 miles in the distance to other firms committing misconduct (intensive margin) will increase $\text{M\_Exp}^{\text{Geo}}$ by 0.033 units, which is associated with an

[25] Extensive margin: this equivalence is motivated by expressing the change in the exposure variable $(\overline{\text{M\_Exp}^{\star}} - \overline{\text{M\_Exp}})$ as a function of an increase in the number of connecting firms committing corporate misconduct ($H > 0$). Omitting the time subscript,

$$\overline{\text{M\_Exp}^{\star}} = \frac{1}{N}\sum_{i}^{N} \frac{\sum_j^N C_{ij} M_j \mathbf{1}_{\{M_j > \widehat{M}\}} \Delta + \sum_j^N C_{ij} M_j (1 - \mathbf{1}_{\{M_j > \widehat{M}\}})}{\sum_j^N C_{ij} \mathbf{1}_{\{M_j > \widehat{M}\}} \Delta + \sum_j^N C_{ij} (1 - \mathbf{1}_{\{M_j > \widehat{M}\}})}$$

[26] Table 7, a 1 SD of the average number of misconducting firms equals about 61 firms (we compute the SD of the time series resulted from multiplying the second and the third column of Table 7).

[27] This marginal effect is computed as $0.089 \times 0.12/0.135 \approx 7.9\%$.

[28] Table 4 Panel (B) shows that on average, two "socially-connected" firms feature about 2.5 "board-board social" links which involve board members overlapping during about 4.4 years in the past.

[29] This estimate is derived as $0.05 \times 0.0625/0.135 \approx 2.31\%$.

[30] A 1 SD of average # of socially-connecting misconducting firms equals about 10 firms in our sample.

[31] Similarly to our previous calculations, this effect comes from $0.05 \times 0.205/0.135 \approx 7.59\%$.

[32] According to Table 6, Panel (B), column (4); the cross-firm SD of $\text{M\_Exp}^{\text{Geo}}$ is about 0.054.

[33] Table 2 (B) column (2); shows that average EM measure for the entire sample is about 0.057. Then, we have that $0.057 \times 0.054/0.057 \approx 5.4\%$.

[34] According to Table 6 (B) column (4); the cross-firm SD of $\text{M\_Exp}^{\text{Brd}}$ is about 0.04.

[35] Analogous to the other results, we have that $0.063 \times 0.04/0.057 \approx 4.42\%$.

increase in the EM measure of 3.3%.[36] From the extensive margin, a 1 SD increase in the average number of firms exhibiting an EM measure in the highest percentile (0.004 units higher M_Exp^{Geo}) relates to an increase in the EM measure of 0.44%.[37]

The economic significance of the M_Exp^{Brd} implied by its elasticity on the EM measure indicates that moving one connecting director of a firm to a misconducting company (intensive margin)[38] —which will augment the firm's M_Exp^{Brd} by 0.087 units —results in an increase in the firm's EM measure of 9.62%.[39] Likewise, a 1 SD increase in the average number of socially-connecting companies committing misconduct (extensive margin) results in an increase in the firm's EM measure of 12.93%.[40]

4.2.3 Multivariate Analysis: Heterogeneity in Social Connections

In order to have a better grasp of the mechanism behind our findings, we exploit the heterogeneity in the characteristics of board members and firms. We explore whether the diffusion of misconduct we document is affected by the standing of the peers, and the perception of the likelihood of being caught and the fine they could face.

It is natural to think that the conduct of people with a higher standing in the community (i.e. business leaders) will have a greater influence on the actions of others. Indeed, in the context of investment decisions, Bursztyn etal (2014) show that people tend to follow more the actions of other investors when these are more sophisticated, consistent with the social learning framework. To look at this we add to the benchmark specification interactions of our social misconduct exposure with proxies for the degree of influence that the peers might have. Table 8, columns (1)-(4) show the output of our multivariate analysis for CM and columns (5)-(8) the one for EM. For CM, the tendency of firms to misbehave when they are connected with other misbehaving companies is boosted when the other firm's board members have greater expertise (experience in the

[36] Consequently, we obtain this effect as $0.057 \times 0.033/0.057 \approx 3.3\%$.
[37] Where this percentage is calculated as $0.063 \times 0.004/0.057 \approx 0.44\%$.
[38] That is, to a firm showing an EM at the highest EM-percentile.
[39] Given the 0.087 increase in the social exposure measure, we obtain this result as $0.063 \times 0.087/0.057 \approx 9.62$.
[40] As the previous results showed in this section, this calculation comes from $0.063 \times 0.117/0.057 \approx 12.93\%$.

industry), business achievements, experience (age), and seat in more boards (although the coefficients are not always estimated so precisely). We find similar effects in the case of EM when looking at expertise and participation in multiple boards.

We explored the possibility that some firms might be more influential because of their centrality in the network. To do this, we added to the benchmark specification the interaction between the board exposure index and a dummy variable that takes the value of one if the firm is connected with at least one high degree centrality firm. We defined a high degree centrality firm as one situated at the 99th percentile of the C_{ijt} distribution. We found that while the effect of being connected with at least one big influencer is always positive, it is nonetheless never significant (not reported). Although this evidence is not conclusive, it does suggest that diffusion is more intense at the core of the network and diminishes as we move to the outer skirts.

4.2.4 Multivariate Analysis: Heterogeneity in Firms' Features

In Table 9 we investigate whether the extent of diffusion of misconduct occurring along the social network differs depending on the context that firms face. We would expect boards not to follow blindly what their peers do, but rather to observe and make a choice based on their assessment of the probability of being caught and the penalty they could receive (Becker [1968]).

For CM, Table 9 shows that the effect of social-proximity to misconduct on firms' future misbehavior tendency increases less (relative to our baseline results in Table 7) for those featuring *above*-median levels of total assets (column (1)), ESG disclosure (column (2)), and analyst coverage (column (3)). The pattern also arises for EM when looking at size (column (5)). Thus, spillovers related to misbehavior appear to be stronger when the actions are less likely to be detected. Of course, these results have to be interpreted with caution since these characteristics may capture other attributes of the firm. For instance, the wealth of board members of smaller firms will be more dependent on their decisions, as pointed out by Jensen and Meckling [1976], and therefore, they could be more cautious when undertaking these practices.

Observing that a firm committing misconduct was heavily penalized may be a big deterrent for behaving similarly, as firms may learn about the potential outcome of their bad behavior. In column (4) we inquire into the role of penalties in the mechanism. For each firm we calculate the weighted-average of neighbors' penalty and then we add a dummy variable taking the value of one if the weighted-average neighbors' penalty of the firm is in the 99th percentile of the distribution, and zero otherwise. The coefficient for the interaction is negative and significant, showing that the extent to which the peer's actions were punished moderates the mimicking of his or her conduct suggesting a "social learning" mechanism for the peer effect to spread (Bursztyn et al. [2014]).

Taken together, this set of results suggest that firms do learn about the likely penalty by looking at their peers and use this information in conjunction with the chances being penalized to determine whether to follow their actions or not.

4.2.5 Multivariate Analysis: Selection Bias

Following previous literature on economic networks, we interpret our baseline estimates with caution as our boards-induced social network and physical network can be endogenously co-determined.

To address this specification challenge, we use our rich data of boards' features to estimate a structural model à la Sørensen [2007] that controls for the potential endogenous matching between firms and boards. Indeed, a structural model based on a two-sided matching model can exploit the characteristics of other boards in the market to separately identify and estimate the influence of firms' induced-networks and the extent of the sorting on firms' tendency to commit misconduct.

Yet, as the estimation of the structural model implemented is numerically intensive, we modify our baseline specification to make it more parsimonious and numerically tractable by the estimation procedure.[41] In particular, following Sørensen [2007], we estimate our specification through the lens of a panel-conditional Poisson model where we

[41] The numerical estimation of the model is performed using the R-package "matchingMarkets" (Klein [2015]), available at https://cran.r-project.org/web/packages/matchingMarkets/matchingMarkets.pdf.

also replace the year fixed-effects with a linear time variable to make the specification more tractable to the procedure used.

For CM, Table 10 columns (1)-(2) show the estimates of the panel Poisson model, which does not correct for the potential sample selection bias from unobserved outcomes in the firm-board matching markets. In accordance with our previous analysis, both measures of misconduct exposure appear to have a strong positive effect on predicting future misconduct tendency. However, if firms and boards match non-randomly on unobserved characteristics correlated with both control variables and misconduct measures, our regression estimates will in general be biased.

For CM, Table 10 columns (3)-(4) report the output from estimating the structural model proposed by Sørensen [2007] and Klein [2015]. The sign and significance of the exposure coefficients are still very significant, showing that our effect is not explained away by the sort of matching we describe. Nevertheless, their magnitudes are reduced. Based on the estimated parameter $\kappa > 0$ of the model which captures a positive covariance between the error terms in the structural model's valuation and outcome equations (Klein [2015]), we interpret the reduction of the marginal effects of the main variables of interest as a manifestation of the existence of unobserved characteristics preferred by firms and boards, on average; and which, tend to affect the firms' misconduct tendency in a positive way.

Notwithstanding the potential bias introduced by unobserved variables not included in our analysis, the estimates of the structural model show that even if our baseline analysis had the ability to control for these unobserved variables, the link between our measures of exposure to misconduct and firms' tendency to misbehave would still prevail. Indeed, Table 10 columns (5)-(6) confirm the relevance of our proposed variables to explain the degree of EM as well, even in the presence of some degree of selection bias.

4.2.6 Multivariate Analysis: Heterogeneity in Local Norms

Hitherto, we have used the state where the firm's headquarters is located as the geographic unit to set the location fixed effects, in the earnings management regressions, to control for geographic time-invariant characteristics, including local norms. But, of course, cities also have their own culture and this may be mapping into our proximity (especially geographic) measures of interaction. In what follows, we turn to alternative definitions of the local area to set fixed effects, which are geographically more granular, in order to test the robustness of our exposure to misconduct measures against the effects of local norms.

Table 11 presents the results of our benchmark model but using alternative geographic units to compute the location fixed effects. The first column is equivalent to that of our benchmark specification because our baseline geographic unit definition is a state. In column (2), the geographical unit is still the state but the estimation considers just firm-year observations that could be matched with a metropolitan statistical area (MSA); therefore, the differences between columns (1) and (2) are due just to sample reduction. Column (3) considers as the local area the metropolitan statistical area (MSA) where the firm's head office is situated. In the following columns, we partition each MSA into two complementary areas delimiting an inner part given by a closed ball of radius $r = \{50 \text{ Km}, 35 \text{ Km}, 20 \text{ Km}\}$ depicted from the MSA's centroid, and an outer part given by the complement of the closed ball with respect to the MSA polygon. For example, column (4) considers that firms, inside a certain MSA but located at a distance less than or equal to 50 Km from the MSA's centroid and those firms located at a distance greater than 50 Km in the same MSA, are part of different geographic entities and consequently subject to different social local norms.

Overall, the estimated coefficients are very similar across the different specifications, showing that our baseline results are robust to the geographical units selected to set the area fixed effects which are intended to control for local norms.

4.2.7 Multivariate Analysis: Further Results

In this section we discuss some additional results regarding the role of peer effects and norms on the diffusion of misconduct. This helps us understand the phenomenon better.

- Complements or Substitutes

  There is some evidence that EM contagion is exacerbated when the exposed firm is geographically closer to the one committing misconduct (and when they share a common auditor) (Chiu et al. [2013]). Consequently, we explore the potential degree of complementarity of social and physical exposure in explaining misconduct. We do this by adding to the specification the interaction of the main explanatory variables with board-induced exposure to misconduct. The results are presented in Table 12. We find no clear indication that the three measures of proximity reinforce each other. If anything, in the case of CM, the social, industry and geographical factors appear to substitute each other. This is as if any type of interaction with your peers were enough to trigger contagion and being too close in all dimensions were, in fact, a deterrent to adopt the same conduct. One possibility is that this is because directors fear being investigated when they are very close in several dimensions to the offending company.

- Speed of Diffusion

  To understand the speed with which a given conduct diffuses across the network, in Table 13 we add to the baseline model the lags of both the social and the physical exposure to misconduct measures. By doing so, we can have a sense of whether the effects are maintained or decay as time passes. The coefficient for the lagged physical exposure measure appears not to be significant. On the contrary, when looking at CM, the lagged social exposure is statistically significant and its effect is negative. This means that, while the effect of geographical exposure to misconduct is permanent, that of social exposure washes away with time, since the cumulative effect of the misconduct exposure -that is, the cumulative sum of the coefficients- converges to zero in two periods, on average. Thus, it doesn't take too long for misbehavior to spread through the social network. The conclusion is the same in the case of EM, although the coefficients are not estimated as precisely.

- Types of Corporate Misconduct

  In Table 14 we look at different classes of misconduct. We define 4 big types of corporate misconduct that are incurred by firms the most: Competition Consumer-related offenses in column (1), Employment-related offenses in column (2), Environment-related offenses in column (3), and Safety-related offenses in column (4). Besides, Table 14 column (5) presents the composite of the entire corporate misconduct sample. The results indicate that the effect of Board-induced exposure, although less precisely estimated in the smaller samples, is pretty consistent across all kinds of misconduct. For the most part, this is also what we find in the case of physical proximity. Industry peer effects, on the other hand, seem to have a more muted effect in cases other than employment offenses. One explanation for this is that behaving properly may be used by firms to create a competitive advantage by distinguishing themselves in the eyes of consumers and regulators.

- Firm's Corporate Misconduct Culture

  Liu [2016] shows that firms with a corrupt corporate culture are more likely to engage in misconduct. In Table 15 we look at how a culture of corruption affects the likelihood that a firm adopts the bad behavior of its peers. To do this we split the sample in two according to the number of violations incurred historically over the 14-year time span (2005-2018). When comparing Columns (1) through (6) to columns (7)-(12), we see a bigger and more significant effect of board exposure in the case of firms with less corrupt culture (less or equal than 4 offenses in). This suggests that once firms adopt a corrupt culture, this becomes the main determinant of misconduct and maintains this behavior regardless of what socially-connected firms are doing. Conversely, geographical exposure to misconduct seems to be stronger for firms with a high misconduct culture. This is as if misconduct disseminates more quickly when firms are geographically closer, a sort of rotten apple in the basket effect.

5 Concluding Remarks

This paper argues that the interaction with peers matters for the decisions of a firm. In particular, we document that a firm's tendency to engage in future corporate misconduct and earnings management increases with its social and physical proximity to firms exhibiting similar past behavior. A structural model estimation shows that, while selection is relevant, the results are not driven by the endogenous matching between firms and directors. The effect is particularly strong when the links between firms involve directors that are likely to be more influential, when these types of conduct are less detectable, and when the neighboring misbehaving firm was not heavily penalized when caught. Thus, firms seem to be following close people that they consider as referents, learning from their actions, and adapting their conduct by also taking into consideration their particular context. Investors and the public alike are paying increasing attention to how corporations conduct business; many types of conduct that were acceptable before are no longer today. Business leaders have had a prominent role in widening the idea of firms being good citizens. See, for instance, the statement made in 2019 by the chief executives of the largest corporations in the Business Roundtable regarding firm goals. Understanding how changing attitudes transmit to others tells us when or whether their calls will materialize into a different way of behaving. Our results have important policy implications: while norms and incentives do matter, focusing on the conduct of a few influential officers may be an efficient and faster way of changing firms'conduct.

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Table 1: Violation Tracker Sample - Corporate Misconduct (CM)

Primary Offense	Freq.	US bil.	Primary Offense	Freq.	US bil.
workplace safety or health vio	13376	0.3181	drug or medical equipment safe	34	2.7013
railroad safety violation	8804	0.1001	anti-money-laundering deficien	30	4.4083
environmental violation	8282	75.6253	interest rate benchmark manipu	30	7.4636
wage and hour violation	2394	7.3781	discriminatory practices	26	0.3933
aviation safety violation	2211	0.1684	financial institution supervis	26	0.1242
labor relations violation	1403	0.4401	pipeline safety violation	23	0.0015
employment discrimination	611	2.2088	hhs civil monetary penalties	23	0.0279
false claims act and related	588	25.5617	federal leasing royalty violat	23	0.1124
consumer protection violation	516	11.9569	excise tax violation	22	0.0101
investor protection violation	329	56.9724	energy market manipulation	21	4.2739
benefit plan administrator vio	265	5.2293	fraud	21	0.9856
motor vehicle safety violation	199	2.5131	energy conservation violation	18	0.0006
offshore drilling violation	180	0.0086	workplace whistleblower retali	16	0.0101
export control violation	164	0.4104	americans with disabilities ac	12	0.0285
banking violation	163	17.3611	tobacco litigation	10	0.0081
family and medical leave act	151	0.0024	servicemembers civil relief ac	7	0.0522
foreign corrupt practices act	151	5.4943	food safety violation	6	0.0179
securities issuance or trading	124	5.7205	foreign exchange market manipu	5	2.7001
price-fixing or anti-competiti	112	6.7488	premerger notification violati	4	0.0031
aviation consumer protection v	110	0.2481	bankruptcy professional violat	4	0.1391
economic sanction violation	109	2.4931	work visa violations	4	0.0355
telecommunications violation	107	1.4677	civil contempt	4	0.0051
accounting fraud or deficienci	100	4.3554	agribusiness violation	3	0001
toxic securities abuses	98	100.0652	child labor or youth employmen	3	0.0004
off-label or unapproved promot	81	20.8568	uniformed services employment	3	0.0002
nursing home violation	72	0.0045	maritime violation	3	0.0003
mortgage abuses	68	61.2373	fair credit reporting act viol	3	0.0121
nuclear safety violation	57	0.0413	service contract act	2	0.0013
privacy violation	52	0.1442	illicit political contribution	2	0.0241
energy market violation	51	0.2803	campaign finance violation	2	0.0005
kickbacks and bribery	51	2.2143	student loan abuses	2	0.0641
employment screening violation	46	0.1265	medicare coverage gap discount	1	0.0001
product safety violation	44	0.0779	sexual harassment	1	0001
tax violations	40	4.0129	payday lending violation	1	0.0191
medicare parts c and d enforce	40	0.0186	obstruction of justice	1	0.0002
controlled substances act viol	39	0.5701	illegal gambling business	1	0.0.0001
data submission deficiencies	36	0.3032	insider trading	1	0.0.0109
Total	41224	394.9633		398	20.6418

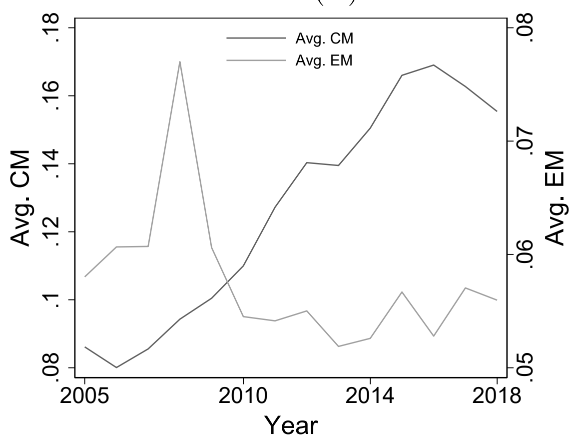
Table 1 reports details of the primary offenses included in the Violation Tracker firm-year file from 2005 to 2018. Observations considered are linked to a parent firm with available financial information at the time of the agency's report.

Table 2: Misconduct over Time

	x = Corporate Misconduct (CM)						x = Earnings Management (EM)					
	All firms			Firms with CM variation								
	Obs.	Mean	Std	Obs.	Mean	Std	Obs.	Mean	Std	p25	p50	p75
2005	3,171	0.096	0.295	741	0.325	0.469	2,638	0.057	0.065	0.016	0.037	0.072
2006	3,315	0.088	0.283	753	0.303	0.460	2,508	0.060	0.068	0.016	0.039	0.075
2007	3,246	0.096	0.295	779	0.317	0.466	2,418	0.060	0.070	0.016	0.037	0.077
2008	3,141	0.105	0.307	805	0.324	0.468	2,314	0.076	0.081	0.023	0.049	0.096
2009	3,014	0.113	0.317	813	0.337	0.473	2,276	0.060	0.064	0.018	0.040	0.076
2010	2,977	0.124	0.330	827	0.360	0.480	2,241	0.054	0.064	0.015	0.034	0.068
2011	2,828	0.141	0.349	843	0.390	0.488	2,141	0.053	0.061	0.016	0.033	0.068
2012	2,699	0.157	0.364	857	0.414	0.493	2,024	0.054	0.064	0.015	0.034	0.068
2013	2,613	0.156	0.363	867	0.389	0.488	1,972	0.050	0.059	0.014	0.032	0.063
2014	2,556	0.169	0.374	886	0.403	0.491	1,956	0.052	0.061	0.015	0.032	0.063
2015	2,573	0.182	0.386	896	0.436	0.496	1,865	0.055	0.061	0.016	0.035	0.068
2016	2,625	0.178	0.382	904	0.431	0.496	1,882	0.052	0.060	0.015	0.033	0.066
2017	2,646	0.171	0.376	914	0.404	0.491	1,933	0.057	0.065	0.017	0.038	0.072
2018	2,581	0.162	0.369	905	0.365	0.482	1,875	0.056	0.065	0.016	0.036	0.065
Total	39,985	0.135	0.342	11,790	0.374	0.484	30,043	0.057	0.066	0.016	0.036	0.072

Table 2 describe CM and EM measures over time by showing the number of firm-year observations and descriptive statistics of the distribution for each year and for the entire firm-year sample (last row).

Panel (C)



Panel (D)

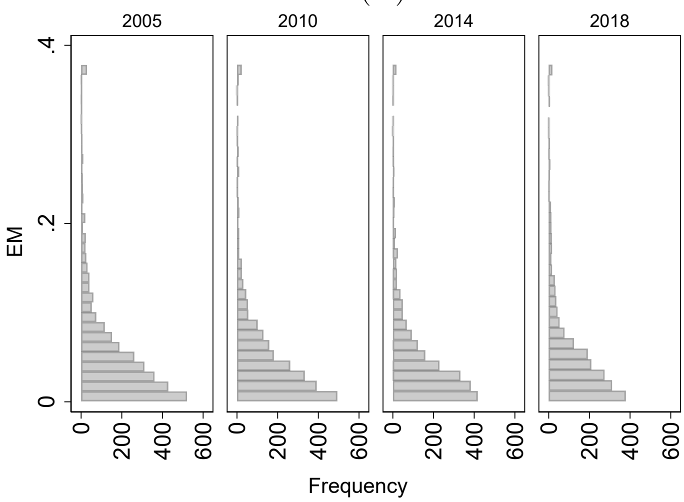


Table 2 panels (A) and (B) report CM and EM measures over time by showing number of firm-year observations, and descriptive statistics of distribution. **Table 2** (C) illustrates the average CM and EM over time. **Table 2** (D) shows the evolution of the EM distribution over time.

Table 3: Board-induced Social Network at the Board-Level

		Panel(A)							Panel(B)						
		# Brd-to-Brd connections, by Board							Δt Brd-to-Brd connections, by Board						
		Mean	Std	p5	p25	p50	p75	p95	Mean	Std	p5	p25	p50	p75	p95
All		15.8	23.5	1.0	4.0	9.0	18.0	55.0	4.3	3.1	1.0	2.0	3.5	5.5	10.1
Age	Low	14.1	23.4	1.0	3.0	7.0	15.0	50.0	3.6	2.7	1.0	2.0	3.0	4.5	8.6
	High	18.8	23.2	2.0	6.0	12.0	22.0	61.0	5.5	3.4	1.5	3.2	4.8	7.0	12.0
Achievement	Low	15.6	23.1	1.0	4.0	9.0	18.0	54.0	4.3	3.1	1.0	2.1	3.5	5.5	10.1
	High	21.9	31.6	1.0	5.0	11.0	26.0	78.0	4.0	2.9	1.0	2.0	3.3	5.1	9.2
Other Activities	Low	15.1	22.3	1.0	4.0	9.0	17.0	52.0	4.3	3.1	1.0	2.1	3.6	5.5	10.3
	High	23.8	33.4	1.0	5.0	12.0	30.0	84.0	3.7	2.6	1.0	2.0	3.1	4.8	8.3
Grad. Education	No	14.9	23.4	1.0	4.0	8.0	17.0	50.0	4.5	3.3	1.0	2.0	3.6	5.8	11.0
	Yes	16.8	23.5	1.0	4.0	9.0	20.0	60.0	4.1	2.7	1.0	2.1	3.5	5.2	9.0
Foreign	No	16.1	24.0	1.0	4.0	9.0	18.0	55.0	4.3	3.1	1.0	2.0	3.5	5.6	10.3
	Yes	13.4	18.6	1.0	3.0	7.0	16.0	50.0	4.0	2.5	1.0	2.3	3.5	5.0	8.4
Women	No	15.5	23.2	1.0	4.0	9.0	18.0	53.0	4.4	3.1	1.0	2.2	3.6	5.6	10.3
	Yes	17.6	25.3	1.0	4.0	9.0	20.0	65.0	3.6	2.8	1.0	1.9	2.9	4.6	9.0

Table 3 reports details, at the board-level, of the boards-induced social network described in Section 2.2 for a representative year in our sample (year 2017). "Low" ("High") row labels represent the below- (above-) median board group according to the variable indicated in the first column.

Table 4: Board-induced Social Network at the Pairing Firms- and Firm- Level

Panel (A): At the Pairing Firms-Level

		# of connected board members, by Firm					# of Brd-to-Brd connections, by Firm					Δt Brd-to-Brd connections, by Firm				
		Mean	Std	p25	p50	p75	Mean	Std	p25	p50	p75	Mean	Std	p25	p75	p50
All		1.6	1.9	1.0	1.0	1.0	2.5	5.8	1.0	1.0	2.0	4.4	3.3	2.0	6.0	3.5
Same Industry	No	1.6	1.9	1.0	1.0	1.0	2.3	4.4	1.0	1.0	1.0	4.4	3.4	2.0	6.0	3.5
	Yes	1.9	2.1	1.0	1.0	2.0	3.9	10.5	1.0	1.0	2.0	4.2	3.1	2.0	5.9	3.3
Same State	No	1.5	1.8	1.0	1.0	1.0	2.1	3.7	1.0	1.0	1.0	4.3	3.3	2.0	6.0	3.1
	Yes	2.2	2.6	1.0	1.0	2.0	5.0	12.1	1.0	1.0	3.0	4.7	3.3	2.0	6.1	4.0
Similar levels of:																
B/M	No	1.6	1.8	1.0	1.0	1.0	2.3	4.6	1.0	1.0	1.0	4.4	3.4	2.0	6.0	3.5
	Yes	1.7	2.0	1.0	1.0	1.0	2.7	6.5	1.0	1.0	2.0	4.4	3.3	2.0	6.0	3.5
Ln(Total assets)	No	1.5	1.6	1.0	1.0	1.0	1.9	3.1	1.0	1.0	1.0	4.3	3.4	2.0	6.0	3.0
	Yes	1.7	2.0	1.0	1.0	1.0	2.7	6.5	1.0	1.0	2.0	4.4	3.3	2.0	6.0	3.6
Age	No	1.5	1.7	1.0	1.0	1.0	2.0	3.4	1.0	1.0	1.0	4.3	3.3	2.0	6.0	3.1
	Yes	1.7	2.1	1.0	1.0	1.0	2.8	7.0	1.0	1.0	2.0	4.4	3.3	2.0	6.0	3.5

Panel (B): At the Firm-Level

		# of connected firms, by Firm									
		implied by Brd-to-Brd *historical* links					implied by Brd-to-Brd *current* links				
		Mean	Std	p25	p50	p75	Mean	Std	p25	p50	p75
All		66.8	101.6	15.0	47.0	97.0	26.4	41.3	6.0	17.0	38.0
Same Industry	No	57.2	92.6	12.0	35.0	80.0	21.9	33.7	5.0	13.0	31.0
	Yes	9.7	19.7	1.0	3.0	9.0	4.5	12.1	0.0	1.0	4.0
Same State	No	57.4	89.1	11.5	37.0	79.5	22.0	30.6	4.0	14.0	31.0
	Yes	9.5	17.0	1.0	4.0	12.0	4.4	13.6	0.0	2.0	5.0
Similar levels of:											
B/M	No	29.7	51.2	6.0	18.0	41.0	11.4	19.0	2.0	7.0	14.0
	Yes	37.2	53.4	8.0	24.0	55.5	15.0	24.0	3.0	9.0	22.0
Ln(Total assets)	No	18.9	20.9	5.0	14.0	26.0	6.7	8.1	2.0	5.0	9.0
	Yes	48.0	88.6	7.0	22.0	71.0	19.7	37.2	3.0	9.0	29.0
Age	No	29.0	52.6	6.0	19.0	40.0	10.8	15.6	2.0	7.0	15.0
	Yes	37.8	53.0	8.0	23.0	54.0	15.6	27.8	3.0	9.0	21.0

Table 4 Panel (A) [Panel (B)] reports details, at the pairing firms- [firm-] level, of the boards-induced social network described in Section 2.2 for a representative year in our sample (year 2017). "No" ("Yes") row labels indicate that the pairing firms belong to a different (the same) half of the data sample according to the variable in the first column. Table 4 Panel (B) contrasts the firms' proximity statistics implied by the boards' *historical* as well as *current* connections to other board members.

Figure 1: Apple Inc.'s Top-10 Social-based Closest Firms

Panel (A): Year 2011

Panel (B): Year 2017

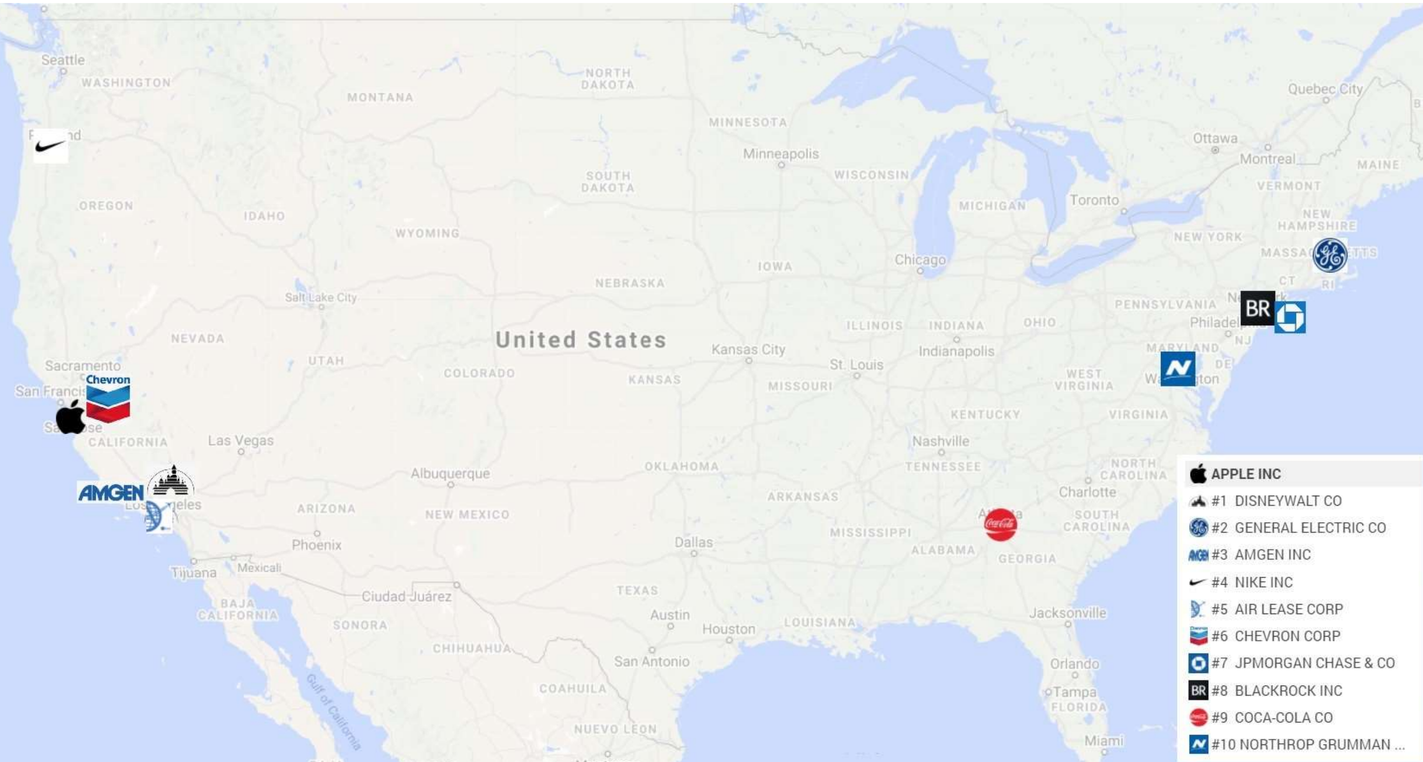


Figure 1 illustrates in the U.S. map the top-10 social-based closest firms for Apple Inc. in 2011 and 2017. Firms in plots' legends are sorted based on the social-proximity measure to Apple Inc.

Figure 2: Boards' Social Network Description

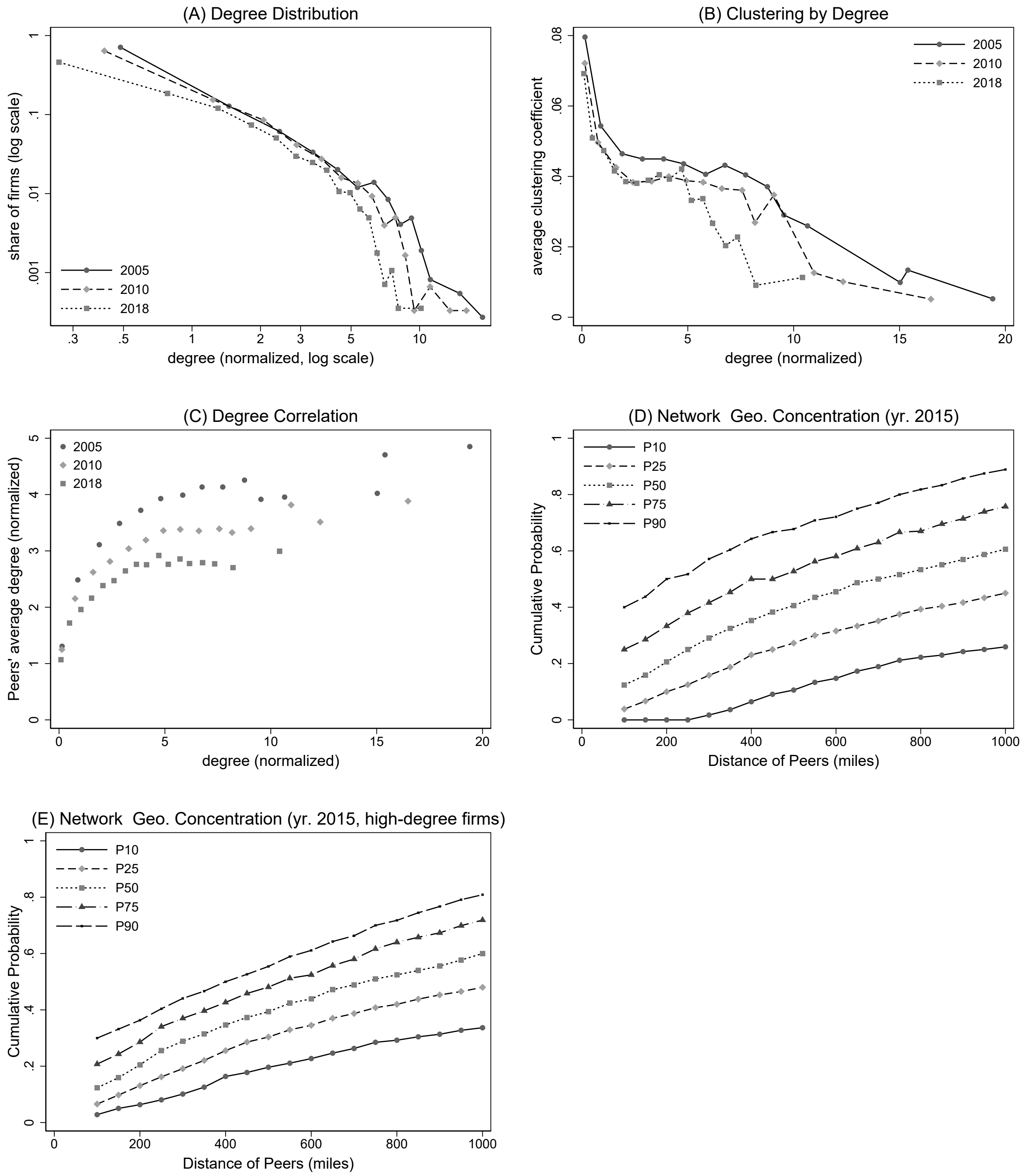


Figure 2 shows summary statistics on the boards graph among US-based corporations for different years. Panel A shows the correlation between a firm's (normalized) degree centrality and the probability of observing a node with that (normalized) degree centrality. Panel B shows the average clustering coefficient for firms of varying normalized degrees. Panel C shows the average normalized degree centrality of a firm's peers by the normalized degree centrality of the own firm. Panel D describes the geographic concentration of board-based company networks. It shows, for various distances, percentiles of the cumulative distribution of a firm's # of peers living within the respective geographic distance.

Table 5: Exposure to Misconduct over Time

Panel (A)												
	x = Corporarte Misconduct (CM)											
	$M\_Exp^{Geo}(x)$						$M\_Exp^{Brd}(x)$					
	Obs.	Mean	Std	p25	p50	p75	Obs.	Mean	Std	p25	p50	p75
2005	741	0.094	0.074	0.051	0.079	0.115	741	0.248	0.168	0.100	0.249	0.376
2006	753	0.103	0.081	0.057	0.085	0.123	753	0.268	0.166	0.135	0.275	0.392
2007	779	0.104	0.080	0.057	0.091	0.126	779	0.282	0.179	0.138	0.288	0.413
2008	805	0.106	0.082	0.062	0.092	0.121	805	0.298	0.177	0.168	0.302	0.437
2009	813	0.113	0.085	0.065	0.097	0.130	813	0.323	0.183	0.186	0.330	0.454
2010	827	0.118	0.089	0.068	0.100	0.140	827	0.344	0.187	0.216	0.344	0.473
2011	843	0.124	0.099	0.070	0.104	0.150	843	0.363	0.193	0.235	0.367	0.489
2012	857	0.137	0.111	0.076	0.114	0.164	857	0.385	0.191	0.252	0.394	0.512
2013	867	0.145	0.114	0.082	0.119	0.172	867	0.399	0.194	0.273	0.419	0.538
2014	886	0.151	0.114	0.087	0.125	0.181	886	0.406	0.194	0.281	0.429	0.539
2015	896	0.153	0.105	0.090	0.133	0.185	896	0.426	0.197	0.305	0.451	0.567
2016	904	0.164	0.122	0.092	0.140	0.197	904	0.450	0.201	0.334	0.478	0.596
2017	914	0.166	0.120	0.095	0.144	0.197	914	0.443	0.194	0.330	0.470	0.584
2018	905	0.167	0.121	0.100	0.142	0.197	905	0.426	0.195	0.307	0.447	0.566
Total	11,790	0.133	0.105	0.073	0.110	0.163	11,790	0.366	0.199	0.222	0.376	0.507

Panel (B)												
	x = Earnings Management (EM)											
	$M\_Exp^{Geo}(x)$						$M\_Exp^{Brd}(x)$					
	Obs.	Mean	Std	p25	p50	p75	Obs.	Mean	Std	p25	p50	p75
2005	2,638	0.057	0.013	0.051	0.057	0.061	2,638	0.033	0.022	0.021	0.029	0.041
2006	2,508	0.056	0.012	0.050	0.056	0.060	2,508	0.033	0.022	0.023	0.030	0.042
2007	2,418	0.054	0.012	0.048	0.054	0.059	2,418	0.033	0.021	0.023	0.030	0.042
2008	2,314	0.058	0.013	0.053	0.058	0.063	2,314	0.037	0.022	0.026	0.034	0.045
2009	2,276	0.060	0.013	0.054	0.059	0.065	2,276	0.037	0.022	0.026	0.035	0.046
2010	2,241	0.059	0.013	0.054	0.059	0.064	2,241	0.037	0.021	0.026	0.034	0.046
2011	2,141	0.051	0.013	0.045	0.050	0.056	2,141	0.031	0.018	0.021	0.029	0.040
2012	2,024	0.050	0.012	0.043	0.048	0.054	2,024	0.030	0.019	0.020	0.027	0.037
2013	1,972	0.050	0.013	0.043	0.048	0.055	1,972	0.028	0.017	0.019	0.025	0.035
2014	1,956	0.049	0.013	0.042	0.048	0.055	1,956	0.027	0.015	0.019	0.025	0.034
2015	1,865	0.049	0.013	0.043	0.048	0.054	1,865	0.027	0.015	0.018	0.025	0.033
2016	1,882	0.049	0.014	0.042	0.048	0.054	1,882	0.027	0.017	0.019	0.025	0.034
2017	1,933	0.051	0.013	0.043	0.049	0.056	1,933	0.028	0.018	0.019	0.026	0.035
2018	1,875	0.052	0.015	0.043	0.050	0.058	1,875	0.025	0.017	0.016	0.023	0.034
Total	30,043	0.054	0.013	0.046	0.053	0.060	30,043	0.031	0.020	0.021	0.029	0.040

Table 5 (A) reports time series descriptive statistics for both exposure to **corporate misconduct**, the one implied by the physical network and the one induced by board members' social network. Analogously, **Table 5** (B) reports time series descriptive statistics for both exposure to **earnings management**, the one implied by the physical network and the one induced by board members' social network.

Table 6: Firm-level Characteristics across Firms' Misconduct Tendency

Panel (A)														
	x = Corporarte Misconduct (CM)													
	M_Event(x) = 0						M_Event(x) = 1						*t*-test	
	Obs.	Mean	Std	p25	p50	p75	Obs.	Mean	Std	p25	p50	p75	Diff.	*p*-value
$M\_Exp^{Geo}(x)$	7,383	0.127	0.099	0.069	0.106	0.157	4,407	0.144	0.114	0.079	0.118	0.172	0.017	0.000
$M\_Exp^{Brd}(x)$	7,383	0.339	0.201	0.181	0.344	0.485	4,407	0.411	0.186	0.291	0.427	0.540	0.072	0.000
$M\_Exp^{Ind}(x)$	7,383	0.226	0.163	0.088	0.189	0.340	4,407	0.292	0.175	0.147	0.286	0.420	0.066	0.000
Ln(Total Assets)	7,383	7.696	1.709	6.516	7.541	8.782	4,407	8.421	1.779	7.158	8.250	9.630	0.725	0.000
Age	7,383	26.887	16.376	14.000	22.000	39.000	4,407	32.846	18.619	17.000	29.000	50.000	5.959	0.000
ROA	7,383	0.126	0.110	0.073	0.122	0.177	4,407	0.137	0.088	0.086	0.131	0.181	0.011	0.000
Cash Holdings	7,383	0.137	0.146	0.031	0.084	0.195	4,407	0.105	0.110	0.027	0.069	0.148	-0.031	0.000
Leverage	7,383	0.215	0.202	0.049	0.162	0.330	4,407	0.245	0.199	0.096	0.195	0.362	0.030	0.000
B/M	7,383	0.671	0.639	0.314	0.518	0.821	4,407	0.647	0.699	0.307	0.503	0.799	-0.024	0.066
Tobin's Q	7,383	1.829	1.194	1.099	1.460	2.114	4,407	1.735	0.987	1.107	1.444	2.004	-0.094	0.000
Annual Return	7,383	0.169	0.538	-0.085	0.118	0.340	4,407	0.163	0.441	-0.065	0.128	0.326	-0.006	0.527
Ret. Volatility	7,383	0.102	0.057	0.066	0.090	0.123	4,407	0.094	0.055	0.059	0.081	0.113	-0.008	0.000
ESG Disclosure	7,383	0.142	0.143	0.000	0.150	0.214	4,407	0.203	0.162	0.000	0.192	0.290	0.061	0.000
Analyst Coverage	7,383	8.667	7.917	3.000	6.000	13.000	4,407	11.452	8.096	5.000	10.000	17.000	2.785	0.000
Dir. Expertise	7,383	0.936	0.193	1.000	1.000	1.000	4,407	0.958	0.140	1.000	1.000	1.000	0.022	0.000
Dir. Other Act.	7,383	0.158	0.155	0.000	0.143	0.250	4,407	0.195	0.171	0.000	0.167	0.300	0.037	0.000
Dir. Grad. Educ.	7,383	0.517	0.247	0.333	0.545	0.700	4,407	0.553	0.220	0.400	0.571	0.714	0.036	0.000
Dir. Achievers	7,383	0.108	0.134	0.000	0.091	0.182	4,407	0.129	0.147	0.000	0.100	0.200	0.021	0.000
Dir. Age	7,383	0.754	0.219	0.667	0.800	0.889	4,407	0.782	0.183	0.692	0.800	0.900	0.028	0.000
Dir. Women	7,383	0.127	0.117	0.000	0.125	0.200	4,407	0.150	0.115	0.083	0.143	0.222	0.023	0.000
Dir. Multi-Boards	7,383	0.458	0.283	0.250	0.444	0.667	4,407	0.518	0.263	0.333	0.500	0.700	0.061	0.000
Dir. Independency	7,383	0.782	0.188	0.714	0.833	0.889	4,407	0.817	0.146	0.750	0.857	0.900	0.035	0.000

Panel (B)														
	x = Earnings Management (EM)													
	M_Event(x) below the median						M_Event(x) above the median						*t*-test	
	Obs.	Mean	Std	p25	p50	p75	Obs.	Mean	Std	p25	p50	p75	Diff.	*p*-value
$M\_Exp^{Geo}(x)$	15,022	0.053	0.013	0.045	0.052	0.059	15,021	0.054	0.014	0.047	0.054	0.060	0.002	0.000
$M\_Exp^{Brd}(x)$	15,022	0.030	0.018	0.020	0.027	0.037	15,021	0.033	0.022	0.021	0.030	0.042	0.003	0.000
$M\_Exp^{Ind}(x)$	15,022	0.045	0.015	0.033	0.047	0.057	15,021	0.051	0.014	0.043	0.055	0.060	0.005	0.000
Ln(Total Assets)	15,022	7.095	2.041	5.687	7.052	8.427	15,021	6.053	2.015	4.577	5.964	7.380	-1.042	0.000
Age	15,022	25.660	17.248	12.000	20.000	38.000	15,021	20.773	14.591	10.000	17.000	27.000	-4.887	0.000
ROA	15,022	0.107	0.139	0.070	0.116	0.170	15,021	0.057	0.223	0.022	0.098	0.160	-0.050	0.000
Cash Holdings	15,022	0.172	0.192	0.034	0.101	0.239	15,021	0.239	0.234	0.053	0.162	0.361	0.067	0.000
Leverage	15,022	0.202	0.203	0.023	0.148	0.317	15,021	0.162	0.202	0.000	0.087	0.249	-0.040	0.000
B/M	15,022	0.687	0.791	0.315	0.526	0.831	15,021	0.651	0.847	0.273	0.489	0.813	-0.036	0.000
Tobin's Q	15,022	1.853	1.239	1.119	1.468	2.130	15,021	2.115	1.814	1.134	1.566	2.403	0.262	0.000
Annual Return	15,022	0.159	0.570	-0.118	0.101	0.331	15,021	0.144	0.702	-0.218	0.053	0.350	-0.015	0.044
Ret. Volatility	15,022	0.112	0.070	0.068	0.097	0.137	15,021	0.138	0.088	0.086	0.120	0.166	0.025	0.000
ESG Disclosure	15,022	0.120	0.151	0.000	0.000	0.203	15,021	0.069	0.119	0.000	0.000	0.148	-0.051	0.000
Analyst Coverage	15,022	7.635	7.605	1.000	5.000	12.000	15,021	5.853	7.066	0.000	3.000	8.000	-1.783	0.000
Dir. Expertise	15,022	0.898	0.253	1.000	1.000	1.000	15,021	0.875	0.280	1.000	1.000	1.000	-0.023	0.000
Dir. Other Act.	15,022	0.150	0.161	0.000	0.125	0.250	15,021	0.122	0.150	0.000	0.091	0.200	-0.027	0.000
Dir. Grad. Educ.	15,022	0.525	0.258	0.364	0.556	0.714	15,021	0.513	0.273	0.333	0.500	0.714	-0.012	0.000
Dir. Achievers	15,022	0.105	0.137	0.000	0.000	0.167	15,021	0.087	0.130	0.000	0.000	0.167	-0.018	0.000
Dir. Age	15,022	0.721	0.252	0.600	0.778	0.889	15,021	0.689	0.277	0.571	0.750	0.875	-0.032	0.000
Dir. Women	15,022	0.115	0.120	0.000	0.111	0.200	15,021	0.091	0.117	0.000	0.000	0.167	-0.024	0.000
Dir. Multi-Boards	15,022	0.439	0.293	0.200	0.429	0.636	15,021	0.400	0.305	0.167	0.375	0.600	-0.040	0.000
Dir. Independency	15,022	0.762	0.219	0.692	0.818	0.889	15,021	0.738	0.235	0.667	0.800	0.875	-0.024	0.000

Table 6 reports descriptive statistics of the main firm-level variables used in the panel regressions of CM and EM. **Panel (A)** presents descriptive statistics for firm-year observations that do not show corporate misconduct (M_Event(CM)=0) and those that exhibit **corporate misconduct** (M_Event(CM)=1). Given the continuous nature of EM, **Panel (B)** reports descriptive statistics across the **earnings management** tendency (below or above the median EM of the entire firm-year sample). "Geo" and "Brd" variable construction follows (1) and misconduct definitions follows Sections 2.1.1 and 2.1.2. The columns report the differences between means and the *p*-values are obtained from a two-tailed Welch's *t*-tests.

Table 7: Multivariate Analysis - Misconduct and Exposure to Misconduct

	Panel Conditional Logit Models x = Corporate Misconduct (CM)								Panel Linear Fixed Effects Models x = Earnings Management (EM)					
	(1) Within	(2) Within	(3) Within	(4) Within	(5) Within	(6) Within	(7) Mg. Effects	(8) Pooled	(9)	(10)	(11)	(12)	(13)	(14)
M_Exp^{Geo}(x)	1.002**		0.925**	0.926**	0.930**	0.967**	0.089	1.243***	0.079***		0.077***	0.073***	0.059**	0.058*
	(0.406)		(0.406)	(0.406)	(0.411)	(0.412)		(0.340)	(0.027)		(0.027)	(0.026)	(0.027)	(0.030)
M_Exp^{Brd}(x)		0.761***	0.737***	0.737***	0.697***	0.549***	0.050	1.383***		0.067**	0.066**	0.064**	0.057**	0.064**
		(0.202)	(0.202)	(0.202)	(0.203)	(0.207)		(0.181)		(0.027)	(0.027)	(0.027)	(0.025)	(0.025)
M_Exp^{Ind}(x)				0.148	0.198	0.059	0.005	3.962***				0.197***	0.196***	0.195***
				(0.397)	(0.400)	(0.403)		(0.279)				(0.066)	(0.066)	(0.065)
Ln(Total Assets)					0.423***	0.321***	0.029	0.678***					-0.009***	-0.009***
					(0.076)	(0.078)		(0.038)					(0.003)	(0.003)
Age					-1.522***	-1.466***	-0.134	0.022***					-0.011	-0.010
					(0.486)	(0.492)		(0.003)					(0.008)	(0.008)
ROA					1.231***	1.193***	0.109	2.855***					-0.022***	-0.022***
					(0.462)	(0.462)		(0.384)					(0.006)	(0.006)
Cash Holdings					-0.269	-0.262	-0.024	-1.441***					-0.038***	-0.038***
					(0.381)	(0.383)		(0.299)					(0.006)	(0.006)
Leverage					-0.535*	-0.370	-0.034	-0.889***					-0.012*	-0.012*
					(0.278)	(0.281)		(0.220)					(0.006)	(0.007)
B/M					0.067	0.077	0.007	0.006					0.001	0.001
					(0.059)	(0.060)		(0.044)					(0.001)	(0.001)
Tobin's Q					0.021	0.007	0.001	-0.006					0.003***	0.003***
					(0.046)	(0.046)		(0.039)					(0.001)	(0.001)
Annual Return					-0.094*	-0.074	-0.007	-0.048					-0.001	-0.001
					(0.054)	(0.053)		(0.050)					(0.001)	(0.001)
Ret. Volatility					1.325**	1.535**	0.141	1.698***					0.002	0.002
					(0.673)	(0.677)		(0.548)					(0.012)	(0.012)
ESG Disclosure						-0.161	-0.015	0.991***						0.003
						(0.346)		(0.304)						(0.005)
Analyst Coverage						0.034***	0.003	0.028***						0.000
						(0.007)		(0.006)						(0.000)
Dir. Expertise						0.100	0.009	1.372***						-0.005
						(0.286)		(0.211)						(0.006)
Dir. Other Act.						-0.036	-0.003	0.027						0.004
						(0.198)		(0.188)						(0.004)
Dir. Grad. Educ.						0.265	0.024	0.145						-0.001
						(0.227)		(0.173)						(0.005)
Dir. Achievers						0.069	0.006	0.090						-0.006
						(0.238)		(0.223)						(0.004)
Dir. Age						0.567***	0.052	0.628***						-0.006
						(0.213)		(0.177)						(0.005)
Dir. Women						0.066	0.006	0.083						-0.003
						(0.368)		(0.314)						(0.008)
Dir. Multi-Boards						-0.055	-0.005	0.218						-0.002
						(0.181)		(0.142)						(0.003)
Dir. Independency						0.521*	0.048	0.262						0.002
						(0.270)		(0.225)						(0.005)
Financial Controls	No	No	No	No	Yes	Yes		Yes	No	No	No	No	Yes	Yes
ESG-Analyst-Board Controls	No	No	No	No	No	Yes		Yes	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	No	No		No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,790	11,790	11,790	11,790	11,790	11,790		39,985	29,503	29,503	29,503	29,503	29,503	29,503
# Groups	967	967	967	967	967	967		5,501						
LR χ^2	140.3	148.4	153.6	153.8	217.6	262.4		1,842.1						
Adjusted R^2									0.288	0.288	0.288	0.288	0.297	0.297

Table 7 follows variable definitions described in Appendix A. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Degree of Influence of Peers

	Panel Conditional Logit Models x = Corporate Misconduct (CM)				Panel Linear Fixed Effects Models x = Earnings Management (EM)			
	(1) Within	(2) Within	(3) Within	(4) Within	(5)	(6)	(7)	(8)
$M\_Exp^{Geo}(x)$	0.955** (0.412)	0.967** (0.412)	0.962** (0.412)	0.932** (0.413)	0.056* (0.031)	0.058* (0.030)	0.058* (0.030)	0.057* (0.029)
$M\_Exp^{Brd}(x)$	-1.113 (0.995)	0.547** (0.228)	0.035 (0.636)	-0.341 (0.298)	-0.252** (0.123)	0.082** (0.031)	0.156* (0.081)	0.002 (0.032)
$M\_Exp^{Brd}(x) \times$ Dir. Expertise	1.763* (1.029)				0.344** (0.138)			
$M\_Exp^{Brd}(x) \times$ Dir. Achievers		0.016 (1.205)				-0.307 (0.241)		
$M\_Exp^{Brd}(x) \times$ Dir. Age			0.671 (0.787)				-0.131 (0.113)	
$M\_Exp^{Brd}(x) \times$ Dir. Multi-Boards				2.291*** (0.557)				0.227* (0.127)
$M\_Exp^{Ind}(x)$	0.056 (0.403)	0.059 (0.403)	0.053 (0.403)	0.028 (0.403)	0.195*** (0.072)	0.196*** (0.065)	0.196*** (0.067)	0.192*** (0.065)
Ln(Total Assets)	0.332*** (0.078)	0.321*** (0.078)	0.323*** (0.078)	0.334*** (0.078)	-0.009*** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)
Age	-1.458*** (0.492)	-1.466*** (0.492)	-1.465*** (0.492)	-1.474*** (0.491)	-0.010 (0.008)	-0.010 (0.008)	-0.010 (0.008)	-0.010 (0.008)
ROA	1.180** (0.462)	1.193*** (0.462)	1.199*** (0.462)	1.232*** (0.464)	-0.021*** (0.007)	-0.022*** (0.006)	-0.022*** (0.006)	-0.022*** (0.006)
Cash Holdings	-0.252 (0.383)	-0.262 (0.383)	-0.260 (0.383)	-0.223 (0.382)	-0.038*** (0.007)	-0.038*** (0.006)	-0.038*** (0.006)	-0.038*** (0.006)
Leverage	-0.376 (0.281)	-0.370 (0.281)	-0.370 (0.281)	-0.404 (0.281)	-0.012* (0.007)	-0.012* (0.007)	-0.012* (0.007)	-0.012* (0.007)
B/M	0.075 (0.059)	0.077 (0.060)	0.076 (0.059)	0.077 (0.059)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Tobin's Q	0.006 (0.046)	0.007 (0.046)	0.007 (0.046)	0.001 (0.046)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Annual Return	-0.073 (0.053)	-0.074 (0.053)	-0.074 (0.053)	-0.073 (0.053)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Ret. Volatility	1.524** (0.677)	1.535** (0.677)	1.546** (0.677)	1.553** (0.677)	0.002 (0.012)	0.002 (0.012)	0.002 (0.012)	0.002 (0.012)
ESG Disclosure	-0.194 (0.346)	-0.161 (0.347)	-0.155 (0.346)	-0.247 (0.347)	0.003 (0.005)	0.003 (0.005)	0.003 (0.005)	0.003 (0.005)
Analyst Coverage	0.034*** (0.007)	0.034*** (0.007)	0.034*** (0.007)	0.032*** (0.007)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Dir. Expertise	-0.325 (0.375)	0.100 (0.286)	0.150 (0.292)	0.174 (0.286)	-0.014** (0.007)	-0.005 (0.006)	-0.006 (0.006)	-0.005 (0.006)
Dir. Other Act.	-0.025 (0.198)	-0.036 (0.198)	-0.033 (0.198)	-0.032 (0.198)	0.004 (0.005)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
Dir. Grad. Educ.	0.316 (0.229)	0.265 (0.227)	0.279 (0.227)	0.274 (0.227)	-0.000 (0.005)	-0.001 (0.005)	-0.001 (0.005)	-0.001 (0.005)
Dir. Achievers	0.090 (0.238)	0.063 (0.512)	0.073 (0.238)	0.114 (0.238)	-0.006 (0.004)	0.004 (0.008)	-0.006 (0.004)	-0.006 (0.004)
Dir. Age	0.621*** (0.215)	0.567*** (0.213)	0.331 (0.349)	0.600*** (0.213)	-0.005 (0.005)	-0.006 (0.005)	-0.002 (0.004)	-0.006 (0.005)
Dir. Women	0.077 (0.368)	0.066 (0.368)	0.076 (0.368)	0.068 (0.369)	-0.003 (0.008)	-0.003 (0.008)	-0.003 (0.008)	-0.003 (0.008)
Dir. Multi-Boards	-0.033 (0.182)	-0.055 (0.181)	-0.049 (0.181)	-0.904*** (0.275)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.010** (0.005)
Dir. Independency	0.601** (0.274)	0.521* (0.271)	0.553** (0.273)	0.594** (0.271)	0.004 (0.005)	0.002 (0.005)	0.001 (0.005)	0.002 (0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	11,790	11,790	11,790	11,790	29,503	29,503	29,503	29,503
# Groups	967	967	967	967				
LR χ^2	265.5	262.4	263.2	279.7				
Adjusted R^2					0.297	0.297	0.297	0.297

Table 8 follows variable definitions described in Appendix A. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Probability of Being Caught and Likely Penalty

	Panel Conditional Logit Models x = Corporate Misconduct (CM)				Panel Linear Fixed Effects Models x = Earnings Management (EM)		
	$D(v,t) = 1$ if v is above the median in year t, where v denotes:						
	(1) v = Ln(Total Assets)	(2) v = ESG Disclosure	(3) v = Analyst Coverage	(4) v = Average Neighbors' Penalty	(5) v = Ln(Total Assets)	(6) v = ESG Disclosure	(7) v = Analyst Coverage
$D(v,t)$	0.313	0.358**	0.350**	0.814	0.010**	0.003	-0.002
	(0.200)	(0.166)	(0.167)	(0.668)	(0.005)	(0.003)	(0.004)
M_Exp$^{\text{Geo}}$(x)	0.690	1.226**	0.598	0.982**	0.108**	0.088*	0.048
	(0.584)	(0.519)	(0.507)	(0.414)	(0.051)	(0.045)	(0.050)
M_Exp$^{\text{Geo}}$(x)$\times D(v,t)$	0.410	-0.461	0.781	-0.693	-0.097	-0.083	0.020
	(0.729)	(0.559)	(0.656)	(1.711)	(0.059)	(0.049)	(0.060)
M_Exp$^{\text{Brd}}$(x)	1.029***	0.784***	0.888***	0.577***	0.087***	0.059**	0.062**
	(0.241)	(0.227)	(0.236)	(0.208)	(0.030)	(0.026)	(0.029)
M_Exp$^{\text{Brd}}$(x)$\times D(v,t)$	-1.485***	-0.891***	-1.036***	-2.282*	-0.108**	0.035	0.007
	(0.365)	(0.332)	(0.337)	(1.283)	(0.047)	(0.066)	(0.085)
M_Exp$^{\text{Ind}}$(x)	0.004	0.073	0.032	0.058	0.195***	0.195***	0.195***
	(0.404)	(0.403)	(0.404)	(0.403)	(0.067)	(0.066)	(0.066)
Ln(Total Assets)	0.363***	0.314***	0.316***	0.321***	-0.009***	-0.009***	-0.009***
	(0.085)	(0.078)	(0.078)	(0.078)	(0.003)	(0.003)	(0.003)
Age	-1.445***	-1.450***	-1.434***	-1.464***	-0.011	-0.010	-0.010
	(0.496)	(0.493)	(0.492)	(0.492)	(0.008)	(0.008)	(0.008)
ROA	1.154**	1.167**	1.162**	1.201***	-0.021***	-0.022***	-0.022***
	(0.464)	(0.463)	(0.463)	(0.462)	(0.007)	(0.006)	(0.006)
Cash Holdings	-0.270	-0.251	-0.276	-0.263	-0.038***	-0.038***	-0.038***
	(0.384)	(0.384)	(0.383)	(0.383)	(0.006)	(0.006)	(0.006)
Leverage	-0.401	-0.373	-0.363	-0.368	-0.012*	-0.012*	-0.012*
	(0.282)	(0.281)	(0.281)	(0.281)	(0.007)	(0.007)	(0.007)
B/M	0.081	0.078	0.077	0.075	0.001	0.001	0.001
	(0.060)	(0.060)	(0.060)	(0.059)	(0.001)	(0.001)	(0.001)
Tobin's Q	0.008	0.010	0.007	0.008	0.003***	0.003***	0.003***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.001)	(0.001)	(0.001)
Annual Return	-0.072	-0.076	-0.073	-0.076	-0.001	-0.001	-0.001
	(0.054)	(0.053)	(0.054)	(0.053)	(0.001)	(0.001)	(0.001)
Ret. Volatility	1.636**	1.594**	1.576**	1.574**	0.002	0.002	0.002
	(0.681)	(0.678)	(0.680)	(0.677)	(0.012)	(0.013)	(0.012)
ESG Disclosure	0.050	0.060	-0.071	-0.153	0.002	0.005	0.003
	(0.351)	(0.428)	(0.349)	(0.346)	(0.005)	(0.007)	(0.005)
Analyst Coverage	0.036***	0.036***	0.032***	0.034***	0.000	0.000	0.000
	(0.007)	(0.007)	(0.008)	(0.007)	(0.000)	(0.000)	(0.000)
Dir. Expertise	0.168	0.116	0.098	0.100	-0.005	-0.005	-0.005
	(0.288)	(0.287)	(0.287)	(0.286)	(0.006)	(0.006)	(0.006)
Dir. Other Act.	-0.010	-0.038	-0.031	-0.037	0.004	0.004	0.004
	(0.198)	(0.198)	(0.198)	(0.198)	(0.004)	(0.004)	(0.004)
Dir. Grad. Educ.	0.267	0.274	0.265	0.264	-0.001	-0.001	-0.001
	(0.228)	(0.227)	(0.227)	(0.227)	(0.005)	(0.005)	(0.005)
Dir. Achievers	0.052	0.041	0.063	0.069	-0.006	-0.006	-0.006
	(0.238)	(0.238)	(0.238)	(0.238)	(0.004)	(0.004)	(0.004)
Dir. Age	0.591***	0.548**	0.554***	0.563***	-0.006	-0.006	-0.006
	(0.213)	(0.213)	(0.213)	(0.213)	(0.005)	(0.005)	(0.005)
Dir. Women	0.079	0.077	0.069	0.071	-0.003	-0.003	-0.003
	(0.369)	(0.368)	(0.368)	(0.368)	(0.008)	(0.008)	(0.008)
Dir. Multi-Boards	-0.067	-0.054	-0.062	-0.060	-0.002	-0.002	-0.002
	(0.182)	(0.181)	(0.181)	(0.181)	(0.003)	(0.003)	(0.003)
Dir. Independency	0.525*	0.527*	0.529*	0.513*	0.002	0.002	0.002
	(0.271)	(0.271)	(0.271)	(0.271)	(0.005)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	Yes	Yes	Yes
Observations	11,790	11,790	11,790	11,790	29,503	29,503	29,503
# Groups	967	967	967	967			
LR χ^2	281.6	271.3	272.8	268.4			
Adjusted R^2					0.297	0.297	0.297

Table 9 follows variable definitions described in Appendix A. $D(v,t)$ is a time-varying dummy variable that takes the value of one if v is above its median in year t, and zero otherwise. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Misconduct at the Firm-Level, Selection Bias

Dependent variable:	x = Corporate Misconduct (CM)				x = Earning Management (EM)	
M_Event(x) = {0,1}	Panel Cond. Poisson		Matching Model		Panel Linear FE	Matching Model
		Mg. Effects		Mg. Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
M_Exp $^{Geo}(x)$	0.467***	0.467	0.489***	0.182	0.042***	0.052***
	(0.175)		(0.122)		(0.011)	(0.009)
M_Exp $^{Brd}(x)$	0.477***	0.477	0.525***	0.195	0.048***	0.037***
	(0.107)		(0.072)		(0.008)	(0.006)
Ln(Total Assets)	0.089***	0.089	0.082***	0.031	-0.010***	-0.007***
	(0.019)		(0.013)		(0.001)	(0.001)
Age	0.003***	0.003	0.005***	0.002	-0.009	-0.001***
	(0.001)		(0.001)		(0.007)	(0.001)
ROA	1.130***	1.130	1.105***	0.411	-0.016***	-0.045***
	(0.223)		(0.157)		(0.004)	(0.002)
Cash holdings	-0.686***	-0.686	-0.702***	-0.261	-0.033***	0.007***
	(0.177)		(0.109)		(0.004)	(0.002)
Leverage	0.391***	0.391	0.446***	0.166	-0.014***	0.001
	(0.123)		(0.079)		(0.004)	(0.002)
B/M	0.018	0.018	0.013	0.005	-0.000	-0.002***
	(0.030)		(0.022)		(0.001)	(0.001)
Annual return	-0.008	-0.008	0.007	0.002	-0.000	-0.001**
	(0.033)		(0.026)		(0.001)	(0.001)
Ret. volatility	0.671*	0.671	0.729***	0.271	-0.012**	0.064***
	(0.356)		(0.264)		(0.006)	(0.005)
ESG Disclosure	0.213	0.213	0.365***	0.136	-0.001	-0.004
	(0.171)		(0.114)		(0.005)	(0.004)
Analyst Coverage	0.010***	0.010	0.01***	0.004	0.000*	0.001***
	(0.003)		(0.002)		(0.000)	(0.001)
ESG Disclosure	0.016	0.016	-0.007	-0.003	-0.001	-0.009***
	(0.145)		(0.095)		(0.003)	(0.002)
Dir. Other Act.	0.029	0.029	0.081	0.03	0.003	0.008**
	(0.117)		(0.093)		(0.003)	(0.003)
Dir. Grad. Edu.	0.014	0.014	-0.049	-0.018	-0.003	-0.001
	(0.094)		(0.061)		(0.003)	(0.002)
Dir. Achievers	0.029	0.029	0.044	0.016	-0.008**	0.001
	(0.143)		(0.106)		(0.004)	(0.003)
Dir. Age	0.249**	0.249	0.261***	0.097	-0.005*	-0.008***
	(0.107)		(0.071)		(0.003)	(0.002)
Dir. Woman	0.076	0.076	0.04	0.015	-0.002	-0.007*
	(0.180)		(0.12)		(0.005)	(0.004)
Dir. Multi-Brd.	-0.007	-0.007	0.012	0.004	-0.002	0.003*
	(0.079)		(0.051)		(0.003)	(0.001)
Dir. Indep.	0.188	0.188	0.114	0.042	-0.000	0.001
	(0.144)		(0.092)		(0.003)	(0.003)
κ			0.275***			0.001
			(0.09)			(0.002)
Observations	11,865	11,865	11,865	11,865	31,669	31,669
LR χ^2	365.2					
# groups	955					
Firm FE					Yes	
Adj R-squared					0.278	

Table 11: Local Norms Heterogeneity

	Panel Linear Fixed Effects Models x = Earnings Management (EM)					
	(1) State	(2) Satate	(3) MSA	(4) MSA-50Km	(5) MSA-35Km	(6) MSA-20Km
M_Exp^{Geo}(x)	0.058*	0.054*	0.054	0.054*	0.054*	0.054
	(0.030)	(0.028)	(0.033)	(0.031)	(0.031)	(0.036)
M_Exp^{Brd}(x)	0.064**	0.070***	0.070***	0.070**	0.070**	0.070***
	(0.025)	(0.023)	(0.024)	(0.028)	(0.026)	(0.024)
M_Exp^{Ind}(x)	0.195***	0.211***	0.211***	0.211***	0.211***	0.211***
	(0.065)	(0.068)	(0.065)	(0.064)	(0.065)	(0.067)
Ln(Total Assets)	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.010	-0.010	-0.010***	-0.010	-0.010	-0.010*
	(0.008)	(0.008)	(0.003)	(0.006)	(0.007)	(0.006)
ROA	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
Cash Holdings	-0.038***	-0.037***	-0.037***	-0.037***	-0.037***	-0.037***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Leverage	-0.012*	-0.011*	-0.011	-0.011*	-0.011*	-0.011*
	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)
B/M	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tobin's Q	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Annual Return	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ret. Volatility	0.002	0.001	0.001	0.001	0.001	0.001
	(0.012)	(0.013)	(0.015)	(0.012)	(0.013)	(0.013)
ESG Disclosure	0.003	0.003	0.003	0.003	0.003	0.003
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Analyst Coverage	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dir. Expertise	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)
Dir. Other Act.	0.004	0.004	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Dir. Grad. Educ.	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)
Dir. Achievers	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006*
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Dir. Age	-0.006	-0.005	-0.005	-0.005	-0.005	-0.005
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Dir. Women	-0.003	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.008)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
Dir. Multi-Boards	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)
Dir. Independency	0.002	0.002	0.002	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Area FE	State	State	MSA	MSA-50Km	MSA-35Km	MSA-20Km
Observations	29,503	28,869	28,869	28,869	28,869	28,869
Adjusted R^2	0.297	0.298	0.291	0.290	0.290	0.289

Table 11 follows variable definitions described in Appendix A. Column (1) presents the benchmark EM model, column (2) presents the benchmark EM model but considers just firm-year observations that could be matched with an MSA. The following columns follow geographic unit definitions described in section 4.2.6. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Complementarity between Social and Geographic Exposure to Misconduct

	Panel Conditional Logit Models x = Corporate Misconduct (CM)				Panel Linear Fixed Effects Models x = Earnings Management (EM)			
	(1) Within	(2) Within	(3) Within	(4) Within	(5)	(6)	(7)	(8)
M_Exp^{Geo}(x)	0.967**	3.169***	3.098***	2.967***	0.058*	-0.000	0.008	0.024
	(0.412)	(0.774)	(0.781)	(0.782)	(0.030)	(0.048)	(0.048)	(0.049)
M_Exp^{Brd}(x)	0.549***	1.263***	1.642***	1.874***	0.064**	-0.034	-0.093	-0.196
	(0.207)	(0.294)	(0.619)	(0.633)	(0.025)	(0.088)	(0.111)	(0.119)
M_Exp^{Ind}(x)	0.059	0.056	0.056	0.899	0.195***	0.195***	0.196***	0.110
	(0.403)	(0.403)	(0.403)	(0.618)	(0.065)	(0.066)	(0.068)	(0.088)
M_Exp^{Geo}(x)$\times$ M_Exp^{Brd}(x)		-5.224***	-5.049***	-4.718***		1.746	1.512	1.037
		(1.522)	(1.541)	(1.550)		(1.541)	(1.548)	(1.582)
M_Exp^{Brd}(x)$\times$ M_Exp^{Brd}(x)			-0.505	-0.223			0.608	0.557
			(0.725)	(0.742)			(0.427)	(0.401)
M_Exp^{Ind}(x)$\times$ M_Exp^{Brd}(x)				-1.777*				2.648
				(0.988)				(1.753)
Ln(Total Assets)	0.321***	0.303***	0.298***	0.296***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.078)	(0.078)	(0.078)	(0.078)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-1.466***	-1.474***	-1.481***	-1.477***	-0.010	-0.010	-0.010	-0.010
	(0.492)	(0.493)	(0.493)	(0.492)	(0.008)	(0.008)	(0.008)	(0.008)
ROA	1.193***	1.125**	1.124**	1.135**	-0.022***	-0.022***	-0.022***	-0.021***
	(0.462)	(0.463)	(0.463)	(0.463)	(0.006)	(0.007)	(0.007)	(0.007)
Cash Holdings	-0.262	-0.228	-0.227	-0.231	-0.038***	-0.038***	-0.038***	-0.038***
	(0.383)	(0.383)	(0.383)	(0.383)	(0.006)	(0.006)	(0.006)	(0.006)
Leverage	-0.370	-0.367	-0.367	-0.365	-0.012*	-0.012*	-0.012*	-0.012*
	(0.281)	(0.281)	(0.281)	(0.281)	(0.007)	(0.007)	(0.007)	(0.007)
B/M	0.077	0.075	0.076	0.078	0.001	0.001	0.001	0.001
	(0.060)	(0.060)	(0.060)	(0.060)	(0.001)	(0.001)	(0.001)	(0.001)
Tobin's Q	0.007	0.011	0.011	0.012	0.003***	0.003***	0.003***	0.003***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.001)	(0.001)	(0.001)	(0.001)
Annual Return	-0.074	-0.080	-0.080	-0.081	-0.001	-0.001	-0.001	-0.001
	(0.053)	(0.053)	(0.053)	(0.053)	(0.001)	(0.001)	(0.001)	(0.001)
Ret. Volatility	1.535**	1.533**	1.532**	1.572**	0.002	0.002	0.002	0.002
	(0.677)	(0.678)	(0.678)	(0.678)	(0.012)	(0.012)	(0.012)	(0.012)
ESG Disclosure	-0.161	-0.119	-0.111	-0.103	0.003	0.003	0.003	0.002
	(0.346)	(0.347)	(0.347)	(0.347)	(0.005)	(0.005)	(0.005)	(0.005)
Analyst Coverage	0.034***	0.034***	0.035***	0.035***	0.000	0.000	0.000	0.000
	(0.007)	(0.007)	(0.007)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Dir. Expertise	0.100	0.104	0.094	0.121	-0.005	-0.005	-0.005	-0.005
	(0.286)	(0.287)	(0.288)	(0.288)	(0.006)	(0.006)	(0.006)	(0.006)
Dir. Other Act.	-0.036	-0.026	-0.028	-0.032	0.004	0.004	0.004	0.004
	(0.198)	(0.198)	(0.198)	(0.198)	(0.004)	(0.004)	(0.004)	(0.004)
Dir. Grad. Educ.	0.265	0.278	0.273	0.282	-0.001	-0.001	-0.001	-0.001
	(0.227)	(0.227)	(0.227)	(0.227)	(0.005)	(0.005)	(0.005)	(0.005)
Dir. Achievers	0.069	0.063	0.056	0.062	-0.006	-0.006	-0.006	-0.006
	(0.238)	(0.238)	(0.239)	(0.239)	(0.004)	(0.004)	(0.004)	(0.004)
Dir. Age	0.567***	0.587***	0.577***	0.570***	-0.006	-0.006	-0.006	-0.006
	(0.213)	(0.213)	(0.214)	(0.214)	(0.005)	(0.005)	(0.005)	(0.005)
Dir. Women	0.066	0.054	0.051	0.049	-0.003	-0.003	-0.003	-0.003
	(0.368)	(0.369)	(0.369)	(0.369)	(0.008)	(0.008)	(0.008)	(0.008)
Dir. Multi-Boards	-0.055	-0.057	-0.063	-0.049	-0.002	-0.002	-0.002	-0.002
	(0.181)	(0.181)	(0.182)	(0.182)	(0.003)	(0.003)	(0.003)	(0.003)
Dir. Independency	0.521*	0.525*	0.511*	0.521*	0.002	0.002	0.002	0.002
	(0.270)	(0.271)	(0.272)	(0.272)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	11,790	11,790	11,790	11,790	29,503	29,503	29,503	29,503
# Groups	967	967	967	967				
LR χ^2	262.4	274.5	274.9	278.2				
Adjusted R^2					0.297	0.297	0.297	0.297

Table 12 follows variable definitions described in Appendix A. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Speed of Diffusion

	Panel Conditional Logit Models x = Corporate Misconduct (CM)							Panel Linear Fixed Effects Models x = Earnings Management (EM)					
	(1) Within	(2) Within	(3) Within	(4) Within	(5) Within	(6) Within	(7) Pooled	(8)	(9)	(10)	(11)	(12)	(13)
M_Exp^{Geo}(x)	0.633		0.515	0.515	0.498	0.537	0.537	0.062		0.059	0.054	0.045	0.046
	(0.524)		(0.528)	(0.528)	(0.534)	(0.533)	(0.533)	(0.038)		(0.039)	(0.038)	(0.056)	(0.057)
Lagged M_Exp^{Geo}(x)	0.512		0.580	0.580	0.621	0.600	0.600	0.013		0.012	0.011	0.002	0.001
	(0.528)		(0.530)	(0.530)	(0.536)	(0.537)	(0.537)	(0.070)		(0.071)	(0.070)	(0.075)	(0.076)
M_Exp^{Brd}(x)		1.217***	1.202***	1.202***	1.187***	1.013***	1.013***		0.075**	0.074**	0.072**	0.070*	0.079**
		(0.252)	(0.252)	(0.252)	(0.253)	(0.259)	(0.259)		(0.035)	(0.035)	(0.035)	(0.037)	(0.036)
Lagged M_Exp^{Brd}(x)		-0.795***	-0.811***	-0.811***	-0.839***	-0.785***	-0.785***		-0.022	-0.022	-0.022	-0.028	-0.032
		(0.251)	(0.251)	(0.251)	(0.252)	(0.254)	(0.254)		(0.039)	(0.039)	(0.039)	(0.040)	(0.041)
M_Exp^{Ind}(x)				-0.056	-0.017	-0.097	-0.097				0.251***	0.253***	0.252***
				(0.422)	(0.425)	(0.427)	(0.427)				(0.054)	(0.055)	(0.055)
Ln(Total Assets)					0.400***	0.311***	0.311***					-0.007**	-0.007**
					(0.082)	(0.084)	(0.084)					(0.003)	(0.003)
Age					-1.309***	-1.259**	-1.259**					-0.007	-0.007
					(0.507)	(0.513)	(0.513)					(0.007)	(0.007)
ROA					1.037**	1.012**	1.012**					-0.026***	-0.025***
					(0.489)	(0.490)	(0.490)					(0.004)	(0.004)
Cash Holdings					-0.288	-0.302	-0.302					-0.039***	-0.039***
					(0.411)	(0.413)	(0.413)					(0.008)	(0.008)
Leverage					-0.500*	-0.361	-0.361					-0.015**	-0.015**
					(0.297)	(0.300)	(0.300)					(0.007)	(0.007)
B/M					0.098	0.106*	0.106*					0.001*	0.001*
					(0.063)	(0.063)	(0.063)					(0.001)	(0.001)
Tobin's Q					0.041	0.030	0.030					0.003***	0.003***
					(0.049)	(0.049)	(0.049)					(0.000)	(0.001)
Annual Return					-0.102*	-0.085	-0.085					-0.001	-0.001
					(0.056)	(0.056)	(0.056)					(0.001)	(0.001)
Ret. Volatility					0.999	1.195*	1.195*					0.009	0.009
					(0.711)	(0.715)	(0.715)					(0.013)	(0.013)
ESG Disclosure						-0.180	-0.180						0.003
						(0.388)	(0.388)						(0.005)
Analyst Coverage						0.031***	0.031***						0.000
						(0.007)	(0.007)						(0.000)
Dir. Expertise						0.388	0.388						-0.007
						(0.353)	(0.353)						(0.007)
Dir. Other Act.						-0.104	-0.104						0.006
						(0.209)	(0.209)						(0.004)
Dir. Grad. Educ.						0.219	0.219						0.001
						(0.244)	(0.244)						(0.005)
Dir. Achievers						-0.061	-0.061						-0.006
						(0.254)	(0.254)						(0.004)
Dir. Age						0.631***	0.631***						-0.005
						(0.226)	(0.226)						(0.006)
Dir. Women						0.252	0.252						-0.002
						(0.386)	(0.386)						(0.009)
Dir. Multi-Boards						-0.116	-0.116						-0.003
						(0.192)	(0.192)						(0.003)
Dir. Independency						0.285	0.285						0.001
						(0.290)	(0.290)						(0.006)
Financial Controls	No	No	No	No	Yes	Yes	Yes	No	No	No	No		Yes
ESG-Analyst-Board Controls	No	No	No	No	No	Yes	Yes	No	No	No	No		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,812	10,769	10,769	10,769	10,769	10,769	10,769	26,619	26,392	26,392	26,392	26,392	26,392
# Groups	943	941	941	941	941	941	941						
LR χ^2	127.6	145.2	150.4	150.4	200.0	235.3	235.3						
Adjusted R^2								0.292	0.292	0.292	0.292	0.300	0.300

Table 13 follows variable definitions described in Appendix A. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Types of Corporate Misconduct

	Panel Conditional Logit Models x = Corporate Misconduct (CM)				
	(1) Competition & Consumer	(2) Employment	(3) Environment	(4) Safety	(5) Overall
$M\_Exp^{Geo}(x)$	-0.164	1.331**	1.266*	1.178**	0.967**
	(2.051)	(0.639)	(0.691)	(0.561)	(0.412)
$M\_Exp^{Brd}(x)$	0.348	0.722*	0.562	0.595**	0.549***
	(1.064)	(0.400)	(0.480)	(0.289)	(0.207)
$M\_Exp^{Ind}(x)$	1.562	2.744***	0.770	-0.155	0.059
	(2.273)	(0.697)	(0.643)	(0.455)	(0.403)
Ln(Total Assets)	0.446**	0.158	0.375***	0.395***	0.321***
	(0.188)	(0.106)	(0.122)	(0.100)	(0.078)
Age	-0.021	-0.666	-1.303	-0.874	-1.466***
	(0.037)	(0.783)	(0.985)	(0.564)	(0.492)
ROA	2.708*	2.369***	0.154	0.579	1.193***
	(1.398)	(0.796)	(0.687)	(0.602)	(0.462)
Cash Holdings	0.828	-0.391	0.206	-0.772	-0.262
	(0.949)	(0.575)	(0.665)	(0.509)	(0.383)
Leverage	-0.105	0.638	-0.932*	-0.762**	-0.370
	(0.696)	(0.413)	(0.482)	(0.362)	(0.281)
B/M	0.211**	0.105	0.077	-0.049	0.077
	(0.107)	(0.087)	(0.105)	(0.076)	(0.060)
Tobin's Q	-0.116	-0.104	-0.092	0.150**	0.007
	(0.136)	(0.072)	(0.088)	(0.065)	(0.046)
Annual Return	0.013	-0.012	0.071	-0.119*	-0.074
	(0.132)	(0.077)	(0.085)	(0.067)	(0.053)
Ret. Volatility	-0.076	0.221	0.418	1.780**	1.535**
	(1.760)	(0.963)	(1.228)	(0.845)	(0.677)
ESG Disclosure	-0.856	-0.231	0.051	-0.165	-0.161
	(0.706)	(0.437)	(0.471)	(0.411)	(0.346)
Analyst Coverage	0.024*	0.023**	0.018*	0.022**	0.034***
	(0.014)	(0.009)	(0.010)	(0.009)	(0.007)
Dir. Expertise	0.418	-0.129	-0.423	0.700*	0.100
	(0.680)	(0.381)	(0.439)	(0.378)	(0.286)
Dir. Other Act.	0.473	0.156	0.185	-0.310	-0.036
	(0.406)	(0.263)	(0.288)	(0.240)	(0.198)
Dir. Grad. Educ.	-0.691	0.123	0.348	0.527*	0.265
	(0.539)	(0.313)	(0.359)	(0.279)	(0.227)
Dir. Achievers	0.198	-0.011	0.539	-0.096	0.069
	(0.472)	(0.295)	(0.342)	(0.292)	(0.238)
Dir. Age	1.363***	0.225	0.957***	0.193	0.567***
	(0.514)	(0.299)	(0.344)	(0.264)	(0.213)
Dir. Women	-0.296	0.730	-0.444	0.002	0.066
	(0.799)	(0.495)	(0.565)	(0.441)	(0.368)
Dir. Multi-Boards	-0.004	0.327	-0.123	-0.039	-0.055
	(0.425)	(0.246)	(0.286)	(0.221)	(0.181)
Dir. Independency	1.784***	0.509	0.463	0.079	0.521*
	(0.691)	(0.378)	(0.435)	(0.339)	(0.270)
Year FE	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	No
Observations	3,812	7,675	5,581	8,799	11,790
# Groups	289	602	440	708	967
LR χ^2	56.1	105.7	85.8	401.1	262.4

Table 14 follows variable definitions described in Appendix A. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Firm's Corporate Misconduct Culture

	Panel Conditional Logit Models x = Corporate Misconduct (CM) Less or equal than 4 offenses committed historically						Panel Conditional Logit Models x = Corporate Misconduct (CM) More than 4 offenses commited historically					
	(1) Within	(2) Within	(3) Within	(4) Within	(5) Within	(6) Within	(7) Within	(8) Within	(9) Within	(10) Within	(11) Within	(12) Within
M_Exp^{Geo}(x)	0.276		0.118	0.114	0.041	0.120	1.467**		1.436**	1.439**	1.329**	1.307**
	(0.634)		(0.640)	(0.642)	(0.646)	(0.649)	(0.627)		(0.627)	(0.627)	(0.632)	(0.636)
M_Exp^{Brd}(x)		1.159***	1.155***	1.157***	1.150***	1.181***		0.443	0.415	0.409	0.395	0.273
		(0.314)	(0.315)	(0.315)	(0.317)	(0.319)		(0.310)	(0.311)	(0.311)	(0.313)	(0.317)
M_Exp^{Ind}(x)				0.563	0.682	0.703				0.476	0.454	0.260
				(0.693)	(0.700)	(0.707)				(0.555)	(0.563)	(0.569)
Ln(Total Assets)					0.264**	0.219*					0.468***	0.346***
					(0.113)	(0.120)					(0.110)	(0.113)
Age					-1.133**	-1.024*					-13.873***	-13.099***
					(0.559)	(0.564)					(0.019)	(0.024)
ROA					1.508**	1.467**					1.178*	1.197*
					(0.712)	(0.710)					(0.663)	(0.666)
Cash Holdings					0.208	0.273					-0.984*	-0.810
					(0.541)	(0.545)					(0.582)	(0.589)
Leverage					0.132	0.163					-0.639	-0.476
					(0.433)	(0.437)					(0.434)	(0.438)
B/M					0.031	0.027					0.077	0.116
					(0.098)	(0.099)					(0.105)	(0.107)
Tobin's Q					-0.013	-0.022					0.116	0.087
					(0.060)	(0.061)					(0.077)	(0.078)
Annual Return					-0.039	-0.026					-0.180**	-0.139*
					(0.091)	(0.091)					(0.080)	(0.081)
Ret. Volatility					2.408**	2.525**					1.180	1.466
					(1.037)	(1.041)					(0.997)	(0.999)
ESG Disclosure						-0.059						-0.111
						(0.623)						(0.471)
Analyst Coverage						0.020*						0.049***
						(0.011)						(0.010)
Dir. Expertise						-0.015						-0.435
						(0.508)						(0.410)
Dir. Other Act.						-0.061						-0.178
						(0.340)						(0.269)
Dir. Grad. Educ.						-0.188						0.239
						(0.362)						(0.330)
Dir. Achievers						-0.175						0.060
						(0.412)						(0.323)
Dir. Age						0.004						0.699**
						(0.352)						(0.301)
Dir. Women						-0.727						0.421
						(0.603)						(0.517)
Dir. Multi-Boards						-0.539*						0.213
						(0.303)						(0.252)
Dir. Independency						0.641						-0.088
						(0.439)						(0.402)
Financial Controls	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
ESG-Analyst-Board Controls	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Firm FE	No	No	No	No	No	No	No	No	No	No	No	No
Observations	5,421	5,421	5,421	5,421	5,421	5,421	5,006	5,006	5,006	5,006	5,006	5,006
# Groups	475	475	475	475	475	475	391	391	391	391	391	391
LR χ^2	75.5	89.0	89.0	89.7	110.4	120.4	109.5	105.8	111.2	112.0	154.4	189.7

Table 15 follows variable definitions described in Appendix A. The threshold is "4 offenses committed historically" because that is the median number of times that a firm commits corporate misconduct over the 14-year timespan (2005-2018) of our panel data. All regressions report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

A Variable Description

Exposure to Misconduct

Each year t, at the firm level, we construct a measure of social-exposure to misconduct as well as a measure of geo-exposure to misconduct.

Exposure to Misconduct implied by Social Network ($\mathbf{M\_Exp^{Brd}}$): Each year t, a firm i's exposures to misconduct is computed by value-weighting (using $\{C_{ijt}^{\text{Brd}}\}$) connecting firms (j) based on their past misconduct (M_{jt}) defined based on misconduct events occurred during the misconduct window $[t-3, t-1]$. In the case of CM events described in Section 2.1.1, M_{jt} will be an indicator taking the value of one if the neighboring firm j experienced misconduct over the misconduct window and zero otherwise. In the case of the earnings management measure described in Section 2.1.2, M_{jt} will be the aggregate earnings management measure of the neighboring firm j exhibited over the misconduct window. Lastly, we compute the firm i's exposure to misconduct implied by its social network as the first expression in equation (1).

Exposure to Misconduct implied by Physical Network ($\mathbf{M\_Exp^{Geo}}$): Each year t, a firm i's exposures to misconduct is computed by value-weighting (using $\{C_{ijt}^{\text{Geo}}\}$) connecting firms (j) based on their past misconduct (M_{jt}) defined based on misconduct events occurred during the misconduct window $[t-3, t-1]$. In the case of CM events described in Section 2.1.1, M_{jt} will be an indicator taking the value of one if the neighboring firm j experienced misconduct over the misconduct window and zero otherwise. In the case of the earnings management measure described in Section 2.1.2, M_{jt} will be the aggregate earnings management measure of the neighboring firm j exhibited over the misconduct window. Lastly, we compute the firm i's exposure to misconduct implied by its physical network as the second expression in equation (1).

Financial Variables

Total Assets: A firm's total book assets at year t corresponds to its total assets (`at`) observed at the last fiscal-year recorded at year $t-1$. Consequently, firm's size is defined as the natural logarithm of total assets (Ln(Total Assets)).

Age: A firm's age measures the time in years since the firm starts filings with the SEC. Compustat tracks most firms as they first start filing with the SEC, and sometimes the first filing contains information from the prior 2 or 3 years before the filing date. The first date of the firm's total assets data in Compustat Annual set is believed to be a close proxy to the age of that company. Yet, since Compustat Annual data starts in 1950, this proxy makes the estimated age biased downwards for most of the firms that were founded before 1950.

ROA: Previous fiscal-year operating income before depreciation (`oibdp`) scaled by the average of the previous two fiscal-year total assets (`at`). If `oibdp` is missing, we use sales (`sale`) minus operating expenses (`xopr`). If sales are missing we use revenues (`revt`).

Cash Holdings: Previous fiscal-year cash equivalents (`che`) scaled by previous fiscal-year total assets (`at`).

Leverage: The leverage of a firm at year t is computed using information recorded at the last fiscal year-end period in year $t-1$. The leverage is defined as the ratio of total debt (i.e. short-term debt (`dlc`) plus long-term debt (`dltt`)) over total debt plus market value of equity (common shares outstanding (`csho`) times price close at the end of fiscal year (`prcc_c`)).

B/M: The Book-to-Market ratio of firm at year t is computed using information recorded at the last fiscal year-end period in year $t-1$, where the book value of equity is estimated as stockholders equity (`seq`) + deferred taxes (`txdb`) + investment tax credit (`itcb`) - preferred stock (`pref`). The market value of equity is estimated as the number of common shares outstanding (`csho`) times price close at the end of fiscal year (`prcc_c`).

Tobin's Q: The Tobin's Q of a firm at year t is computed using information recorded at the last fiscal year-end period in year $t-1$. Particularly, it corresponds to the ratio of (total assets + market value of equity - book value of equity) and total assets.

Annual Return: The annual return of a firm at year t is computed as its stock return over the 12 months prior the last fiscal period recorded in year $t-1$.

Return Volatility: The annual return volatility of a firm at year t is computed as the standard deviation of its stock return exhibited over the 24 months prior the last fiscal period recorded in year $t-1$.

Board Members Variables

Each year t, we obtain from BoardEx a sample of active directors —i.e. those who started their position before year t (`datestartrole` $< t$) and to year t, still hold them (`dateendrole` $> t$) —to build the following firm-level board variables.

Dir. Expertise: average number of the firm's year-t board members who —according to the BoardEx Individual Profiles data base —held a position prior year t in the same industry (SIC-2) that the firm belongs to.

Dir. Other Activities: average number of "other activities" performed by the firm's year-t board members from year $t-3$ to year $t-1$ according to the BoardEx Individual Profiles data base (i.e. clubs, memberships, non-profit activities, among others).

Dir. Graduate Education: average number of the firm's year-t board members who received a graduate degree before year t according to the BoardEx Individual Profiles data base.

Dir. Achievers: average number of academic and professional "achievements" accomplished by the firm's year-t board members from year $t-3$ to year $t-1$ according to the BoardEx Individual Profiles data base.

Dir. Age: average age of the firm's year-t board members according to the BoardEx Individual Profiles data base.

Dir. Women: average number of women on the firm's year-t board according to the BoardEx Individual Profiles data base.

Dir. Multi-Boards: average number of the firm's year-t board members who participate in more than one board in year t according to the BoardEx Individual Profiles data base.

Dir. Independency: average number of the firm's year-t board members who are classified as "independent" in year t according to the BoardEx Individual Profiles data base (i.e. their `ROLENAME` field contains the word "independent" on it).

Additional Variables

ESG Disclosure: logarithm of one plus the ESG disclosure score issued by Bloomberg for the firm at the current fiscal year t.

Analyst Coverage: logarithm of one plus the number of analysts that have issued an earnings forecast for the firm for the current fiscal year t, in the last month; according to IBES data set.

B Selection Model

The model has two different sets of agents. There are firms I and directors J. Each director can match to a single firm board, and each firm has a limited capacity of board members; it can employ q_i. $M = IxJ$ represents the set of all potential matches. A match consists of a director j working on firm i. Firms have preferences over board members' characteristics, and directors have preferences over firms' characteristics (like location and social distance). The equilibrium concept employed here is stability, from the perspective of cooperative game theory (meaning a match is a situation where no director nor firm wants to deviate from).

A valuation represents agents' preferences. They are unobserved in the data, and in the empirical model, they are latent variables. Thus, the valuation of any given match of $ij \in M$ is given by:

$$V_{ij} = W_{ij}\alpha + \nu_{ij} \tag{4}$$

where W_{ij} is a vector of observed characteristics, α is a parameter to be estimated, and the error term ν_{ij} contains factors that are unobserved in the data.

The second part of the structural model is the outcome equation. For each $i, j \in M$ let:

$$Y_{ij} = X_{ij}\beta + \epsilon_{ij} \tag{5}$$

where X_{ij} contains observed characteristics, β is the parameter to be estimated, and Y_{ij} is the outcome variable of interest. In our case, directors misconduct. The error terms are assumed to be independent of X and W, and this assumption identifies the parameters of the model.

The estimated parameters estimate the outcomes of all potential matches, not just the observed ones. The estimated coefficient associated with physical and social proximity reflects the predicted change in the misbehavior of a given board member worker following an increase in physical or social proximity, after controlling for the sorting in the market, representing the effects of proximity on directors' misbehavior.