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Can Ratings Have Indirect Effects? Evidence from the Organizational Response to Peers' Environmental Ratings

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Abstract

Organizations are increasingly subject to rating and ranking by third-party evaluators. Research in this area tends to emphasize the direct effects of ratings systems that occur when ratings give key audiences, such as consumers or investors, more information about a rated firm. Yet, ratings systems may also indirectly influence organizations when the collective presence of more rated peers alters the broader institutional and competitive milieu. Rated firms may be more responsive to ratings systems when surrounded by more rated peers, and ratings may generate diffuse or spillover effects even among unrated firms. We test these arguments by analyzing how rated and unrated firms change their pollution behavior when more firms in their peer group are rated on environmental performance. Results indicate that the presence of more rated peers is often associated with emissions reductions. This relationship varies, however, by whether a firm was rated, whether the rating was positive or negative (if rated), and, often, features of the competitive and regulatory environment.

Keywords

ratings, peers, environment, institutional theory, corporate social responsibility

Organizations are increasingly rated, ranked, certified, and otherwise subject to publicized forms of external evaluation (Fombrun 2007). The growth of systems whereby third parties publicly evaluate and compare organizations is a relatively recent phenomenon, intensifying within the past two decades (Bartley 2007; Power 1997; Strathern 2000). Even in a short timeframe, evidence of the profound impact of ratings systems has accumulated across empirical contexts such as restaurants (Jin and Leslie 2003; Luca 2011), universities (Espeland and Sauder 2007; Sauder and Espeland 2009), and public firms (Chatterji and Toffel 2010).

By offering information to the public, third-party systems of evaluation can influence investors and consumers to shift from firms that receive lower ratings toward firms evaluated more favorably (Luca 2011; Pope 2009; Sorensen 2007). Thus, researchers primarily explain the organizational response to external ratings and rankings by citing the potential negative consequences of receiving an unfavorable evaluation. Espeland and Sauder's work (Espeland and Sauder 2007; Sauder 2008; Sauder and Espeland 2009) on

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changes that occurred among law schools due to the *U.S. News and World Report* rankings provides a rich account of how this can occur. Drawing on interviews with law school administrators, employers, and alumni, Sauder and Espeland (2009) show that law schools initially decried the *U.S. News* rankings. However, external audiences, such as prospective students and employers, valued the rankings as a tool for comparing the quality of legal education. Rather than risking the loss of support from important external constituencies, law schools turned toward activities that would boost their standing in *U.S. News* even though the benefits to students were less clear. Sauder and Espeland (2009) conclude that systems of external evaluation can mediate the relationship between organizations and relevant audiences, resulting in effects felt at the organizational and field levels.

In this article, we study environmental performance ratings of public firms to examine another way ratings systems may influence organizations. Rather than focusing exclusively on how ratings directly affect rated firms, we highlight indirect effects that may occur among both rated and unrated firms when they are surrounded by rated peers. To theorize how the effects of ratings systems might operate through peers, we draw on Anand and Peterson's (2000) conceptualization of ratings systems as instances of "market information regimes." According to Anand and Peterson (2000:272), market information regimes "provide a focus of attention around which groups of organizations consolidate" and serve as "the medium through which producers observe each other and market participants make sense of their world." Thus, we argue that the mere presence of a widely accepted ratings system may alter the institutional and competitive milieu for both rated and unrated firms by drawing attention to certain issues and enhancing their legitimacy as domains upon which organizations may be evaluated. By doing so, ratings systems can set the stage for indirect effects that may occur through processes normally implicated in diffusion, such as competition, coercion, mimesis, or inter-organizational learning.

The role of peers in conditioning how firms respond to ratings systems has received little examination thus far. Moreover, studies have not yet analyzed how ratings might affect unrated firms. This relative inattention to the indirect effects of organizational ratings is surprising, given that the diffusion of behaviors across peers is commonplace in other aspects of organizational life. We address this gap in the literature by theorizing about and testing for changes in firm behaviors that occur as a result of variation in the extent to which a firm's peer group consists of rated firms, with a particular focus on whether there is evidence of diffuse effects on unrated firms.

This study makes several key contributions. Building on work that shows ratings systems can prompt organizational changes, we offer a more nuanced understanding of why and when this is likely to be the case. First, we demonstrate that in certain settings peers comprise a key channel through which the influence of ratings flows. Second, by testing whether unrated organizations respond to the presence of rated peers, we speak to the potential for ratings systems to drive field-wide change when only some firms are formally subject to evaluation. This is important because many ratings systems are not comprehensive in their coverage, and there is little evidence on the reactions of unrated firms. Finally, we provide evidence indicating that the effects of rated peers depend on local regulatory and competitive conditions.

EMPIRICAL SETTING

To test our arguments, we study environmental ratings of public firms in the United States, analyzing how a firm's emission of toxic pollutants is associated with the firm's own rating status (i.e., a positive or negative rating, relative to being unrated) as well as the percent of a firm's peers that are rated. We focus on the environmental ratings issued by KLD Research and Analytics, Inc., a pioneer in socially responsible investing and ratings on corporate social responsibility. Two key considerations drove our choice of this setting.

First, developing a better understanding of the factors that lead firms to reduce their pollution is substantively important given that corporations have a large impact on the environment. Second, because our arguments about the indirect effects of ratings systems are predicated on ratings systems having direct effects whereby rated firms respond to being evaluated, we sought a setting where prior research had shown such an association. We now summarize that research, and, relatedly, briefly discuss how firms can reduce their emissions.

Our contention that firms reduce their emissions as a result of the KLD ratings is based primarily on the findings of Chatterji and Toffel (2010), who studied the expansion of the KLD ratings and found that newly rated firms that received a poor evaluation tended to reduce their emissions more than either their unrated peers or firms that received a more favorable evaluation. They argued that this pattern emerged because information about a firm's environmental performance might influence investors, consumers, and employees, thereby prompting organizations to improve. In the case of the KLD environmental ratings, the primary audience has been socially responsible investors who incorporate information about a firm's performance in domains such as the environment or diversity into their investment decisions. In addition, ratings might influence consumers (Sen and Bhattacharya 2001), employees (Ramus and Killmer 2007; Savitz and Weber 2007), and even investors who are not interested in a firm's environmental performance per se, but who might interpret poor environmental ratings as indicative of increased liabilities (e.g., potential environmental clean-ups), excess costs (e.g., out-of-date technologies that are more costly and less "green"), or the risk of reputational damage from regulatory action or community protest (Delmas 2002; Delmas and Toffel 2008; Stephan 2002; Vasi and King 2012).

For the KLD ratings to have served as a catalyst for pollution reduction in the short-term, firms must have been able to quickly take action to curb emissions. Because this is a core assumption for our project, we provide an overview of common steps firms can take to quickly reduce emissions. The main industries that generate toxic emissions listed in the U.S. Environmental Protection Agency's (EPA) Toxic Releases Inventory (TRI) include metal mining; electric utilities; primary metals; chemical manufacturing, processing, or importing; paper; hazardous waste and solvent recovery; and food. Across industries, TRI recommends the following approaches to reducing emissions, listed in order from most to least preferable: source reduction, recycling, energy recovery, treatment, disposal, or other releases (TRI 2013a). Some improvements are costly and dependent on available technology (e.g., finding an alternative to or cleaner way of burning fuel), but many can be implemented quickly, result in immediate emissions reductions, and are relatively low-cost or even produce savings. For instance, firms can cut back on raw materials wasted during production, reuse chemicals, or prevent spills and leaks. Table 1 lists several examples of activities firms have undertaken in the near-term to reduce emissions.

DIFFUSION PROCESSES AND RATINGS

Taking these facts about the empirical setting as a starting point, we now turn to theorize the indirect effects of ratings. Following a brief overview of diffusion research, we discuss how the presence of rated peers might influence rated firms and spark diffuse effects among unrated ones. In this article, we use the term "indirect effects" to refer broadly to changes in firm behaviors among either rated or unrated firms due to the presence of rated peers. We use the terms "diffuse effects" and "spillovers" interchangeably to denote changes in the behaviors of unrated firms that occur when more rated peers are present.

Diffusion processes are central in organizational life, as evidenced by a large body of research on phenomena such as the spread of organizational forms (Fligstein 1985; Palmer, Jennings, and Zhou 1993), governance structures (Davis and Greve 1997; Shipilov, Greve,

Table 1. Emission Reduction Examples

Operating Improvements	• A bolt nut, screw, rivet, and washer manufacturer reported regular equipment inspection and preventative maintenance, process solution analysis, solution change-overs based on actual usage and depletion (instead of time intervals), and employee training. • An organic chemical manufacturer implemented a program to review all production recipes with the intention of decreasing all production "cooking" time to maximize production and efficiency. Through this review the company reduced holding and feeding times of their production processes. • A computer/electronic products firm reduced lead emissions by changing the frequency of solder plating bath replacement from once every 18 months to once every 24 months. • An electrical equipment firm reduced copper emissions by lowering the margin of error in cutting copper wire from 10 percent to 7 percent.
Process Modifications	• A plastics materials and resin manufacturing facility has implemented an in-line toluene recovery system to reuse recovered toluene as a raw material in their processes rather than generating waste. • A metals manufacturer eliminated the use of toluene by replacing it with a water-based cleaning solution. • A paper mill has incorporated a retubed boiler to increase efficiency during production.
Spill and Leak Prevention	• A merchant wholesaler of chemical and allied products added simple spill and leak prevention techniques into their process by using dedicated process-specific equipment to minimize the need for replacements or cleanings of transfer hoses. The facility also modified their filling equipment with auto shut-off and drip cups to eliminate loss during the filling process. • A chemicals firm implemented a "zero leak" policy, where shift supervisors make rounds every four hours to look for leaks or releases.

Source: Adapted from TRI reports (2013b) available at: http://www2.epa.gov/toxics-release-inventory-tri-program/pollution-prevention-p2-and-tri and http://www2.epa.gov/sites/production/files/documents/2011_tri_na_overview_management_of_chems.pdf.

and Rowley 2010), positioning and entry into new markets (Greve 1996; Haveman 1993), stock exchange membership (Rao, Davis, and Ward 2000), levels of environmental disclosure (Cho and Patten 2007), shareholder activism (Reid and Toffel 2009), grievance procedures (Sutton et al. 1994), corporate compliance offices (Edelman 1992), and management standards (Delmas and Toffel 2008; King and Lenox 2001) (for a review, see Strang and Soule 1998). Prior work posits a variety of mechanisms undergirding diffusion, including competition, learning, and institutional processes of social construction (Dobbin, Simmons, and Garrett 2007). Although these mechanisms represent distinct processes whereby behaviors spread, multiple influences may operate simultaneously (DiMaggio and Powell 1983; Mizruchi and Fein 1999). Are these mechanisms more likely to occur in the presence of ratings and more rated peers?

First, classical work on the role of competition in promoting diffusion, such as Burt's (1987) study of the adoption of the drug tetracycline among doctors who were structurally equivalent, shows that individuals occupying similar network positions tend to observe and imitate their peers' behaviors to maintain their standing relative to one another. To the extent that ratings formalize and publicize a firm's position relative to its peers on some dimension about which evaluating audiences care, we propose that ratings may generate competition in new areas. This is especially likely to be the case when a firm is surrounded by more peers who are rated, for two reasons. Foremost, rated peers make ratings more salient. In addition, when more firms are rated, evaluating audiences such as consumers and investors likely have more options to choose from if they want to avoid a poorly rated firm. This intensifies the pressure to avoid a poor rating.

Second, ratings systems may spark enhanced inter-organizational learning, another key mechanism through which spillovers have been posited to occur (e.g., Haunschild and Miner 1997; Levinthal and March 1993; March and Simon 1958). This may happen in at least two ways. Ratings systems may provide a greater impetus for firms to engage in learning, as laggard firms seek to emulate successful peers. In addition, ratings may indirectly facilitate inter-organizational learning, as the ratings clearly identify a set of high-performing firms whom others may seek out to understand best practices. These processes should be activated to the extent a firm's peer group includes more rated peers, providing more opportunities for learning.

Third, although many accounts of why firms respond to ratings emphasize instrumental motives, such as those implicit in competition, firms may also react to ratings for institutional reasons related to shared norms. Classically, DiMaggio and Powell (1983) outlined coercive, mimetic, and normative mechanisms driving similarities among firms. Coercive isomorphism includes firms' desire to please third parties on whom they depend for resources, as well as more subtle pressures, such as firmly entrenched expectations regarding appropriate behaviors. By drawing attention to certain issues, such as the environment, third-party ratings systems contribute to their legitimacy and relevancy, thereby helping to shape norms and set standards of suitable behaviors: they define "what counts" (Espeland and Stevens 1998). In addition, as firms individually change their behaviors, new ways of doing things may become institutionalized, effectively altering local norms (Tolbert and Zucker 1983). Mimetic isomorphism operates as firms look to one another in determining the appropriate response under conditions of uncertainty; firms use others' behaviors as a form of social proof (Briscoe and Safford 2008; Rao, Greve, and Davis 2001). Normative isomorphism occurs as groups of experts develop and disseminate recommended courses of action through professional channels (DiMaggio and Powell 1983). To the extent that more firms are grappling with being rated, these institutional processes of diffusion may be more likely to emerge among peers, either informally through discussion and mimesis or more formally through industry associations and the like.

In the realm of environmental practices, a limited number of studies provide qualitative evidence of how institutional forms of diffusion operate among firms. For example, Kollman and Prakash (2002) examine why firms in the United Kingdom, Germany, and the United States seek third-party certification of their environmental management systems (e.g., ISO 14001). They found that the decision to pursue certification is influenced by members of the organizational field, most notably industry associations and regional chambers of commerce. Studying why firms "go green," Bansal and Roth (2000) found that mimicry is especially common. The authors conclude that a "dominant approach of these firms was to imitate their peers. As firms operating in close proximity were usually subject to the same regulations and social norms, they often operated with similar standards in a socially cohesive environment" (p. 728).

Overall, ratings systems may activate traditional diffusion processes in several ways. As a result, rated firms should be more likely to alter their behaviors to align with a ratings system when their peer group consists of more rated firms. Thus, we predict the following:

> *Hypothesis 1:* The greater the percent of a rated firm's peer group that is rated, the more a firm will reduce its emissions.

DIFFUSE EFFECTS ON UNRATED FIRMS

In many fields, only a subset of organizations are rated. Whether ratings systems influence unrated firms has yet to be thoroughly examined. From one perspective, the idea that the indirect effects we proposed earlier among rated firms might also occur among unrated firms may seem surprising. After all, rated firms are typically described as responding to ratings primarily to avoid the negative consequences of a poor rating or to obtain the benefits of a good rating; instrumental motives seem key. Because unrated firms do not receive a public evaluation, they would seem to lack direct incentives for altering their behavior. By this logic, the presence of a ratings system and rated peers would probably not influence unrated firms.

However, not all of the diffusion-related processes outlined earlier are predicated on instrumental motives or direct incentives specific to rated firms. For example, unrated firms may belong to the same professional associations as their rated peers and share other venues of socialization that reinforce norms of appropriateness. Exposure in such forums may set the stage for firms to emulate similar others, regardless of whether they themselves are rated (Jonsson, Greve, and Fujiwara-Greve 2009; Strang and Meyer 1993). Likewise, unrated firms that are for whatever reason interested in improving their environmental performance can better identify best practices when ratings pinpoint exemplar firms.[1]

Finally, unrated firms might reduce their emissions in response to the presence of rated peers for anticipatory or preemptive reasons. If managers believe their firms will be rated eventually—an expectation that may be especially strong if many of their peers are already rated—they may take immediate steps to reduce their emissions. Preemptive changes in firm behavior have arisen in other domains. For example, Kochan, Katz, and McKersie (1994:30) argue that favorable workplace practices spread from unionized to non-unionized workplaces partly because "the threat of unionization limited managers' discretion and induced them to provide wages and other benefits so as to deflect demands for unionization." In a related vein, Shimshack and Ward (2005) show how fining a few firms for water pollution led to a disproportionate reduction in pollution statewide, because it enhanced the regulator's reputation for stringency. They conclude, parallel to our arguments, that focusing only on the behavioral changes of penalized firms overlooks the power of generalized deterrence, possibly understating the efficacy of sanctioning. Overall, although unrated firms do not experience all of the pressures that lead rated firms to change, several channels remain by which diffuse effects, or spillovers, might occur among unrated firms surrounded by other rated peers. Thus, we predict the following:

> *Hypothesis 2:* The greater the percent of an unrated firm's peer group that is rated, the more the firm will reduce its emissions.

Variation across Regulatory and Competitive Environments

Although we predict that the presence of more rated peers will generally be associated with a reduction in emissions, the impact of peers likely varies across different settings. Contexts differ in terms of how much relevant audiences care about the issues on which firms are being rated, as well as how capable audiences are of sanctioning firms for a poor rating. These factors may lead to differences in the extent to which firms respond to their rated peers. For example, in settings where relevant stakeholders, such as employees, regulators, investors, or customers, care a great deal about what ratings measure and have the power to penalize firms that receive a poor rating, the impact of rated peers might be substantial. In contrast, where relevant audiences are powerless or are uninterested in what the ratings measure, firms may have less cause to emulate their rated peers. These issues have not been addressed by prior work, which focuses primarily on demonstrating the overall effects of a given ratings system rather than highlighting variation.

In our analyses, we explore how firms' responses vary across settings, focusing in particular on business environments that differ on two key dimensions: regulation and competition. We discuss each in turn. First, laws are a well-known catalyst of diffusion, in part because the meaning of legal compliance can be ambiguous, leading firms to imitate each other (Edelman, Uggen, and Erlanger 1999; Sutton and Dobbin 1996). Regulation can also provide a basis for inter-firm cooperation, as Arrighetti, Bachmann, and Deakin (1997) demonstrate in a study of how the regulatory environment influenced inter-firm relationships in Germany, Britain, and Italy. Regulation and ratings may interact such that peers are especially influential in highly regulated environments. At the same time, however, third-party ratings are sometimes discussed as a possible substitute for government regulation. If this is the case, rated peers might be more influential in less regulated settings, where there is likely more room for improvement.

Parallel arguments seem plausible for contexts that vary in terms of how competitive they are, and hence how much customers or investors are able to penalize firms with a poor rating. On the one hand, rated peers may matter more in more competitive settings, where consumers likely have many alternatives and can easily switch away from firms that receive a negative rating and where diffusion processes among firms tend to be stronger (Bothner 2003). On the other hand, in less competitive settings, firms may have more slack resources to devote to improvements that lead to better ratings on social issues, such as the one studied here. As a result, the response to rated peers may be greater in those settings. Given the unclear theoretical predictions as to where rated peers will be most influential, as well as our lack of a research setting where we can cleanly parse apart the causal effects of ratings, peers, and context (i.e., through random assignment), we do not hypothesize about this question. Instead, we report the observed associations in each setting and interpret them as providing interesting and important, yet preliminary, empirical evidence that speaks to the question of variation across contexts.

Real Change versus Decoupling or Misreporting?

Our hypotheses predict that having more rated firms in the peer group of a focal firm will lead to greater reductions in pollution. Another possibility, however, is that firms may respond in a more symbolic manner (e.g., by establishing departments, policies, and management systems) that may affect a firm's rating but have little substantive impact on pollution. Rather than leading to real reductions in pollution, the prevalence of rated peers could lead to decoupling, or a gap between symbolic and substantive behavior (Meyer and Rowan 1977). Finally, firms might respond by engaging in outright deception (e.g., misreporting of emissions data). Both of these alternatives are plausible in the case of environmental ratings; a number of scholars discuss the possibility of "greenwashing" (e.g., Laufer 2003) or "gaming the system" (e.g., Schendler and Toffel 2011) as a response to external demands for change.

It would be naïve to suggest that firms never underreport their emissions or seek to improve their ratings without actually reducing pollution. But in this context there is reason to believe that both emissions reporting and ratings correspond with actual levels of emissions. First, KLD's ratings are the oldest and most prominent social and environmental ratings, and they have been subject to extensive academic scrutiny (see, e.g., Chatterji, Levine, and Toffel 2009). Second, if there were rampant gaming of the ratings system such that taking ceremonial actions without making real changes was a viable route to improving one's rating, we would expect ratings to improve while actual emissions stayed the same, or expect ratings to stay the same while emissions got worse (for a parallel argument in the credit rating industry, see Rona-Tas and Hiss 2010). Instead, log emissions among rated firms in our sample dropped 66.7 percent between 2001 and 2004, and the proportion of good ratings among rated firms in our sample also declined, going from 11.5 percent of all rated firms in our sample in 2001 to 4.7 percent of rated firms in 2004. The percent of poor ratings decreased, but not as sharply, dropping from 29.5 percent of rated firms in 2001 to 20.9 percent in 2004.[2] Third, in terms of misreporting emissions, prior work indicates that decoupling is most likely to occur in instances where monitoring is weak (Meyer and Rowan 1977; Short and Toffel 2010). TRI reporting, however, is required by law, and firms face financial penalties for misreporting (see, e.g., Lagana 2013). Overall, the specific features of this setting lead us to believe that firms will respond to the presence of rated peers by reducing their emissions, although ceremonial responses and deception are also possible. We later provide empirical evidence supporting this interpretation of our results.

DATA AND METHODS

We test our arguments by analyzing how changes in firm-level emissions are associated with the percent of a firm's peer group that is rated.

KLD Ratings

As mentioned previously, we study the environmental ratings issued by KLD Research and Analytics, Inc. A pioneer in socially responsible investing, in 1990 KLD developed the Domini 400 Social Index (now the FTSE 400 KLD Social Index), which selects firms on the basis of environmental, social, and governance factors, in addition to more traditional financial investment criteria. The index serves as a benchmark that allows investors to ascertain the impact of social and environmental screening on investment results. In conjunction with the development of the index, KLD began issuing ratings on companies' social performance in seven broad areas: community, corporate governance, diversity, employee relations, environment, human rights, and products.

We focus on KLD's environmental ratings. KLD rates firms as having a "strength" or a "concern" in several subareas related to the environment. Firms can also receive what we view as a neutral rating, in that they have neither strengths nor concerns in a given area. In the environmental domain, companies can have strengths in the following areas: beneficial products or services; pollution prevention; recycling; clean energy; communications; property, plant, and equipment; and other strengths. Companies can have concerns in terms of hazardous waste; regulatory problems; ozone-depleting chemicals; substantial emissions; agricultural chemicals; climate change; and other concerns.

KLD bases its ratings on public documents (e.g., regulatory filings and corporate reports); published reports from the media and governmental and nongovernmental organizations; and direct communications with company managers. The ratings draw on some objective information (e.g., emissions data), but KLD analysts' subjective interpretations also play a role (e.g., in assessing the seriousness of a lawsuit filed against a firm). For this article, it is not important whether the KLD ratings are a strictly accurate reflection of a firm's "true" environmental performance. Rather, it only matters that the KLD ratings take on the status of an independent social fact from the perspective of external audiences, and that firms believe the ratings are at least somewhat linked to their behaviors (so that firms would expect improvements in their behavior to be efficacious in leading to a better rating).

The KLD ratings have several attractive features relevant to our theoretical interests. We exploit the fact that KLD expanded its ratings to begin covering all members of the Russell 1000 Index in 2001 and all Russell 2000 members in 2003. The Russell 1000 and 2000 are subsets of the Russell 3000 Index, a broad-based index of 3,000 publicly held U.S. companies that together represent 98 percent of all investable U.S. firms by market capitalization. The Russell 1000 includes the largest 1,000 firms in the Russell 3000 Index. The Russell 2000 includes the remaining 2,000 (smaller) firms. Because the decision to rate firms was based explicitly on characteristics unrelated to environmental performance and was not driven by the rated firms themselves, we avoid the possibility that self-selection into being rated drives the improvements in emissions that we observe.

Dependent Variable

The dependent variable in this analysis is a measure of environmental performance: the number of pounds of toxic emissions generated by a firm in a given year. Data on emissions come from the U.S. Environmental Protection Agency's (EPA) Toxic Releases Inventory (TRI). The Emergency Planning and Community Right-to-Know Act of 1986 established the TRI and related reporting requirements; all U.S. facilities in mandated industry sectors that manufacture, process, or otherwise use any of 650 specified chemicals above a certain threshold and have more than 10 employees are required to report the amount of various toxic chemicals they release into the environment each year. These data are self-reported, although the EPA inspects regulated sites and levies penalties, including monetary fines, for noncompliance with the reporting requirement.[3] Given the types of businesses that must report, data for this study primarily represent firms in manufacturing, metal mining, electric power generation, chemical manufacturing, and hazardous waste treatment.

TRI data have been widely used by researchers as a measure of corporate environmental performance (see, e.g., Chatterji et al. 2009; Chatterji and Toffel 2010; Cho and Patten 2007; Delmas and Montiel 2009; Konar and Cohen 1997). We use a version of the TRI cleaned and aggregated from the facility level to the firm level by the Investor Research Responsibility Center.[4] Because emissions levels are skewed, we take the log of total pounds of emissions after adding 1.

The TRI dataset includes information on pollution levels for firms rated by KLD as well as unrated firms. Thus, our sample includes all newly rated public firms, as well as unrated public firms that are required to report to the TRI. Our analytic approach is to examine how changes in the emissions of both newly rated and unrated firms are associated with the share of their peers that are rated. By comparing outcomes for rated firms relative to unrated ones, as well as controlling for time trends, we net out many external factors that may shape trajectories in pollution levels among all firms even in the absence of KLD ratings.

Independent Variables

Following Chatterji and Toffel (2010), we assigned firms a "poor" rating if KLD assessed them as having no strengths and at least one concern. We coded firms as "good/mixed" if they had at least one strength (regardless of the number of concerns), and we coded firms as "neutral" if they had no concerns and no strengths. Our analyses use two indicator variables to capture, respectively, whether a firm was rated good/mixed/neutral or poor in a given year, with unrated firms forming the omitted reference category.[5] Figure 1 shows the percent of rated firms in each rating category over time. The figure breaks out "neutral" firms separately, although they are combined with good/mixed firms in our analyses. As the figure shows, most rated firms received a neutral evaluation.

To test our hypotheses regarding the indirect effects of ratings, we measure the percent of a firm's product-market peers that KLD rated in a given year. We identified a firm's product-market peer group using Hoberg and Phillips's (2010a, 2010b) text-based network industry classifications; they categorized firms as peers on the basis of the similarity of the text contained in the required product description section of public firms' 10-K filings with the Securities and Exchange Commission (SEC). In particular, Phillips and Hoberg (2013)

> calculate firm-by-firm pairwise similarity scores by parsing product descriptions from the firm 10-K and forming word vectors for each firm to compute continuous measures of product similarity for every pair of firms

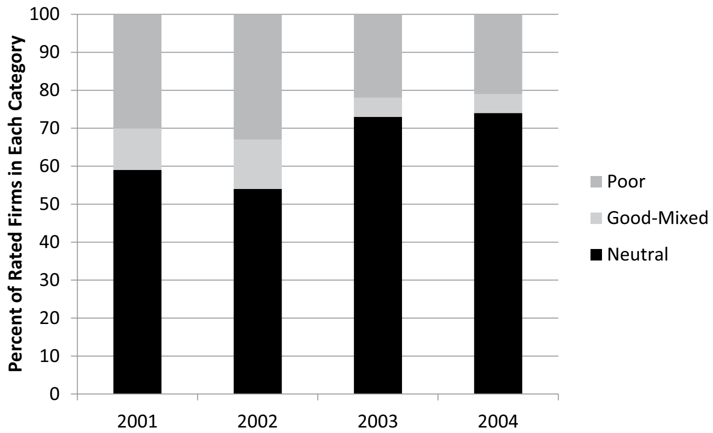

Figure 1. Distribution of Rated Firms by Rating Type over Time

> in our sample each year (a pairwise similarity matrix). This is done using the cosine similarity method, which is applied after basic screens to eliminate common words are applied. For any two firms *i* and *j*, we thus have a product similarity, which is a real number in the interval [0,1] describing how similar the words used by firms *i* and *j* are.

Phillips and Hoberg then define peer firms as those that are more similar than a specified threshold level, which is set to mirror the level of coarseness found in the Standard Industrial Classification (SIC) system. That is, any two firms chosen at random from Compustat would have a 2.05 percent chance of being in the same three-digit SIC code, and the threshold for being designated peers is the same in Hoberg and Phillips's system. One advantage of this novel and unobtrusive system is that firms can be considered peers even though they might not share the same SIC code. For more details on this classification system and its advantages relative to others, such as SIC codes or the North American Industry Classification System (NAICS) codes, see Hoberg and Phillips (2010a, 2010b) and Hoberg, Phillips, and Prabhala (2014).

Based on this definition of product peers, we calculated the percent of a firm's peers that were rated (i.e., the total number of rated firms within the focal firm's product-market peer group, divided by the total number of firms in the product-market peer group, multiplied by 100). In our descriptive statistics, we report the percent of product-market peers that were rated. In our regression models, however, we used a mean-centered version of the variable. Figure 2 shows how the mean percent of peers rated increased throughout the period of analysis.

To test our hypotheses, which proposed that a greater percent of peers rated would be associated with larger emissions reductions for rated and unrated firms, we created interactions between the percent of peers rated and whether a firm was rated poor or good/mixed/neutral. In this interaction specification, the coefficient on the percent of peers rated pertains to the effects of peers on unrated firms, and the sum of the coefficients on the main percent of peers rated variable and the respective interaction terms represents the total indirect effects of peers on each type of rated firm.

Control Variables

We control for firm-level and peer-group factors that may influence a firm's emissions. In particular, we measure firm size using total employees, total revenues, and total assets, all obtained from Compustat. We measure these variables in the same year as a firm's

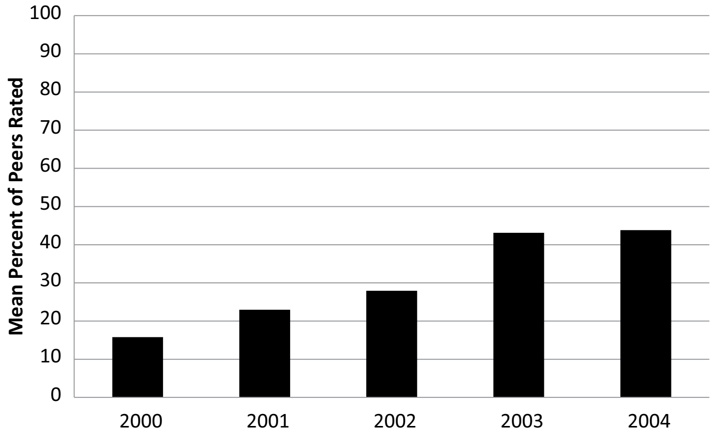

Figure 2. Mean Percent of Peers Rated over Time

emissions, but results are robust to a lagged variable specification. Because a firm's emissions levels may change due to the acquisition or divestiture of facilities, we also control for how many facilities firms reported to the TRI. Following Chatterji and Toffel (2010), we also include a binary variable to indicate firms that are environmentally inefficient, meaning their production-normalized environmental impact is relatively high. We define this on the basis of having a ratio of pounds of toxic emissions to total revenues above the median for firms in the respective industry peer group in a given year.

To rule out potential sources of spuriousness, we include a set of variables measured at the peer-group level. First, we include a variable measuring the percent of a firm's peers that were among the largest one-third of all public firms in terms of logged assets. This variable helps rule out the possibility of imitation of large firms, as large firms are more likely to be rated. Second, to ensure that effects of the ratings are net of any other causes of changes in actual emissions levels that might be common across a firm and its peers (e.g., technological advancements), we control for the mean logged emissions of peers in the prior year as well as whether the mean change in emissions from the prior year to the current one for firms in the focal organization's peer group is negative (i.e., an indicator of whether, on average, peer firms had reduced their emissions).

We use a linear time variable to control for secular trends in emissions as well as to capture other macro-level factors that would be constant across firms within a year, such as the level of activity in the environmental movement, economic conditions, or the proportion of all firms that are rated.[6]

Finally, we use firm fixed effects to control for unobserved time-invariant attributes of firms that might affect the propensity to pollute (e.g., culture, location, and industry). As noted earlier, our analysis takes advantage of an exogenous shock that occurred when KLD expanded its coverage to include Russell 1000 firms in 2001 and Russell 2000 firms in 2003. Thus, using fixed effects, we can examine how the same firm's emissions changed over time as its own rating status shifted and the percent of its peers that are rated changed. We use robust standard errors clustered on firms to account for correlated error terms within firms.

Sample

Our analyses include all unrated and newly rated firms that have at least one facility reporting to the TRI. The fact that we study emissions, which only firms from certain industries are required to report, means that although the KLD ratings expansion included

Table 2. Descriptive Statistics for Variables Used in Analysis of Toxic Chemical Emissions

	Mean	Std. Dev.	Min.	Max.
Ln Emissions (Pounds)	8.86	5.43	0	18.85
Ln Assets ($ millions)	7.26	1.28	4.57	13.96
Ln Number of Employees (thousands)	1.86	.85	.21	5.19
Ln Sales ($ millions)	7.12	1.18	3.78	11.87
Ln Number of Reporting Facilities	1.71	.84	.69	4.63
Year	2002	1.43	2000	2004
Environmental Inefficiency (1 = inefficient) $_{t-1}$	.62	.48	0	1
Rated Poor $_{t-1}$	.08	.28	0	1
Rated Good/Mixed/Neutral $_{t-1}$	.28	.45	0	1
Product-Market Peer Variables				
Percent Product-Market Peers Rated $_{t-1}$	26.08	17.61	0	100
Percent Product-Market Peers Large $_{t-1}$	53.62	23.11	0	100
Ln Mean Product-Market Peer Emissions $_{t-1}$	7.47	4.03	0	17.18
Mean Peer Emissions Declined (1 = yes)	.52	.50	0	1
High Competition (1 = yes)	.54	.50	0	1
High Regulation (1 = yes)	.35	.48	0	1

Note: N = 854 firm-years, 252 firms.

several thousand firms, many of them are not pertinent to our analyses because they do not engage in a type of business subject to TRI reporting requirements. For example, a services company that does no manufacturing might be rated by KLD but would not be required to report to TRI. We also lose some (primarily small, private, and unrated) firms that report to TRI because of a lack of control variables in Compustat.

Overall, our sample represents newly rated and never-rated firms in industries such as manufacturing, metal mining, electric power generation, chemical manufacturing, and hazardous waste treatment industries. It includes 854 firm-years (252 firms). Table 2 shows descriptive statistics, and Table 3 contains bivariate correlations for all the variables used in our analyses.

RESULTS

We present three main sets of results. First, Table 4 presents models that regress firms' emissions levels on their ratings as well as the percent of their product-market peers that are rated. These models capture average associations between the presence of more rated peers and emissions for rated and unrated firms, respectively, during the 2000 to 2004 timeframe. Second, in Tables 5 and 6, respectively, we disaggregate these findings to show variation across different competitive and regulatory contexts. Third, in Table 7 we offer evidence suggesting that reported emissions changes reflect real improvements rather than misreporting. All models include firm fixed effects to control for time-invariant firm characteristics (e.g., culture and location) that might influence a firm's emissions levels.

Model 1 of Table 4 includes control variables as well as the binary variables indicating whether the focal firm received a good/mixed/neutral rating or a poor rating, with unrated firms as the omitted reference category. Evidence of a secular decrease in emissions levels is clear in all models, as indicated by the negative and significant year variable. The negative and significant coefficient for firms rated poor indicates that these firms tended to reduce their emissions more than unrated firms, consistent with prior research (Chatterji and Toffel 2010). Firms rated good/mixed/neutral also reduced their emissions relative to unrated firms.[7] Turning to the main substantive questions of interest, Model 2

Table 3. Correlation Matrix of Variables Used in Analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	1												
(2)	.216*	1											
(3)	.157*	.712*	1										
(4)	.248*	.901*	.818*	1									
(5)	.450*	.394*	.539*	.541*	1								
(6)	−.392*	.108*	.007	.084*	−.047	1							
(7)	.363*	.133*	.046	.101*	.206*	−.066	1						
(8)	.107*	.316*	.140*	.300*	.143*	.225*	.084*	1					
(9)	−.394*	.136*	.086*	.094*	−.100*	.619*	−.055	−.189*	1				
(10)	−.137*	.226*	.085*	.208*	.118*	.572*	−.021	.276*	.358*	1			
(11)	.319*	.411*	.212*	.389*	.285*	−.016	.053	.243*	−.132*	.458*	1		
(12)	−.067	−.010	−.020	−.002	.019	.355*	.030	.024	.148*	.128*	−.038	1	
(13)	.309*	.060	.038	.135*	.344*	−.043	−.140*	.203*	−.217*	.299*	.489*	−.121*	1

Note: (1) Ln Emissions (lbs); (2) Ln. Assets; (3) Ln. Number of Employees (000s); (4) Ln. Sales; (5) Ln. Number of Reporting Facilities; (6) Year; (7) Environmental Inefficiency; (8) Rated Poor $_{t-1}$; (9) Rated Good/Mixed/Neutral $_{t-1}$; (10) Percent Product-Market Peers Rated $_{t-1}$; (11) Percent Product-Market Peers Large $_{t-1}$; (12) Mean Product-Market Peer Emissions Declined (1 = yes); (13) Ln Mean Product-Market Peer Emissions $_{t-1}$.

Table 4. Estimated Coefficients from Regressions of Logged Total Pounds of Toxic Chemical Releases on Product-Market Peers, 2000 to 2004

	(1)	(2)	(3)	(4)
Ln Assets	.003	−.413	−.414	−.476
	(1.093)	(1.086)	(1.095)	(1.091)
Ln Employees	1.761	1.673	1.287	1.393
	(1.548)	(1.480)	(1.396)	(1.381)
Ln Sales	−1.579	−1.412	−1.393	−1.446
	(.865)	(.840)	(.846)	(.868)
Ln Number of Reporting Facilities	1.233*	1.249*	1.179*	1.193*
	(.576)	(.571)	(.589)	(.579)
Year	−.860***	−.505***	−.643***	−.552***
	(.137)	(.132)	(.131)	(.131)
Inefficiency Indicator $_{t-1}$	−.185	−.236	−.192	−.256
	(.371)	(.362)	(.356)	(.366)
Rated Poor $_{t-1}$	−1.791*	−1.250	.605	.967
	(.825)	(.826)	(1.433)	(1.398)
Rated Good/Mixed/Neutral $_{t-1}$	−2.580***	−1.894***	−1.687***	−1.493
	(.502)	(.536)	(.495)	(.494)
Percent Peers Rated $_{t-1}$		−.068***	−.009	−.019
		(.015)	(.017)	(.017)
Percent Peers Rated $_{t-1}$ x Rated Poor $_{t-1}$			−.151*	−.148*
			(.067)	(.065)
Percent Peers Rated $_{t-1}$ x Rated Good/ Mixed/Neutral $_{t-1}$			−.088***	−.082***
			(.022)	(.021)
Percent Peers in Top 1/3 by Size $_{t-1}$				.024*
				(.012)
Mean Peer Emissions Declined				−.980***
				(.259)
Mean Ln Peer Emissions $_{t-1}$				.059
				(.072)
Constant	1738.323***	1028.491***	1306.399***	1121.966***
	(269.952)	(261.312)	(259.708)	(260.250)
R-squared (within)	.37	.39	.42	.44

Note: N = 854 firm-years; 252 firms. Robust standard errors clustered on firms in parentheses. All models include firm fixed effects.
*p < .05; **p < .01; ***p < .001 (two-tailed tests).

incorporates the percent of a firm's product-market peers that were rated in the prior year. The variable is negative and significant, indicating that having more rated peers is associated with lower emissions for the focal firm. A one-point increase in the percent of peers rated corresponds to an approximately 6.6 percent (=100 percent x [1 – exp(–.068)]) decrease in emissions. Model 3 incorporates interactions between the percent of peers rated and the indicators for whether the focal firm received a poor or good/mixed/neutral rating, respectively, to test whether rated peers are associated with a decline in emissions among unrated firms as well as firms in either ratings category. Both interaction terms are negative and significant, indicating that firms receiving any kind of rating tended to reduce their emissions more than unrated firms as more of their peers were rated.[8] To determine whether the presence of more rated peers is associated with a decline in emissions for unrated firms, we examine the coefficient on the (non-interacted) percent of peers rated variable in Model 3. The coefficient is negative ($\beta = -.009$) but non-significant ($p = .60$), suggesting that being surrounded by more rated peers is not associated with emissions reductions among unrated firms.

In Model 4, we test whether results are robust to the inclusion of variables capturing the percent of a firm's peers that are large (i.e., in the top one-third in terms of logged assets), the mean logged emissions level of a firm's peers in the prior year, and an indicator of whether the mean year-to-year change in emissions among a firm's peers is negative (i.e., peer emissions declined, on average). Overall, the controls operate as expected, and the substantive results presented earlier remain largely unchanged in size and statistical significance. As Model 4 shows, the variable indicating that peer emission declined is associated with lower emissions by the focal firm. This variable proxies for factors that peers have in common—such as technologies, regulation, or market conditions—and that might cause a firm's emissions to decline as its peers' emissions fall, independent of ratings. Results suggest that common industry factors do produce a negative association between a focal firm's emissions and an emissions decline by the firm's peers. But this alone does not account for the tendency of rated firms to reduce their emissions more when more of their peer group is rated; the coefficients on the percent of peers rated variable and its interactions remain similar in Models 3 and 4. In addition, controlling for a decline in peer emissions can be thought of as testing whether the observed influence of rated peers is mediated by actual reductions in peer emissions, which might be driven by the ratings. Again, while this may occur, it alone does not explain the results; the effects of the peer variables and their interactions remain similar across Models 3 and 4.

Finally, by including the percent of a firm's peers that are large, we also control for the possibility that the association between a firm's emissions and the percent of its peers that are rated is primarily driven by firms imitating prominent (i.e., large) peers. Because size is the primary determinant of whether a firm is rated, this control is particularly important. However, as Model 4 shows, while the percent of a firm's peers that are in the top one-third of all public firms in terms of size is positively associated with emissions by the focal firm, our substantive results of interest are robust to this control. As an additional robustness check, when we reran models using peers as defined by NAICS codes, we obtained results similar in direction and magnitude although somewhat attenuated in statistical significance (likely due to the additional noise in this measure of peers).

Spillovers and Competition

The results thus far are consistent with Hypothesis 1, which predicted that rated firms will reduce their emissions more as their peer group includes more rated firms. Unrated firms do not appear to be responsive, contrary to Hypothesis 2. However, as we will show, these findings vary across settings. To explore how firms respond differently depending on their competitive environment, we first designated firms as belonging to industries that were relatively high or low in terms of competitive intensity. This was defined on the basis of whether the sales-based Herfindal-Hirschman index (HHI) of the three-digit NAICS industry to which a firm belonged was below or above the median across industries in our data. We then ran models in which we interacted the indicator of a high-competition industry with all of the control variables used in Model 4 of Table 4.[9] We examined the results for significant interactions of control variables with the high-competition indicator to determine whether the effects of any control variables differed with the level of competition. We found only one significant interaction, which we incorporated into our baseline model. Table 5 presents results from a series of regression models, beginning with a baseline model of controls and ratings as well as the interaction of ratings with the high-competition indicator (Model 1). We then add the percent of peers

Table 5. Estimated Coefficients from Regressions of Logged Total Pounds of Toxic Chemical Releases on Product-Market Peers in High- and Low-Competition Settings, 2000 to 2004

	(1)	(2)	(3)
Ln Assets	.227	−.493	−.686
	(1.089)	(1.094)	(1.076)
Ln Employees	1.640	1.126	1.029
	(1.545)	(1.402)	(1.360)
Ln Sales	−1.595	−1.003	−.956
	(.891)	(.865)	(.841)
Ln Number of Reporting Facilities	1.147*	1.212*	1.392*
	(.563)	(.569)	(.560)
Year	−.809***	−.567***	−.523***
	(.134)	(.132)	(.127)
Inefficiency Indicator $_{t-1}$	−1.067*	−.921	−.778
	(.490)	(.518)	(.502)
Percent Peers in Top 1/3 by Size $_{t-1}$	.001	.018	.018
	(.011)	(.012)	(.011)
Mean Peer Emissions Declined	−1.222***	−.975***	−.803**
	(.278)	(.260)	(.271)
Mean Ln Peer Emissions $_{t-1}$	.096	.062	.068
	(.070)	(.071)	(.068)
High Competition x Inefficiency Indicator $_{t-1}$	1.486*	1.249*	1.099
	(.641)	(.625)	(.607)
Rated Poor $_{t-1}$	−1.134	−.003	−2.125
	(1.242)	(1.372)	(1.702)
Rated Good/Mixed/Neutral $_{t-1}$	−3.080***	−2.159**	−2.509**
	(.739)	(.736)	(.804)
High Competition x Rated Poor $_{t-1}$	−.558	3.772	9.797***
	(1.620)	(1.916)	(2.829)
High Competition x Rated Good/Mixed/Neutral $_{t-1}$	1.276	1.023	1.495
	(.807)	(.783)	(.932)
Percent Peers Rated $_{t-1}$		−.013	−.025
		(.017)	(.026)
Percent Peers Rated $_{t-1}$ x Rated Poor $_{t-1}$		−.215**	.100
		(.077)	(.108)
Percent Peers Rated $_{t-1}$ x Rated Good/Mixed/Neutral $_{t-1}$		−.083***	−.051
		(.021)	(.040)
High Competition x Percent Peers Rated $_{t-1}$			.011
			(.029)
High Competition x Percent Peers Rated $_{t-1}$ x Rated Poor $_{t-1}$			−.466***
			(.133)
High Competition x Percent Peers Rated $_{t-1}$ x Rated Good/Mixed/Neutral $_{t-1}$			−.051
			(.045)
Constant	1634.682***	1150.100***	1063.820***
	(264.852)	(261.450)	(252.226)
R-squared	.39	.45	.48

Note: Total N = 854 firm-years; 252 firms. All models include firm fixed effects. Robust standard errors clustered on firms in parentheses.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

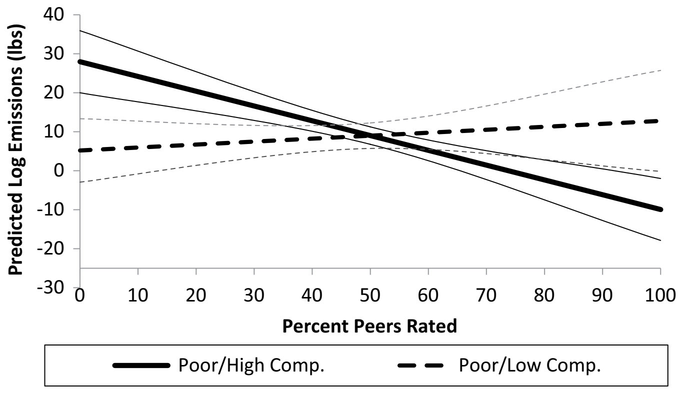

Figure 3. The Relationship between Percent of Peers Rated and Emissions for Firms Rated Poor, by Level of Market Competition
Note: Estimates based on Model 3 in Table 5. All other variables set to the mean. Dotted lines indicate the 95 percent confidence interval.

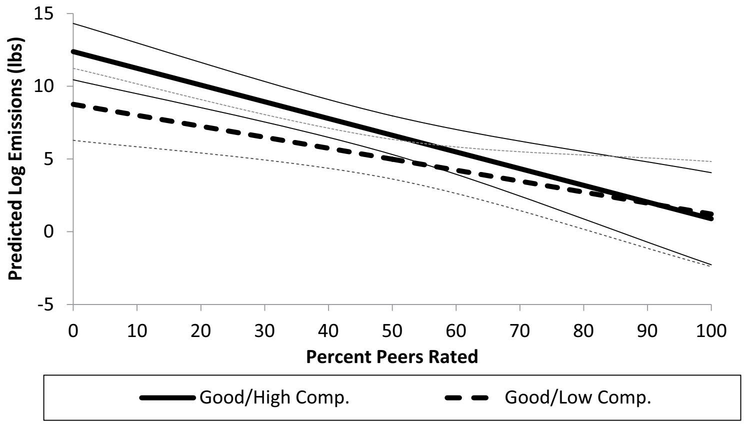

Figure 4. The Relationship between Percent of Peers Rated and Emissions for Firms Rated Good/Mixed/Neutral, by Level of Market Competition
Note: Estimates based on Model 3 in Table 5. All other variables set to the mean. Dotted lines indicate the 95 percent confidence interval.

rated as well as the interaction of this variable and the firm's own rating (Model 2), and, finally, incorporate three-way interactions of the percent of peers rated, the firm's own rating, and high competition (Model 3).

To identify the scenarios under which having a higher percent of peers rated might lead a focal firm to reduce its emissions, we interpret the coefficients from the fully specified model (Model 3). In addition, Figures 3, 4, and 5 provide a graphic depiction of the relationship between emissions and the percent of peers rated for firms in each ratings category (i.e., unrated, rated poor, and rated good/mixed/neutral) across different competitive environments.

We begin with firms rated poor.[10] To determine whether firms rated poor in less competitive settings reduce their emissions as a function of rated peers, we test whether the sum of the coefficients on the percent of peers rated ($\beta_{\text{percent peers rated}} = -.025$) plus the interaction of percent of peers rated and a poor rating for the focal firm is significant ($\beta_{\text{percent peers rated x rated poor}} = .100$). Results suggest a lack of indirect effects among firms rated poor in this setting (p = .47). In contrast, performing a parallel calculation for firms rated poor in more competitive settings indicates that these firms tend to reduce their emissions substantially as the percent of their peers that are rated increases (p < .001).[11] Figure 3 highlights the difference in the relationship between the percent of peers rated and the focal firm's emissions for firms rated poor in different settings. Firms rated poor in more competitive environments reduce their emissions; the effect is positive but non-significant for firms rated poor in less competitive settings.[12]

We now examine how firms rated good/mixed/neutral behave in different settings. To determine how emissions are associated with the percent of peers rated for firms in less competitive settings, we test whether the sum ($\beta_{\text{percent peers rated}} + \beta_{\text{percent peers rated x rated good/mixed/neutral}}$) is significantly different from zero. Results suggest that these firms tend to reduce their emissions more as more of their peers are rated (p < .01). We perform a parallel test for firms rated good/mixed/neutral in more competitive settings and find a similar relationship between the percent of peers rated and emissions (p < .01).[13] Figure 4, which shows the relationship between the percent of peers rated and logged emissions for firms rated good/mixed/neutral in different environments, highlights the similarities in how these types of firms behave across contexts.

Finally, examining how unrated firms in less competitive environments respond to the presence of rated peers, the non-significant coefficient on the percent of peers rated indicates a lack of spillover effects on unrated firms in this setting. To determine whether the presence of more rated peers is associated with an emissions reduction for unrated firms in more competitive settings, we test whether the sum of the coefficients on the percent of peers rated and the interaction of percent peers rated and the high-competition indicator is significant. Results suggest an absence of significant spillovers (p = .50) here as well. These results are depicted in Figure 5, which shows a lack of spillover effects to unrated firms in both settings.

Spillovers and Industry Regulation

Because regulatory forces may also shape how firms react to ratings and rated peers, we examine variation in the relationship between rated peers and emissions across contexts that differ in regulatory intensity. To do so, we follow Chatterji and Toffel (2010) and classify firms as belonging to industries that were regulated to a greater or lesser degree using Cho and Patten's (2007) classification of two-digit SIC codes along this dimension. Paralleling our earlier approach to testing for variation across competitive settings, we first ran models in which we interacted all control variables from Model 4 of Table 4 with an indicator for whether a firm was in a more regulated industry. We did not find any significant interactions among the control variables (nor was the indicator of belonging to a more regulated industry significant), so we used as our baseline a model with control variables, ratings variables, and ratings interacted with the high-regulation industry indicator. This model appears as Model 1 of Table 6. Model 2 incorporates the percent of peers rated and its interaction with the ratings categories, and Model 3 adds the three-way interactions of percent peers rated, the firm's own rating, and the indicator of belonging to a highly regulated industry. As before, our discussion centers on the fully specified model (Model 3).

Focusing first on firms rated poor in less regulated industries, we examine the relationship between emissions and having a greater percent of peers rated by testing whether the sum of the coefficients for the percent of peers rated and the interaction of that variable with rated poor (i.e., $\beta_{\text{percent peers rated}} + \beta_{\text{percent peers rated x rated poor}}$) is significantly different from zero. The sum is positive but non-significant (p = .44), indicating a lack of peer effects for firms rated poor in less regulated environments. Turning to firms rated poor in more regulated environments, however, we find that these firms reduced their emissions substantially in the presence of rated peers (p < .01).[14] Figure 6 provides a graphic representation of these findings. The importance of

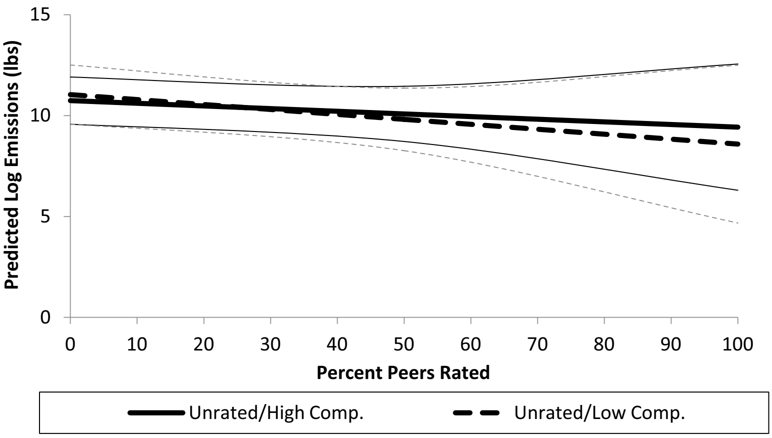

Figure 5. The Relationship between Percent of Peers Rated and Emissions for Unrated Firms, by Level of Market Competition
Note: Estimates based on Model 3 in Table 5. All other variables set to the mean. Dotted lines indicate the 95 percent confidence interval.

the regulatory environment is apparent; firms rated poor in more regulated environments reduced their emissions as the percent of peers rated increased, but they were non-responsive to peers in less regulated environments.

To determine whether peers matter for firms rated good/mixed/neutral in less regulated settings, we test whether the sum of the coefficients on the percent of peers rated ($\beta_{\text{percent peers rated}}$ = .004) and the percent of peers rated interacted with the indicator for being rated good/mixed/neutral ($\beta_{\text{percent peers rated x rated good/mixed/neutral}}$ = –.097) is significantly different from zero. The result is negative and significant ($p < .01$). A parallel test for firms rated good/mixed/neutral in more regulated environments indicates that they also reduce their emissions as more peers are rated ($p < .01$). Figure 7 illustrates this relationship, showing the similarities in how firms rated good/mixed/neutral behave regardless of regulatory scrutiny. This may raise the concern that firms rated good/mixed/neutral possess some unobserved characteristic that makes them both more responsive to peers and more likely to reduce their emissions. Recall, however, that our results are within-firm (i.e., using fixed effects), which greatly limits the possible unobserved factors that might be involved.

Finally, we examine how the response of unrated firms to the presence of more rated peers varies across regulatory contexts. The non-significant effect of the percent peers rated variable (p = .83) shows that unrated firms in less regulated industries do not respond to the presence of rated peers, indicating a lack of diffuse effects in this setting. To determine how unrated firms in more regulated industries respond, we test whether the sum of the coefficients on the percent of peers rated and the interaction of high regulation and percent of peers rated is negative and significant. Results confirm this is the case (p = .02), suggesting the presence of rated peers does influence unrated firms in more regulated industries. Thus, it appears that the pressure of being in a highly regulated industry leads even unrated firms to respond to the presence of ratings through the channel of rated peers. Figure 8 depicts this relationship.

In summary, these analyses provide important insight into the role of peers as a channel through which ratings exert their influence. The results presented in Table 4 indicate that, on average, rated firms respond to the presence of rated peers but unrated firms remain impervious. Yet, further analyses broken down by competitive and regulatory environments reveal a more nuanced picture. The

Table 6. Estimated Coefficients from Regressions of Logged Total Pounds of Toxic Chemical Releases on Product-Market Peers in High- and Low-Regulation Settings, 2000 to 2004

	(1)	(2)	(3)
Ln Assets	−.077	−.777	−.722
	(1.101)	(1.101)	(1.099)
Ln Employees	1.898	1.534	1.232
	(1.550)	(1.399)	(1.397)
Ln Sales	−1.527	−1.090	−.881
	(.898)	(.857)	(.836)
Ln Number of Reporting Facilities	1.224*	1.183*	1.201*
	(.569)	(.576)	(.573)
Year	−.799***	−.536***	−.492***
	(.135)	(.132)	(.129)
Inefficiency Indicator $_{t-1}$	−.275	−.233	−.285
	(.379)	(.361)	(.350)
Percent Peers in Top 1/3 by Size $_{t-1}$	.003	.024*	.021
	(.011)	(.012)	(.012)
Mean Peer Emissions Declined	−1.149***	−.987***	−.902***
	(.273)	(.261)	(.267)
Mean Ln Peer Emissions $_{t-1}$	.081	.074	.053
	(.067)	(.068)	(.069)
Rated Poor $_{t-1}$	−2.278	−1.033	−3.752
	(1.521)	(1.704)	(2.345)
Rated Good/Mixed/Neutral $_{t-1}$	−2.435***	−1.520**	−2.046***
	(.546)	(.544)	(.559)
High Regulation x Rated Poor $_{t-1}$	1.075	3.534	8.109**
	(1.785)	(1.809)	(2.757)
High Regulation x Rated Good/Mixed/Neutral $_{t-1}$	.061	−.082	.927
	(.911)	(.893)	(1.055)
Percent Peers Rated $_{t-1}$		−.019	.004
		(.017)	(.018)
Percent Peers Rated $_{t-1}$ x Rated Poor $_{t-1}$		−.181**	.089
		(.067)	(.123)
Percent Peers Rated $_{t-1}$ x Rated Good/Mixed/Neutral $_{t-1}$		−.082***	−.097***
		(.021)	(.022)
High Regulation x Percent Peers Rated $_{t-1}$			−.080*
			(.034)
High Regulation x Percent Peers Rated $_{t-1}$ x Rated Poor $_{t-1}$			−.308*
			(.139)
High Regulation x Percent Peers Rated $_{t-1}$ x Rated Good/Mixed/Neutral $_{t-1}$			.054
			(.053)
Constant	1614.294***	1090.062***	1000.260***
	(266.162)	(260.866)	(255.397)
R-squared	.38	.45	.47

Note: Total N = 854 firm-years; 252 firms. All models include firm fixed effects. Robust standard errors clustered on firms in parentheses. We coded the following industries as high regulation, based on Cho and Patten (2007): mining (SIC 10), oil exploration (13), paper (26), chemical and allied products (28), petroleum refining (29), metals (33), and utilities (49).
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$ (two-tailed tests).

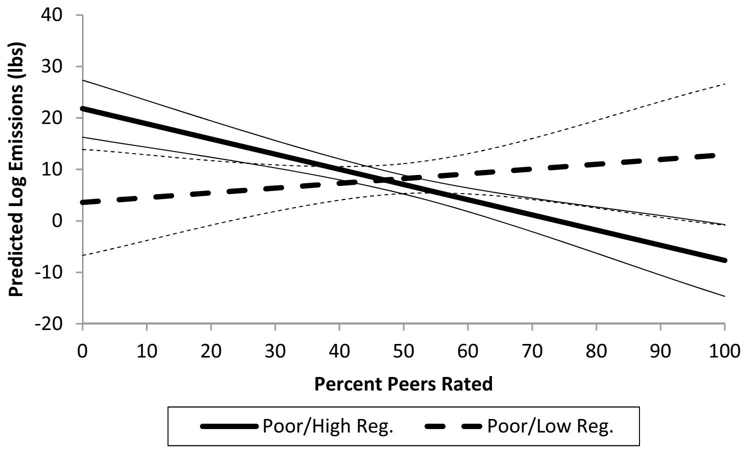

Figure 6. The Relationship between Percent of Peers Rated and Emissions for Firms Rated Poor, by Level of Industry Regulation
Note: Estimates based on Model 3 in Table 6. All other variables set to the mean. Dotted lines indicate the 95 percent confidence interval.

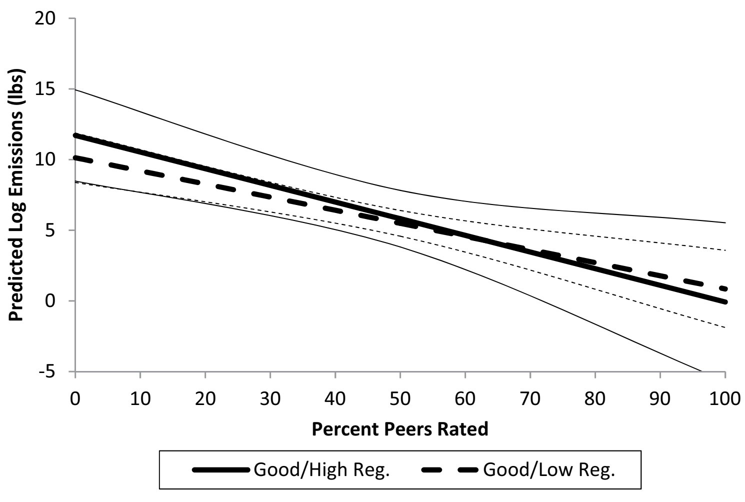

Figure 7. The Relationship between Percent of Peers Rated and Emissions for Firms Rated Good/Mixed/Neutral, by Level of Industry Regulation
Note: Estimates based on Model 3 in Table 6. All other variables set to the mean. Dotted lines indicate the 95 percent confidence interval.

negative association between the percent of peers rated and a focal firm's emissions is present among firms rated poor in either high-competition or high-regulation environments as well as firms rated good across contexts and unrated firms in highly regulated contexts. Given that ratings systems are sometimes portrayed as a lever that external stakeholders might use to pressure poorly performing firms to improve, the results for firms rated poor are of special interest. It is striking that in this setting, ratings systems only serve to "discipline" these firms when they operate in parallel with regulatory scrutiny or competition. We also found that context is critical for the occurrence of spillovers to unrated firms; the percent of an unrated firm's peer group that is rated is associated with an emissions reduction for unrated firms only in more regulated environments. This

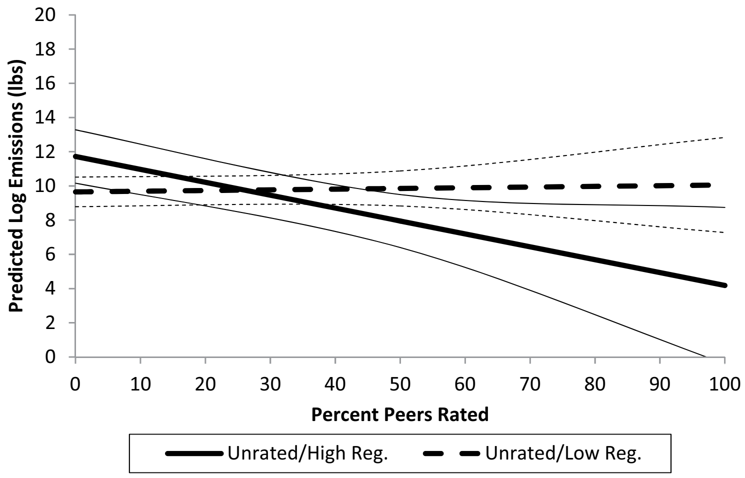

Figure 8. The Relationship between Percent of Peers Rated and Emissions for Unrated Firms, by Level of Industry Regulation
Note: Figure based on Model 3 in Table 6. All other variables set to the mean. Dotted lines indicate the 95 percent confidence interval.

finding provides evidence of Schneiberg and Bartley's (2008:51) speculation that "how twenty-first-century systems of regulation work in practice may also depend on how they overlap with one another and with older forms of regulation." In the case of toxic emissions, there appears to be a dynamic interplay when hard and soft forms of regulation intersect, amplifying the effects of ratings so that even unrated firms are influenced in high-regulation contexts.

Misreporting or Real Reductions in Emissions?

One important question regarding our results is whether the observed association between ratings, rated peers, and pollution reflects true reductions in emissions or misreporting. Although researchers have characterized the TRI as one of the most commonly used "objective measures of environmental performance" (Vasi and King 2012:580), TRI data are self-reported, which makes intentional misreporting possible. However, the EPA conducts inspections and imposes penalties for violations, which should mitigate this activity. Given the lack of objective data on emissions that might serve as a point of comparison for the self-reported TRI data used in our analyses, we cannot definitively determine the extent of misreporting. We do, however, present results of a test that suggests misreporting does not drive our findings.

Our test relies on the idea that firms differ in terms of the incentives and costs they might face for misreporting. We exploit variation in the "cost" of misreporting that occurs due to differences across states in the rate of facilities inspections. We propose that firms should be less likely to engage in misreporting if they think the costs of doing so will be high, that is, if they are likely be caught (e.g., due to more frequent inspections) and punished severely (e.g., through fines and other penalties). To determine whether our effects are at least partly due to real reductions in emissions, rather than exclusively due to misreporting, we examine the effects of ratings and rated peers on emissions in settings where the probability of being caught for misreporting is relatively higher because inspections of regulated facilities are more common. If we observe that the effect of being rated or the effect of rated peers is smaller or even nonexistent in places where inspections are more frequent, we might suspect misreporting. If this is not the case, we can be more confident that our results represent real reductions in emissions.

To test this, we use data from the EPA's Enforcement and Compliance History Online (ECHO) database, which contains state-level data on inspections, violations, enforcement actions, and penalties imposed on regulated facilities for air, water, or hazardous waste emissions (EPA 2014). To parallel our data, we focus on hazardous waste emissions and calculate the proportion of all regulated facilities in each state that were inspected. Unfortunately, these data are readily available only for 2009 to 2013. We use the earliest data, from 2009, although in reviewing these data, we do not observe dramatic shifts over time in terms of the states where inspections were more or less common.[15] We designated states as being above or below the median in terms of the rate of inspections, and we created a binary indicator coded 1 if a firm was headquartered in a state with a relatively higher rate of inspections and 0 otherwise. We then ran models with the addition of interaction terms between the ratings variables and being headquartered in a state where the probability of inspection is relatively high. Table 7 presents these results. Model 1 shows that the interactions of high-inspection state and each ratings variable are negative and non-significant, indicating that firms react similarly to being rated, regardless of the cost of misreporting. Because reductions in emissions do not appear to be smaller where inspections are more common (i.e., we do not find a positive and significant interaction term), we conclude that misreporting is unlikely to drive our results.

Model 2 adds a variable for the proportion of a firm's peers that are rated. This observed association is negative and significant, similar to results reported earlier. Model 3 incorporates the interaction of the percent of peers rated and the indicator for being headquartered in a high-inspections state. In this model, the coefficient for the percent of a firm's peers that are rated remains negative and significant while the interaction term is negative and non-significant. This result seems inconsistent with gaming the system; if misreporting explains our results, we would expect the presence of rated peers to lead to a smaller reported reduction in emissions (i.e., a positive interaction term) in settings where inspections are more frequent. In summary, we acknowledge that gaming the system no doubt occurs to some degree, as evidenced by the fact that the EPA has caught and fined firms for misreporting. However, these additional analyses lead us to believe that misreporting is not the primary driver of our findings.

CONCLUSIONS

This article responds to Schneiberg and Bartley's (2008) call for further examination of the mechanisms through which newly emerging forms of private governance, such as ratings, influence organizations. We theorized about how ratings might operate through the presence of rated peers, leading to indirect effects on both rated and unrated firms. We also examined how these effects might vary across competitive and regulatory contexts. In the context of the KLD environmental ratings and firms' pollution output, our analyses reveal that the presence of more rated peers was often, but not always, associated with a reduction in pollution.

One overarching conclusion from our analyses is that any given ratings system is unlikely to be a uniformly powerful catalyst for change across different settings; rather, ratings seem to work in tandem with peers and contextual factors. If one considers the extreme case, this may be intuitive; if a firm were the only one in its field to be rated, and if no important constituencies cared about the rating, perhaps the firm would act as if the rating did not exist.[16] Yet, potential outcomes in less extreme conditions have remained unclear because prior work rarely examines either indirect effects or contextual contingencies in the power of ratings systems to prompt change, an oversight we attribute to the fact that most studies examine a single industry or field (thus holding constant the

Table 7. Estimated Coefficients for Tests for Misreporting of Emissions from Regressions of Logged Total Pounds of Toxic Chemical Releases on Product-Market Peers, 2000 to 2004

	(1)	(2)	(3)
Ln Assets	.117	−.426	−.474
	(1.096)	(1.090)	(1.083)
Ln Employees	1.822	1.774	1.772
	(1.530)	(1.458)	(1.461)
Ln Sales	−1.676	−1.479	−1.487
	(.865)	(.852)	(.850)
Ln Number of Reporting Facilities	1.232*	1.250*	1.311*
	(.557)	(.550)	(.550)
Year	−.804***	−.417**	−.412**
	(.134)	(.131)	(.131)
Inefficiency Indicator $_{t-1}$	−.247	−.205	−.217
	(.383)	(.368)	(.366)
Percent Peer Firms in Top 1/3 by Size $_{t-1}$	.003	.027*	.026*
	(.011)	(.012)	(.012)
Mean Peer Emissions Declined	−1.140***	−1.087***	−1.054***
	(.273)	(.263)	(.265)
Mean Ln Peer Emissions $_{t-1}$	.072	.098	.090
	(.068)	(.073)	(.074)
Rated Poor $_{t-1}$	−1.388	−.752	−1.176
	(.913)	(.943)	(.987)
Rated Good/Mixed/Neutral $_{t-1}$	−1.923**	−1.279*	−1.725*
	(.599)	(.616)	(.678)
High-Inspections State x Rated Poor $_{t-1}$	−.233	−.250	.460
	(1.568)	(1.534)	(1.604)
High-Inspections State x Rated Good/Mixed/Neutral $_{t-1}$	−1.021	−.757	.060
	(.794)	(.774)	(.993)
Percent Product-Market Peers Rated $_{t-1}$		−.075***	−.053*
		(.016)	(.021)
High-Inspections State x Percent Peers Rated			−.037
			(.027)
Constant	1624.379***	850.671**	841.762**
	(265.622)	(260.140)	(259.398)
R-squared (within)	.38	.41	.41

Note: N = 854 firm-years; 252 firms. All models include firm fixed effects. Robust standard errors clustered on firms in parentheses.
*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

external context) or study only rated firms. As ratings systems proliferate (Fombrun 2007), however, understanding such variation in effects has become increasingly important. Overall, we view this article as an initial step toward understanding the complex pathways through which ratings may (or may not) shape organizational fields.

We studied the relationship between ratings, rated peers, and emissions in a setting that afforded us some leverage to understand how distinct types of firms (i.e., rated versus unrated) that inhabit different types of competitive and regulatory environments might respond to the spread of ratings to peer firms. We acknowledge the limitations of testing for peer effects using observational data. We lack the benefit of random assignment of peers or ratings, which would allow us to definitively claim that the presence of rated firms generated indirect effects, causing changes in peers' behaviors. However, we emphasize that our analyses use fixed effects, which enabled us to examine changes within firms, holding constant time-invariant factors that might lead to a spurious relationship between emissions and the percent of peers rated. In addition, our analyses include controls for firm size, which drives KLD's selection of which firms to rate, as well as controls for changes in actual emissions levels, which capture underlying drivers of co-movement in the emissions of a firm and its peers. Controlling for these factors greatly reduces the possibility of spurious correlations and should increase confidence in our results. Nonetheless, testing whether the associations observed here persist in the face of exogenous variation in the presence of rated peers, perhaps through a natural experiment, would be beneficial. Moreover, it would be valuable to conduct similar research over an extended timeframe to examine whether firms continue to respond to ratings and rated peers, or whether their effects wane as organizations become accustomed to the added scrutiny. In addition, an analysis that spans a longer time horizon might show that unrated firms, which in our study were largely unresponsive to their rated peers, do in fact respond to their rated peers in a manner similar to what we observed for rated firms, but that the effect simply takes longer to arise.

Despite limitations, our analyses suggest several implications for policymakers and designers of ratings systems. First, if policymakers hope to effect organizational change in cases where organizations are unlikely to initiate it on their own, they would be wise not to assume that ratings alone will be sufficient. Ratings typically provide organizational audiences with novel information about firms; whether the availability of new information is consequential enough to elicit a response from organizations depends, in part, on whether organizations think the new information will prompt a reaction from consumers, competitors, and regulators. It is the possibility of a reaction by these parties that seems to give teeth to ratings. Thus, emerging types of private regulation, such as ratings, should not be seen as a surefire substitute for more traditional ways of bringing about change (i.e., laws and regulation or the discipline of market forces). Rather, it may be more sensible to view ratings as a complement to regulation and competition. Second, our study implies that rating everyone in a field may not always be optimal from an efficiency perspective; under some conditions, ratings systems generate spillovers that extend to unrated firms. In general, our findings call for careful consideration of multiple factors in predicting whether a ratings system is likely to bring about organizational change.

Finally, we believe this article sets the stage for further study of several intriguing questions surrounding ratings systems. First, it would be interesting to know whether firms respond more strongly to peers that are rated negatively, perhaps because they make more salient the negative consequences of a poor rating, or whether firms respond to a greater degree when surrounded by others rated favorably, possibly due to enhanced knowledge transfer or status competition. We hesitate to draw conclusions about these questions in the setting at hand because of the relatively small proportion of firms that received poor and good ratings as opposed to neutral ones. Second, while we emphasized the influence of a firm's product-market peers, it would be interesting to understand whether, over time, ratings systems create new de facto peer groups of similarly rated firms. Overall, our novel findings contribute to a greater understanding of how ratings systems prompt organizational change and indicate the fruitfulness of further investigations into the mechanisms through which third-party evaluations operate.

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Notes

1. In making this claim, we are agnostic as to whether ratings systems accurately reflect actual outcomes on a given dimension (i.e., if a rating can accurately capture whether a firm is good or bad for the environment); however, ratings systems would have to be at least somewhat grounded in reality for firms to see a benefit in changing their behaviors to avoid a poor rating. See Chatterji and Levine (2008) for a discussion of the validity of corporate social responsibility ratings. Firms may respond to the presence of rated peers because they observe peers improving their behaviors, and they seek to learn from them. Note, however, that spillover effects of ratings may occur even net of learning that occurs on the basis of peer outcomes. That is, we expect that the presence of more peers who are rated may influence a focal firm above and beyond any spillover effects that derive from firms observing actual changes in the behaviors (i.e., emissions levels) of their peers.
2. The decline in good and poor ratings went hand-in-hand with an increase in neutral ratings.
3. Examples of penalties can be found at http://www2.epa.gov/toxics-release-inventory-tri-program/tri-compliance-and-enforcement.
4. This firm-level database is no longer compiled, which limits the timeframe of our analysis.
5. Chatterji and colleagues (2009) provide evidence that KLD's "concern" ratings more accurately capture actual firm environmental performance than do the "strength" ratings. Our coding scheme, which differentiates between firms with concerns only and all other firms, reflects this fact and is consistent with prior work (i.e., Chatterji and Toffel 2010). An alternative would be to use continuous variables, counting, respectively, the total strengths and total concerns that KLD awarded each firm (Chatterji et al. 2009; Griffin and Mahon 1997; Johnson and Greening 1999; Ruf et al. 2001) We ran models that include these variables and found similar peer effects as well as significant effects of the total "concerns" although generally not of "strengths." Results are robust to this alternate approach.
6. Due to the expansion of the number of firms rated in our sample in 2001 and 2003, we cannot include dichotomous year indicators, which is the more conventional and flexible way of handling time trends over a short period. When included as dichotomous indicators, those two years are highly correlated with our ratings variables. Although not perfect, the linear year variable allows us to control for general time trends while avoiding severe collinearity in our models. In models not reported here, we regressed log emissions on dummies for each year in our analysis and observed that the dummies indicate an approximately linear decline in ratings, which suggests that a linear time variable is acceptable. In addition, in models not reported here, we also included a variable for the number of years a firm had been rated. Results are robust to the inclusion of this variable.
7. A Wald test indicates that the size of the coefficients on firms rated good/mixed/neutral and poor do not significantly differ from one another ($F = .80$; d.f. = 1, 251; $p = .37$).
8. We ran a Wald test to determine whether the percent of peers rated was associated with a greater emissions reduction for firms rated poor than for firms rated good/mixed/neutral, as suggested by the coefficients on the interaction terms ($\beta_{\text{poor}} = -.151$ versus $\beta_{\text{good/mixed/neutral}} = -.088$). Based on these results, we were unable to reject the null hypothesis that the coefficients are equal ($F = .85$; d.f. = 1, 251; $p = .36$).
9. We also ran separate regressions on subsamples of firms in high- and low-competition industries. We opted to present the models with three-way interactions because they are more efficient than subsample splits (Brambor, Clark, and Golder 2006), although they are somewhat more difficult to interpret. To ease interpretation, we present graphs of the effects, which we created using the "margins" command in Stata 13.
10. The positive and significant coefficient on the interaction of high competition and rated poor suggests firms rated poor with the mean level of peers actually increase their emissions relative to unrated firms when they are in more competitive markets. This result is somewhat inconsistent with the idea that ratings "discipline" organizations to align their behavior with what is valued by ratings systems (Sauder and Espeland 2009). However, one plausible explanation is that in more competitive environments, firms rated poor have made a strategic decision to focus on market outcomes at the expense of environmental considerations.
11. For this calculation, we tested whether the sum, ($\beta_{\text{percent peers rated}} + \beta_{\text{percent peers rated x rated poor}} + \beta_{\text{high competition x percent peers rated}} + \beta_{\text{high competition x percent peers rated x rated poor}}$), is significantly different from zero.
12. We generated these figures using the "margins" command in Stata 13 with all control variables held at their means.

13. For this calculation, we tested whether the sum, ($\beta_{\text{percent peers rated}} + \beta_{\text{percent peers rated x rated good/mixed/neutral}} + \beta_{\text{high competition x percent peers rated}} + \beta_{\text{high competition x percent peers rated x rated good/mixed/neutral}}$), is significantly different from zero.
14. For this calculation, we tested whether the sum, ($\beta_{\text{percent peers rated}} + \beta_{\text{percent peers rated x rated poor}} + \beta_{\text{high regulation x percent peers rated}} + \beta_{\text{high regulation x percent peers rated x rated poor}}$), is significantly different from zero.
15. According to the EPA website, facility size is a major driver of inspections. Given that the average size of facilities in a given state is likely to change relatively slowly, using the 2009 inspection data should not be a concern.
16. A cynical view might suggest firms would not respond at all to ratings under such a scenario, consistent with the idea that responses to ratings are driven entirely by extrinsic motivations. However, ratings might provide intrinsic motivations to firms, leading to a response even where external penalties are unlikely. Future work might fruitfully explore this question.

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