Social Networks and Corporate Social Responsibility*

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Abstract

I show that corporate social responsibility (CSR) spreads through the social networks of firms' directors. This result is obtained using a novel identification strategy exploiting the imperfect overlap between industry, geographic and social peers, a diff-in-diff relying on directors' deaths, and a regression discontinuity design based on CSR proposals. Social network effects are concentrated in firms pursuing product differentiation strategies for which CSR is more likely to add value, firms strategically positioned in the social network to acquire valuable information, and firms in which the incentives of managers and shareholders are aligned. This suggests that some firms aim to create value by using social networks as a market for information exchange on CSR. I find little evidence for alternative explanations such as social norms.

JEL classification: D85, G30, G34, M14

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Are corporate social responsibility policies transmitted across firms through the social networks of their executives and directors? If so, which factors explain this phenomenon? Using social network data covering 83,604 top executives and directors of Russell 3000 firms from 2001 to 2016, I show that firms' CSR decisions are influenced by the CSR decisions of their social peers. My findings are consistent with the notion that some firms use social networks as a strategic information sharing tool with the aim of increasing firm value. Overall, this paper suggests that social learning through corporate social networks leads to a social multiplier in CSR investment decisions that not only amplifies the externalities of CSR on society but may also be consistent with profit maximization incentives.

In theory, social peer effects in CSR can arise for at least two reasons. On the one hand, firms may benefit from using the social networks of their executives and directors to obtain information about how to optimally design CSR projects and create value. The underlying reason is that the benefits of CSR are often intangible and are only realized over the long-term or in specific states of the world such as financial crises (e.g., Lins, Servaes, and Tamayo (2017), Edmans (2020)). It is therefore challenging to precisely estimate the net present value (NPV) of alternative CSR projects and implement optimal CSR policies. Firms that are able to overcome these investment frictions by learning from their social peers may therefore be better equipped to design CSR policies and gain a competitive edge over their industry rivals.

On the other hand, executives and directors may mimic their social peers to maximize their private utilities. This can happen in at least two ways. First, executives and directors may internalize their peers' pro-CSR ideals and gain utility from acting according to those ideals (e.g., Akerlof and Kranton (2000)). Second, even if executives and directors do not internalize their peers' ideals, they may still decide to mimic their peers and abide by social norms of behavior to extract benefits such as peer esteem and board appointments (e.g., Bénabou and Tirole (2011a), Levit and Malenko (2016), Akerlof (2017)). For example, directors may find it in their best interest to be supportive of diversity policies whenever their peers also support such policies, even if they believe such policies are unlikely to create value and even if such policies do not stem from their own ideals.

Despite intuitive theoretical foundations, the identification of peer effects in CSR is challenging due to the difficulty of (i) separating peer effects from common unobserved shocks, and (ii) disentangling whether firms respond to the CSR decisions of their peers or to some other peer characteristic (Mansky (1993)). I deal with these empirical challenges by extending the identification strategy of Bramoullé, Djebbari, and Fortin (2009), which explores the fact that not all the peers of a firm's social peers are socially connected with that firm. The CSR decisions of these indirect peers can thus be used as a valid instrumental variable for the CSR decisions of the firm's social peers. I build on this strategy by exploiting the fact that the CSR decisions of firms in the same industry are strategic complements (Cao, Liang, and Zhan (2019)). I thus define the indirect peers of a firm i as the industry peers of firm i's social peers that do not have social, industry or geographic ties with firm i. The identifying assumption is that, conditional on a high-dimensional set of control variables and industry-by-year, headquarters region-by-year and state-of-incorporation-by-year fixed effects, the CSR decisions of indirect peers only systematically affect the CSR decisions of firm i through its social peers. In addition, I focus the analysis on peer effects between social peers in different industries to fully disentangle industry and social peer effects.

I find that social peer effects are present for both the environmental and social dimensions of CSR. Firms with average levels of CSR increase their CSR by 16% in response to a one standard deviation increase in the average CSR of their social peers. Such a magnitude is comparable to the industry peer effects of CSR documented by Cao, Liang, and Zhan (2019). This finding is robust to a wide range of exercises, including applying network community detection algorithms to form communities and control for time-varying endogenous network formation, simulating placebo networks to alleviate the concern that the results are driven by latent common factors, employing different combinations of fixed effects, first-differencing the regression equations, alternating between contemporaneous and lagged specifications, using alternative definitions of peers based on different industry and geographic boundaries, excluding board interlocks in which firms share the same directors, excluding firms with a very low or a very high number of social peers, using CSR scores from the Thomson Reuters ESG database instead of the MSCI ESG database, applying the partial identification method of Oster (2019) and controlling for a multitude of firm-level and peer-level variables. In addition, I show that the result holds when employing two quasi-natural experiments: (i) a difference-in-differences (diff-in-diff) design based on the deaths of directors and executives, and (ii) a regression discontinuity design based on shareholder-sponsored CSR proposals.

Having shown that social peer effects in CSR are a robust empirical regularity, I turn to the question of which individuals are responsible for the peer effects. I find that peer effects occur through the social networks of directors but not through those of executives. This is plausible for at least three reasons. First, directors are better positioned than executives to exchange information by virtue of sitting on the boards of several firms throughout their careers. Second, firms typically have more directors than they have top executives. This makes it easier for firms to acquire information through their board than through their top executives. To illustrate, in my sample the average firm can reach four times as many firms through the directors network compared to the executives network. Third, CSR encompasses several strategic considerations which are of interest to the board. The same strategic considerations are likely not to be directly related to the job descriptions of all top executives.

To understand why directors play such an important role, I look inside the boardroom. If directors drive peer effects either because they have a comparative advantage in information acquisition or because it is part of their job description to be informed, peer effects should on average be stronger for firms with CSR board committees in place. Directors sitting on these committees are responsible for monitoring and providing advice on CSR policy and are, therefore, more likely to actively engage in information acquisition on this issue. In line with this hypothesis, I find that firms with CSR committees mimic more than firms without such committees. Also, while firms with CSR committees mimic other firms with CSR committees the most, they also mimic firms without those committees. This is in contrast with firms without CSR committees which mostly mimic firms without CSR committees. Since firms without CSR committees tend to be smaller and have smaller social networks, my findings suggest these firms mimic less because they lack access to valuable information held by larger firms with specialized CSR committees and more CSR know-how.

Next, to better understand the nature of social peer effects in CSR, I turn to the question of which firms mimic. Two findings emerge. First, peer effects are concentrated in firms pursuing product differentiation strategies and firms operating in industries with high CSR intensity. Following previous literature (e.g., Servaes and Tamayo (2013), Albuquerque, Koskinen, and Zhang (2019)), I measure product differentiation based on advertisement expenditures. Given the evidence in this literature that CSR is used as a value-enhancing product differentiation strategy, my results suggest that firms try to obtain information from their social peers in different industries to gain a competitive edge over industry rivals.

Second, peer effects are stronger for large firms that are strategically positioned in the corporate social network to acquire valuable information. I quantify the strategic positioning in the network with two variables that are designed to capture information social capital, that is, the ability of a node to acquire and spread valuable information in a network: decay centrality (Jackson (2008)) and diffusion centrality (Banerjee et al. (2013)). This result holds when controlling for the number of social peers and firm size, thus alleviating the concern that the results are spuriously driven by a size effect. This is, to the best of my knowledge, the first piece of direct evidence in favor of the conjecture of Dougal, Parsons, and Titman (2015) that large firms have a comparative advantage in learning from their social peers due to their privileged position in the corporate social network.

I further address the question of why firms mimic by constructing more direct tests of whether peer effects are driven by social learning or by alternative channels such as social norms. To test for social learning, I would ideally measure whether or not firms mimic their social peers with the intention of learning and creating value. Since intentions are unobservable, I test instead for whether or not peer effects are stronger for firms in which the incentives of managers and shareholders are more aligned. The underlying assumption is that firms with more aligned incentives are more likely to mimic their social peers with the goal of learning and creating value. Consistent with a social learning explanation, I find peer effects are concentrated in firms with higher CEO pay-sensitivity to performance (delta), stronger board independence and, to a lesser extent, higher levels of industry competition. Moreover, I find peer effects are stronger for firms in which the convexity of CEO compensation (vega) is higher. Insofar as convexity in compensation contracts is often used to incentivize risk-averse managers not to pass up on risky positive NPV projects (Guay (1999)), this is in line with the idea that social learning alleviates a CSR underinvestment problem caused by investment frictions such as uncertainty and irreversibility (e.g., Guiso and Parigi (1999)).

I test for an alternative channel related to the evidence that CSR decisions are influenced by the social norms of executives and directors (e.g., DiGiuli and Kostovetsky (2014), Cronqvist and Yu (2017)). If social peer effects are caused by social norms, peer effects should be stronger for firms with more social capital along the dimensions of (i) civic engagement and pro-social preferences, and (ii) ability to enforce punishment threats that sustain cooperation and pro-social behavior.

I quantify these dimensions of social capital by exploiting two facts. First, there is large county-level variation in several measures of geographic social capital that have been widely used in the literature (e.g., Guiso, Sapienza, and Zingales (2004), Lin and Pursiainen (2018)), namely: organ donation density, voter turnout, number of tax-exempt non-profit organizations per capita, and number of non-profit or recreational associations. Second, there is substantial evidence that firms absorb the social norms of the county where they are headquartered and that these norms influence corporate decision-making (e.g., Jha and Chen (2014), Hasan, Hoi, Wu, and Zhang (2017a), Hasan, Hoi, Wu, and Zhang (2017b)). Following the literature, I assign county-level measures of social capital to firms based on the location of firms' headquarters. At odds with this social norms channel, however, I do not find evidence that peer effects depend on geographic social capital. This holds when using each variable individually, when constructing variables based on peers' social capital and when constructing measures based on the principal component of the individual variables.

My paper contributes to the burgeoning literature documenting drivers of CSR (e.g., Flammer (2015b), Dimson, Karakaş, and Li (2015), Dai, Liang, and Ng (2020), Flammer and Kacperczyk (2019a), Dyck et al. (2019)) and to the broader literature on peer effects in corporate finance (e.g., Shue (2013), Leary and Roberts (2014), Kaustia and Rantala (2015), Fracassi (2017) and Grennan (2019)). The closest paper to mine is Cao, Liang, and Zhan (2019), who document that industry peer effects in CSR arise because firms mimic each other to stay competitive. The key difference is that, in contrast to industry peer effects that arise out of competitive dynamics unrelated to social networks, the peer effects documented in this paper occur through cross-industry collaborative social interactions.

A long-standing question in CSR research is whether CSR is a tool to create long-term value (e.g., Edmans (2011) and Deng, Kang, and Low (2013)) or a manifestation of agency problems (e.g., DiGiuli and Kostovetsky (2014) and Masulis and Reza (2014)). I contribute to this debate by showing that, contrary to the predictions of the agency view of CSR, firms with fewer agency problems put more effort to learn from their social peers and actively engage in CSR.

My paper also speaks to the literature on the role of the board of directors in corporate governance. Whereas previous studies have explored functions of the board such as monitoring, advising, CEO hiring and firing and setting CEO compensation (e.g., Adams, Hermalin, and Weisbach (2010)), I show that the board also influences CSR policy. A contemporaneous study by Iliev and Roth (2020) documents that firms increase their CSR if their directors sit on the boards of foreign firms exposed to country-wide sustainability regulations. My paper complements theirs by identifying a distinct channel through which directors influence CSR.

Furthermore, I shed light on the extent to which different dimensions of firm social capital complement or substitute for one another. As pointed out by Servaes and Tamayo (2017), firm social capital, broadly understood as the level of trust and cooperation between the firm and its stakeholders, is multidimensional and we know little about how these different dimensions interact with each other. I fill the gap by providing evidence that more information social capital (i.e., better connected directors) induces firms to accumulate more social capital in the form of CSR. In addition, I show there is little evidence that geographic social capital mediates peer effects. This suggests that not all dimensions of firm social capital are complements.

1 Data and Summary Statistics

1.1 Social Network Construction

I construct social networks based on individual connections of top executives and directors for the largest 3000 publicly traded US companies (Russell 3000) with at least $10 million in assets. The data is sourced from the BoardEx database and covers the period 2001-2016.

Following Fracassi (2017), I define top executives as the top five executives based on compensation data from ExecuComp. Since the ExecuComp universe is the S&P 1500, I cannot apply this definition to all Russell 3000 sample firms. In those cases, I define the top executives to be the CEO, CFO and COO. The final sample comprises 83,604 individuals.

Building on Fracassi and Tate (2012), I consider four types of Boolean individual-level networks: current employment, past employment, other activities, and education networks. Current employment networks capture professional relationships that occur when two individuals sit on the same board or C-suite. Past employment networks are defined in the same way except for the fact that they capture past relationships that are no longer active in the current year. As for the other activities network, individuals are defined to be connected if they have active roles in the same clubs, charities or organizations. I assume that active memberships are those that are not simply described as *member* in BoardEx (e.g., President, trustee). As for the education network, individuals are said to be connected if they graduated from the same university with the same degree type within one year of one another.

I then aggregate the individual-level networks into firm-level networks. For each year and network type, I define two firms to be linked if at least two individuals working in those firms are connected in the underlying individual-level network. To capture board interlocks, two firms are also considered to be connected if they share a director. In addition, to reduce the possibility of capturing spurious social connections, I require the headquarters of firms that are socially connected through education, other activities and past employment networks to lie in the same Combined Statistical Area (CSA). CSAs, as defined by the United States Office of Management and Budget (OMB), are geographic polygons that combine areas with strong economic, social and commuting links. There are 172 combined statistical areas in the US, the largest of which is New York - Newark, with over 22 million inhabitants. As in Fracassi (2017), I sum across the four types of networks for each year separately and row-normalize the network matrices to obtain time-varying network weights. For a detailed explanation of the network construction approach, refer to the Internet Appendix A.

1.2 Data on Corporate Social Responsibility

I use data from the MSCI ESG Stats Database to construct CSR scores. Following previous literature (e.g., Cao, Liang, and Zhan (2019)), I focus on the following CSR categories: employee relations, community relations, environment, and workforce diversity. This approach reduces the likelihood that the CSR measure captures governance, product market competition and other industry-specific information. Binary scores in each category are available in the form of strengths and concerns in various subcategories. I follow Flammer and Kacperczyk (2019a, 2019b) and sum over all the strengths within each category. Since the maximum number of strengths within each category can vary over time, I scale by the total possible number of strengths for each firm-year. In a final step, I sum the scaled scores across all four categories to obtain an overall measure of CSR.[1] In robustness tests, I also use CSR scores from the Thomson Reuters ESG database. I compute these alternative scores by averaging the environmental and social scores constructed by Thomson Reuters.

1.3 Other Variables

I use several proxies to measure the extent to which managers and shareholders' incentives are aligned. The first two proxies are CEO delta and CEO vega. Following Core and Guay (2002) and Coles, Daniel, and Naveen (2006), delta is defined as the dollar-value sensitivity of the executive's stock and option portfolio to a one percentage point change in the stock price. Vega is the dollar-value sensitivity of the executive's portfolio to a 1/100 change in the annualized volatility of stock returns. I also use the Herfindahl-Hirschman index of Hoberg and Phillips (2016) as a measure of industry competition. The index is based on sales data and defined as the sum of the squared market shares of all firms in a given industry and year.

To quantify the extent to which firms are embedded in a social network rich in social capital, I use known proxies for county-level social capital (e.g., Rupasingha, Goetz, and Freshwater (2006)): non-profit or recreational association density, registered tax-exempt non-profit organization density, voter turnout, and organ donation density. I obtain firm-specific measures of social capital by assigning county-level social capital to each firm based on headquarters location. Internet Appendix B provides a detailed description of these variables.

[1]Until recently, a typical approach in the literature was to subtract the concerns from the strengths. However, this procedure can be unreliable due to conceptual differences between strengths and concerns (e.g., Mattingly and Berman (2006), Flammer (2018)). In untabulated results I do not find evidence for social peer effects in CSR concerns.

I collect voting data on shareholder-sponsored CSR proposals from the Institutional Shareholders Services (ISS) voting analytics database and from SharkRepellent. The ISS database covers S&P 1500 firms from 2003 to 2016 and SharkRepellent covers Russell 3000 firms from 2005 to 2016. The data on the deaths of directors is retrieved from BoardEx.

I employ the standard control variables in the literature related to firm size, leverage, profitability, liquidity, dividend payout, indebtedness and institutional ownership. Accounting variables are sourced from Compustat and institutional ownership data from Thomson Reuters. Detailed variable definitions are provided in the Appendix Table A.1.

1.4 Summary Statistics

The plots in Figure 1 below show the cross-firm distribution of network degree centrality, that is, the number of social connections a given firm has. Degree centrality is measured as of 2009, the median sample year. Slightly over 50% of the firms have less than 50 connections, with fewer than 1% of firms having more than 250 connections. The average number of connections is 66 and the maximum is 365. Hence, there is a small number of firms with a large number of connections and a large number of firms with few connections.

This suggests that there is substantial cross-firm variation in access to information and that the benefits of information exchange may only accrue to a limited number of firms. Lins, Servaes, and Tamayo (2017) conjecture that the high cost of CSR investments may be a reason for why not all firms engage in CSR. To the extent that smaller and more financially constrained firms also tend to have fewer network connections, lack of access to information via social networks might magnify the costs of engaging in CSR even further for these firms.

[Figure 1 About Here]

Table 1 provides summary statistics on the main variables for the full sample as well as for the lowest and highest terciles of the distribution of degree centrality. Firms with higher degree centrality tend to be larger, more profitable, distribute more dividends, spend more on advertising relative to their sales, have more debt and invest more in both R&D and CSR. Further statistics outlining the features of the network are available in Internet Appendix C.

[Table 1 About Here]

2 Empirical Model and Identification Strategy

2.1 The Empirical Model

In line with a growing literature in finance (e.g., Leary and Roberts (2014), Grennan (2019), Silva (2019)), I employ the standard linear-in-means model of peer effects:

$$y_{ijklt} = \alpha + \beta \bar{y}_{-ijklt} + \lambda' \bar{X}_{-ijklt} + \gamma' X_{ijklt} + \mu_{jt} + \delta_{kt} + \zeta_{lt} + \epsilon_{ijklt} \quad (1)$$

The dependent variable y_{ijklt} is the CSR score of firm i in year t, operating in industry j, headquartered in CSA region k and incorporated in state l. Firm i's CSR is assumed to be a linear function of the mean outcome of its peer group ($\bar{y}_{-ijklt}$). The mean outcome for firm i is defined as the weighted average of the CSR scores across all its peers, excluding firm i itself. The weights are proportional to the strength of the social connection between each firm pair. As in Leary and Roberts (2014), I focus on a contemporaneous measure of peer effects. Nevertheless, I show that the results are robust to employing lagged specifications. The model further controls for the average characteristics of firm i's peer group ($\bar{X}_{-ijklt}$), its own characteristics (X_{ijklt}) and a set of three-digit SIC industry-by-year (μ_{jt}), headquarters CSA-by-year (δ_{kt}) and state-of-incorporation-by-year (ζ_{lt}) fixed effects.

2.2 The Identification Problem

As shown by Mansky (1993), the identification of peer effects is challenging for two reasons. First, it is necessary to separate peer effects that occur through social interactions (e.g., mimicking due to social learning) from correlated effects that arise due to latent common factors that induce changes in CSR in all firms within a peer group. Examples of correlated effects that have been documented in the literature are state-wide regulations that affect CSR, such as: state unemployment insurance benefits (Flammer and Luo (2015)), inevitable disclosure doctrines (Flammer and Kacperczyk (2019a)), and constituency statutes (Flammer and Kacperczyk (2019b)). Second, the behavior of a firm within a peer group simultaneously affects and is affected by other firms in the group, generating collinearity between the mean CSR decisions and the mean characteristics of the group. This so-called reflection problem makes it difficult to identify whether firms' CSR responds to the CSR decisions of its peers or to some other peer characteristic.

2.3 The Identification Strategy

My identification strategy builds on Bramoullé, Djebbari, and Fortin (2009) and Giorgi, Pellizzari, and Redaelli (2010), who formally show that the reflection and correlated effects problems can be solved in networks with partially overlapping peer groups. The firm-level social networks that are the focus of this paper satisfy this requirement. The underlying intuition is that social networks are rich in intransitive triads, meaning that firms are not connected with all the peers of their peers - thus generating indirect peers. Therefore, the actions of a firm's indirect peers affect that firm's actions through its peer group. This, in turn, generates within peer-group variation and breaks the reflection problem.

In practice, this strategy is operationalized by using the behavior of a firm's indirect peers as an instrumental variable for the CSR decision of a firm's peer group. I extend this idea by exploiting the fact that firms are part of geographic, social and industry networks, all of which are partially overlapping with respect to each other. This allows me to define the indirect peers of each firm i as the industry peers of the social peers of firm i and to use their CSR policies as an instrument for the CSR policies of firm i's social peers. In addition, I impose that (i) indirect peers are neither social peers nor industry peers of firm i, and (ii) indirect peers and firm i are headquartered in different geographic areas (CSAs).

The validity of this strategy hinges on the instrument being strong and satisfying the exclusion restriction. The expectation that the instrument is strong is supported by previous literature documenting economically significant industry peer effects in CSR decisions (Cao, Liang, and Zhan (2019)). The exclusion restriction is that, conditional on CSA-by-year, state-of-incorporation-by-year and industry-by-year fixed effects (and remaining control variables), the average CSR decision of the industry peers of the social peers of a firm, which do not share any geographic, industry or social links with that firm, should only affect the CSR decision of that firm through its social peers. This seems reasonable for several reasons.

First, since I impose that there are no social, industry or geographic links between indirect peers and the firm being instrumented, there is no obvious channel based on industry competition, transfer of information over social networks or local events through which indirect peers would directly affect the firm. It is possible, however, that an indirect peer of a firm is involved in an attention grabbing event with news coverage and that the event leads both the indirect peer and the firm to change CSR in tandem. For example, a human rights scandal relating to an indirect peer outsourcing activities to a socially irresponsible firm in another country could produce this effect. Note, however, that such events are rare both across time and across firms, making it unlikely that such events systematically confound the results. Moreover, since the instrument is constructed as the average of CSR scores over a large number of indirect peers, the instrument is bound to have very little correlation with such rare firm-specific events. To alleviate this concern further, I show in robustness tests that the results do not change if I restrict the sample to firms that have many indirect peers.

Second, it is reasonable to assume that the instrument is orthogonal to the omitted variables causing endogenous sorting into social networks. Suppose there is such a variable (e.g., political views) that causes both social connections and CSR investment in firms. It would have to be the case that the average CSR decisions of indirect peers are systematically correlated with this variable. This is unlikely because I impose that the indirect peers are not social, geographic or industry peers of the firm being instrumented. Despite that, I reduce this concern in robustness tests by using community detection algorithms to identify network communities and controlling for network community-by-year fixed effects.

Third, I include high-dimensional fixed effects that capture a wide-range of common unobserved shocks. Industry-by-year peer effects control for time-varying industry-specific shocks as well as industry peer effects in CSR. In addition, CSA-by-year fixed effects separate social peer effects from geographic peer effects in CSR. These could arise due to, for example, exposure to common laws, geographic variation in social norms (e.g., Rupasingha, Goetz, and Freshwater (2006)) and local agglomeration economies (e.g., Dougal, Parsons, and Titman (2015)). In order to better control for the time varying-effect of laws, I also include state-of-incorporation-by-year fixed effects. Furthermore, I show the results are robust to defining indirect peers based on different geographic (state instead of CSA) and industry (one-digit SIC instead of three-digit SIC) boundaries and applying first differences to equation (1), which eliminates time-invariant firm unobservables.

Fourth, I show that the results break down when using placebo networks. If correlated effects were driving the results, we should find peer effects in these placebo networks. Therefore, the lack of evidence for such spurious effects is evidence for the reliability of this identification strategy. Nevertheless, I acknowledge that no strategy based on a non-shock instrumental variable can completely rule out endogeneity concerns. For this reason, I complement this IV strategy with a quasi-experimental regression discontinuity design based on close-call CSR proposals and a diff-in-diff based on the deaths of executives and directors.

3 Do Social Peers Mimic Each Other?

3.1 Baseline Results

Table 2 presents the results from estimating model (1) via two-stage least squares (2SLS). The instrument is the average CSR score of indirect peers. All the coefficients are measured in standard deviation units to ease interpretation. t-statistics are reported in parentheses and standard errors are heteroskedasticity-robust and clustered at the firm-level. All regressions include firm-level controls for the same variables that are listed as peer-level controls. I present results using both the benchmark contemporaneous specification (columns (1) through (3)) and a lagged specification (columns (4) through (6)). The lagged specifications alleviate concerns about reverse causality bias.[2]

[Table 2 About Here]

The results in column (1) show that firms increase CSR by 0.437 standard deviations in response to a one standard deviation shock to social peers' CSR (t-statistic of 2.623), suggesting a pass-through effect of at least 40%. This corresponds to a 16% increase in CSR for a firm with an average level of CSR. Note that a one standard deviation shock to the average CSR of social peers is equivalent to a one standard deviation shock to the CSR of all peers (Giorgi, Frederiksen, and Pistaferri (2020)). Since the average firm in the sample has 66 peers in the median year (2009), this is a very large shock. Hence, the large economic magnitude of peer effects should be interpreted in light of the large magnitude of the shock.

[2]Note that recent advances in the causal inference literature suggest lag identification seldom eliminates endogeneity bias and often makes the bias worse (e.g., Bellemare, Masaki, and Pepinsky (2017)). Intuitively, lagging merely shifts the endogeneity problem by one year. I conduct the falsification tests of Bellemare, Masaki, and Pepinsky (2017)) to choose the appropriate model and a lagged model is rejected.

The results in column (4) show that lagging all right-hand side variables, including the instrument, has little impact on the statistical and economic significance of the results. In both lagged and contemporaneous regressions, the Kleiberg-Paap F-statistic is large and well above the standard cutoff value of 10, suggesting the instrument is sufficiently strong. The coefficient sign of the first stage instrument is positive, in line with the previous literature documenting positive industry peer effects of CSR (Cao, Liang, and Zhan (2019)).

One concern is that I allow social peers to be industry peers. While industry-by-year fixed effects should absorb time-varying industry peer effects, it may be that there is within-industry heterogeneity in industry peer effects that are not captured by the fixed effects. To alleviate this concern I re-estimate the regressions excluding all social peers who are also industry peers. The results, reported in columns (2) and (5), suggest the fixed effects do a good job in capturing time-varying industry peer effects as the coefficients barely change.

In columns (3) and (6) I include two additional controls: customer awareness and R&D investment. Servaes and Tamayo (2013) find that the ability of CSR to create value is concentrated in firms with high customer awareness, as measured by the advertisement expenditure ratio. If firms with high customer awareness tend to have peers with high customer awareness, peer effects may spuriously reflect time-varying commonalities in that variable. As for R&D investment, Shen, Tang, and Zhang (2019) show that innovative firms use CSR as a signal of long-run orientation to overcome information frictions related to risky transaction-specific investments between the firm and its stakeholders (e.g., suppliers). Since there are economically significant social peer effects in R&D (e.g., Fracassi (2017), Zacchia (2019)), peer effects in CSR may just be an artifact of R&D peer effects. The results show that the estimates are not confounded by the exclusion of these variables. .

3.2 Robustness Tests

In this section I tighten the identification strategy in several ways. First, I apply the partial identification method of Oster (2019) to gauge the extent to which the results are contaminated by biases stemming from time-varying unobservables. Intuitively, I estimate a range within which the true effect lies under the assumption that the degree of selection on unobservables is of the same magnitude as the degree of selection on observables. If the range includes zero one cannot reject the possibility that controlling for all relevant unobservables would render the effect of interest insignificant. Based on the baseline specification with all controls, I find that the range is [0.45,0.56] which suggests that the instrumental variable strategy is able to purge out the endogeneity bias effectively.

Second, I show that the results are robust to: (i) excluding firms with fewer than 10 peers; (ii) excluding firms with more than 250 peers; (iii) imposing that firms and their indirect peers cannot be in the same one-digit SIC industry (instead of three-digit SIC industry); (iv) controlling for the average CSR score of product market peers as defined by the 10-K text-based network industry classifications of Hoberg and Phillips (2010, 2016); (v) using only S&P 1500 firms; (vi) excluding direct board interlocks in which firms share the same directors; (vii) imposing that firms and their indirect peers cannot be headquartered in the same state (instead of CSA); (viii) using headquarters state-by-year fixed effects instead of CSA-by-year fixed effects; (ix) using firm and year fixed effects; (x) lagging the instrument and not lagging the variable being instrumented; (xi) lagging the instrument and the control variables and not lagging the variable being instrumented; (xii) lagging the instrument twice and all the right-hand side variables once; (xiii) not including any controls; (xiv) falsification tests based on placebo networks; (xv) applying community detection algorithms to form network communities and control for time-varying endogenous network formation; (xvi) using CSR scores from an alternative data provider (Thomson Reuters); (xvii) restricting the sample period to end in 2013 instead of 2016. This battery of robustness tests alleviates concerns related to overmeasurement and undermeasurement error of social connections, dependence of results on the definition of geographic and industry boundaries, firm-specific time-invariant unobservables, reverse causality, unobservable common shocks, endogenous network formation, lack of comparability of CSR scores across data providers, and methodological changes in CSR scores the data provider MSCI implemented after 2013. For brevity, all these robustness test results are reported in the Internet Appendix Table IA.1 through Table IA.5. Sections D and E of the Internet Appendix explain the methodologies underlying the placebo network simulations and the community detection algorithms.

Third, I provide evidence that the results are robust to employing two different quasi-natural experiments. This reduces the concern that the results are driven by a hard to detect failure of the IV to eliminate all sources of omitted variable bias. First, I follow Fracassi (2017) and use a diff-in-diff approach based on the deaths of executives and directors as an exogenous shock that breaks social connections. Second, I employ a regression discontinuity design based on CSR proposals in the spirit of Cao, Liang, and Zhan (2019) and Dai, Liang, and Ng (2020). Results and detailed explanations on the design of the quasi-natural experiments can be found in sections F and G of the Internet Appendix.

4 Which Individuals Mimic?

The analysis thus far suggests social peers mimic each others' CSR policies. A natural follow-up question is which types of individuals are responsible for the mimicking. As a starting point, I investigate whether social peer effects are driven by the board of directors or the top management team. To address this question, I define social networks that only include either social connections between directors or social connections between executives. I then re-estimate model (1) for both networks separately. In both cases, I impose that indirect peers cannot be socially connected with the firm in question through either network. I also decompose CSR into its social and environmental components to allow for the possibility that different types of individuals mimic different types of CSR.

[Table 3 About Here]

I present the results in Panel A of Table 3. In columns (1) and (2) I report the estimates of peer effects over the directors networks for environmental and social CSR, respectively. The peer effects associated with the social component of CSR are substantially larger than those associated with the environmental component. In particular, a one standard deviation shock to social peers' environmental CSR leads to a 4.5% increase in environmental CSR for the average firm. An equivalent shock to the social component of peers' CSR leads to a 20.8% increase. Columns (5) and (6) show this finding also holds when using the aggregate network of executives and directors instead of the directors network.

One possible explanation for this asymmetry is that firms can obtain more useful information about the social component of CSR from social peers in different industries compared to what they can learn about the environmental component. This is plausible because the social component of CSR includes dimensions such as employee relations and workforce diversity that are often material to firms across different industries. In contrast, the environmental component of CSR tends to be more material for specific industries such as nonrenewable resources and transportation sectors (e.g., Khan, Serafeim, and Yoon (2016)), thus making it harder to learn from social peers in different industries.

In columns (3) and (4) I present the results using the executives network. The peer effects estimates are smaller compared to those obtained using the directors network and are only statistically significant for the environmental component of CSR. The concentration of peer effects in the directors network may be due to directors being better positioned than executives to acquire valuable information on behalf of firms. Not only are directors typically better connected than executives by virtue of sitting in several boards throughout their careers, but firms also tend to have more directors than top-level executives.[3] In addition, directors are more likely than executives to sit on boards of firms in different industries. To illustrate, in my sample the average firm is socially connected to four times as many firms through the directors network as it is through the executives network.

In Panel B I show the results are robust to first-differencing the model, thus alleviating the concern that the results are driven by firm-specific time-invariant unobservables. There is however one exception: there is no evidence in Panel B for peer effects in either of the two CSR components when using the executives network. Given the evidence that executives networks do not play a role, I focus the analysis on peer effects over directors networks in the remainder of the paper.

Next, I look inside the boardroom to better understand why directors play such an important role. If peer effects are driven by socially connected directors exchanging information on CSR, peer effects should on average be stronger for firms with specialized CSR committees whose job description revolves around CSR. To test this hypothesis, I extend the baseline model by interacting the average CSR scores of social peers with dummy variables capturing whether or not a firm has a specialized CSR committee in a given year.[4]

[Table 4 About Here]

I report the results in Table 4. I present results using specifications in levels (columns (1) through (3)) and in first differences (columns (4) through (6)). All regressions control for

[3] US firms have on average 9 directors (e.g., Adams (2017)). In contrast, I consider at most the top five executives by compensation when building the executives network.

[4] BoardEx provides the names of board committees. I identity the CSR committees based on the following keywords: *environment*, *social responsibility*, *corporate responsibility*, *civic responsibility*, *community*, *ethics*, *sustainability*, *social*, *diversity*, *CSR*, *culture*, *integrity*, *public policy*, and *public responsibility*. Since the SEC only requires firms to disclose details about compensation, audit and nominating committees, there is a possibility that the classification identifies too few firms as having specialized CSR committees. Nevertheless, this is unlikely to generate substantial measurement error because firms lack incentives to hide information about the existence of particular committees (e.g., Adams (2005)).

the percentage of social peers that have CSR committees in place. This mitigates potential selection biases not purged out by the IV. I also construct social networks that only capture social connections with firms that have CSR committees and social networks that only capture social connections with firms that do not have such committees. The allows to disentangle whether firms mimic peers without committees (columns (2) and (5)), peers with committees (columns (3) and (6)) or both (columns (1) and (4)).

In line with the hypothesis, the results in columns (1) and (4) indicate that firms with CSR committees mimic two to three times as much as firms without committees. I further document in columns (2) and (5) that firms with and without CSR committees both mimic social peers without committees. This suggests the result is not merely driven by firms with CSR committees tending to invest in a similar manner because they have similar committees. In contrast, social peers without CSR committees do not mimic firms without CSR committees (columns (3) and (6)).

Overall, this is consistent with the conjecture of Dougal, Parsons, and Titman (2015) that small firms have relatively few opportunities to learn from their social peers because their executives and directors are not as well-connected as those of larger firms. In my sample firms with CSR committees have on average 106 peers while firms without such committees have on average 59 peers. Firms with CSR committees are also, on average, almost six times as large as firms without committees in terms of total assets. Therefore, smaller firms without CSR committees may optimally choose to mimic less because they do not have access to valuable information that larger well-connected firms with such committees do. Cross-firm differences in access to valuable information may thus partially explain the large cross-firm variation in CSR investment observed in practice. I test for this hypothesis in the next section.

5 Which Firms Mimic?

Next, I try to characterize the types of firms that mimic the most. Recent findings in the literature suggest that CSR is a form of value-enhancing product differentiation strategy that builds customer loyalty and reduces firm systematic risk (e.g., Servaes and Tamayo (2013), Flammer (2015b), Albuquerque, Koskinen, and Zhang (2019)). If social peer effects arise due to firms exchanging information on CSR with the goal of creating firm value, peer effects should be stronger for firms with higher product differentiation. Following Albuquerque, Koskinen, and Zhang (2019), I use the advertisement expenditures ratio as a proxy for product differentiation. As an alternative proxy, I also consider industry CSR intensity as a revealed preference measure of competition on CSR-based product differentiation. Although not without drawbacks, this measure alleviates the concern that some firms pursue a product differentiation strategy while spending little on advertising (e.g., Tesla).

To test this hypothesis I interact social peers' CSR scores with indicator variables that classify each firm-year as having either below median or above median values of product differentiation in a given year. The results from specifications in levels (first differences) are shown in columns (1) and (2) (columns (4) and (5)) of Table 5. Consistent with the hypothesis, the results show that social peer effects are concentrated in firms pursuing product differentiation strategies and firms operating in industries with high CSR intensity. The results thus suggest that industry and social peer effects reinforce each other. The more competition on CSR there is an industry, the more firms rely on information from social peers in other industries to obtain a competitive edge.

[Table 5 About Here]

I further test whether or not larger firms mimic more than smaller firms. The motivation is twofold. First, boards of larger firms tend to put more weight on stakeholder interests (e.g., Adams (2005)). If the results are due to boards paying attention to stakeholder interests, social peer effects should be stronger for larger firms. Note that the fact that larger firms are more attentive to stakeholders interests does not mean that these firms are not maximizing firm-value. Large investments in CSR may simply be more value-enhancing for large firms than for small firms (e.g., Magill, Quinzii, and Rochet (2015)). For example, small firms may mimic less because they lack customer awareness and financial resources that justify an expensive CSR-based product differentiation strategy. Second, large firms are more likely to be better positioned in the corporate social network to obtain valuable information (e.g., Dougal, Parsons, and Titman (2015)). I test this hypothesis by interacting social peers' CSR scores with indicator variables that define small (large) firms as those that have below (above) median total assets in a given year. The results in columns (5) and (6) support the expectation that social peer effects are indeed concentrated in larger firms.

The results thus far indicate that larger firms and firms with CSR committees mimic the most. It is unclear, however, whether this is the case simply because smaller firms have less to benefit from investing in CSR or also because smaller firms are not well-positioned in the network to acquire valuable information. To disentangle these two effects I construct a direct test of whether or not peer effects depend on information social capital, that is, the ability of firms to access valuable information through their social networks. I measure this concept with the decay centrality measure of Jackson (2008).

Decay centrality is designed to capture the ability of a node in a network to acquire and spread information in the network. Intuitively, the measure counts the number of firms that each firm can reach in the network within a given number of steps, weighting each count by a factor that decreases with the number of steps and increases with a parameter capturing information usefulness. This parameter captures the intuition that information becomes less useful as it is passed along the network because some noise is added to the information at each step. I report results using a parameter value of 0.5, that is, I assume information usefulness halves with each step. The results are almost identical if I assume that information usefulness does not deteriorate as it travels along the network. If social peer effects in CSR are driven by firms' ability to obtain valuable information, the peer effects estimates should be stronger for firms with high decay centrality, even after controlling for variables related to firm size.

I re-estimate model (1) allowing the peer effects coefficient to vary as a function of whether firms belong to the bottom, middle or top tercile of the distribution of decay centrality in a given year. In addition to the full set of controls included throughout the paper, I also control for the number of social peers to ensure decay centrality is not just capturing the fact that some firms have more social connections than others. I further control for the local clustering coefficient of Watts and Strogatz (1998) which measures how close-knit the local network around each firm is.[5] Firms in close-knit groups are likely able to effectively exchange information with other firms in the group because it is feasible to sustain within-group cooperation with threats of within-group punishment such as word-of-mouth sanctions (e.g., Lippert and Spagnolo (2011)). There is, however, a crucial distinction. While firms in close-knit groups are likely to share information, they are likely unable to obtain the most valuable information that circulates in the network as a whole. This happens because close-knit communities tend to be isolated from the rest of the network, limiting access to new and innovative ideas (e.g., Burt (2000), Burt (2004)). By controlling for the clustering coefficient, I reduce the likelihood that decay centrality captures access to non-valuable information.

I report the results in columns (1) and (4) of Table 6 using specifications in levels and first differences, respectively. I find that the effect sizes increase with decay centrality, suggesting that a firm's position in the social network is a strong determinant of whether a firm mimics or not. In columns (2) and (5) I show that this result is robust to using the diffusion centrality measure of Banerjee et al. (2013). This measure generalizes the notion of decay centrality by

[5]The Watts and Strogatz (1998) local clustering coefficient varies between zero and one. A score of one (zero) occurs when all (none) of a firms' connections are connected to each other. In my sample 25% of the sample firms exhibit high clustering coefficients above 0.5. Refer to section C of the Internet Appendix for an in-depth discussion and a histogram depicting the sample distribution of the local clustering coefficient.

taking into account that it is more likely that information travels between two nodes in the network if there are multiple paths connecting those nodes.

[Table 6 About Here]

Next, I investigate whether or not firms with higher clustering coefficients also mimic more. Such a finding would open the possibility that some firms mimic based on non-valuable information. The peer effects estimates in columns (3) and (6) suggest this is not the case: only firms in the bottom tercile of the distribution of clustering coefficient mimic their peers.

Overall, the findings in this section suggest that firms use the social networks of their directors to acquire valuable information on CSR with the goal of obtaining a competitive edge over their industry rivals. Moreover, this effect is concentrated in large firms with high levels of information social capital, suggesting that the ability of firms to use social networks to obtain valuable information is very uneven across firms.

6 Why Do Firms Mimic?

In this section I delve deeper into the question of why firms mimic the CSR policies of their social peers. I briefly explain the theoretical motivation underlying two economic channels related to social learning and social norms that may drive social peer effects and proceed by testing these channels.

6.1 Social Learning Channel

In theory, peer effects can arise if socially connected firms share information and learn from one another (e.g., Ellison and Fudenberg (1993, 1995), Banerjee and Fudenberg (2004), Acemoglu et al. (2011)). Firms have incentives to share information because it is typically challenging to determine whether or not a given CSR investment is worth pursuing. This is the case for several reasons. First, some of the benefits of CSR are intangible (e.g., reputation), are only realized over the long term or are state-dependent. For example, Amiraslani et al. (2017) show that CSR paid off in the form of improved ability to raise debt capital during the 2008-09 financial crisis but not during normal periods. Second, only recently did CSR become a widely used strategic tool to which substantial research and business efforts are dedicated, creating limits to learning how to optimally design CSR from academic literature and from co-workers' past experiences. Third, CSR encompasses a wide range of topics requiring different types of expertise that may not be readily available to all firms.

These factors create an environment of uncertainty for firms trying to estimate the NPV of alternative CSR projects. In addition, CSR investments are often irreversible and costly. To illustrate, for the average firm in their sample in 2006, Lins, Servaes, and Tamayo (2017) estimate the cost of increasing CSR investment from the 1st to the 4th quartile of the cross-firm distribution of CSR to be $203.5 million. This may matter because in the presence of uncertainty about the net benefits of irreversible costly investments, firms often choose to postpone investments (e.g., Guiso and Parigi (1999)). Postponing investments, however, can lead to a situation of costly underinvestment if firms fall behind their industry rivals.

The exchange of information among social peers may allow firms to tackle this challenge in two ways. First, insofar as firms have the option of mimicking successful projects and avoiding value-destroying projects, information sharing spreads the downside risk of of choosing value-destroying sequences of trial-and-error CSR investments over time. This, in turn, incentivizes trial-and-error experimentation and can lead to faster learning across peers. Second, even if firms do not mimic specific projects, they may still learn from peers through the exchange of ideas about the intangible benefits of broad types of CSR (e.g., diversity versus health) and the optimal timing of these investments. If this exchange of ideas leads to similar opinions about the optimal design of CSR policies, peer effects will arise due to learning even if firms do not mimic specific projects.[6]

Thus, the social learning channel posits that social networks mitigate uncertainty and limits to learning by allowing firms to exchange information on how to optimally design value-creating CSR policies. Hence, under the social learning channel, the incentives for information sharing and learning stem solely from the desire to maximize firm value. If this is the case, peer effects should be stronger for firms with stronger ex-ante incentives to maximize firm value, that is, firms with better incentive alignment between shareholders and managers. If instead social peer effects are a manifestation of non-profit maximization motives (e.g., irrational herding or reputation concerns), we would expect either (i) peer effects to be strongest when incentive alignment is weakest, or (ii) no difference in peer effects across firms with different incentives.

I test the social learning channel by interacting the average CSR scores of the social peers with dummy variables indicating whether or not a given firm-year belongs to the bottom, middle or top tercile of the within-year distribution of a given incentive alignment proxy. I capture alignment of incentives with (i) CEO pay-related managerial incentives, (ii) the quality of board monitoring, (iii) institutional ownership, and (iv) industry competition.

First, I measure CEO pay-related managerial incentives with CEO delta and CEO vega. CEO delta is a measure of CEO pay-sensitivity to performance. Hence, if firms try to learn from their social peers with the goal of maximizing value, their incentives to do so

[6] It is also possible that a firm learns from its peers about which types of CSR projects are not worth pursuing. This does not preclude peer effects. Firms with failed projects can exchange information about those projects for information about successful projects. The firms with failed projects benefit by learning how to create value with CSR investments and firms with successful projects learn how to avoid destroying value. For example, a firm i with a failed project can obtain information about a successful project S_j from social peer j, give that information to another peer k who is not itself socially connected to j in exchange for information about another successful project S_k and share the information on project S_k with firm j. This allows firms i and j (i and k) to invest in project S_k (S_j), resulting in contemporaneous peer effects between firm i and its peers.

are stronger the higher CEO delta is.[7] CEO vega is a measure of the convexity of managerial compensation. It captures incentives given to managers, via stock options, to avoid costly underinvestment by incentivizing risk-averse managers to invest in risky positive NPV projects (Guay (1999)). Since uncertainty and limits to learning can theoretically lead to costly underinvestment in CSR, social learning could be a valuable tool for high vega firms interested in allocating resources to risky CSR projects. Second, I measure the quality of board monitoring by the fraction of independent directors on the board because independent directors can, in principle, be a good governance force aligning the incentives of managers and shareholders (e.g., Adams, Hermalin, and Weisbach (2010)). Third, I use institutional ownership as a measure of incentive alignment because sophisticated institutional investors are independent stakeholders with a comparative advantage over retail investors in monitoring (e.g., Ferreira and Matos (2008), Borochin and Yang (2017)). Fourth, I measure industry competition with the Herfindahl-Hirschman index. Firms in more competitive industries tend to have more aligned incentives because they face more pressure to reduce agency problems (e.g., Giroud and Mueller (2010), Kim and Lu (2011)).

The results are reported in Table 7. I report the results in first differences to eliminate all time-invariant omitted variables. This rules out concerns that, for example, firms with higher CEO delta are fundamentally different from firms with low CEO delta along unobservable dimensions. I further control for all four measures of network specific geographic social capital described in Section 1.3. This alleviates the concern that the identification of the social learning channel is confounded by the social norms channel discussed in the next subsection. I also control for the incentive alignment variables at the peer level. This makes it less likely that the results are driven by a network effect in corporate governance practices

[7] It is conceivable that higher CEO delta is not always consistent with profit-maximization incentives. I alleviate this problem to some extent by testing whether or not firms in the top tercile of the distribution of delta mimic more than firms in the bottom tercile. The test should be valid as long as incentives are on average better aligned for firms in the top tercile of the distribution of delta relative to firms in the bottom tercile. It is thus not necessary to assume that incentive alignment increases monotonically with delta.

across firms (e.g., Bouwman (2011)). For example, it could be the case that better incentive alignment leads firms to invest more in CSR and that firms with well-aligned incentives tend to be socially connected with firms that also have well-aligned incentives. It is also worth noting that there is a reduced number of observations in the regressions involving delta, vega and fraction of independent directors. This happens because these variables are sourced from ExecuComp and ISS which only cover S&P 1500 firms.

[Table 7 About Here]

The results show that (i) the economic significance of peer effects increases monotonically with firm value maximization incentives in all cases with the exception of the specifications in which incentive alignment is proxied for by institutional ownership or industry concentration, (ii) the bulk of the peer effects is concentrated in firms in the top terciles of delta, vega, fraction of independent directors and, to a lesser extent, industry competition, and (iii) the magnitude of peer effects is high and precisely estimated for firms with high vega, consistent with social learning alleviating underinvestment problems by reducing investment frictions such as uncertainty and limits to learning.[8]

Overall, these results provide evidence that firms mimic their social peers only when managers have strong incentives to maximize firm value. This is consistent with the idea that social networks are a value-creating resource that firms can strategically use to overcome uncertainty and costly underinvestment. As a consequence, these findings also cast doubt on explanations based on non-profit maximization motives such as irrational herding.

[8]Another explanation is that CEO vega is capturing excessive risk-taking and short-term incentives. This is very unlikely. First, if this was the case, we would not expect peer effects to be stronger when board monitoring and CEO delta are higher. More monitoring should curb excessive risk-taking and higher delta, by itself, incentivizes underinvestment in risky projects because CEO wealth is not diversified (e.g Coles, Daniel, and Naveen (2006)). Second, excessive risk-taking in CSR strongly increases the probability of CEO dismissal when performance is poor (Hubbard, Christensen, and Graffin (2017)). Hence, from an ex-ante perspective, there is a large downside risk to gambling. Third, contracts with high vega tend to be structured, albeit imperfectly, in a way that curbs excessive risk-taking incentives (e.g., Kubick, Robinson, and Starks (2018)). Fourth, it is more likely that short-term oriented CEOs prefer to cut on CSR spending to meet performance targets rather than investing more in CSR.

Furthermore, these results provide a mechanism that can at least partially explain the negative association between CSR investment and agency frictions documented by Ferrell, Liang, and Renneboog (2016). In detail, my results suggest that when agency frictions are low, firms are able to use their social networks to obtain information that decreases uncertainty about CSR investments. This, in turn, decreases the real option value of waiting for more information before investing and leads to more CSR investment.

It is also interesting to note that the finding that social peer effects are not stronger when institutional ownership is higher is consistent with the idea that institutional investors can influence CSR directly (e.g., Dyck et al. (2019)), thus reducing the need for board intervention. Iliev and Roth (2020) also provide evidence for this substitution effect by showing that sustainability regulations in foreign countries are less likely to spill over to US firms via international board interlocks when institutional ownership concentration is higher. In Internet Appendix Table IA.11 I show that social peer effects in CSR are also stronger when ownership concentration is lower.

6.2 Social Norms Channel

Given the evidence that social norms and values affect CSR decisions (e.g., DiGiuli and Kostovetsky (2014), Cronqvist and Yu (2017)), it is also possible that the social transmission of CSR occurs via an identity economics channel (e.g., Akerlof and Kranton (2000), Bénabou and Tirole (2011a)).

In the identity economics framework, a director jointly maximizes a standard utility function related to how much CSR increases profit as well as an identity utility function related to his ideals about whether or not firms have a societal role beyond firm value maximization. Social peers' identities can influence CSR choices in two ways. First, directors may internalize their social peers' pro-CSR ideals through mechanisms of persuasion (DeMarzo, Vayanos, and Zwiebel, 2003) and peer esteem (Akerlof (2016, 2017)). If so, identity utility is highest if

CSR choices match the ideal norms of behavior that are associated with the peers' identities and, therefore, their CSR choices. Second, failure to conform with social peers' behavior may lead to punishment. For example, by shunning employee diversity policies or taking a soft stand on the importance of protecting the environment, a director may negatively affect how pro-CSR peers perceive her and risks punishment in the form of foregone social benefits, such as peer esteem and future board appointments (e.g., Levit and Malenko (2016)). If the punishment is strong enough, the desire to conform will lead to peer effects in CSR. This is especially so because social networks are known to be important sources of job opportunities and financial returns to executives and directors (e.g., Hwang and Kim (2009), Fracassi and Tate (2012), Engelberg, Gao, and Parsons (2013), Ishii and Xuan (2014)).

If social peer effects in CSR are driven by identity and social norms, peer effects should be stronger for firms whose executives and directors have social networks that are rich in the following two dimensions of social capital: (i) social capital as a measure of civic engagement and pro-social preferences, capturing the likelihood that peers believe they have a role beyond value maximization; (ii) social capital as a measure of the extent to which networks can enforce punishment threats that sustain cooperation and pro-social behavior.

To quantify social capital at the network level, I exploit the fact there is ample cross-sectional variation in geographic social capital at the county-level in the US and that there is evidence that firms absorb the social norms of the county where the firm is headquartered.[9] Geographic social capital is likely to capture the desired dimensions of firm-level social capital because high social capital counties are, by definition, communities in which trust, reciprocity and pro-social behavior are sustained through internalized community values and networks of relationships. In such communities, individuals act with the well-being of the community in mind and expect others to do the same. This expectation is self-fulfilling because shared

[9]For instance, Hasan, Hoi, Wu, and Zhang (2017a) find that firms engage in less tax evasion in US counties with more social capital. Hasan, Hoi, Wu, and Zhang (2017b) find that firms headquartered in low social capital counties have access to cheaper debt. Jha and Chen (2014) find evidence that audit firms infer trustworthiness of clients based on whether firms are headquartered in a low or high social capital county.

norms of behavior are rewarded by the community and deviant behavior is punished.[10]

Following an extensive literature (e.g., Putnam (2000), Guiso, Sapienza, and Zingales (2004), Rupasingha, Goetz, and Freshwater (2006), Lin and Pursiainen (2018)), I measure geographic social capital with county-level data on organ donation per capita, association density per capita, registered organization density per capita, voter turnout and the first principal component of the last three variables. I then assign county-level data to each firm based on the location of firm headquarters. I do not account for headquarters relocations because Compustat only provides data on the most recent headquarters. This is, however, unlikely to affect the results because relocations are very rare (e.g., Parsons, Sulaeman, and Titman (2018)). To create a measure of the geographic social capital embedded in the local network of each firm, I average the social capital variables across each firm's social peers, including the firm itself.

Table 8 reports the findings of whether or not peer effects are stronger for firms whose local social networks are richer in social capital. I split firms in terciles based on the distribution of social capital in each year. Each column (1) through (5) shows the results using one of the social capital variables. Across most specifications, the peer effects in the lowest and highest tercile are similar and, in all five cases, peer effects are the strongest for firms in the middle tercile. This indicates that peer effects do not increase monotonically with social capital. I confirm this by formally testing for equality of peer effects in the highest and lowest tercile of social capital. With the exception of the regression using registered organization density as a proxy for social capital (p-value of 0.051), I always fail to reject the null of equality at the 10% level.

[10] Furthermore, insofar as individuals internalize community values and norms and derive satisfaction (e.g., self-esteem) from behaving according to those values and norms, individuals can punish themselves for deviating from the norm. Such punishments can include feeling guilty, shame, lack of self-esteem and discomfort arising from cognitive dissonance. Ultimately, as pointed out by Bénabou and Tirole (2011b), the standards of communities regarding the enforcement of punishments and rewards for pro-social behavior will affect not only dynamics of stigma and esteem but also moral sentiments of shame and pride.

[Table 8 About Here]

One possible caveat of these results is that the local network measure of geographic social capital is not the relevant measure. It could be the case that a firm's own social capital, as opposed to local network social capital, fully determines the extent to which a firm mimics its peers. This could arise if own social capital leads some firms to always want to invest in a level of CSR that is deemed adequate by its social peers, irrespective of peers' social capital. As shown in the Internet Appendix Table IA.12, this turns out not to be the case. All in all, there is no evidence that social peer effects are driven by social norms.

7 Conclusion

This study provides evidence that CSR policies are transmitted across firms through their directors' social networks. Based on rich social network data for 83,604 top executives and directors of Russell 3000 firms, my estimates indicate that firms with average levels of CSR increase their CSR by 16% in response to a one standard deviation increase in the average CSR scores of their social peers. Overall, the economic magnitude of social peer effects is comparable to the industry peer effects of CSR documented by Cao, Liang, and Zhan (2019).

Social network spillovers seem to be driven by firms exchanging information with their social peers in different industries with the goal of creating firm value and obtaining a competitive edge over their industry rivals. The effect is uneven across firms, with most of the mimicking being done by (i) firms pursuing product differentiation strategies for which CSR is more likely to add value, (ii) firms that are strategically positioned in the social network to obtain valuable information, and (iii) firms in which the profit maximization incentives of managers and shareholders are better aligned.

Overall, the results reveal a bright side of corporate social networks for both firms and society at large. For firms, the results suggest that social networks may allow for the design of better CSR policies in a manner that is consistent with aligned profit maximization incentives. For society, the existence of peer effects implies the existence of a social multiplier in CSR investing, thus amplifying the positive externalities of CSR on society.[11]

There may also be a dark side, however. The fact that social peer effects seem to be driven by social learning is consistent with the existence of frictions in CSR investment, such as uncertainty and limits to learning. Otherwise, social learning would not be necessary in the first place. If so, many firms may be underinvesting in CSR due to their inability to overcome investment frictions. Therefore, the large cross-firm variation in CSR investment that exists nowadays may partly be an outcome of cross-firm differences in exposure to investment frictions and differences in ability to mitigate those frictions.

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[11]The existence of a social multiplier is implied by the existence of peer effects. See Glaeser, Sacerdote, and Scheinkman (2003) for a proof. Intuitively, any shock that increases the CSR of a firm i will lead to an increase in CSR of social peers via peer effects. The increase in CSR of social peers will, in turn, lead to increases in CSR investment by their own social peers.

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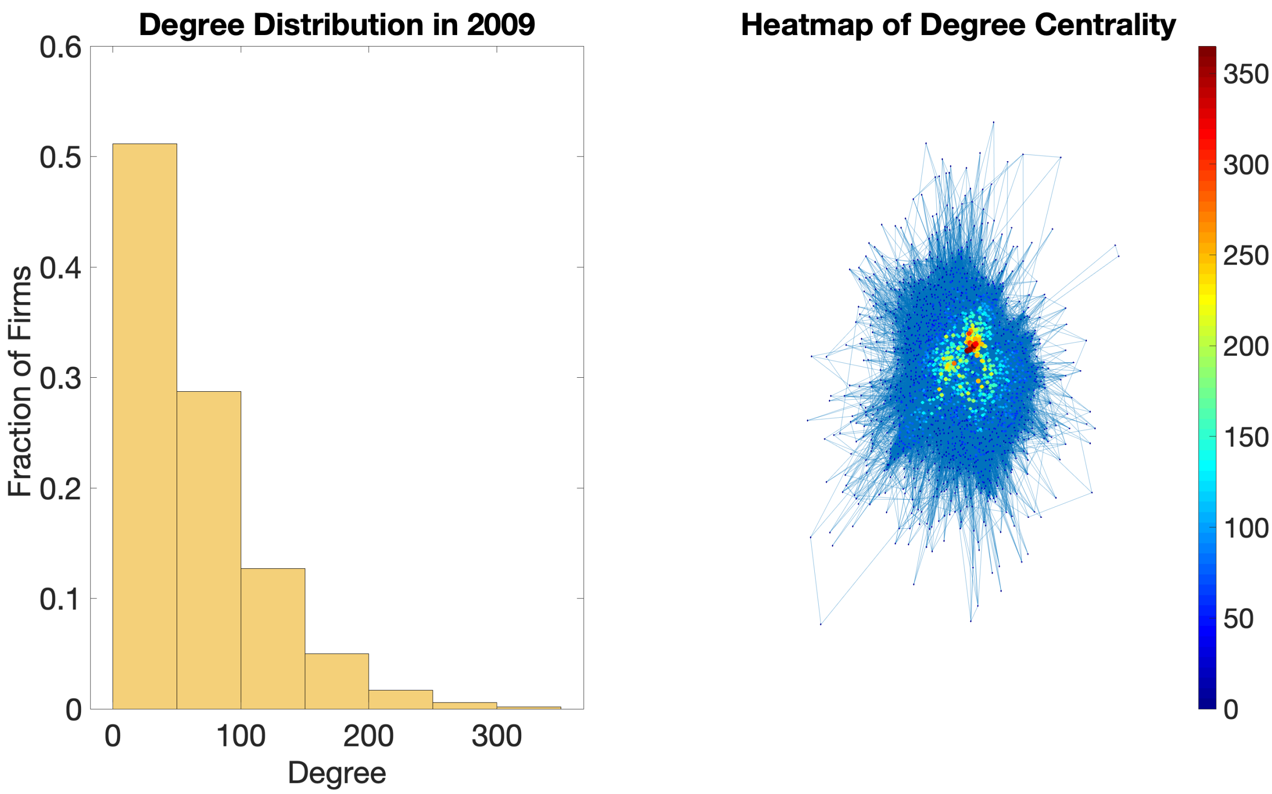

Figure 1. Network Degree Distribution.
The histogram on the left depicts the degree distribution of firm-level social connections in 2009 (the median year in the sample). The degree (or degree centrality) of a given firm is defined as the number of social connections that firm has. The heatmap on the right displays the firm-level social network in 2009 and the degree centrality of each firm. Warmer colors indicate higher degree centrality. To ease visualization of the heatmap, I exclude firms that have strictly less than two peers.

Table 1

Summary Statistics

This table reports the summary statistics for the main variables used throughout the paper. See Appendix Table A.1 for variable definitions. The columns under the *Low Degree (L)* (*High Degree (H)*) label contain means and standard deviations for the firm-years that belong to the lowest (highest) tercile of the distribution of degree centrality. The degree centrality of a given firm is defined as the number of social connections the firm has. The column *H minus L* presents the difference in means between the high and low degree centrality subsamples. The last two columns present statistics for the full sample. All control variables are winsorized at the 1% and 99% levels. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Low Degree (L)		High Degree (H)		H Minus L	Full Sample	
	Mean	SD	Mean	SD	Diff. Means	Mean	SD
Firm Attributes							
Size	6.997	1.467	8.560	1.800	1.563***	7.644	1.730
MB Ratio	2.677	3.431	3.205	4.256	0.528***	2.984	3.893
Debt Ratio	0.218	0.219	0.252	0.194	0.034***	0.236	0.210
ROA	0.026	0.113	0.031	0.105	0.005***	0.024	0.116
Net Income	71.992	236.692	800.194	1,643.976	728.202***	344.856	1,065.201
Cash Ratio	0.164	0.196	0.158	0.179	-0.006**	0.169	0.196
Divid. Ratio	0.012	0.023	0.015	0.022	0.003***	0.013	0.022
Inst. Own.	0.615	0.288	0.595	0.289	-0.019***	0.607	0.286
Cust. Awa.	0.009	0.021	0.013	0.028	0.004***	0.010	0.024
R&D	12.606	36.694	186.755	486.038	174.149***	80.743	303.665
CSR score	1.113	0.248	1.476	0.625	0.363***	1.261	0.467
Sample							
No. Firms	2,821						
Sample Period	2001-2016						
No. Obs.	25,808						

Table 2

Do Social Peers Mimic Each Other?

This table reports the results of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of executives and directors. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Contemporaneous			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' CSR	0.437***	0.450***	0.455***	0.377**	0.391**	0.399**
	(2.623)	(2.712)	(2.827)	(1.979)	(2.060)	(2.200)
Peers' Size	-0.141*	-0.136*	-0.131*	-0.089	-0.089	-0.094
	(-1.652)	(-1.665)	(-1.873)	(-0.916)	(-0.966)	(-1.213)
Peers' MB Ratio	-0.001	-0.001	-0.002	0.005	0.006	0.005
	(-0.121)	(-0.116)	(-0.240)	(0.621)	(0.713)	(0.608)
Peers' Debt Ratio	0.023*	0.018	0.016	0.021	0.018	0.014
	(1.740)	(1.452)	(1.295)	(1.478)	(1.261)	(0.985)
Peers' ROA	0.006	0.004	0.005	0.017	0.015	0.013
	(0.501)	(0.378)	(0.431)	(1.177)	(1.211)	(1.112)
Peers' Net Income	-0.002	-0.016	-0.008	-0.014	-0.027	-0.029
	(-0.067)	(-0.454)	(-0.311)	(-0.351)	(-0.686)	(-1.042)
Peers' Cash Ratio	-0.065	-0.062	-0.045	-0.044	-0.049	-0.042
	(-1.394)	(-1.525)	(-1.499)	(-0.868)	(-1.090)	(-1.291)
Peers' Divid. Ratio	-0.026**	-0.023*	-0.025**	-0.022	-0.017	-0.021
	(-1.979)	(-1.668)	(-2.014)	(-1.519)	(-1.111)	(-1.518)
Peers' Inst. Own.	0.007	-0.002	-0.004	0.007	-0.002	-0.005
	(0.788)	(-0.195)	(-0.434)	(0.680)	(-0.252)	(-0.554)
Peers' Cust. Awa.			-0.020			-0.014
			(-1.341)			(-0.885)
Peers' R&D			-0.026			-0.005
			(-0.825)			(-0.134)
Kleiberg-Paap F-stat	78.543***	64.563***	65.471***	58.380***	47.681***	51.236***
First Stage Instrument	0.199***	0.202***	0.207***	0.186***	0.189***	0.197***
	(8.860)	(8.040)	(8.090)	(7.640)	(6.910)	(7.160)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	Yes	No	No	Yes
Ex. Industry Peers	No	Yes	Yes	No	Yes	Yes
No. Obs.	25,808	25,808	25,808	22,958	22,958	22,958

Table 3

Which Individuals Mimic? The Role of Directors versus Executives

This table reports the results of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Results are presented by CSR dimension (social versus environmental) and by network type (executives versus directors). The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Panel A: Levels					
	Directors Network		Executives Network		Aggregate Network	
	Environmental	Social	Environmental	Social	Environmental	Social
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' CSR	0.308***	1.059***	0.184**	-0.179	0.378***	1.049***
	(3.028)	(3.429)	(2.323)	(-1.362)	(3.716)	(2.874)
Kleiberg-Paap F-stat	169.453***	34.347***	158.057***	65.460***	175.982***	24.729***
First Stage Instrument	0.288***	0.311***	0.238***	0.282***	0.297***	0.282***
	(13.020)	(5.860)	(12.570)	(8.090)	(13.270)	(4.970)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	24,738	24,738	21,990	21,990	24,875	24,875

	Panel B: First Differences					
	Directors Network		Executives Network		Aggregate Network	
	Environmental	Social	Environmental	Social	Environmental	Social
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Peers' CSR	0.407**	0.786***	-0.018	-0.074	0.495***	0.760***
	(2.404)	(3.654)	(-0.162)	(-0.481)	(3.381)	(3.031)
Kleiberg-Paap F-stat	73.894***	46.300***	79.016***	37.758***	75.739***	39.815***
First Stage Instrument	0.192***	0.386***	0.162***	0.254***	0.207***	0.760***
	(8.600)	(6.800)	(8.890)	(6.140)	(8.700)	(3.030)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	21,997	21,997	19,154	19,154	22,116	22,116

Table 4

Which Individuals Mimic? The Role of CSR Board Committees

This table reports the results of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of directors. In columns (2) and (5) ((3) and (6)) the social peer group only includes social peers without (with) CSR board committees in place. In columns (1) and (4) the social peer group includes all social peers irrespective of whether or not they have a CSR board committee. The magnitude of peer effects is allowed to vary as a function of whether or not firms have a CSR board committee in a given year. $D_{Committee}$ is equal to one if the firm has a CSR committee in a given year. D_{Not} is equal to one for the remaining observations. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. *P(C = N)* is the p-value obtained from testing the hypothesis that peer effects are equal across firms with and without CSR board committees. The Sanderson-Windmeijer F-stat refers to the Sanderson and Windmeijer (2016) weak instrument F-test for models with multiple endogenous variables. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Levels			First Differences		
	Includes All Social Peers (1)	Peers Without CSR Board Committees (2)	Peers With CSR Board Committees (3)	Includes All Social Peers (4)	Peers Without CSR Board Committees (5)	Peers With CSR Board Committees (6)
Peers' CSR × D_{Not}	0.523***	0.537***	-0.071	0.207**	0.304***	0.001
	(3.221)	(3.362)	(-0.520)	(2.025)	(2.674)	(0.009)
Peers' CSR × $D_{Committee}$	0.991***	1.015***	0.415***	0.751***	0.864***	0.600***
	(6.335)	(6.673)	(2.765)	(7.128)	(7.600)	(4.864)
Sanderson-Windmeijer F-Stat						
Ind. Peer's CSR × D_{Not}	69.400***	71.700***	78.830***	94.970***	74.520***	64.280***
Ind. Peer's CSR × $D_{Committee}$	91.950***	97.270***	112.010***	119.680***	95.720***	79.990***
First Stage Instrument						
Ind. Peer's CSR × D_{Not}	0.234***	0.233***	0.136***	0.268***	0.247***	0.137***
	(9.040)	(9.400)	(10.360)	(11.190)	(9.780)	(9.960)
Ind. Peer's CSR × $D_{Committee}$	0.740***	0.709***	0.634***	0.768***	0.736***	0.669***
	(31.240)	(29.230)	(19.880)	(39.200)	(38.160)	(18.710)
P(C = N)	0.000	0.000	0.000	0.000	0.000	0.000
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	25,664	25,553	19,300	22,833	22,730	17,174

Table 5

Which Firms Mimic? The Role of Product Differentiation and Size

This table reports the results of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of directors. The magnitude of peer effects is allowed to vary as a function of either industry CSR intensity, product differentiation or firm size. D_{High} is a binary indicator equal to one if one of these variables is larger than or equal to the median of the within-year distribution of that variable. D_{Low} is equal to one for the remaining observations. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. *P(H = L)* is the *p*-value obtained from testing the hypothesis that peer effects are equal across firms in the *Low* and *High* groups. The Sanderson-Windmeijer *F*-stat refers to the Sanderson and Windmeijer (2016) weak instrument *F*-test for models with multiple endogenous variables. *t*-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Levels			First Differences		
	Industry CSR Intensity (1)	Product Differentiation (2)	Firm Size (3)	Industry CSR Intensity (4)	Product Differentiation (5)	Firm Size (6)
Peers' CSR × D_{Low}	0.129	0.488***	0.296*	0.068	0.155	-0.013
	(0.802)	(3.141)	(1.953)	(0.736)	(1.473)	(-0.131)
Peers' CSR × D_{High}	0.769***	0.479***	0.581***	0.408**	0.223**	0.366***
	(3.125)	(3.284)	(4.186)	(2.241)	(2.355)	(4.145)
Sanderson-Windmeijer F-Stat						
Ind. Peer's CSR × D_{Low}	18.120***	76.940***	70.340***	86.870***	89.430***	86.530***
Ind. Peer's CSR × D_{High}	27.800***	80.860***	78.610***	35.340***	98.170***	93.820***
First Stage Instrument						
Ind. Peer's CSR × D_{Low}	0.189***	0.373***	0.349***	0.304***	0.383***	0.395***
	(4.590)	(14.420)	(11.820)	(9.060)	(15.880)	(16.170)
Ind. Peer's CSR × D_{High}	0.200***	0.519***	0.577***	0.206***	0.545***	0.561***
	(5.370)	(21.800)	(25.150)	(5.900)	(26.610)	(29.830)
P(H = L)	0.043	0.746	0.000	0.063	0.029	0.000
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	25,664	25,664	25,664	22,833	22,833	22,833

Table 6

Which Firms Mimic? The Role of Information Social Capital

This table reports the results of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of directors. The magnitude of peer effects is allowed to vary as a function of either decay centrality, diffusion centrality or clustering coefficient. D_{High}, D_{Med} and D_{Low} are binary indicators equal to one if the associated variable in a given firm-year belongs to the third, second and first tercile of the within-year distribution of that variable, respectively. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. *P(H = L)* is the p-value obtained from testing the hypothesis that peer effects are equal across firms in the highest and lowest terciles. The Sanderson-Windmeijer F-stat refers to the Sanderson and Windmeijer (2016) weak instrument F-test for models with multiple endogenous variables. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Levels			First Differences		
	Decay Centrality (2)	Diffusion Centrality (1)	Clustering Coefficient (3)	Decay Centrality (5)	Diffusion Centrality (4)	Clustering Coefficient (6)
Peers' CSR × D_{Low}	0.279*	0.282*	0.616***	0.046	0.044	0.405***
	(1.823)	(1.860)	(4.861)	(0.452)	(0.435)	(4.626)
Peers' CSR × D_{Med}	0.327**	0.341***	0.399***	0.132	0.176**	0.154
	(2.456)	(2.647)	(2.876)	(1.511)	(2.003)	(1.579)
Peers' CSR × D_{High}	0.691***	0.718***	0.207	0.504***	0.535***	-0.082
	(5.624)	(6.227)	(1.421)	(6.375)	(6.919)	(-0.755)
Sanderson-Windmeijer F-Stat						
Ind. Peer's CSR × D_{Low}	61.910***	67.090***	86.160***	78.220***	77.490***	100.890***
Ind. Peer's CSR × D_{Med}	75.510***	83.020***	80.560***	103.210***	101.120***	93.610***
Ind. Peer's CSR × D_{High}	78.360***	83.020***	72.280***	103.510***	112.800***	85.010***
First Stage Instrument						
Ind. Peer's CSR × D_{Low}	0.315***	0.330***	0.596***	0.348***	0.342***	0.627***
	(11.190)	(12.210)	(24.280)	(12.960)	(12.970)	(33.430)
Ind. Peer's CSR × D_{Med}	0.610***	0.600***	0.575***	0.584***	0.584***	0.546***
	(36.910)	(36.720)	(28.840)	(41.320)	(42.570)	(33.870)
Ind. Peer's CSR × D_{High}	0.748***	0.728***	0.431***	0.755***	0.754***	0.434***
	(54.220)	(49.150)	(15.580)	(69.010)	(61.150)	(19.210)
P(H = L)	0.000	0.000	0.000	0.000	0.000	0.000
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	25,664	25,664	25,664	22,833	22,833	22,833

Table 7

Why Do Firms Mimic? The Social Learning Channel

This table reports the output of two-stage least squares (2SLS) regressions of changes in firm CSR scores on changes in social peers' CSR scores. Social peers are defined based on the social networks of directors. The magnitude of peer effects is allowed to vary as a function of either firm-level CEO delta, CEO vega, fraction of independent directors, institutional ownership or industry competition. D_{High}, D_{Med} and D_{Low} are binary indicators equal to one if the associated variable in a given firm-year belongs to the third, second and first tercile of the within-year distribution of that variable, respectively. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness, R&D investment and the following local network measures of social capital: organ donation density, voter turnout, registered organization density and association density. The coefficients are measured in standard deviation units. $P(H = L)$ is the p-value obtained from testing the hypothesis that peer effects are equal across firms in the highest and lowest terciles. The Sanderson-Windmeijer F-stat refers to the Sanderson and Windmeijer (2016) weak instrument F-test for models with multiple endogenous variables. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	CEO Delta (1)	CEO Vega (2)	Fraction Indep. Directors (3)	Institutional Ownership (4)	Industry Competition (5)
Δ Peer's CSR × D_{Low}	0.060	0.076	0.136	0.188*	0.185*
	(0.494)	(0.641)	(0.725)	(1.897)	(1.815)
Δ Peer's CSR × D_{Med}	0.193	0.153	0.262	0.180*	0.240**
	(1.639)	(1.313)	(1.413)	(1.827)	(2.367)
Δ Peer's CSR × D_{High}	0.345***	0.445***	0.452***	0.196*	0.215**
	(3.031)	(4.124)	(2.600)	(1.932)	(2.065)
P(H = L)	0.000	0.000	0.000	0.810	0.472
Sanderson-Windmeijer F-Stat					
Δ Ind. Peer's CSR × D_{Low}	65.410***	64.000***	43.510***	98.970***	101.730***
Δ Ind. Peer's CSR × D_{Med}	67.490***	69.580***	47.470***	102.540***	97.210***
Δ Ind. Peer's CSR × D_{High}	67.120***	71.500***	45.340***	97.330***	97.060***
First Stage Instrument					
Δ Ind. Peer's CSR × D_{Low}	0.549***	0.575***	0.559***	0.569***	0.549***
	(21.280)	(22.810)	(18.280)	(28.480)	(27.250)
Δ Ind. Peer's CSR × D_{Med}	0.557***	0.527***	0.502***	0.518***	0.552***
	(25.500)	(20.680)	(20.710)	(27.840)	(26.660)
Δ Ind. Peer's CSR × D_{High}	0.603***	0.619***	0.584***	0.537***	0.482***
	(24.610)	(27.580)	(24.110)	(27.870)	(22.350)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes
No. Obs.	15,151	15,151	12,185	22,798	22,448

Table 8

Alternative Explanations: The Social Norms Channel

This table reports the output of two-stage least squares (2SLS) regressions of changes in firm CSR scores on changes in social peers' CSR scores. Social peers are defined based on the social networks of directors. The magnitude of peer effects is allowed to vary as a function of each firm's local network geographic social capital. Local network geographic social capital is measured as the peer group average, including the firm itself, of one of the following variables: organ donation density, voter turnout, registered organization density, association density or the first principal component of the previous three variables. D_{High}, D_{Med} and D_{Low} are binary indicators equal to one if the associated variable in a given firm-year belongs to the third, second and first tercile of the within-year distribution of that variable, respectively. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. *P(H = L)* is the p-value obtained from testing the hypothesis that peer effects are equal across firms in the highest and lowest terciles. The Sanderson-Windmeijer F-stat refers to the Sanderson and Windmeijer (2016) weak instrument F-test for models with multiple endogenous variables. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Local Network Geographic Social Capital				
	Organ Donation (1)	Voter Turnout (2)	Registered Org. Density (3)	Association Density (4)	Principal Component (5)
Δ Peer's CSR × D_{Low}	0.084	0.180*	0.113	0.121	0.112
	(0.818)	(1.668)	(1.049)	(1.132)	(1.012)
Δ Peer's CSR × D_{Med}	0.316***	0.300***	0.295***	0.302***	0.311***
	(3.266)	(3.155)	(3.212)	(3.112)	(3.244)
Δ Peer's CSR × D_{High}	0.191*	0.120	0.243***	0.160	0.123
	(1.682)	(1.107)	(2.667)	(1.422)	(1.131)
P(H = L)	0.165	0.423	0.051	0.613	0.882
Sanderson-Windmeijer F-Stat					
Δ Ind. Peer's CSR × D_{Low}	101.990***	113.260***	91.520***	95.970***	93.140***
Δ Ind. Peer's CSR × D_{Med}	114.100***	109.310***	127.680***	111.260***	111.230***
Δ Ind. Peer's CSR × D_{High}	96.170***	96.550***	129.820***	112.170***	107.680***
First Stage Instrument					
Δ Ind. Peer's CSR × D_{Low}	0.471***	0.473***	0.432***	0.431***	0.418***
	(18.800)	(18.540)	(17.120)	(15.470)	(14.820)
Δ Ind. Peer's CSR × D_{Med}	0.558***	0.579***	0.553***	0.561***	0.545***
	(29.420)	(26.800)	(31.050)	(23.960)	(25.940)
Δ Ind. Peer's CSR × D_{High}	0.426***	0.447***	0.554***	0.432***	0.465***
	(14.750)	(17.220)	(22.510)	(16.710)	(18.800)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes
No. Obs.	22,653	22,653	22,653	22,653	22,653

Appendix Table A.1

Variable Definitions and Data Sources

This table provides the definitions and data sources of the variables used throughout the paper.

Corporate Social Responsibility Variables	
CSR scores	Sum of KLD strengths over the following categories: employee relations, community relations, environment and workforce diversity. The score is normalized by the possible number of strengths for each firm-year and ranges between one and five. Sourced from the MSCI ESG Stats Database (formerly known as Kinder, Lydenberg and Domini & Co. (KLD)).
Alternative CSR scores	Average of the environmental and social sustainability scores of Thomson Reuters. These scores are based on the sustainability performance of each firm relative to its industry rivals in a given year. Sourced from the Thomson Reuters ESG database.
Firm-Level Control Variables	
Size	Natural logarithm of total assets in millions of dollars (Compustat item AT).
MB Ratio	Market value of equity (Compustat item PRCC_F) divided by the book value of equity (Compustat item BKVLPS).
Debt Ratio	Total long-term debt (Compustat ites DLTT plus DLC) divided by total assets (Compustat item AT).
ROA	Income before extraordinary items (Compustat item IB) divided by total assets (Compustat item AT).
Net Income	Net income before extraordinary items and discontinued operations in millions of dollars (Compustat item XSGA).
Cash Ratio	Cash balances (Compustat item CHE) divided by total assets (Compustat item AT).
Dividend Ratio	Cash dividends (Compustat items DVC plus DVP) divided by total assets (Compustat item AT).
Customer Awareness/Product Differentiation	Cost of advertising media (radio, television, newspapers, periodicals) and promotional expenses (Compustat item XAD) divided by total sales (Compustat item SALE).
R&D	Stock of research and development expenses (Compustat item XRD) computed by capitalizing R&D expenses following the perpetual inventory method of the Bureau of Economic Analysis (Sliker (2007)). Data on the consumer price index is sourced from Global Financial Data.
Institutional Ownership	Fraction of firm stock owned by institutional investors. Sourced from Thomson Reuters.

Appendix Table A.1 (Continuation) This table provides the definitions and data sources of the variables used throughout the paper.

Peer-Level Control Variables	For each firm-level control variable, there is a corresponding peer-level control variable constructed as a weighted average of the values of the firm-level control variable across all of a firm's social peers, excluding the firm itself. The weights are the normalized strengths of social connections between firm-pairs in a given year.
Economic Channels Variables	
CEO Delta	Change in the dollar value of the CEO's stock and option portfolio for a one percentage point change in stock price. Sourced from ExecuComp.
CEO Vega	Change in the dollar value of the CEO's stock and option portfolio for a 0.01 change in the annualized standard deviation of stock returns. Sourced from ExecuComp.
Fraction of Independent Directors	Fraction of independent directors on the board. Sourced from Institutional Shareholder Services.
Industry Competition	Herfindahl-Hirschman index computed as the sum of the squared market shares of all firms in a given industry. A firm's market share is computed as the ratio of its sales to total industry sales. The industries are defined based on the TNIC-3 text-based network industry classification of Hoberg and Phillips (2016). Sourced from the Hoberg-Philips data library.
Organ Donation Density	Number of organ donations per capita in each state. Sourced from the Organ Procurement and Transplantation Network (OPTN).
Registered Organization Density	Number of tax-exempt non-profit organizations per capita in each county. Sourced from the National Center for Charitable Statistics (NCCS).
Association Density	Number of non-profit and/or recreational associations per capita in each US county. The following association types are included: civic and social organizations, bowling centers, gold course and country clubs, fitness and recreational centers, sports teams and clubs, religious organizations, political organizations, labor unions and similar labor organizations, business associations, and professional organizations. Sourced from the County Business Patterns (CBP) compiled by the Census Bureau.
Voter Turnout	Ratio of the number of votes cast in the closest presidential election to the population eligible to vote. Data on votes cast and population eligible to vote are obtained from the American Community Survey and the MIT Election Lab, respectively.
Principal Component Index	Principal component of registered organization density, association density and voter turnout. Following Lin and Pursiainen (2018), the principal component is computed for each year separately after standardizing and winsorizing each variable each year at 1% and 99% levels.

Appendix Table A.1 (Continuation) This table provides the definitions and data sources of the variables used throughout the paper.

Institutional Ownership Concentration Variables	
Inst. Own. HHI Index	Herfindahl-Hirschman index computed as the sum of the squared ownership stakes of institutional investors. Sourced from Thomson Reuters.
Inst. Own. by Largest Five	Fraction of firm stock owned by the largest five institutional investors. Sourced from Thomson Reuters.
Inst. Own. by Blockholders	Fraction of firm stock owned by institutional investors with ownership stakes of at least 5%. Sourced from Thomson Reuters.
Network Topology Variables	
Degree Centrality	Number of firms a given firm is socially connected with through the social networks of its directors. Social network data is sourced from BoardEx.
Decay Centrality	Network topology variable that measures the extent to which a firm is strategically positioned in the social network to acquire valuable information from its social peers. Refer to Jackson (2008) for technical details. Social network data is sourced from BoardEx.
Diffusion Centrality	Network topology variable that measures the extent to which a firm is strategically positioned in the social network to acquire valuable information from its social peers. Refer to Banerjee et al. (2013) for technical details. Social network data is sourced from BoardEx.
Local Clustering Coefficient	Fraction of pairs of a firm's social peers that are connected to each other. Refer to Watts and Strogatz (1998) for technical details. Social network data is sourced from BoardEx.

Internet Appendix to "Social Networks and Corporate Social Responsibility"

A Details on Social Network Construction

To ensure the analysis is free of survivorship bias, I follow a network construction approach similar to that of Engelberg, Gao, and Parsons (2013). First, since BoardEx coverage is very limited before 2000, I constrain the sample period to run from 2001 until 2016. Second, BoardEx does not provide CUSIP or ticker symbol information for inactive firms. For these cases, I use the Levenshtein (1966) textual algorithm to match the names of inactive firms to firm names in the Compustat Funda tables. The algorithm is applied several times until no further matches are identified. All matches are manually checked to avoid errors.

Following Fracassi (2017), I define top executives as the top five executives based on compensation data from ExecuComp. Since there is no common individual-level identifier between BoardEx and ExecuComp, I employ the Levenshtein (1966) algorithm again to textually match executives names in each firm-year. All the matches are manually checked. One difficulty is that the names in the two databases often come in different formats, in which case the textual algorithm may fail to produce a correct match. For instance, one database might use the nickname Chuck Smith to refer to Charles Smith or Doctor Smith in the other database. It is also frequent that surnames of female executives change or that one of the databases does not clearly distinguish between members of the same family (e.g., James Smith can refer to James Smith Jr. or James Smith Sr.). I resolve these ambiguities by manually searching for name and professional history information on LinkedIn, company websites, SEC reports, Bloomberg executives profiles and news articles.

Since the ExecuComp universe is restricted to the S&P 1500, I cannot identify the top five executives by compensation for all Russell 3000 sample firms. In those cases, I define the top executives to be the CEO, CFO and COO of the firm. My final sample consists of 83,604 individuals based on which I construct 83,604-by-83,604 time-varying networks.

In constructing the education network I follow the general strategy of Engelberg, Gao, and Parsons (2013), but with a few differences worth noting. As a first step, I assign each of the several thousands of degree descriptions into 7 categories: (i) undergraduate, (ii) masters and non-research post-graduate degrees, (iii) MBA, (iv) PhD and post-doc, (v) non-research law degrees, (vi) medical degrees, (vii) and other qualifications. Unlike Engelberg, Gao, and Parsons (2013), I create a specific category for medical degrees. The motivation is that the facilities where medical students are trained are often geographically separate from those of non-medical students, thus diminishing the chance of meaningful social interaction. I also exclude online programs and short-term certifications that only require a few days or weeks of contact hours. Since many short-term courses are repeated several times within a year for different cohorts, it is often impossible to assign names to cohorts and infer social connections.

In the second step, I map each institution into a unique identifier to correct for the fact that BoardEx assigns different names and abbreviations to the same institution. For instance, I assign KU Leuven to the same identifier as the Catholic University of Leuven. I further account for name changes by checking the history of each institution and I conduct international translations whenever necessary. For example, Arthur D. Little School of Management was renamed Hult Business School in 2003 and Rensselaer's Education for Working Professionals was known as Hartford Graduate Center. The Academie du Droit Internationale de la Haye is assigned the same identifier as Hague Academy of International Law. I also assign university research centers to the respective university campus. For example, the Carolina Center for Genome Sciences is assigned to the University of North Carolina at Chapel Hill, one of the 17 campuses of the University of North Carolina system.

In the third step, I refine the matching by excluding ambiguous cases. For instance, I exclude the Indian Institute of Technology since there are 23 campuses in 23 states across

India. However, when information is available elsewhere (e.g., Bloomberg Executives Profile or LinkedIn), I use that information to pin down the specific campus or college where individuals studied. I exclude cases in which the link between an individual and an institution takes the form of a fellowship instead of a degree. I also ignore academic links to professional organizations such as the American Academy of Forensic Sciences. Such institutions do not grant degrees and often have members spread over many states and even countries. In addition, BoardEx does not provide information about whether or not individuals are active in these organizations, making it impossible to define meaningful social connections.

Given the extensive amount of manual matching involved in the construction of the education network, the matching is done twice, once by me and once by a research assistant. I then compare the output of both matches and correct mistakes.

B Detailed Description of Social Capital Proxies

I use several proxies for geographic social capital: organ donation, association density, registered organization density, voter turnout, and a modified version of the social capital index of Rupasingha, Goetz, and Freshwater (2006).

Organ donation density is the number of organ donations per capita in each state, calculated using data from the Organ Procurement and Transplantation Network (OPTN). The organ donation measure has been used in previous studies in the finance and economics literature as a proxy for social capital (e.g., Guiso, Sapienza, and Zingales (2004), Buonanno, Montolio, and Vanin (2009) and Hasan, Hoi, Wu, and Zhang (2017b)).

Association density is the number of non-profit and/or recreational associations per capita in each US county, obtained from the County Business Patterns (CBP) compiled by the Census Bureau. The following association types are included: civic and social organizations, bowling centers, golf courses and country clubs, fitness and recreational centers, sports teams and clubs, religious organizations, political organizations, labor unions and similar labor organizations, business associations and professional organizations. Registered organization density is the number of tax-exempt non-profit organizations per capita in each county, sourced from the National Center for Charitable Statistics (NCCS). Voter turnout is the ratio of the number of votes cast in the closest presidential election to the population eligible to vote. Data on votes cast and population eligible to vote are obtained from the American Community Survey and the MIT Election Lab, respectively.

These three measures build on the work of Putnam (2000) in the sociology literature and were introduced in the economics literature by Rupasingha, Goetz, and Freshwater (2006) in the form of a social capital index. Since then, this index has dominated the empirical literature on social capital (e.g., Hasan, Hoi, Wu, and Zhang (2017a), Hasan, Hoi, Wu, and Zhang (2017b), Lin and Pursiainen (2018)). The social capital index is usually constructed as the first principal component of these three measures and the county-level response rate to the Census Bureau's decennial census.

I deviate from the index construction methodology of Rupasingha, Goetz, and Freshwater (2006) because, as explained in detail in Lin and Pursiainen (2018), the index comes with several methodological shortcomings. These include the variables being contaminated by significant outliers (e.g., voting rates higher than 100%) and the index not being available on a yearly basis (thus requiring data extrapolation across years). Following Lin and Pursiainen (2018), I deal with these issues in two ways. First, I do not use census response rates data to eliminate the need to extrapolate data across years. Instead, I construct the index as the first principal component of association density, registered organization density and voter turnout. Second, I winsorize each variable at the 1% and 99% levels within each year to remove the influence of extreme observations. In a final step, I standardize the variables within each year to capture cross-sectional differences in social capital as opposed to time trends and compute the within-year first principal component of the three variables.

It is also worth noting that I deviate slightly from the literature in that I use both the principal component and the three individual variables as alternative proxies for social capital. Two reasons justify proceeding in this way. First, I allow for the fact that these measures capture different dimensions of social capital. Regional and organizational density capture the frequency of social interactions and proxy for the existence of dense networks that enforce cooperation (Putnam (2000)). Voter turnout and organ donation, however, are measures of civic engagement (Scrivens and Smith (2013)).[1] There is, to the best of my understanding, little motivation to ignore the possibility that different dimensions of social capital matter in different settings. Second, the measure of organizational density has received some criticism as it ignores the emergence of new forms of organizations and technologies that sustain interpersonal networks (e.g., Sobel (2002)). Therefore, variation in these measures may reflect a substitution between types of organizations instead of actual changes in social capital. Hence, given these concerns, using a principal component methodology may mask important dynamics. Nevertheless, I show that the results are robust to using the principal component approach.

As in the extant literature, I obtain firm-specific measures of social capital by assigning county-level measures of social capital to each firm based on the county where the firm is headquartered. A drawback of this measure is that it does not account for the fact that many of a firms' social peers are headquartered in a different county. Therefore, it may be a poor proxy for the amount of social capital in a firms' social network. To account for this possibility, I also create a measure of a firm-specific local network social capital (as opposed to own social capital) by averaging the social capital of all the peers of that firm, including the firm itself.

[1] Refer to Scrivens and Smith (2013) for an in-depth discussion on the different dimensions of social capital and corresponding empirical measures.

C Network Summary Statistics

The histogram in Figure IA.1 depicts the distribution of the clustering coefficient of Watts and Strogatz (1998). This coefficient measures how close-knit the local network around each firm is. A score of one (zero) occurs when all (none) of a firms' connections are connected to one another. We observe that 25% of the firms exhibit high clustering coefficients above 0.5. To put this in perspective note that, if the network was generated by a Erdős and Rényi (1959) random graph model, the expected clustering coefficient would be 15 times smaller than the observed mean coefficient of 0.4.[2] This suggests that the structure of corporate social networks may be able to sustain information exchange and social norms of behavior within close-knit groups through schemes of reward and punishment. This is the case because locally dense networks allow social peers to jointly punish those who fail to cooperate, thus making deviations costlier (e.g., Karlan et al. (2009), Lippert and Spagnolo (2011)).

[Figure IA.1 About Here]

Figure IA.2, left panel, compares the spatial correlation of CSR scores among firms that are at different distances from each other in the social network.[3] To remove trend effects, I compute the statistic separately for each year and then average across years. I also exclude social connections among firms in the same one-digit SIC division to remove industry peer effects. We observe a strong positive correlation amongst directly connected firms. Most striking is that the cross-firm commonality in CSR completely vanishes once we consider indirect social peers. This result is reassuring in that it is inconsistent with the existence of

[2]The Erdős and Rényi (1959) random graph model is a model that generates a random network by randomly connecting pairs of nodes with some prespecified probability. The expected value of the local clustering coefficient for the Erdős and Rényi (1959) random graph is equal to the probability that any two given nodes are connected. Hence, computing the sample probability that any two given nodes are connected enables me to compute the expected value of the clustering coefficient under the assumption that the network is generated by the Erdős and Rényi (1959) random graph model.

[3]This corresponds to Moran's I statistic, a measure of spatial correlation for nodes located at different distances in the network and that takes into account the strength of connections (Kelejian and Prucha (2001)).

strong unobservable common shocks that could bias the results. If omitted common shocks would completely drive the spatial correlation, we would expect to find stronger positive correlations between the CSR policies of firms that are not directly connected. Moreover, the fact that correlations are high and low exactly when they should be also suggests that the social networks are able to capture meaningful social links despite involving substantial aggregation of individual-level social networks.

[Figure IA.2 About Here]

A related question is whether or not the absence of strong positive correlations between CSR policies of indirectly linked firms is consistent with firms bridging information selectively between their social peers (consistent with information selection effort and information being valuable). Indeed, the observed pattern could simply be a mechanical artifact of a sparse network. In sparse networks, the average shortest path length across all pairs of nodes is large and, therefore, it is difficult for information originating in a given node to percolate across the network. In denser networks with a few highly connected hubs, however, information originating in a given node in the network is likely to quickly reach a highly connected hub which can then spread the information to many other nodes (e.g., Pastor-Satorras and Vespignani (2001), Barthélemy et al. (2004), Acemoglu, Bimpikis, and Ozdaglar (2014), Rantala (2019)).

To provide some insight into this question, I plot the 10th, 50th and 90th percentiles of the cross-firm distribution of the fraction of firms that are within a given distance of each sample firm, averaged over the period 2001-2016. The results are shown in the right panel of Figure IA.2. Consistent with the idea that social networks are small worlds in which everyone is just a few hops away from everyone else (e.g., Milgram (1967), Barabási (2003)), most firms can reach the entire network within 3 steps. More precisely, half of the firms can reach at least half of the network within 2 steps and 90% of the firms can reach at least 90% of the entire network within 3 steps. Overall, and with the caveat of being purely descriptive, this evidence suggests that the architecture of US corporate social networks is able to sustain the exchange of valuable information on CSR.

D Network Placebo Tests

The main challenge underlying the empirical setting of the paper is to separate endogenous peer effects from correlated effects. While the results from other robustness tests and the partial identification strategy suggest that correlated effects play a limited role, I conduct a stricter test of this statement by forming placebo peer groups. If the results are driven by latent common factors, we would expect to find that the average CSR of a firm's social peers is systematically related to the CSR decisions of other firms.

I construct placebo peer groups by randomly matching each firm's social and indirect peer groups to another firm each year. A welcome feature of this approach is that it preserves the specific latent common factors captured by the average CSR score of social peers that potentially bias the results. The matching process is repeated 1,000 times, both with and without replacement. The regressions control for state-of-incorporation-by-year fixed effects, industry-by-year fixed effects, CSA-by-year fixed effects and all firm-level and peer-level control variables used throughout the paper, including the additional controls customer awareness and R&D. The results reported in Table IA.4 show that the t-statistics and associated coefficient estimates obtained in the non-placebo regression (3) in Table 2 occur in fewer than 1% of the placebo simulations. Moreover, the mean and median values of estimated placebo peer effects are zero. This suggest that the results are unlikely driven by latent common factors. Plots with the full distribution of placebo coefficients and t-statistics are shown in the Internet Appendix Figure IA.3.

[Table IA.4 About Here]

E Tests of Endogenous Sorting Into Networks

An additional concern is that the results are driven by endogenous sorting into networks. For instance, DiGiuli and Kostovetsky (2014) document that firms with Democrat directors and CEOs invest less in CSR compared to Republican-leaning firms. If Democrats are more likely to be socially connected to Democrats than to Republicans, peer effects may be an artifact of common preferences across socially linked firms. To alleviate this concern, I use a community detection algorithm, the Louvain algorithm (Blondel et al. (2008)), to partition the social networks into densely connected communities of firms. This makes it possible to employ different types of network community-by-year fixed effects that vary with average community size and to cluster standard errors to account for within-community dependence. The results are shown in Table IA.5. Depending on the size of the communities, the magnitude of the peer effects and associated t-statistics are either very similar or slightly larger than the baseline estimates in Table 2. The stability of the estimates is, therefore, consistent with the notion that the instrumental variable is orthogonal to the omitted variables that simultaneously influence firm network formation and CSR investment decisions.

[Table IA.5 About Here]

F Evidence from Deaths of Executives and Directors

This quasi-natural experiment mirrors the one in Fracassi (2017) and proceeds in two stages. In a first stage I regress firm-level CSR scores on the set of control variables and high-dimensional fixed effects used throughout the paper:

$$y_{ijklt} = \alpha + \lambda' \bar{X}_{-ijklt} + \gamma' X_{ijklt} + \mu_{jt} + \delta_{kt} + \zeta_{lt} + \epsilon_{ijklt}, \tag{IA.1}$$

where the unit of observation is a firm i in year t, operating in industry j, headquartered in CSA region k and incorporated in state l. The dependent variable y_{ijklt} is the CSR score of firm i. The model further controls for the average characteristics of firm i's peer group ($\bar{X}_{-ijklt}$), its own characteristics (X_{ijklt}) and a set of three-digit SIC industry-by-year (μ_{jt}), CSA-by-year (δ_{kt}) and state-of-incorporation-by-year (ζ_{lt}) fixed effects.

The residuals of this regression capture the idiosyncratic component of firms' CSR policy that is orthogonal to time-varying common shocks and firm-specific observables. I then define a measure of idiosyncratic CSR comovement for each firm-pair-year as the absolute value of the difference between the idiosyncratic CSR policies of that firm-pair in that year:

$$\tilde{y}_{a,b,t} \stackrel{\text{def}}{=} |\epsilon_{a,t} - \epsilon_{b,t}|, \tag{IA.2}$$

where the pair *(a,b)* indexes a firm-pair. The larger the value of this measure, the less the CSR policies of the firms comove. A value of zero indicates perfect comovement.

In a second stage I collect all firm-pairs that experience a death during the sample period. There are 4,263 deaths in total. Thirty-seven percent of firm-pairs experience a death and 3.5% of those experience a death that was connecting the firm-pair. Using this sample, I run the following diff-in-diff regression:

$$\tilde{y}_{a,b,t} = \alpha + \beta_1 Death_{a,b,t} + \beta_2 Death_{a,b,t} \times Connected_{a,b,t} + \phi' W_{a,b,t} + \tau_{a,b} + \omega_t + \eta_{a,b,t} \tag{IA.3}$$

In words, I regress the idiosyncratic CSR comovement measure on a dummy variable (*Death*) that equals one after a death event occurs and on the interaction between this variable and another dummy variable (*Connected*) that equals one if the firm-pair is in the treatment group. The treatment group is composed of firm-pairs for which at least one deceased individual was connecting the firm-pair. The control group consists of the remaining firm-pairs for which the deceased were not connecting the pair. I also include firm-pair fixed effects ($\tau_{a,b}$), year fixed effects (ω_t) and firm-pair control variables ($W_{a,b,t}$). The control variables are the pairwise sums and the absolute values of the pairwise differences of all firm-level control variables listed in Appendix Table A.1. I exclude firm-pairs in which the deceased worked in both firms simultaneously. This rules out the possibility that comovement is driven by the preferences of one individual instead of being driven by social interactions. Standard errors are clustered at the firm-pair level.

I present the results in Table IA.6. Columns (1), (3) and (5) show the results using the network of directors, executives and both, respectively. The remaining columns (2), (4) and (6) add firm-pair control variables. The results indicate that the death of a director connecting a firm-pair leads to a decrease in idiosyncratic CSR comovement relative to the death of a director that is not connecting the firm-pair. There is, however, no evidence that the death of an executive connecting a firm-pair impacts CSR comovement more than the death of an executive not connecting the firm-pair. Overall, this is consistent with the results of the IV analysis.[4]

[Table IA.6 About Here]

In Table IA.7 below I show the results are robust to (i) allowing the treatment effect to be a function of the number of deaths involving a given firm-pair, and (ii) excluding firm pairs in the same one-digit SIC industry.

[Table IA.7 About Here]

G Evidence from Close-call CSR Proposals

In this section I use a regression discontinuity design to examine the response of firms' CSR decisions to the passage of close-call shareholder-sponsored CSR proposals by their social peers. The identifying assumption is that whether the social peers of a firm pass or fail CSR proposals around the pass threshold (e.g., 51% versus 49% of the votes) is as good

[4]Note that the effect of the death of an individual not connecting a firm-pair is to increase comovement in CSR policies. This is consistent with the results of Fracassi (2017) who also finds a similar effect on the comovement of firms' investment spending. A plausible reason for this is that the changes in leadership that follow deaths lead to the adoption of less idiosyncratic investment policies. Refer to Fracassi (2017) for a discussion of this.

as random with respect to the other determinants of that firm's CSR. This seems reasonable in light of the fact that previous literature using CSR proposals in a similar setting has consistently failed to find evidence for manipulation (e.g., Flammer (2015a), Cao, Liang, and Zhan (2019), Dai, Liang, and Ng (2020)). Under this assumption, I estimate the causal peer effects of CSR by comparing the CSR outcomes of firms whose peers failed to pass CSR proposals by a small number of votes with the CSR outcomes of firms whose peers barely passed CSR proposals. The estimation is done using nonparametric local linear regression and the Imbens and Kalyanaraman (2012) optimal bandwidth selection method.[5]

I test for violations of the identifying assumption in two ways. First, I confirm that there is no evidence of a discontinuity around the approval threshold using the non-parametric density estimator test of Cattaneo, Jansson, and Ma (2020). The p-value of the test is 0.28. The method of Cattaneo, Jansson, and Ma (2020) improves on the test of McCrary (2008) by providing robust bias-corrected confidence intervals and by overcoming the need to pre-bin the data, thus yielding more statistical power. Second, I show in Table IA.8 that there is little evidence of strong pre-treatment differences in firm attributes within narrow voting windows of 5% or less around the pass threshold. I also find, however, that there is evidence for pre-treatment differences in four firm attributes once I consider a voting window of 10%. While this does not necessarily invalidate the design, I report the results with and without controls to mitigate potential selection biases.

[Table IA.8 About Here]

I construct treatment and control groups as follows. A non-voting firm-year is assigned to the treatment (control) group if at least one social peer proposal passes (fails) in the previous year. Therefore a firm is either in the control or the treatment group. Furthermore, as in

[5] In a previous version of the paper I used global polynomial regression. The switch to local linear regression methods is motivated by the desire to avoid the shortcomings of global polynomial methods discussed in Gelman and Imbens (2019).

Cuñat, Gine, and Guadalupe (2012) and Flammer (2015a), I aggregate the votes of all the peer proposals associated with a given non-voting firm in a given year as follows. If the firm is in the treatment group, I sum the distances to the pass threshold across all peer proposals that pass. Similarly, if a firm is in the control group, I sum across all failed proposals. This ensures that observations will only lie within a short-window of the threshold if all the peer proposals that pass or fail are individually close to threshold. In addition, if the peers of a firm vote on proposals in year *t*, I only include the firm in the analysis if the firm did not pass any proposals itself in the period ranging from year *t-2* until *t+1*. This ensures that I do not spuriously attribute peer effects to firms passing proposals around the same time their peers happen to be voting on their own proposals. I also exclude social peers in the same three-digit SIC industry to abstract from industry peer effects.[6]

This leads to a total of 25,648 non-voting firm-years. However, it is important to stress that only 14 proposals, out of a total of 3,010 proposals, pass within the 10% threshold. The small number of passing proposals is consistent with previous literature (e.g., Flammer (2015a)). Hence, while this strategy in principle scores high on internal validity, its external validity is not guaranteed.

I report the results in Panel A of Table IA.9 using both triangular and rectagular kernels. I present results with control variables (columns (2) and (4)) and without (columns (1) and (3)). In addition, the results in columns (3) and (4) are obtained using only variation in CSR scores that is orthogonal to three-digit SIC industry-by-year fixed effects. These orthogonalized CSR scores are obtained through a first stage regression as the residuals of an ordinary least squares regression of CSR scores on industry-by-year fixed effects. To

[6]An alternative approach in the literature (Cao, Liang, and Zhan (2019) and Dai, Liang, and Ng (2020)) consists of stacking all pairs of voting and non-voting firms together in a regression discontinuity design framework. My method has two desirable features compared to the stacking approach. First, the running variable deterministically assigns observations to either the treatment or control group. Second, the effect of proposals far away from the threshold is separated from the effect of proposals close to the threshold. Suppose a firm is associated with two proposals j_1 and j_2 that pass with 5% and 30%, respectively. Further assume that the firm responds to j_2 but not j_1. In this scenario, the estimate obtained via stacking will attribute the (non-causal) effects of proposal j_2 far away from the threshold to proposal j_1 close to the threshold.

mitigate selection biases, I use all firms used in the IV analysis in this first stage regression irrespective of whether or not they (or their peers) vote for proposals. This orthogonalization step is important because it alleviates the concern that social peer effect estimates are picking up industry peer effects.

The most conservative estimates in columns (2) and (4) indicate that firms increase their CSR scores by 20% to 30% of a standard deviation in response to their social peers passing CSR proposals. In comparison, Cao, Liang, and Zhan (2019) find that firms increase their CSR scores by 30% of a standard deviation in response to their industry peers passing CSR proposals. Hence, the economic magnitudes of social and industry peers effects of CSR are comparable.

[Table IA.9 About Here]

A major concern with this approach is the possibility that the results depend on the choice of how proposals are aggregated. To alleviate this concern, I define an alternative aggregation rule (henceforth denoted by *MaxMin* aggregation method to distinguish it from the previous aggregation method). Instead of summing across proposal votes to define the running variable, I define the running variable based on the most extreme outcomes of peer proposal votes. If the firm is in the treatment group, I set the running variable to be equal to the largest voting distance to the threshold across all peer proposals that pass. If a firm is in the control group, I set the running variable to be equal to the lowest voting distance to the threshold across all peer proposals that fail. For instance, if a firm is associated with five proposals that pass by 5%, the running variable takes value 5%. If I would aggregate by summing across proposals the running variable would take the value of 25% instead. Since each individual proposal is close to the threshold, and therefore a valid source of exogenous variation, it is reasonable to argue that the running variable should also take a value close to the threshold. Another advantage of aggregating via the *MaxMin* method is that it increases statistical power by moving observations closer to the threshold.

The results in Panel B of Table IA.9 show the conclusions are robust to using the *MaxMin* method. In Panel C of Table IA.9 I show the results occur through the network of the board of directors and not through the network of executives. This is exactly the pattern observed when using the IV and the diff-in-diff analyses. The fact that the results are robust across such disparate methodologies suggests that social peer effects of CSR are a causal phenomenon.

In Table IA.10 I conduct a series of robustness tests. First, I show the results are robust to using alternative bandwidths. Second, I show that there is no evidence for discontinuity jumps around placebo thresholds. This is reassuring because the existence of discontinuities at placebo thresholds would be a warning sign that the discontinuities at the true threshold could be contaminated by those same omitted factors that cause jumps at the placebo thresholds.

[Table IA.10 About Here]

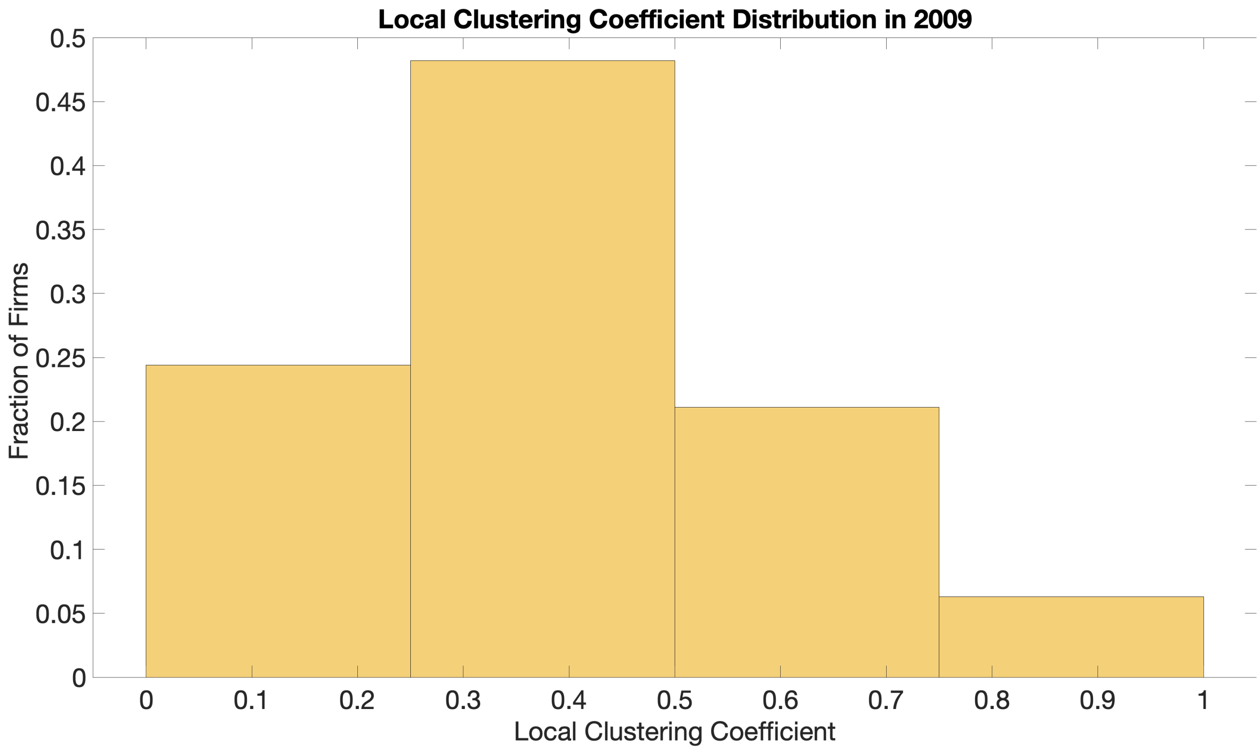

Figure IA.1. Local Clustering Coefficient Distribution.
This figure shows the distribution of the local clustering coefficient of Watts and Strogatz (1998) for the corporate social network in 2009 (the median year in the sample). The local clustering coefficient for a given firm is defined as the number of connections among the social peers of that firm divided by the number of possible connections. It takes value one (zero) if all (none) of a firm's connections are connected to each other.

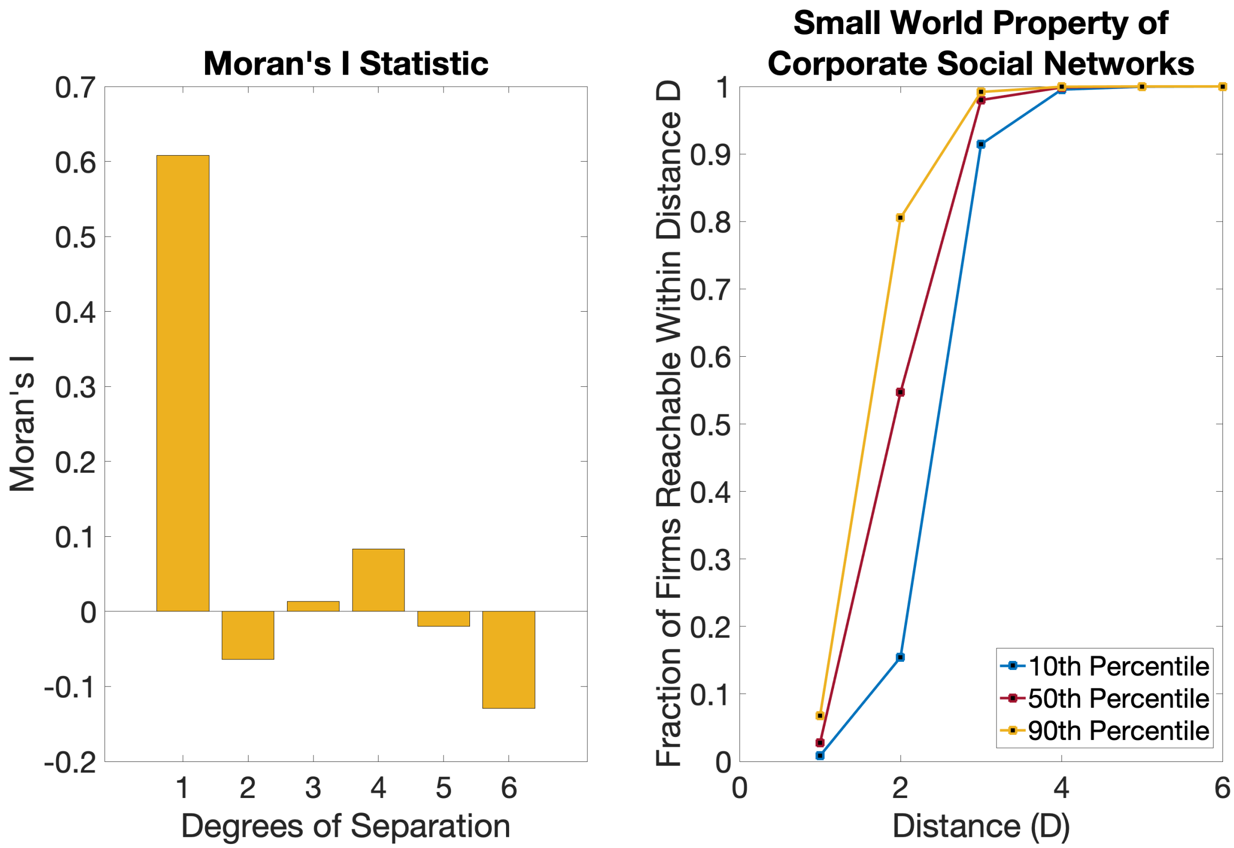

Figure IA.2. Spatial cross-correlation of CSR scores and small world property of corporate social networks.
The histogram on the left shows the spatial cross-correlation (Moran's I statistic) of CSR scores of socially connected firms for various degrees of separation between 2001 and 2016. To control for time trends in CSR scores, Moran's I statistic is first computed separately for each year and then averaged over the time dimension. To remove industry peer effects, I only consider social peers in different one-digit SIC industries. The plot on the right depicts the 10th, 50th and 90th percentiles of the cross-firm distribution of the fraction of firms that are within a given distance of each sample firm in the corporate social network. The fractions are computed separately for each firm-year-distance combination and then aggregated across firms over the period 2001-2016 for each distance.

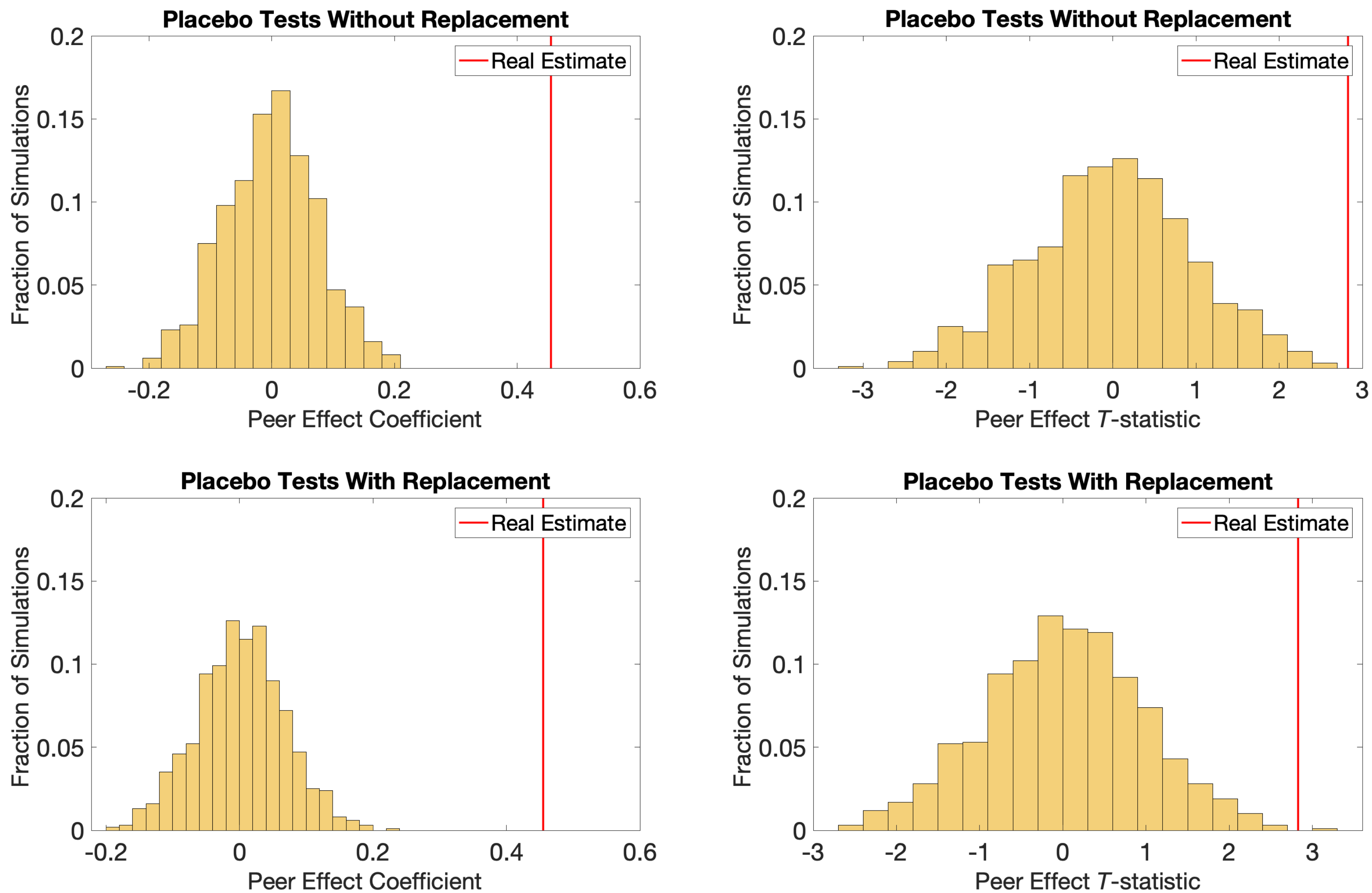

Figure IA.3. Distribution of Placebo CSR Peer Effect Estimates.
These histograms show the distribution of placebo CSR peer effect estimates and associated t-statistics obtained from 1000 runs of model (3) in Table 2. In each run, the social and indirect peer groups of each firm are randomly matched to a firm that is active in that year. The top plots are obtained from simulations with random matching without replacement. The bottom plots are obtained from simulations with random matching with replacement. The red lines indicate the location of the real (non-placebo) estimates.

Table IA.1

Robustness Tests of Baseline Results

This table reports the output of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores under a variety of different specifications. Social peers are defined based on the social networks of executives and directors. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The control variables include all firm-level and peer-level control variables described in Appendix Table A.1. The coefficients are measured in standard deviations. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Alternative Definitions of Peer Groups

	Excludes Firms with < 10 Peers (1)	Excludes Firms with > 250 Peers (2)	Excludes Ind. Peers in Firm's SIC1 Industry (3)	Excludes Ind. Peers in Firm's Headquarters State (4)	Excludes Direct Board Interlocks (5)	Includes S&P 1500 Firms Only (6)	Controls for Hoberg-Philips Peers' CSR score (7)
Peers' CSR	0.712***	0.462***	0.458***	0.383**	0.402**	0.556**	0.444***
	(3.012)	(2.867)	(2.751)	(2.394)	(2.326)	(2.553)	(2.687)
Kleiberg-Paap F-stat	90.072***	65.018***	76.889***	67.829***	52.268***	51.157***	59.609***
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Incorp. State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	23,377	25,567	25,541	25,808	25,668	17,516	23,808

Panel B: Additional Combinations of Fixed Effects and Alternative Specifications

	Headquarters State-by-Year FE (1)	Firm and Year FE (2)	Lagged Instrument (3)	Lagged Inst. and Controls (4)	Twice Lagged Instrument (5)	Twice Lagged Inst. Board Net. (6)	No Controls (7)
Peers' CSR	0.299**	0.151*	0.598**	0.600**	0.581*	0.665**	0.363**
	(2.241)	(1.883)	(2.242)	(2.097)	(1.809)	(1.995)	(2.266)
Kleiberg-Paap F-stat	79.742***	119.705***	31.979***	28.267***	24.289***	23.400***	48.435***
CSA-by-year FE	No	No	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Incorp. State-by-year FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Headquarters State-by-year FE	Yes	No	No	No	No	No	No
Firm and Year FE	No	Yes	No	No	No	No	No
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	No
Lagged Controls	No	No	No	Yes	Yes	Yes	No
Lagged Instrument	No	No	Yes	Yes	Yes	Yes	No
No. Obs.	25,787	25,794	22,958	22,958	20,126	20,020	25,808

Table IA.2

Robustness Tests of Baseline Results: Constraining Sample Period to End in 2013

This table reports the results of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores when restricting the sample period to 2001-2013. Social peers are defined based on the social networks of executives and directors. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Contemporaneous			Lagged		
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' CSR	0.569***	0.606***	0.598***	0.570**	0.623**	0.626**
	(2.588)	(2.598)	(2.871)	(2.049)	(2.053)	(2.293)
Peers' Size	-0.225**	-0.230**	-0.209**	-0.198	-0.213	-0.199*
	(-2.004)	(-2.011)	(-2.391)	(-1.449)	(-1.483)	(-1.843)
Peers' MB Ratio	-0.005	-0.005	-0.005	-0.002	-0.002	-0.003
	(-0.639)	(-0.586)	(-0.620)	(-0.212)	(-0.209)	(-0.354)
Peers' Debt Ratio	0.037**	0.030**	0.025*	0.032*	0.026	0.020
	(2.482)	(2.093)	(1.818)	(1.923)	(1.607)	(1.276)
Peers' ROA	0.010	0.004	0.001	0.027*	0.022*	0.017
	(0.716)	(0.335)	(0.064)	(1.747)	(1.688)	(1.383)
Peers' Net Income	-0.017	-0.034	-0.016	-0.019	-0.039	-0.028
	(-0.354)	(-0.674)	(-0.509)	(-0.351)	(-0.674)	(-0.786)
Peers' Cash Ratio	-0.091	-0.088*	-0.061*	-0.087	-0.089	-0.066
	(-1.619)	(-1.660)	(-1.755)	(-1.262)	(-1.355)	(-1.605)
Peers' Divid. Ratio	-0.036**	-0.033*	-0.036**	-0.031*	-0.025	-0.029*
	(-2.286)	(-1.934)	(-2.406)	(-1.828)	(-1.280)	(-1.714)
Peers' Inst. Own.	0.002	-0.007	-0.010	0.005	-0.006	-0.009
	(0.233)	(-0.765)	(-1.046)	(0.449)	(-0.499)	(-0.868)
Peers' Cust. Awa.			-0.018			-0.020
			(-1.008)			(-0.970)
Peers' R&D			-0.053			-0.046
			(-1.152)			(-0.766)
Kleiberg-Paap F-stat	45.480***	36.167***	43.626***	32.980***	26.032***	32.373***
First Stage Instrument	0.173***	0.167***	0.186***	0.155***	0.146***	0.161***
	(6.740)	(6.010)	(6.600)	(5.740)	(5.100)	(5.690)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	Yes	No	No	Yes
Ex. Industry Peers	No	Yes	Yes	No	Yes	Yes
No. Obs.	21,521	21,521	21,521	18,734	18,734	18,734

Table IA.3

Robustness Tests of Baseline Results: Thomson Reuters CSR Scores

This table reports the output of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of executives and directors. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). *E+S* refers to the aggregate CSR scores which are constructed as the average of the environmental and social sustainability scores. Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The control variables include all firm-level and peer-level control variables described in Appendix Table A.1. The coefficients are measured in standard deviations. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Includes All Firms

	Contemporaneous			Lagged		
	E+S	Environmental (E)	Social (S)	E+S	Environmental (E)	Social (S)
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' CSR	0.319**	0.295*	0.369**	0.321*	0.292	0.350*
	(2.215)	(1.906)	(2.304)	(1.870)	(1.553)	(1.854)
Kleiberg-Paap F-stat	53.616***	46.859***	43.729***	40.847***	34.542***	32.744***
First Stage Instrument	0.205***	0.202***	0.191***	0.193***	0.190***	0.178***
	(7.320)	(6.850)	(6.610)	(6.390)	(5.880)	(5.720)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	8,802	8,802	8,802	7,623	7,623	7,623

Panel B: Excludes Firms With Only One Social Peer

	Contemporaneous			Lagged		
	E+S	Environmental (E)	Social (S)	E+S	Environmental (E)	Social (S)
	(1)	(2)	(3)	(4)	(5)	(6)
Peers' CSR	0.344**	0.326**	0.382**	0.335**	0.315*	0.356**
	(2.547)	(2.206)	(2.526)	(2.125)	(1.806)	(1.999)
Kleiberg-Paap F-stat	61.069***	54.860***	50.590***	49.586***	43.388***	38.422***
First Stage Instrument	0.213***	0.211***	0.197***	0.199***	0.200***	0.179***
	(7.810)	(7.410)	(7.110)	(7.040)	(6.590)	(6.200)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	8,755	8,755	8,755	7,602	7,602	7,602

Table IA.3 (Continuation)

Robustness Tests of Baseline Results: Thomson Reuters CSR Scores

This table reports the output of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of executives and directors. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). *E+S* refers to the aggregate CSR scores which are constructed as the average of the environmental and social sustainability scores. Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The control variables include all firm-level and peer-level control variables described in Appendix Table A.1. The coefficients are measured in standard deviations. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel C: Excludes Firms With Less Than 10 Social Peers or More Than 100 Peers						
	Contemporaneous			Lagged		
	E+S (1)	Environmental (E) (2)	Social (S) (3)	E+S (4)	Environmental (E) (5)	Social (S) (6)
Peers' CSR	0.508***	0.606***	0.433**	0.572***	0.617**	0.483**
	(2.726)	(2.763)	(2.212)	(2.705)	(2.501)	(2.134)
Kleiberg-Paap F-stat	63.383***	50.630***	52.343***	47.681***	41.981***	48.061***
First Stage Instrument	0.198***	0.179***	0.204***	0.178***	0.171***	0.174***
	(7.960)	(7.120)	(7.230)	(6.910)	(6.480)	(5.990)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	6,624	6,624	6,624	5,710	5,710	5,710

Table IA.4

Falsification Tests

This table shows the mean and percentiles of the distribution of placebo peer effects based on 1,000 runs of model (3) in Table 2. In each run, each sample firm-year is randomly matched with another firm's social and indirect peer groups in that year. Results are shown for the cases of random matching with and without replacement. Social peers are defined based on the social networks of executives and directors. The instrument is the average CSR score of indirect placebo peers. A firm's indirect placebo peers are defined as the three-digit SIC industry peers of the social peers of a randomly selected firm subject to the restrictions that the indirect peers and that firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). All regressions include all firm-level and peer-level control variables described in Appendix Table A.1. Each peer-level control variable is computed as a weighted average of that variable across a firm's real (non-placebo) social peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The coefficients are measured in standard deviation units. All regressions include state-of-incorporation-by-year fixed effects, CSA-by-year fixed effects and industry-by-year fixed effects. Standard errors are heteroskedasticity-robust and clustered at the firm-level.

	Without Replacement		With Replacement	
	Coefficient	t-statistic	Coefficient	t-statistic
Percentile 1%	-0.171	-2.187	-0.157	-2.249
Percentile 5%	-0.130	-1.630	-0.108	-1.589
Percentile 10%	-0.101	-1.318	-0.086	-1.255
Percentile 50%	0.001	0.004	0.002	0.023
Percentile 90%	0.096	1.247	0.086	1.207
Percentile 95%	0.128	1.623	0.113	1.640
Percentile 99%	0.177	2.142	0.156	2.201
Mean	-0.001	-0.018	0.002	0.021

Table IA.5

Tests of Endogenous Sorting into Networks

This table reports the output of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores when controlling for endogenous sorting into networks. Social peers are defined based on the social networks of executives and directors. The Louvain algorithm (Blondel et al. (2008)) is used to partition the social network each year into communities of different sizes: small, intermediate and large. Communities are defined as sets of firms that are highly connected among themselves and sparsely connected to firms outside the community. Each size category corresponds to one of the three algorithm recursions needed for convergence. These communities are used to cluster standard errors and define community-by-year fixed effects. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. The Kleiberg-Paap F-stat is the cluster-robust Kleibergen and Paap (2006) F-statistic for weak instruments. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at either the firm-level or double clustered at the firm-level and community-by-year level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Small Network Communities (1)	Intermediate Network Communities (2)	Large Network Communities (3)	Small Network Communities (4)	Intermediate Network Communities (5)	Large Network Communities (6)
Peers' CSR	0.539***	0.469***	0.455***	0.539***	0.469**	0.455**
	(3.078)	(2.871)	(2.827)	(3.009)	(2.594)	(2.557)
Kleiberg-Paap F-stat	63.373***	66.228***	66.855***	55.006***	55.803***	46.294***
First Stage Instrument	0.208***	0.207***	0.209***	0.208***	0.207***	0.209***
	(7.960)	(8.140)	(8.180)	(7.420)	(7.470)	(6.800)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Community-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes
Community Clustered SEs	No	No	No	Yes	Yes	Yes
No. Community-Years	905	62	18	905	62	18
No. Obs.	25,741	25,808	25,808	25,741	25,808	25,808

Table IA.6

Quasi-Experimental Evidence from the Deaths of Directors and Executives

This table reports the output of a difference-in-differences regression measuring the impact of the deaths of directors and executives socially connecting two firms on the comovement of CSR scores of those firms. The dependent variable is a measure of idiosyncratic CSR comovement at the firm-pair-year level. Idiosyncratic CSR scores are computed as the residuals of a regression of firm-level CSR scores on CSA-by-year, three-digit SIC industry-by-year and state-of-incorporation-by-year fixed effects as well as the full set of firm-level and peer-level controls described in Appendix Table A.1. Idiosyncratic CSR comovement for a given firm-pair-year is defined as the absolute value of the difference in idiosyncratic CSR scores for that firm-pair in that year. *Death* is equal to one in the period after the death of the individual and zero before. *Connected* is equal to one if the deceased was socially connecting the firm-pair. The controls in columns (2), (4) and (6) are the pairwise sums and the absolute values of the pairwise differences of all firm-level control variables listed in Appendix Table A.1. All regressions control for firm-pair fixed effects and year fixed effects. All non-categorical variables are standardized. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-pair level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Directors Network		Executives Network		Aggregate Network	
	(1)	(2)	(3)	(4)	(5)	(6)
Death	-0.015***	-0.019***	-0.026*	-0.034**	-0.020***	-0.024***
	(-3.416)	(-4.467)	(-1.773)	(-2.336)	(-4.879)	(-5.852)
Death × Connected	0.027**	0.024**	-0.009	-0.001	0.027**	0.024**
	(2.268)	(2.035)	(-0.182)	(-0.026)	(2.399)	(2.131)
Peers' Size Diff.		0.093***		0.024		0.013***
		(10.519)		(1.266)		(2.701)
Peers' MB Ratio Diff.		0.008***		0.023***		0.017***
		(7.211)		(3.772)		(11.058)
Peers' Debt Ratio Diff.		-0.006*		-0.007		0.003
		(-1.767)		(-0.886)		(1.399)
Peers' ROA Diff.		0.006***		0.022***		0.011***
		(2.681)		(3.091)		(6.128)
Peers' Net Income Diff.		0.005*		0.003		0.007**
		(1.663)		(0.385)		(2.418)
Peers' Cash Ratio Diff.		-0.002		-0.043***		-0.018***
		(-0.498)		(-4.605)		(-6.817)
Peers' Divid. Ratio Diff.		-0.024***		0.004		0.009**
		(-5.134)		(0.273)		(2.516)
Peers' R&D Diff.		0.057**		-0.168**		-0.127***
		(2.405)		(-2.314)		(-5.332)
Peers' Inst. Own. Diff.		-0.012***		0.014***		0.004**
		(-6.872)		(2.607)		(2.416)
Peers' Cust. Awa. Diff.		0.028***		-0.019		-0.015*
		(2.952)		(-0.633)		(-1.841)
R^2	0.450	0.450	0.447	0.448	0.450	0.451
No. Obs.	851,102	851,102	74,049	74,049	865,883	865,883

Table IA.7

Quasi-Experimental Evidence from the Deaths of Directors and Executives: Robustness Tests

This table reports the output of a difference-in-differences regression measuring the impact of the deaths of directors and executives socially connecting two firms on the comovement of CSR scores of those firms. The sample is restricted to firm-pairs not belonging to the same three-digit SIC industry. The dependent variable is a measure of idiosyncratic CSR comovement at the firm-pair-year level. Idiosyncratic CSR scores are computed as the residuals of a regression of firm-level CSR scores on CSA-by-year, three-digit SIC industry-by-year and state-of-incorporation-by-year fixed effects as well as the full set of firm-level and peer-level controls described in Appendix Table A.1. Idiosyncratic CSR comovement for a given firm-pair-year is defined as the absolute value of the difference in idiosyncratic CSR scores for that firm-pair in that year. *Death* is equal to one in the period after the death of the individual and zero before. In the binary treatment, *Connected* is equal to one if the deceased was socially connecting the firm-pair. In the continuous treatment, *Connected* is the number of deceased individuals socially connecting the firm-pair. The controls in columns (1) through (6) are the pairwise sums and the absolute values of the pairwise differences of all firm-level control variables listed in Appendix Table A.1. All regressions control for firm-pair fixed effects and year fixed effects. All non-categorical variables are standardized. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-pair level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Directors Network		Executives Network		Aggregate Network	
	Binary Treatment (1)	Continuous Treatment (2)	Binary Treatment (3)	Continuous Treatment (4)	Binary Treatment (5)	Continuous Treatment (6)
Death	-0.015***	-0.015***	-0.042***	-0.043***	-0.021***	-0.021***
	(-3.456)	(-3.496)	(-2.807)	(-2.821)	(-4.957)	(-4.967)
Death × Connected	0.025**	0.024**	0.005	0.008	0.024**	0.022**
	(2.015)	(2.237)	(0.100)	(0.162)	(2.063)	(2.150)
Peers' Size Diff.	0.092***	0.092***	0.023	0.023	0.013***	0.013***
	(10.157)	(10.149)	(1.144)	(1.143)	(2.643)	(2.643)
Peers' MB Ratio Diff.	0.008***	0.008***	0.022***	0.022***	0.017***	0.017***
	(6.894)	(6.894)	(3.451)	(3.450)	(10.463)	(10.463)
Peers' Debt Ratio Diff.	-0.005	-0.005	-0.010	-0.010	0.003	0.003
	(-1.411)	(-1.405)	(-1.184)	(-1.184)	(1.176)	(1.171)
Peers' ROA Diff.	0.007***	0.007***	0.025***	0.025***	0.012***	0.012***
	(2.995)	(2.996)	(3.341)	(3.340)	(6.511)	(6.510)
Peers' Net Income Diff.	0.004	0.004	0.002	0.002	0.006**	0.006**
	(1.282)	(1.280)	(0.247)	(0.247)	(2.061)	(2.059)
Peers' Cash Ratio Diff.	-0.002	-0.002	-0.041***	-0.041***	-0.018***	-0.018***
	(-0.364)	(-0.367)	(-4.179)	(-4.180)	(-6.586)	(-6.585)
Peers' Divid. Ratio Diff.	-0.025***	-0.025***	0.003	0.003	0.010***	0.010***
	(-5.310)	(-5.320)	(0.213)	(0.215)	(2.782)	(2.789)
Peers' R&D Diff.	0.061**	0.061**	-0.162**	-0.162**	-0.137***	-0.137***
	(2.411)	(2.408)	(-1.986)	(-1.987)	(-5.363)	(-5.362)
Peers' Inst. Own. Diff.	-0.012***	-0.012***	0.012**	0.012**	0.004**	0.004**
	(-6.703)	(-6.706)	(2.166)	(2.166)	(2.262)	(2.260)
Peers' Cust. Awa. Diff.	0.026***	0.026***	-0.009	-0.009	-0.015*	-0.015*
	(2.738)	(2.739)	(-0.285)	(-0.285)	(-1.777)	(-1.779)
R^2	0.451	0.451	0.451	0.451	0.452	0.452
No. Obs.	819,908	819,908	69,362	69,362	834,005	834,005

Table IA.8

Regression Discontinuity Design Test of Pre-Treatment Differences in Treatment and Control Groups

This table tests the validity of the regression discontinuity design by comparing whether or not treated and control firms are fundamentally different in terms of several attributes. The attributes are measured in the year prior to the vote date. The composition of treatment and control groups is defined in terms of different bandwidths around the voting threshold: 1%, 2.5%, 5% and 10%. The table reports the difference in means between treatment and control groups for each attribute as well as the t-statistic associated with the test of the null hypothesis that the difference in means is zero. To account for multiple hypothesis testing, the table further reports the number of attributes for which the null hypothesis is rejected using the Benjamini and Hochberg (1995) Procedure. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Bandwidth Around Threshold							
	1%		2.5%		5%		10%	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Firm Attributes								
Size	-0.028	-0.054	-0.508	-1.158	-0.733	-3.245	-0.968	-7.106
MB Ratio	-0.508	-0.661	-0.348	-0.607	-0.293	-1.017	-0.093	-0.579
Debt	-0.512	-0.929	-0.194	-0.445	0.210	0.917	-0.061	-0.485
ROA	-0.294	-0.747	-0.353	-0.851	-0.556	-2.501	-0.314	-2.748
Income	-0.447	-0.712	-0.515	-0.903	-0.466	-1.623	-0.685	-3.436
Cash	-0.148	-0.408	0.401	1.264	-0.088	-0.504	-0.033	-0.358
Dividend	-0.771	-1.031	-0.747	-1.434	-0.382	-1.430	-0.228	-1.518
R&D	-0.314	-0.437	-0.401	-0.624	-0.372	-1.119	-0.578	-2.510
Inst. Own.	0.210	0.400	0.376	0.901	0.465	2.066	0.223	1.707
Cust. Awa.	-0.378	-0.591	-0.088	-0.183	0.044	0.179	-0.060	-0.456
No. Obs.	142		350		443		705	
Benjamini-Hochberg Procedure								
No. rejections assuming:								
False Discovery Rate = 10%	0		0		2		4	
False Discovery Rate = 5%	0		0		1		4	

Table IA.9

Quasi-Experimental Evidence from Close-call CSR Proposals

This table reports the output of regression discontinuity design regressions measuring the response of firms' CSR decisions to the passage of close-call CSR shareholder proposals by their social peers in the previous year. The estimation is done using nonparametric local linear regression and the Imbens and Kalyanaraman (2012) optimal bandwidth selection method. *Industry-Year Adj.* indicates that only variation in CSR scores that is orthogonal to industry-by-year fixed effects is used. These orthogonalized CSR scores are obtained as the residuals of an ordinary least squares regression of CSR scores on three-digit SIC industry-by-year fixed effects. The control variables include all firm-level control variables described in Appendix Table A.1. The regression coefficients are measured in standard deviation units. t-statistics are reported in parentheses. Standard errors are clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Baseline Results

	(1)	(2)	(3)	(4)
Triangular Kernel	0.743***	0.208**	0.826***	0.314***
	(6.521)	(2.129)	(11.785)	(6.099)
Rectangular Kernel	0.815***	0.305***	0.807***	0.306***
	(6.806)	(2.928)	(11.887)	(5.922)
Industry-Year Adj.	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	Optimal Bandwidth			

Panel B: *MaxMin* Aggregation Method

	(1)	(2)	(3)	(4)
Triangular Kernel	0.741***	0.254***	0.883***	0.293***
	(7.381)	(3.136)	(8.588)	(3.770)
Rectangular Kernel	0.775***	0.261***	0.923***	0.325***
	(7.655)	(3.064)	(8.591)	(3.762)
Industry-Year Adj.	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	Optimal Bandwidth			

Panel C: Directors versus Executives Networks

	Directors Network		Executives Network	
	(1)	(2)	(3)	(4)
Triangular Kernel	0.257***	0.274***	0.042	0.217
	(3.257)	(3.445)	(0.273)	(1.620)
Rectangular Kernel	0.290***	0.324***	0.048	0.218*
	(3.451)	(3.748)	(0.294)	(1.671)
Industry-Year Adj.	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Bandwidth	Optimal Bandwidth			

Table IA.10

Quasi-Experimental Evidence from Close-call CSR Proposals: Robustness Tests

This table reports the output of regression discontinuity design regressions measuring the response of firms' CSR decisions to the passage of close-call CSR shareholder proposals by their social peers in the previous year. The estimation is done using nonparametric local linear regression and the Imbens and Kalyanaraman (2012) optimal bandwidth selection method. Proposals are aggregated using the *MaxMin* method. *Industry-Year Adj.* indicates that only variation in CSR scores that is orthogonal to industry-by-year fixed effects is used. These orthogonalized CSR scores are obtained as the residuals of an ordinary least squares regression of CSR scores on three-digit SIC industry-by-year fixed effects. The control variables include all firm-level control variables described in Appendix Table A.1. The regression coefficients are measured in standard deviation units. *t*-statistics are reported in parentheses. Standard errors are clustered at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Smaller Bandwidths

	(1)	(2)	(3)	(4)
Triangular Kernel	0.704***	0.223**	0.830***	0.218**
	(6.083)	(2.312)	(6.792)	(2.295)
Rectangular Kernel	0.681***	0.235**	0.835***	0.278**
	(5.214)	(2.117)	(6.083)	(2.536)
Industry-Year Adj.	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	80% of Optimal Bandwidth			

Panel B: Larger Bandwidths

	(1)	(2)	(3)	(4)
Triangular Kernel	0.806***	0.328***	1.090***	0.411***
	(9.674)	(5.199)	(13.238)	(6.858)
Rectangular Kernel	0.760***	0.268***	0.971***	0.408***
	(8.151)	(3.542)	(10.349)	(5.634)
Industry-Year Adj.	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	120% of Optimal Bandwidth			

Panel C: Placebo Discontinuity Tests

	(1)	(2)	(3)	(4)
Triangular Kernel	0.025	0.231	0.474	-0.061
	(0.342)	(1.215)	(1.143)	(-0.256)
Rectangular Kernel	0.026	0.207	0.012	-0.061
	(0.361)	(1.128)	(0.070)	(-0.256)
Industry-Year Adj.	No	No	No	No
Controls	No	No	No	No
Placebo Threshold	-20%	-10%	10%	20%
Bandwidth	Optimal Bandwidth			

Table IA.11

Why Do Firms Mimic? The Role of Institutional Ownership

This table reports the output of two-stage least squares (2SLS) regressions of firm CSR scores on social peers' CSR scores. Social peers are defined based on the social networks of directors. The magnitude of peer effects is allowed to vary as a function of one of the following measures of institutional ownership concentration: institutional ownership Herfindahl-Hirschman (HHI) index, ownership by the five largest institutional shareholders and institutional ownership by blockholders. D_{High}, D_{Med} and D_{Low} are binary indicators equal to one if the associated variable in a given firm-year belongs to the third, second and first tercile of the within-year distribution of that variable, respectively. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. *P(H = L)* is the p-value obtained from testing the hypothesis that peer effects are equal across firms in the highest and lowest terciles. The Sanderson-Windmeijer F-stat refers to the Sanderson and Windmeijer (2016) weak instrument F-test for models with multiple endogenous variables. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Levels			First Differences		
	Inst. Own. HHI Index (1)	Inst. Own. Largest 5 (2)	Inst. Own. Blockholders (3)	Inst. Own. HHI Index (4)	Inst. Own. Largest 5 (5)	Inst. Own. Blockholders (6)
Peer's CSR × D_{Low}	0.564***	0.525***	0.483***	0.314***	0.260***	0.256**
	(3.980)	(3.514)	(3.232)	(3.360)	(2.671)	(2.409)
Peer's CSR × D_{Med}	0.475***	0.471***	0.455***	0.182*	0.177*	0.218**
	(3.227)	(3.181)	(3.047)	(1.844)	(1.790)	(2.020)
Peer's CSR × D_{High}	0.361**	0.416***	0.393**	0.033	0.063	0.082
	(2.364)	(2.719)	(2.543)	(0.322)	(0.609)	(0.722)
P(H=L)	0.000	0.001	0.004	0.000	0.000	0.000
Sanderson-Windmeijer F-Stat						
Ind. Peer's CSR × D_{Low}	83.510***	78.830***	81.080***	99.000***	97.540***	94.620***
Ind. Peer's CSR × D_{Med}	79.420***	83.780***	86.070***	91.200***	98.310***	90.530***
Ind. Peer's CSR × D_{High}	77.120***	84.870***	85.420***	90.070***	96.320***	93.730***
First Stage Instrument						
Ind. Peer's CSR × D_{Low}	0.597***	0.515***	0.525***	0.620***	0.553***	0.579***
	(24.240)	(18.320)	(19.210)	(36.300)	(27.180)	(27.770)
Ind. Peer's CSR × D_{Med}	0.588***	0.567***	0.548***	0.548***	0.578***	0.578***
	(29.790)	(24.830)	(22.550)	(28.000)	(30.160)	(29.840)
Ind. Peer's CSR × D_{High}	0.422***	0.522***	0.535***	0.451***	0.489***	0.482***
	(15.270)	(22.040)	(21.910)	(20.360)	(25.190)	(24.210)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	25,664	25,661	23,489	22,833	22,827	20,175

Table IA.12

Social Norms Channel: Robustness Tests

This table reports the output of two-stage least squares (2SLS) regressions of changes in firm CSR scores on the changes in social peers' CSR scores. Social peers are defined based on the social networks of directors. The magnitude of peer effects is allowed to vary as a function of each firm's own geographic social capital. Own geographic social capital is proxied by of one of the following variables: organ donation density, voter turnout, registered organization density, association density or the principal component of the previous three variables. D_{High}, D_{Med} and D_{Low} are binary indicators equal to unity if the associated variable in a given firm-year belongs to the third, second and first tercile of the within-year distribution of that variable, respectively. The instrument is the average CSR score of indirect peers. A firm's indirect peers are defined as the three-digit SIC industry peers of the social peers of that firm subject to the restrictions that the indirect peers and the firm: (i) operate in different industries; (ii) are not social peers; (iii) are headquartered in different combined statistical areas (CSA). Every control variable is first differenced and included in all regressions at both the firm-level and the peer-level. Each peer-level variable is computed as a weighted average of that variable across a firm's peers, excluding the firm itself. The weights are the normalized strengths of social connections between the firm and each of its social peers. The additional controls are customer awareness and R&D investment. The coefficients are measured in standard deviation units. $P(H = L)$ is the p-value obtained from testing the hypothesis that peer effects are equal across firms in the highest and lowest terciles. The Sanderson-Windmeijer F-stat refers to the Sanderson and Windmeijer (2016) weak instrument F-test for models with multiple endogenous variables. t-statistics are reported in parentheses. Standard errors are heteroskedasticity-robust and clustered at the firm-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Own Geographic Social Capital				
	Organ Don. (1)	Voter Turnout (2)	Reg. Density (3)	Org. Density (4)	PC Index (5)
Δ Peer's CSR × D_{Low}	0.204*	0.225**	0.184*	0.163	0.183*
	(1.938)	(2.173)	(1.865)	(1.585)	(1.783)
Δ Peer's CSR × D_{Med}	0.237**	0.171*	0.094	0.198*	0.142
	(2.290)	(1.709)	(0.888)	(1.940)	(1.344)
Δ Peer's CSR × D_{High}	0.093	0.135	0.261**	0.204*	0.221**
	(0.800)	(1.216)	(2.528)	(1.885)	(2.060)
P(H = L)	0.177	0.235	0.130	0.554	0.594
Sanderson-Windmeijer F-Stat					
Δ Ind. Peer's CSR × D_{Low}	112.880***	104.270***	96.640***	98.060***	103.100***
Δ Ind. Peer's CSR × D_{Med}	112.300***	110.510***	107.970***	103.150***	98.660***
Δ Ind. Peer's CSR × D_{High}	88.800***	99.850***	106.780***	113.710***	106.230***
First Stage Instrument					
Δ Ind. Peer's CSR × D_{Low}	0.516***	0.539***	0.548***	0.540***	0.517***
	(17.940)	(19.890)	(22.970)	(20.160)	(18.500)
Δ Ind. Peer's CSR × D_{Med}	0.476***	0.554***	0.510***	0.553***	0.489***
	(15.590)	(23.770)	(20.090)	(24.820)	(18.490)
Δ Ind. Peer's CSR × D_{High}	0.394***	0.421***	0.543***	0.483***	0.523***
	(12.330)	(16.800)	(25.300)	(20.110)	(24.620)
CSA-by-year FE	Yes	Yes	Yes	Yes	Yes
Industry-by-year FE	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes
Peer-Level Controls	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
Ex. Industry Peers	Yes	Yes	Yes	Yes	Yes
No. Obs.	22,653	22,653	22,653	22,653	22,653