Boardroom Networks and Political Ideology in Shaping Firms' Environmental Strategies

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Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

I declare that the third chapter is joint work with Dakshina G. De Silva and Aurelie Slechten and the fourth chapter is joint work with Dakshina G. De Silva, Anita Schiller and Aurelie Slechten, while other chapters of this thesis have been composed solely by myself.

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Abstract

This thesis aims to study how firms' environmental strategies are shaped with a focus on board directors. For this study, I compile the Database on Director Network, Toxic Releases and Political Activities and use toxic releases from the US Environmental Protection Agency (EPA)'s Toxics Release Inventory (TRI) Program as the key environmental performance indicator. By using the database compiled, I first study how director networks are formed. My findings show that firms are likely to appoint influential directors with good environmental performances. Further, directors with environmental characteristics similar to the other board members or their firm are more likely to be chosen as board members. I also show that boards of directors with good environmental performances or in which directors have diverse environmental performance backgrounds will improve firms' environmental quality.

Then I examine the effect of political ideology in shaping firms' environmental strategies. My results show that although political ideology is less significant in determining a firm's environmental strategy than board directors' previous environmental performance records, Republican-leaning firms have poorer environmental performances. To address the endogenous concerns, I also follow a similar approach to study network formation with the inclusion of politics-related measures and find firms also tend to appoint directors who share similar political ideologies. These findings help to explain the political polarization in the private sector from a network formation aspect and provide further evidence of the role of political ideology in shaping environmental strategies.

Keywords: Network Formation, Firm Organization, Toxic Release, Board of directors, Political Processes

JEL Classification: D85, L21, Q5, D72

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Chapter 1

Introduction

1.1 The Transition to a Green Economy

We are seeing increasing actions from both the public and private sectors to tackle environmental issues and promote sustainable growth. For example, in the public sector, 195 members of the United Nations Framework Convention on Climate Change signed the Paris Agreement. The goal of this Agreement is to limit global warming to well below 2 degrees Celsius, compared to pre-industrial levels.[1] Meanwhile, in the private sector, there is an increasing investment in sustainability related fields. The auto industry has invested more than $400 billion over the past decade in transitioning to a net-zero economy.[2] The financial sector has formed the Net Zero Asset Managers initiative (NZAM) and the Glasgow Financial Alliance for Net Zero (GFANZ) to accelerate the decarbonization of the economy.[3] Further, the very recent science breakthrough in nuclear fusion reaction boosts the hope for limitless, zero-carbon power (Financial Times, 2022d).

However, there are setbacks as well. Increasing political polarization has attributed a decline in support for environmental protection. In the United States, political divisions around climate have grown over the past 30 years (Dunlap and McCright, 2008). For example, just over 30 years ago, Clean Air Act Amendments of 1990 was passed with overwhelming bipartisan majorities and the current Senate minority leader, Mitch McConnell, was among those voting Yea.[4] However, in 2022, the Inflation Reduction Act, which is

[1] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

[2] https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/mobilitys-net-zero-transition-a-look-at-opportunities-and-risks

[3] NZAM: https://www.netzeroassetmanagers.org, GFANZ: https://www.gfanzero.com.

[4] The voting record can be found on https://www.senate.gov/legislative/LIS/roll_call_votes/vote1012/vote_101_2_00055.htm.

mainly a climate bill, was passed by only Democratic votes without a single vote from the Republican party.[5] Further, the Republican party has been increasingly criticizing the sustainability-considered investment approaches taken by asset managers like BlackRock and accusing them to prioritize climate "activism" over fiduciary duty (Financial Times, 2022a,b,i). Their efforts have pressured the world second-largest asset manager, Vanguard, to quit NZAM (Financial Times, 2022h). In addition, the Florida Republican Governor Ron DeSantis has pulled $2bn worth of assets from BlackRock marked as the largest anti-ESG divestment by any Republican state (Daily Main, 2022a). The Republicans are also introducing legislation that would prevent federal agencies from requiring applicants to disclose their greenhouse gas emissions (Daily Main, 2022b). Meanwhile, media coverage of environmental issues has also become increasingly politicized and polarized, whereby more political actors are featured and scientific actors less so (Chinn et al., 2020). More unfortunately, the ongoing Russo-Ukrainian War has caused an energy crisis. The International Energy Agency (IEA) predicts that the war will accelerate a peak in the world's consumption of fossil fuel (Financial Times, 2022f). High energy prices have attracted more investment in fossil fuels (Financial Times, 2022e) and slowed down the ESG transition (Financial Times, 2022c).

1.2 Importance of this Thesis

This thesis studies how a firm's environmental policy is shaped in the context of board director networks. Hillman and Dalziel (2003) suggest board directors have two functions, one is to monitor management (agency theory based), the other is to facilitate access to external information and resources (resource dependence theory based). This study covers both functions on shaping environmental strategies by studying the direct effect of directors' environmental records as well as the external influence brought from their professional networks.

Environmental economics has become a major subdiscipline of economics since early 1960s.[6] There have been extensive studies on the effect of board composition/characteristics on firm environmental performance. These board characteristics include board indepen-

[5] The text of the Inflation Reduction Act can be found on `https://www.congress.gov/bill/117th-congress/house-bill/5376/text`; the Act's voting record can be found on `https://www.senate.gov/legislative/LIS/roll_call_votes/vote1172/vote_117_2_00325.htm`.

[6] See Pearce (2002) for a history of environmental economics.

dence, board size, gender diversity, and many others.[7] In comparison, the study on individual board directors' characteristics, especially environment-related characteristics, is relatively limited. Some literature has studied the effect of board directors with legal expertise on firms' environment-related regulation violation (e.g. Hillman et al. (2000)). And some has studied the experience of serving in an environment related committee (e.g. Walls et al. (2012)). Compared with the existing literature, this thesis creates a quantitative and dynamic measure for individual directors' environment-related expertise based on the performances of their employers.

In addition, as a director is expected to bring in external information and resources, her/his professional network should contribute to her/his qualification as a board director (Larcker et al., 2010) and have an impact on firm environmental policy (Homroy and Slechten, 2019). There has been literature showing director network can influence corporate governance (e.g. Bizjak et al. (2009), Armstrong and Larcker (2009), and Fich and Shivdasani (2012)). However, the study of director professional network on firm environmental performance is limited. The existing literature has largely focused on director interlocks when studying director professional networks (e.g. Davis (1996), Kang (2008), and Homroy and Slechten (2019)). While this thesis aims to capture spillover effects on environmental performances from more distanced connections on environmental performances by mapping networks covering all possible firms in North America. Moreover, with the network setup, I am able to study how director networks are formed, particularly the role of environmental expertise played in this process. To my best knowledge, this is the first to study the effect of environmental performances in appointing directors.

Further, there has extensive literature pointing out environmental issues have been increasingly politicized and polarized (e.g. Buttel and Flinn (1978), Longo and Baker (2014), and Harring and Sohlberg (2017)). Firms' environmental performances are affected by their political ideology (e.g. Gupta et al. (2019) and Semadeni et al. (2022)) which can be observed via political donations (Gupta et al., 2017). However, there are multiple motivations behind political donations (Fisher, 1994). The existing literature has developed two major views on political donation motivations: consumption view (Verba et al., 1995) and investment view (Tobin, 1958; Hall and Wayman, 1990). Consumption

[7] For example, Ibrahim and Angelidis (1995) and McKendall et al. (1999) study board independence, Kassinis and Vafeas (2002) study board size, and Liao et al. (2015) study gender diversity.

view suggests that political donations are merely means by which citizens express their political opinions, while investment view suggests donation decisions are made strategically to gain interests potentially including undemocratic influence. There have been studies trying to disentangle the motives of donors (e.g. Schnattschneider (1960), Aranson and Hinich (1979), and Jensen and Murphy (1990)), some have claimed consumption view is superior (e.g. Ansolabehere et al. (2003) and Gordon et al. (2007)) while some provide evidence indicating firms use political donations to reduce regulatory risk (e.g. Adams and Hardwick (1998), Hassan et al. (2019)). This thesis uses toxic releases as the key environmental performance measure from the Toxics Release Inventory (TRI) Program. The TRI Program has been generally consistent since it begun and involves no penalty relating to pollution; therefore, the private sector does not have incentive to use political donations to influence the Program. This provides a unique opportunity to focus on the effect of political ideology on firm environmental performance.

1.3 Objective of this Thesis

The objective of this thesis is to explore how a firm's environmental strategy is shaped in the context of board director professional network. I first compile a comprehensive database that includes the information necessary for this study. Then I try to answer the following three questions using the database: 1) how board directors are appointed, with a focus on their previous environmental performance records; 2) how directors' past environmental records influence their firms' environmental performances; and 3) what the role of political ideology in determining firms' environmental performances is. Answering these three questions helps to understand how firms internalize environmental issues and produces policy implications regarding how to accelerate transitioning to a clean economy.

1.4 Results of the Study

The third chapter, "Director appointments, boardroom networks, and firm environmental performance", examines the role of directors' environmental performance records in their appointments and their firms' environmental performances. The results indicate that firms do not only like to appoint directors who share more similarities, but also like to appoint influential directors with good environmental performances. Further, directors with good environmental records tend to help their firms to improve environmental performances. As a result, the action of appointing directors with good environmental records helps to improve firms' environmental performances. Finally, even when firms do not change their board directors, board directors can bring positive effects when they are connecting to other firms with better environmental performances.

The fourth chapter, "Board Networks, Corporate Political Donations, and Environmental Performance", examines the effect of political ideology in shaping firms' environmental strategies. The results indicate Republican-leaning firms tend to release more toxic chemicals to the environment. Further, I examine the role of political ideology in director appointment and find firms are more likely to appoint directors who share similar political ideology. This finding helps to explain the political polarization in the business sector. Finally, my findings from Chapter 3 are shown consistent that directors' previous environmental records have significant impacts on their appointments and their firms' environmental performances.

1.5 Structure of this Thesis

The thesis is organized as follows. The next chapter, "Database on Director Network, Toxic Releases and Politics", presents how the datasets used in this thesis are compiled. In the third chapter, "Director appointments, boardroom networks, and firm environmental performance", I study the effects of directors' environmental performance records on director appointments and firm environmental performance. The fourth chapter, "Board Networks, Corporate Political Donations, and Environmental Performance", extends the study in the third chapter by considering how political ideology affect firm environmental performance. In the final chapter, I conclude my findings, provide policy implications, and lay out future studies relating to this thesis.

Chapter 2

Database on Director Network, Toxic Releases and Politics

2.1 Introduction

This chapter shows the process of compiling a comprehensive database to study how board directors develop their environment-related experiences and help to shape their firms' environmental strategies. To compile such dataset, I carefully choose these six independent databases: 1) The US Environmental Protection Agency (EPA)'s Toxics Release Inventory (TRI) Program, 2) the BoardEx database, 3) the US Census data, 4) Bonica (2016b)'s Database on Ideology, Money in Politics, and Elections: Public version 2.0 (DIME), 5) the data for the US Senate, House and Presidential elections' results from MIT Election Data and Science Lab (Data and Lab, 2017b,a, 2018), and 6) institutional holding information and ESG scores obtained via Refinitiv's Eikon.

This thesis uses toxic chemical releases and management as key indicators for firms' environmental performances from the TRI Program. Besides toxic releases are a direct, quantitative and objective measure for environmental performance, there are three major benefits. The first benefit is the TRI Program produces a more complete database. The TRI Program requires all facilities in the United States to report their toxic chemical releases and management if they meet certain criteria.[1] Therefore, the TRI dataset provides complete and continuous information of the US businesses regarding their chemical-related environmental performances, while some other datasets (e.g. CDP full GHG emission dataset) only focus on certain groups of firms (e.g. publicly listed companies). Further, having facility-level data provides a valuable benefit of controlling for many local factors

[1] More information is provided in Section 2.2.1.

that are difficult or impossible to observe. This is very important especially when studying environmental issues in the US, because facilities are subject to the rules and regulations at the federal, state, and local levels.

Second, analyzing the effect of political ideology on toxic chemical releases can show how political polarization has divided people on environmental issues, given toxic chemical pollution was once a uniting issue. The TRI Program was established by the Emergency Planning and Community Right-to-Know Act (EPCRA). The EPCRA was created, in response to the two dreadful chemical release accidents in mid-1980s, to protect public health, safety, and the environment from chemical hazards.[2] This act was passed by the Congress with 413 votes to 0, then by the Senate with 86 votes to 13, and finally signed into law by a Republican President Ronald Reagan in 1986.[3]

The third and final major benefit is the TRI Program produces a unique opportunity to focus on the effect of political ideology on environmental performance. This thesis uses political donations to indicate firm political ideology. As mentioned previously, there are consumption view and investment view on the motivations behind political donations and it is difficult to distinguish them. However, there is not enough economic motivation to target the TRI Program specifically because the TRI Program has been consistent in general (De Silva et al., 2021) and does not involve any penalty as long as firms report their toxic releases as requested. Therefore, we can focus on the effect of political ideology by excluding the possibility of relationship between toxic releases and a firm's investment-driven motive.

The BoardEx database is chosen to capture characteristics and networks of board directors, because board directors are expected to play a more significant role in shaping their firms' environmental strategies. In the United Kingdom, the Company Act 2006 first introduced a new duty on directors to "have regard to [among other things] the impact of the firm's operations on the community and the environment". More recently, in 2021, two directors of Exxon-Mobil were removed by an activist investor, Engine No. 1, regarding

[2]In 1984, a Union Carbide plant in Bhopal (India) released approximately 40 tons of Methyl Isocyanate (MIC, a lethal chemical used in manufacturing pesticides) into the air, the gas diffused and eventually killed, by some estimates, 5,000 people and injured 500,000 more. Half a year later, in 1985, in the United States, 500 gallons of aldicarb oxime and highly toxic MIC was leaked from another plant of Union Carbide. Although this accident did not kill any one, 134 locals were treated at hospitals.

[3]The Act's voting record can be found on `https://www.congress.gov/bill/99th-congress/house-bill/2005/actions`.

the oil firm's climate strategy (CNN, 2021).

The BoardEx data provides a precious opportunity to map director professional networks. The database records all possible information about firms and their directors that can be obtained from credible sources. By taking advantage of this database, I am able to create a network that covers a large number of firms and their directors in the US for each year. The existing literature has largely studied the effect of board composition on firm environmental performance(e.g. De Villiers et al. (2011)), while the studies on the effect of director networks on environmental performance are rather limited and largely focus on interlocks (shared directorship)(e.g. Homroy and Slechten (2019)). The networks produced from the BoardEx data enable me to study the influence on environmental performance from a more complete network perspective. Further, since the director networks are changing over time, I am able to study how director professional networks are formed.

Moreover, the BoardEx dataset includes individuals' positions in their firms, their compensations, education background, gender and other characteristics. Many of these characteristics can play crucial roles in shaping firms' environmental strategies. For example, Elmagrhi et al. (2019) focus on the role of female directors in shaping firms' environmental policies. Some of these characteristics are not used in this thesis, but can be potentially useful for future research. In addition, the BoardEx database provides key information of firms that can be useful to obtain information from other sources. For example, BoardEx provides publicly listed firms' stock tickers which allow me to extract their information of U.S. Securities and Exchange Commission (SEC) filings, Environmental, Social and Governance (ESG) scores via third party platforms (e.g. Yahoo Finance, Eikon).[4]

The DIME by Bonica (2016b) provides political donation information of individuals and organizations based on the Federal Election Commission (FEC) register data. Environmental issues have been increasingly politicized and polarized (Chinn et al., 2020), and become a left-right political issue (Harring and Sohlberg, 2017; Dunlap, 2019). Politicians' political ideology can be easily identified by their parties and their public speeches. However, for individuals in the private sector, we can only observe their ideology based on their voting patterns as well as political donations. We do not know how each individual vote; therefore, we have to rely on political donation records to identify their political

[4]SEC filings include shareholding structures, merge and acquisitions, director appointments and etc.

ideology. In the US, any political donation that exceeds $200 has to be reported to the FEC. The DIME is a cleaned and standardized version of the FEC data, so using the DIME can save time on data pre-processing.

Besides these three key datasets, I also include other datasets that include factors that affect firms' environmental performances. The US Census data is included to control for facilities' geographic and demographic information which has been shown to have impacts on environmental performance by De Silva et al. (2016, 2021). I also obtain ESG scores for firms included in the TRI dataset. The ESG scores are drawing more attention and used as key indicators for examining firm social responsibility performances including environmental performance. An increasing number of institutional investors have adopted ESG investing practices.[5] Both Yahoo Finance and Eikon provide ESG scores for listed firms, I use ESG scores from Eikon because it provides ESG scores for more listed firms for more years.[6] Besides, I also use Eikon to acquire institutional holding information for listed firms, which has been shown to play a role in shaping companies' environmental strategies (Ilhan et al., 2019; Krueger et al., 2020; Naaraayanan et al., 2021). In addition, the data from Data and Lab (2017a,b, 2018) providing the US House, Senate and Presidential election results are included to identify political ideology of facilities' local population.

This chapter is organized as follows. Section 2 lays out different sources of data with their descriptions and summary statistics. In Section 3, I show how I compile the databases used in this thesis. And finally, I conclude this chapter by explaining how the compiled databases help this study and other relevant studies in Section 4.

2.2 Sources of Data

This sector presents descriptions and summary statistics of the original sources of data used in this thesis.

[5] `https://www.pwc.co.uk/financial-services/assets/pdf/esg-transformation-july-2021.pdf`

[6] ESG scores from Yahoo Finance are from Sustainlytics, a global provider of ESG information for publicly listed firms; ESG scores obtained via Eikon are from Thomas Reuters.

2.2.1 The TRI Program

The US EPA's TRI program was established by Section 313 of the EPCRA.[7] It is a resource where policy makers, firms, local communities can learn about toxic chemical releases and management reported by private and federal facilities. The TRI Program is mandatory that any facility in the US has to report to the TRI Program if it meets all the following three criteria. The first criterion is the facility should belong to an industry sector that is covered by the TRI Program. Second, the facility should employ 10 or more full-time or equivalent employees. The third criterion is the facility should manufacture, process, or otherwise use a TRI-listed chemical in the quantities above the threshold levels for the given year. Once they meet all three criteria, facilities have to report each TRI-listed chemical it manufactures, processes, or otherwise use in quantities above the reporting threshold to the TRI Program by July 1 of each year. Non-compliance may lead to civil penalties, including monetary fines and may also require correction of the violation. The TRI Program currently covers 770 individual chemicals that typically have severe adverse effects on human health and the environment.

Facilities have to report the amounts of production-related toxic chemical waste released (to air, water, and/or land) and managed (through energy recovery, recycling and/or treatment).[8] Energy recovery, recycling and treatment (RRT) are waste management practices that are environmentally friendly and preferable to releasing to the environment. In the TRI dataset, the amount of toxic waste (released or managed) is recorded as toxicity in pounds (regardless of the chemical) to facilitate the comparison between different toxic chemicals.

Tables 2.1, 2.2 and 2.3 provide summary statistics for the TRI data between 2000 and 2017.[9] In Table 2.1, a *polluting facility* is defined as a facility reporting a release of toxic chemicals to the TRI Program. There are 19,915 unique firms with 42,212 facilities that a firm has an average of 2.24 facilities. In the TRI data, a facility has an average probability of 53.2% to report a release and the average proportion of polluting facilities per firm is 43.4%. The average amount of toxic waste released by a facility is 124,680 pounds, while the amount of toxic wastes managed through RRT is 618,934 pounds. Approximately

[7] `https://www.epa.gov/toxics-release-inventory-tri-program`

[8] The definition of these terms is given on the EPA website: `https://www.epa.gov/toxics-release-inventory-tri-program/common-tri-terms`.

[9] The 2017 TRI data was the most recent available data when this study started.

80% of the facilities released toxic chemicals at least once over the sample period. Table 2.2 provides a yearly breakdown of the unique number of facilities and firms along with toxic chemicals released and managed. We can see that the numbers of firms and facilities for each year do not change significantly over time. On average, there are about 35,000 facilities per year. Further, it presents a trend that facilities' environmental performances are improving over time. The amount of toxic releases per facility is decreasing and the amount of toxic chemicals manged through RRT per facility is increasing over time in general. Table 2.3 presents summary statistics based on industrial sectors. The chemical industry has the most facilities and firms, and the publishing industry has the least facilities and firms. The most polluting industry based on total releases is metal mining, while the publishing industry is the cleanest sector among the industries covered by the TRI Program.

2.2.2 BoardEx

BoardEx is a global data firm that specializes in relationship capital management.[10] Its relationship capital management database contains more than 2 million profiles of public, private, and non-for-profit organizations and more than 1.5 million individuals around the globe.[11] All BoardEx data are collected from credible sources. These sources are company websites, annual reports and accounts, public filings (if the company is publicly listed) and select news outlets.[12] In this study, I use the North America BoardEx dataset to identify relationships between firms and directors. This dataset not only allows me to build the networks for US firms and directors, but also captures part of the international director networks since some multinational firms conduct business activities in North America. BoardEx contains very rich information of firms' personnel information. It has information about historical, current and upcoming board directors and executives along with their positions, job titles, start and end dates.

Tables 2.4 and 2.5 present summary statistics for the North America BoardEx database. Between 2000 and 2017, there are 119,607 unique directors in 157,997 unique firms. A firm has an average of approximately 2.5 directors. This average is lower than expected,

[10]BoardEx database is not publicly available and the license is obtained by Lancaster University Management School.

[11]`https://www.boardex.com/`

[12]More information regarding BoardEx's data quality can be found on `https://www.boardex.com/data-quality/`.

because the BoardEx database includes director information for both private firms and publicly listed firms. Unlike publicly listed firms who have the obligation to report any board change, private firms do not necessarily make their board change available. Furthermore, since BoardEx only gather information from credible sources, the availability of private firms' information becomes further limited. While, the publicly listed firms have an average number of 9.128 directors.[13]

Using the information provided by the North America BoardEx database, I build a network in which directors and firms are treated as nodes and a firm's appointment of a board member represents the establishment of a link connecting the given director and firm. Figures 2.1 and 2.2 show samples of sub-networks for three chosen directors colored in red. Firms are colored in yellow and other directors are colored in blue. Figure 2.1 only show nodes (i.e. directors and firms) which are no further than two edges away from the three chosen directors. After adding more distanced nodes in the graph by increasing the distance from 2 to 4 as shown in Figure 2.2, the size of the sub-network grows exponentially that the number of nodes increases by $1,316$ and the number of edges increases by $1,815$.

Table 2.5 presents the unique number of firms and directors by year. It also shows that the number of firms and directors included in the BoardEx database is increasing over time. Despite the increase in the number of firms, the average number of directors per firm decreases over the years. This indicates directors are serving on more boards and firms are likely to become more connected. I use eigenvector centrality to capture director- and firm-level network influence. Eigenvector is a centrality measure that takes into account the centrality of a node's first-degree connections. It is, therefore, based on the pattern of the entire network. A value of one for the eigenvector centrality measure represents the most influence node in the entire network at a given time. Those nodes with scores of zero are isolated nodes (i.e. not connected to any other firm or director).

Further, since BoardEx provides detailed information on firms' board committees and executives, I am able to enrich board directors' records. I first identify whether a director has been serving as a CEO in another firm or not by searching her/his BoardEx ID in the BoardEx executive dataset. Then I identify directors serving on those board committees

[13]This number is very close to the average board size obtained in Coles et al. (2008).

that have an environment/pollution control focus. An “environmental committee” is defined as a committee whose name contains any of the following keywords: “environment”, “sustain”, “responsibility”, and “social”. The variable, *proportion of directors in environmental committees*, is defined as the proportion of board directors of firm j serving on at least one environmental board committee (either in firm j or any other firm). I also compute directors’ market exposure (i.e. the number of years they appear in BoardEx). On average, a director’s market exposure is about 10.6 years while s/he tends to stay in a firm for around 5.6 year.

2.2.3 The US Census data

The US Census tract information is published by the United States Census Bureau. Census tracts are relatively small and permanent statistical subdivisions of a county during a 10-year census period. The minimum population of a tract is $1,200$ and the maximum is $8,000$. As this database covers a period of more than one census period, I consider 2010 locations as fixed geographic locations. The US Census data include information regarding population, minority ratio (non-white population ratio), population who has received higher education (college degree), and median household income since 2007. I also include tracts’ population density information along with their Social Vulnerability Index provided by Agency for Toxic Substances and Disease Registry.[14]

Prior to 2007, the census data did not have estimated information for the 2010 locations. Following a similar approach used by De Silva et al. (2016) and De Silva et al. (2021), I linearly impute and estimate the missing values for population density, minority ratio, higher education ratio and median household income between 2000 and 2008. Table 2.6 reports the summary statistics for the US Census data after imputation. There are $73,082$ unique tracts based on 2010 Census data and each has an average population of $4,134$ and an average number of $1,039$ households. The average US median household income for a tract is $\$64,272$, the average higher education ratio is 25.6%, the average minority ratio is 24.4%, and the average population density is $5,165$ people per square mile.

There are some tracts in the US Census that include military installations and do not report any information. These tracts are identified as special tracts and there are 961

[14]The provided population density values are calculated based on the US Census data.

such tracts (as shown in Table 2.6). Further, based on tracts' geo-codes, I identify tracts that are located along the Canadian and Mexican borders and tracts that are located in a Metropolitan Statistical Area (MSA), in urban counties, rural counties, and coastal counties. As shown in Table 2.6, there are 60,909 tracts located in MSA counties, 10,569 tracts located in urban counties, 1,604 tracts located in rural counties, and 20,628 tracts in coastal counties, while 1,521 tracts border with Mexico and 2,933 tracts border with Canada.

2.2.4 DIME

The Database on Ideology, Money in Politics, and Election Public Version 2.0 (DIME) was compiled by Bonica (2016b) and contains political donation information for organizations and firms. The DIME is based on the FEC register data and was developed as part of the project on Ideology in the Political Marketplace by Bonica (2014).[15]

In the United States, any individual contribution transaction of more than $200 to individual candidates, parties, campaign and political action committees (PACs) is required to be registered with the FEC. The DIME has cleaned and standardized names, addresses, occupation and employer titles and assigned unique identifiers for all individual and organizational donors. The DIME also includes the common-space CF-scores created by Bonica (2014) for political ideology comparisons. CF-score ranges from -2 to 2. A positive value represents a Republican-leaning donor or recipient, a negative value represents a Democrat-leaning donor or recipient, and 0 indicates being politically unaffiliated. The database has CF-scores measured for 70,871 candidates and 12,271 political committees as recipients and 14.7 million individuals and 1.7 million organizations as donors.

Although the time span of the DIME is from 1979 to 2014, I only use the political donation data between 2000 and 2014 due to the consideration of complete information. After excluding data before 2000 and after 2014, the DIME contains 14,318,211 while there are 8,676 unique organizations and 14,309,535 unique individuals. Table 2.7 is a data summary for organizational donation and Table 2.8 summarizes donation information for individual donors. On average, organizations contribute more money to the Democratic party than to the Republican party while individuals donate more to the Republican party.

[15] https://ssdsdata.sites.stanford.edu/dime

In addition, organizations make larger political contributions than individuals that the average amount of organizational donation per year is $5, 267.68 and the average amount of individual donation per year is $315.64.

2.2.5 Other databases

I have also added some additional databases to provide extra information regarding political environment and environmental performance. The Environmental, Social and Governance (ESG) scoring system has been drawing lots of public attention and adopted widely by financial institutions. In this study, I gather ESG scores made by Thomas Reuters via Refinitiv's Eikon for additional environmental performance measures.[16] Refinitiv is a subsidiary of London Stock Exchange Group. It is one of the world's largest providers of financial markets data and infrastructure and its product Eikon is an open-technology solution providing access to industry-leading data, insights, and exclusive and trusted news.[17] ESG scores are only available for publicly listed firms in our database since 2002 and some publicly listed firms may have been evaluated under the ESG scoring system later than others. Thomas Reuters ESG scores measure companies' ESG performance based on 10 different ESG topics that there are three environmental categories, four social categories and three governance categories. I include individual Environmental pillar scores, Resource Use pillar scores, Social pillar scores and Governance pillar scores for all available companies along with their overall ESG pillar scores. Resource Use is one of the three environmental categories. The other two environmental categories are Emissions and Innovation which are less relevant in this study. ESG pillar scores are all calculated based on the aggregate of all the relevant critical category scores.

Besides publicly listed firms' ESG scores, I also include their institutional holding information via Eikon. There are two major holding types - "Holdings by Institutions", and "Holdings by Strategic Entities". There are 517 unique companies' holding information from 2000 to 2017.[18] Strategic entities can be companies, holding companies and/or individuals who do not buy stakes (shares) for investment management purposes, rather strategic stakes (e.g. concentrated stock position or substantial equity position for enhancing acquisition, hedge, yield enhancement). Within the category, "Holdings by Strategic

[16] The license is provided by Lancaster University Management School

[17] https://www.refinitiv.com/en/products/eikon-trading-software

[18] Similarly, these firms do not necessarily have complete information for the entire period.

Entities", there are five sub-categories, "Holdings by Government Agency", "Holdings by Holding Companies", "Holdings by Corporations", "Holdings by individual investors", and "Holdings by Other Insider Investors". Within the category, "Holding by institutions", there are two sub-categories, "Investment Managers" and "Brokerage Firms". Brokerage firms include research firms and independent research firms. Investment managers include 15 types: bank and trust, endowment fund, finance company, foundation, government agency - investment advisor, hedge fund, investment advisor, insurance company, pension fund, private equity, venture capital, investment advisor/hedge fund, sovereign wealth fund, investment management company and miscellaneous investment manager. There is a quarterly record for each firm's holding information in the database and I take the average values for each given year.

To capture the external political environment, I include county level voting results for US presidential, senate and house elections from Data and Lab (2017a,b, 2018). In this paper, I use presidential election results as the main indicator of a county's political ideology position. If a county votes for a Republican presidential candidate, this county is considered as a Republican-leaning county for the 4 year presidential election cycle. And vice versa, a county is considered to be a Democratic-leaning county if it votes for a Democratic presidential candidate. The other two election results are included in our data as additional information that may be helpful for further study into local political ideology.

2.3 Data compiling

2.3.1 Database on Director Network and Toxic Releases (DNT)

The datasets described in the previous section have different structures. The first step of the matching procedure consists in restructuring the BoardEx dataset. In this dataset, data are arranged at firm-director level: a given director is recorded under her/his employer along with her/his start and end dates in a given firm. To match with the format of other datasets, I transfer the data structure to firm-director-year. There is no need to restructure other datasets, since their data are already recorded on an annual basis.

Then, I obtain board information of facilities' parent firms from the BoardEx database. Since these two databases are created by various institutions and authors, firms do not have unified ID numbers across the two databases and can be recorded under different names. I start with matching BoardEx firms with TRI facilities' parent firms by their names. When firms share the same firm names, I treat them as the same firms. However, this method is only able to match small proportions of the two datasets. In order to improve the matching accuracy, I conduct further research on firms' other official information from their websites and government registers. The additional information enables me to match firms by their names, board structures, key personnel, addresses, merge and acquisition records, and etc. Using such method, I am able to obtain board information from the BoardEx data for a greater proportion of TRI facilities.

This approach also enables me to tackle three major challenges. First, firms can change their names. For example, 3M Co. was initially called as Minnesota Mining & Manufacturing Co. prior to 2002. Since there is no other company called as Minnesota Mining & Manufacturing Co. even after 2002, firms called as 3M Co., Minnesota Mining & Manufacturing Co. or other similar names are considered to be the same firm.[19] The second challenge is merging and acquisition (M&A) that BoardEx does not necessarily record M&A information. For example, the acquisition of Forest River Inc. by Berkshire Hathaway in 2005 is not recorded by BoardEx. Therefore, I need to rely on other sources to match facilities to correct owners after M&A.[20] In the example case of Forest River Inc., I match all facilities under Forest River Inc. to Berkshire Hathaway after 2005 even when some of them still report their parent company as Forest River Inc. The third challenge is to match subsidiaries to their parent firms. Some TRI facilities fail to report their correct parent firms, while BoardEx does not provide ownership structure for firms. Therefore, I need to conduct ownership structure research. Some cases can be easily identified by company names. For example, Volkswagen Group of America is controlled by Volkswagen AG. However, some cases are more complicated. For example, Union Underwear Co. Inc. is the subsidiary of Fruit of the Loom Ltd., while it is also the parent company of Russell Brands. In this case, I match all facilities owned by Union Underwear Co. Inc. and Russell Brands to Fruit of the Loom Ltd. After conducting further research, I am able to match 2,895 TRI-reporting firms controlling 19,099 facilities with at least one board director recorded by BoardEx from 2000 to 2017.

[19] Typos and abbreviations exist in both the TRI data and the BoardEx data.

[20] Other sources include relative newspaper articles, SEC filings and companies' websites.

The next step is to fill in the missing years based on a firm's (or director's) first and last appearance in both datasets. A firm may appear in one dataset but not in the other for a given year. For example, some private firms may not have continuous records of their board structure changes in the BoardEx dataset because they do not have the obligation to disclose their board information to the public. Also in the TRI data, facilities do not have to report to the TRI Program if they do not meet all the three criteria, so some facilities may not be recorded for some period of time when they do not fully meet the reporting criteria. This filling process is based on the rationale that, if a firm exists in one dataset for a given year, it should also exist in the other for that same year. After filling, I use the facilities' geo-codes to find their locations in the US Census tracts and obtain their local demographic and geographic information.[21] During this process, I drop any facility that is not located in the US mainland. Finally, I use the firms' stock tickers provided by BoardEx to obtain their Thomas Reuters ESG scores and institutional holding information via Refinitiv's Eikon.

Table 2.9 provides summary statistics for the DNT.[22] The DNT has 2,873 TRI-reporting firms with at least 1 board director. These firms account for approximately 46% of all TRI-reporting facilities and each firm has an average of 6.5 facilities. 2.3% of all facilities belong to a firm with an environmental board committee. The proportion of directors serving on an environmental committee in a given year is 2.7%. This dataset also includes 16,162 TRI firms without a board director which own 22,063 facilities.[23] This indicates that firms with board members tend to be larger firms comparing with firms without board members recorded by BoardEx. 37% of the TRI facilities with board information recorded belong to a publicly listed firm, while all publicly listed TRI firms have their board information from BoardEx because they have the obligation to disclose their board information. Further, 2.3% of the facilities belong to a firm with an environmental board committee and the proportion of directors serving on an environmental committee in a given year is 2.7%. All the TRI reporting facilities are located in 18,183 unique tracts out of the 73,082 tracts defined by the 2010 US Census.

[21] Population density is computed based on the total population obtained from the US Census and the tract area from the Social Vulnerability Index provided by Agency for Toxic Substances and Disease Registry.

[22] The table covers a period of 2001-2017. All explanatory variables in this study are lagged, facilities that are observed only once during the sample period are dropped. Some environmental performance measures will be defined in the third chapter.

[23] There are $40,900$ unique facilities run by $19,035$ firms in total. The numbers are lower, because facilities outside the US mainland are dropped and lagged values are taken.

2.3.2 Database on Director Network, Toxic Releases and Politics (DNTP)

I complement the DNT dataset with information from DIME. I first restructure the DIME by aggregating transactions based on year, donor and political party, because data are recorded at the donor-recipient transaction-level in the DIME. During this process, there are some outliers existing in the DIME. For example, ActBlue was recorded to make over 10 billion dollars in the DIME in 2012 and 2014. I correct such errors by cross-checking the donation records with OpenSecrets.[24]

After restructuring the DIME and correcting the outliers, I match corporate donors with their matched firms from the DNT. Firms are forbidden to make any direct contributions to political campaigns under the Federal Election Campaign Act. However, they are able to set up Separate Segregated Funds, or Connected Political Action Committees (PAC), led by a treasurer. The connected PAC may receive and solicit donations from a restricted class (normally managers and shareholders) and the administrative costs of such PAC are absorbed by the firm sponsoring the PAC. PAC contributions to political campaigns are overseen by top executives within the firm and its board directors.

Under such circumstance, I match firms with their connected PACs. I first match them by names. For example, American Crystal Sugar Co. Political Action Committee is matched to American Crystal Sugar Co. In the DIME, some connected PACs are simply recorded under their firms' names directly. For example, there are multiple corporate donors in the DIME called "3M Co." which are connected PACs sponsored by 3M Co. Then I follow a similar approach of compiling the DNT to find more matches that I conduct further search using their official websites, addresses, key business personnel, government documents and records.

In addition, I follow my previous rule that I match subsidiaries' connected PACs with their parents companies. For example, we match Metal Masters Foodservice Equipment Co., Inc. (which is a PAC) to its parent company, Eagle Group, Inc.. Matching subsidiaries to their parent firms enables me to better monitor foreign political activities in the US. There are some foreign firms using their American subsidiaries to make political

[24] `https://www.opensecrets.org`

donations in the US. For example, BAE Systems plc is a British multinational company and it is making political contributions in the US via its American subsidiaries. A more interesting example is Huawei, a firm blacklisted by the US government, was making political contributions in the US via its US entity, Huawei Technologies USA.[25]

Further, I also match executive PACs and leadership PACs, which are categorized as corporate donors in the DIME, with their firms, because these PACs have similar source of funds as the connected PACs. Following this rule, I am able to match donors like "Aetna CEO" with its sponsor firm, Aetna Inc. Some organizational/corporate donations are made by employee committees. There are mainly two kinds of employee committees. One kind is firm's employee committee, e.g. AT&T Inc. Employee PAC; and the other kind is industrial employee committee, e.g. Airline Pilots Association International PAC. Such PACs have different sources of funds compared with connected PACs and employees and their employers are separate entities who do not necessarily share the same interests or political agenda. Therefore, I do not match any form of employee committee to their employers.

After matching corporate donors, I then match individual donors. This process is simpler. The DIME records donors' first names, last names and employers. While the DNT records directors' and CEOs' first names, last names and employers as well.[26] Hence, I can simply match individual donors and CEOs with their matched records in the DNT based on their first names, last names and employers. Two individuals are matched only when their first names, last names and employers are all matched. I do not match individuals using their initials, because different directors from the same board have the likelihood to share same last names and initials especially when the firms are family owned.

Further, I obtain the house, senate and presidential election results from Data and Lab (2017a,b, 2018). The DNT already has the geo-code for tracts; therefore, I can use geo-codes to map tracts to their counties and find facilities' local election results accordingly. Local house, senate and presidential election results provide implications of the political agenda of local population. Among the three elections, presidential election result is the

[25]The official rule on the addition of Huawei to the Entity List can be found on `https://www.federalregister.gov/documents/2019/08/21/2019-17921/addition-of-certain-entities-to-the-entity-list-and-revision-of-entries-on-the-entity-list`

[26]Firms' CEO information is extracted directly from the original BoardEx dataset following a similar approach used in compiling the DNT.

one that best describes local political agenda as presidential election always draws the most attention and gains the most public exposure.

Table 2.10 provides summary statistics for the newly compiled DNTP.[27] The DNTP has 514,764 observations in total with 40,509 unique facilities owned by 18,787 firms, while there are 1,416 firms have more than 2 directors controlling 12,177 facilities between 2000 and 2014. At the firm level, firm and its board have a probability of 98.7% not to make any political donation at all on average; however, for firms with 3 or more directors, this probability drops to 83.8%. In my dataset, 0.6% of the firms are publicly listed, while 7.1% of the firms with 3 or more directors are publicly listed. Publicly listed firms have the obligation to disclose their board members and they tend to more directors than private firms. As larger firms tend to have more directors, firms with 3 or more directors control an average of over 10 facilities, comparing with the average of 2.245 in the entire DNTP. The average of firm's CF-score are 0.006, but this number increases to 0.071 in a subset of only firms with 3 or more directors. The average of CEO's CF-score is 0.0001 and the average of board's CF-score is 0.007; on the other hand, firms with 3 or more directors have an average of 0.0002 CEO's CF-score and an average of 0.049 board's CF-score. These differences are largely due to the assumption that individuals and firms are politically unaffiliated if they do not any record in the DIME (i.e. I fill their missing CF-scores with 0s).

At the facility level, the differences between facilities controlled by firms with any number of directors and facilities controlled by only firms with 3 or more directors are much smaller. Facilities in the entire dataset have a probability of 53.5% to pollute and facilities in the subset of only firms with 3 or more directors have a probability of 50.05% on average. The average toxic releases of facilities in the DNTP release 123,039.2 pounds while the average in the subset is 170,025.2 pounds. The average of total toxicity treated (RRT) by a facility is 592,915.9 pounds, comparing with 610,475.6 pounds in the subset. Further, there is no significant difference in facilities' demographic factors.

[27] Some politics related measures will be explained in the fourth chapter.

2.4 Conclusion

The Database on Director Network and Toxic Releases (DNT) and the Database on Director Network, Toxic Releases and Politics (DNTP) are two comprehensive datasets with rich information on firms, directors and facilities. The two datasets share same information on director networks, facilities' toxic releases, local demographic and geographic information for the period of 2000 to 2014. The DNTP contains additional information regarding firms', CEOs' and directors' political donation records and political ideology measures (i.e. CF-scores). However, due to the availability of political donation records provided by the DIME, the DNTP only covers the period up to 2014 while the DNT covers a longer period up to 2017.

These two datasets help to study how firms' environmental policies are shaped. In the third chapter, I will take advantage of the network structure provided by the DNT to study two questions. One is how a candidate's environmental performance and networks affect director appointment. The other is how a director's past environmental performance and network positioning affect her/his firm's chemical releases. Then in the fourth chapter, I will use the DNTP to study the role of political ideology in shaping firms' environmental policies by not only examining how a firm's political ideology affects its toxic releases but also studying how political ideology affects firms' director appointments.

However, there are some limitations in the data. The major limitation is data availability. BoardEx only collects data from a select range of sources. Therefore, information of gender, education background, and other key factors is not available for every individual in the database, while these factors have been proved by the existing literature to have impacts on environmental performances (e.g. Alazzani et al. (2017), Lu and Herremans (2019), and García Martín and Herrero (2020)).

Despite the limitations, the databases presented in this chapter will be useful beyond this dissertation. For example, I could extend the next chapter by using the DNT database to compare whether a clean or dirty director has a greater influence over her/his firm's environmental policy. Also, the DNTP can be used to study the role of networking in developing political ideology. In addition, since the two datasets cover rich information about firms' leadership (CEOs and directors), we can use them to compare the roles played by different leadership positions in shaping firms' environmental performances. Therefore, the databases have lots of potentials for studying topics surrounding environment, politics, and corporate management.

Figures

Figure 2.1: Directors' sub-network with a distance of 2

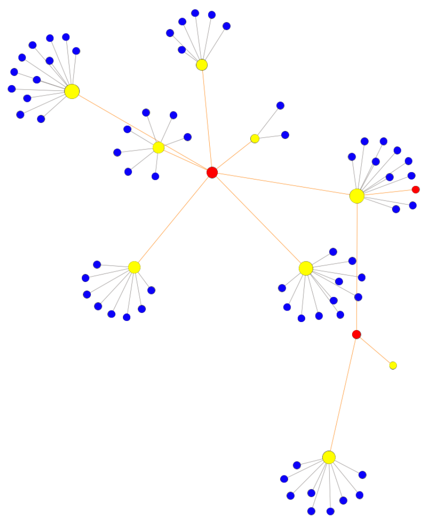
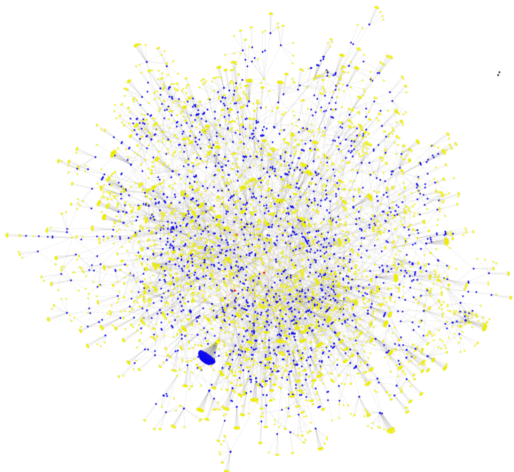


Figure 2.2: Directors' sub-network with a distance of 4



Tables

Table 2.1: TRI data summary statistics

Variable	Mean or count
Number of unique firms	19,915
Number of unique facilities	42,212
Average number of plants per firm	2.242
	(7.575)
Average toxic releases per facility (in thousands of pounds)	124.680
	(4,200.330)
Average RRT per facility (in thousands of pounds)	618.934
	(620.002)
Average proportion of polluting facilities per firm	0.434
	(0.301)
Average probability to report a release per facility	0.532
	(0.499)

Standard deviations are in parentheses.

Table 2.2: TRI data summary statistics by year

Year	Unique number of		Toxic releases per facility[a]	RRT per facility[a]
	Facilities	Firms		
2000	36,486	16,987	186.224	740.841
2001	36,209	16,739	158.446	594.913
2002	35,653	16,240	137.118	597.855
2003	35,405	15,969	129.340	584.572
2004	35,131	15,793	123.292	608.702
2005	35,019	15,591	127.551	578.923
2006	34,848	15,441	127.876	564.808
2007	34,647	15,286	122.698	567.309
2008	34,394	15,108	115.639	553.574
2009	33,853	14,905	101.518	500.511
2010	33,939	14,994	113.424	519.122
2011	33,808	14,952	122.743	545.603
2012	33,916	14,934	108.545	594.225
2013	33,908	14,944	123.510	606.455
2014	33,926	14,979	117.881	708.813
2015	33,958	14,953	102.088	702.357
2016	34,067	15,079	103.128	709.174
2017	34,394	15,194	115.684	794.873

[a] In thousands of pounds.

Table 2.3: TRI industry sector data summary statistics

Industry Sector	Unique number of		Toxic releases per facility[a]
	Firms	Facilities	
Apparel	16	21	2,231.71
Beverages	76	164	46,502.84
Chemical Wholesalers	259	812	1,858.80
Chemicals	3,002	5,925	98,599.44
Coal Mining	95	179	86,867.46
Computers and Electronic Products	1,360	2,191	4,362.11
Electric Utilities	329	888	1,008,985.10
Electrical Equipment	519	1,149	9,116.14
Fabricated Metals	3,326	5,515	18,232.35
Food	885	2,741	54,218.04
Furniture	384	646	17,865.09
Hazardous Waste	88	360	662,878.39
Leather	73	90	18,458.95
Machinery	1,028	2,119	5,422.72
Metal Mining	66	128	13,383,882.00
Miscellaneous Manufacturing	533	836	15,244.63
Nonmetallic Mineral Product	871	3,840	15,163.07
Other	376	1,237	58,112.79
Paper	345	755	396,704.74
Petroleum	376	1,161	137,381.63
Petroleum Bulk Terminals	318	1,024	3,436.34
Plastics and Rubber	1,598	2,627	29,018.49
Primary Metals	1,472	2,612	355,596.27
Printing	210	378	42,681.02
Publishing	15	18	373.39
Textile Product	58	112	3,332.00
Textiles	209	324	11,068.16
Tobacco	19	53	92,041.75
Transportation Equipment	1,271	2,647	31,907.57
Wood Products	610	1,352	17,537.35

[a] In thousands of pounds.

Table 2.4: BoardEx summary statistics

Variable	Mean or count
Number of unique firms	157,997
Number of unique directors	119,607
Average number of directors per firm	2.518
	(3.012)
Average number of firms per director	2.064
	(1.913)
Director is a CEO	0.113
	(0.316)
Director's average existing period in BoardEx	10.624
	(5.684)
Average term of a director in a firm	5.560
	(4.668)
Director's probability of being a board member in a polluting firm	0.049
	(0.217)

Standard deviations are in parentheses.

Table 2.5: BoardEx data summary statistics by year

Year	Number of unique firms	Number of unique directors
2000	46,239	52,367
2001	47,375	55,567
2002	47,894	57,855
2003	48,939	60,594
2004	50,881	63,765
2005	53,005	66,266
2006	54,905	68,805
2007	57,184	70,961
2008	58,180	72,171
2009	59,135	72,740
2010	60,921	73,799
2011	61,992	74,990
2012	63,259	76,454
2013	64,395	78,193
2014	65,146	79,719
2015	65,356	80,759
2016	64,503	80,969
2017	88,851	84,686

Table 2.6: U. S. Census tract summary statistics

Variable	Mean or count
Number of unique tracts (based on 2010 Census data)	73,082
Total population	4,133.523
	(1,878.227)
Population density (per square mile)	5,165.112
	(11,482.190)
Number of households	1,039.065
	(507.029)
Median household income	64,271.900
	(29,285.710)
College ratio	0.256
	(0.215)
Minority ratio	0.244
	(0.249)
Number of special tracts	961
Tract is located in a Mexico border County	1,521
Tract is located in a Canada border County	2,933
Tract is located in an MSA County	60,909
Tract is located in an urban County	10,569
Tract is located in a rural County	1,604
Tract is located in a costal County	20,628

Standard deviations are in parentheses.

Table 2.7: Organization Donation Summary Statistics 2000 - 2014

Variables	Mean or count
Number of observations	34,292
Number of recipients	8,676
Total donation made by one organization	5,267.68
	(126,845.60)
Total donation made to the Republican party by one organization	65,888
	(2,104,037)
Total donation made to the Democratic party by one organization	59,001.08
	(1,000,822)

Standard deviations are in parentheses.
Donations contain negative values representing political donation refunds.

Table 2.8: Individual Donation Summary Statistics 2000 - 2014

Variables	Mean or count
Number of observations	30,126,452
Number of recipients	14,309,535
Total donation made by one individual	315.64
	(6,686.63)
Total donation made to the Republican party by one individual	1,169.61
	(68,900.33)
Total donation made to the Democratic party by one individual	850.37
	(35,465.61)

Standard deviations are in parentheses.
Donations contain negative values representing political donation refunds.

Table 2.9: Database on Director Network and Toxic Releases (DNT): 2001-2017

Variables	All	With directors	Without directors
Panel A: Sample Counts			
Total number of observations (facility level)	582,722	288,277	294,445
Number of unique firms	19,035	2,873	16,162
Number of unique facilities	40,990	18,927	22,063
Number of unique directors	17,224	17,224	0
Number of unique tracts (with at least one facility)	18,183	11,172	12,550
Panel B: Firm-level Statistics			
Board's average pollution ratio	0.049	0.359	0
	(0.179)	(0.293)	
Range of the board's relative pollution degree centrality	0.041	0.435	0
	(0.174)	(0.399)	
Firm's influence (10^{-4})	0.051	0.306	0
	(5.292)	(13.014)	
Firm has an environmental committee	0.004	0.023	
	(0.062)	(0.150)	
Proportion of directors in environmental committees	0.005	0.027	
	(0.049)	(0.118)	
Panel C: Facility-level Statistics			
Probability of polluting	0.532	0.530	0.534
	(0.499)	(0.499)	(0.499)
Total toxic releases by facility (in thousands of pounds)	121.538	151.602	92.105
	(4,214.303)	(2,212.775)	(5,509.371)
Total RRT by facility (in thousands of pounds)	612.145	793.167	434.914
	(12,532.12)	(949.263)	(14,917.53)
Facility belongs to a listed firm	0.183	0.370	0
	(0.387)	(0.483)	
Panel D: Facility-level Demographic and Geographic Characteristics			
Median household income	56,484.18	56,559.55	56,410.39
	(23,104.16)	(23,293.22)	(22,917.36)
Minority ratio	0.231	0.232	0.229
	(0.238)	(0.237)	(0.239)
College ratio	0.194	0.195	0.192
	(0.172)	(0.175)	(0.168)
Population density	1,422.282	1,225.626	1,614.818
	(2,538.237)	(2,156.295)	(2,850.125)
Probability of locating in a special tract	0.014	0.016	0.012
	(0.117)	(0.127)	(0.107)
Probability of a plant located in an MSA County	0.760	0.751	0.769
	(0.427)	(0.432)	(0.421)
Probability of a plant located in an urban County	0.222	0.231	0.214
	(0.416)	(0.421)	(0.410)
Probability of a plant located in a costal County	0.173	0.175	0.171
	(0.378)	(0.380)	(0.376)
Probability of being located in a Mexico border County	0.010	0.010	0.009
	(0.096)	(0.099)	(0.093)
Probability of being located in a Canada border County	0.042	0.038	0.046
	(0.200)	(0.191)	(0.209)

Standard deviations are in parentheses.

Table 2.10: Database on Director Network, Toxic Releases and Politics (DNTP): 2001-2014

Variable	All firms	Firms with 3 or more directors
Panel A: Sample Counts		
Total number of observations (facility level)	514,764	138,677
Number of unique firms	18,787	1,416
Number of unique facilities	40,509	12,177
Panel B: Firm-level statistics		
No donation made	0.987	0.838
	(0.113)	(0.365)
Relative donation to the Republicans	0.009	0.103
	(0.080)	(0.260)
Board's average pollution ratio	0.049	0.469
	(0.179)	(0.303)
The range of the board's relative pollution degree centrality	0.041	0.610
	(0.173)	(0.316)
Diversity in directors' CF-scores	0.030	0.480
	(0.187)	(0.558)
Difference in board's and firm's CF-score	0.013	0.116
	(0.088)	(0.183)
Firm's influence (10^{-4})	0.027	0.787
	(5.428)	(21.515)
Publicly listed	0.033	0.504
	(0.178)	(0.500)
Firm's CF scores	0.006	0.071
	(0.066)	(0.213)
CEO's CF scores	0.0001	0.0002
	(0.003)	(0.012)
Board's CF scores	0.007	0.049
	(0.007)	(0.106)
Number of facilities	2.245	10.199
	(7.565)	(19.470)
Panel C: Facility-level statistics		
Probability of polluting	0.535	0.505
	(0.499)	(0.500)
Total toxic releases by facility	123,039.2	170,025.2
	(4,047,159)	(2,748,379)
Total RRT by facility	592,915.9	610,475.6
	($1.03 * 10^7$)	(5,983,524)
Panel D: Facility-level demographic statistics		
Median household income	55,693.27	56,541.83
	(22,379.63)	(22,668.51)
Minority ratio	0.231	0.229
	(0.239)	(0.236)
College ratio	0.208	0.198
	(0.173)	(0.176)
Population density	1,417	1,250
	(2,528)	(2,216)
Probability of locating in a Republican state	0.569	0.585
	(0.495)	(0.492)

Standard deviations are in parentheses.

Chapter 3

Director appointments, boardroom networks, and firm environmental performance

3.1 Introduction

Firms and their boards of directors are increasingly held accountable for their social and environmental impacts. This is illustrated by the recent removal of two directors from ExxonMobil following pressure from an activist investor, Engine No. 1, regarding ExxonMobil's climate strategy (CNN, 2021). Over the last 15 years, there has also been a legislative push towards corporate accountability for sustainability issues. In the United Kingdom, the Companies Act 2006 stipulates that directors should "have regard to [among other things] the impact of the company's operations on the community and the environment". In this context, it is important to identify corporate governance characteristics that can influence a firm's impact on the environment.

The board of directors is a key element of corporate governance, primarily tasked with monitoring and advising senior management on strategic decisions that affect the firm's value. Reducing its negative impact on the environment is an activity that involves large expenses (e.g. new waste management practices), and may have significant effects on the firm's capital structure (Walls et al., 2012) and value (Konar and Cohen, 2001). In this chapter, I examine how directors' professional network can improve a firm's environmental performance. Directors sitting on multiple boards exchange ideas and bring in information, which can help with their monitoring and advising roles (Larcker et al., 2013; Omer et al., 2020). Boards connected to firms with good environmental performance are more likely to learn about trends, best practices, and current challenges and might be in a better position to affect firms' environmental strategy. A novel contribution of this chapter compared to the literature examining the effect of board connections on environmental performance is that I do not take the director network as given but empirically model the director appointment process.

My analysis proceeds in two steps. First, I investigate whether a candidate's environmental record in other companies is a factor that existing board members and/or shareholders take into account when they appoint their board members. A positive answer implies that, besides other performance measures, they also value environmental performance when determining the suitability of a director for the board. This leads to my next question: how does a firm's board of directors influence its environmental performance? In particular, I want to investigate whether good environmental performance spreads through directors professional networks. That is, I test whether a director's environmental record, measured by the environmental performance of the other firms s/he was overseeing in the previous year, affects her/his current firm's environmental performance. The two-step approach is important. By modeling directors' network formation (through the appointment process), I am able to address endogeneity concerns related to the use of the actual number of direct director-firm links in the second step of our analysis.

The Database on Director Network and Toxic Releases (DNT) compiled in the first chapter is a comprehensive director-firm-level dataset on environmental performance and board characteristics and networks. The DNT is compiled based on data from BoardEx North America, the United States (US) Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) Program, and the US Census between 2000 and 2017. BoardEx is a global data company that compiles public information on board directors and senior management of publicly listed and large private companies. The TRI is a national database, established by law, which requires private and government facilities to report annually their pollution prevention activities and how they manage their production-related toxic waste. I build a dynamic firm-director network for North America using information provided by BoardEx. I then match BoardEx data with the TRI and measure environmental performance at the facility-level using data on total chemical releases to air, water, and land. I define a board member's environmental performance by calculating the proportion of their connections to polluting facilities (i.e., facilities that report a release to the TRI Program) relative to all her/his connected facilities during the previous period.

I start my analysis by examining the directors' network formation, using a Bayesian model approach similar to Christakis et al. (2020) and De Silva et al. (2022). My results indicate that firms (or their boards) tend to appoint directors who share more similarities (proxied by pollution-related homophily measures) with existing board members or to the firms themselves. Candidates who are more central (i.e., more influential) in the network have a significantly higher chance of being appointed, while candidates with poorer environmental performances are less welcome even if they are central. This could be due to consideration about the firms' reputation and regulatory risk. If an influential director with a 'toxic' environmental record is appointed to a firm, the firm can face criticism from the public and draw the attention of regulators, which can indirectly affect profits.

I, then, turn to the second dimension of our problem, i.e., the influence of directors on their firm's environmental performance. As firms very often own more than one facility in the US, we examine facility-level outcomes and exploit the panel structure of our data. I estimate how a board's environmental record influences a facility's probability to report a toxic release by adopting a probit model. We also estimate the impact on facility-level toxic material released by using simple linear and censored regression techniques. The influence of board members over their firm is measured by the average of all existing board directors' environmental performance. I control for location-specific demographic (and geographic) characteristics that can affect a facility's location and pollution decisions using US Census data. I also control for the institutional shareholding of firms because institutional ownership and investor activism are shown to be associated with better environmental performance (Naaraayanan et al., 2021; Liang et al., 2022).

My findings suggest that a facility's or firm's environmental performance is significantly affected by its board directors' previous experience. When a boardroom has a higher proportion of directors with good environmental records in other firms, the facilities overseen by this board tend to have less polluting incidents. Facilities can reduce their chemical releases in different ways. Using data on waste management activities (energy recovery, recycling, and treatment—RRT) provided by the TRI Program, I find that one channel through which a board of directors can affect their facilities' toxic releases is by increasing the proportion of total chemical waste managed through RRT.

Another possible interpretation of these results could be that firms' concerns about environmental issues could drive both the decision to hire a new director with a good environmental record and improvement of their facilities' environmental performance. To eliminate this possibility, I consider a reduced sample of firms whose boards did not change for at least two consecutive years. This restricted sample also allows me to rule out that my results are driven by other board characteristics (e.g. education, gender) as those characteristics remain constant when the board does not change. With this reduced sample, we show that an improvement in existing directors' environmental performance (due to an increase in the environmental performance of the facilities they are overseeing in other firms) leads to lower toxic waste releases for their focal firm. This last result is consistent with earlier findings (Homroy and Slechten, 2019) that a mechanism through which directors affect environmental performance is by leveraging their network to have access to better information.

My analysis relies on the assumption that directors have the ability to influence their firms' environmental performance shortly after their appointment. Compared to toxic waste prevention activities, which may require substantial investments and may take a few years to be implemented, RRT are waste management practices that can be used on a relatively short-term basis and can be carried out by specialized firms in the remediation industry. De Silva et al. (2021) provide evidence that firms from the remediation industry take the presence of TRI-reporting firms in an area into account in their location decisions, suggesting that they are indeed offering waste management services to TRI-reporters. I also investigate the validity of this underlying assumption by considering only newly appointed directors and examining their impact on the environmental performance of the facilities they oversee up to four years after their appointment. My results show that the magnitude of the effect of appointing a clean director compared to a director with a poor environmental record on toxic chemicals released and managed through RRT is the largest one year after the appointment.

I contribute to the literature in several ways. First, I complement the growing literature connecting board directors' characteristics and firm environmental performance (Walls et al., 2012; De Villiers et al., 2011) by studying the role of directors' networks. A key distinction of this chapter is the fact that I do not take the director network as given, but empirically model the director appointment process. The network I use for our analysis consists of all firms—regardless of their size—in North America (and not only publicly listed ones). Additionally, I use a quantitative measure of pollution (based on TRI data) with much greater range and variability than score-based environmental measures (e.g., KLD index) or environmental litigation, which are the measures of environmental performance mostly found in the literature. A few exceptions include Homroy and Slechten (2019) who use the level of greenhouse gas emissions or Berrone and Gomez-Mejia (2009) who also rely on TRI data, but focus on the impact of environmental performance on CEO pay. My quantitative measure of pollution allows me to study not only how well connected a director is, but also how 'toxic' their connections are. Another advantage of using TRI data as a measure of environmental performance is that this data are subject to comprehensive coverage in the media and scrutiny by regulators.

Second, recent papers have examined the role of network connections on the director selection process (Cai et al., 2021; Kramarz and Thesmar, 2013; Cashman et al., 2013).[1] My research adds to this literature by documenting the role of directors' environmental performance in their network formation. Moreover, while the existing literature on director selection typically relies on first- or second-degree centrality to measure director connections, I use eigenvector centrality, which takes into account the importance of a node's first-degree connections and can be interpreted as a measure of director influence within the network. Finally, I contribute more broadly to the literature on board connectedness and access to information (Cohen et al., 2008; Larcker et al., 2013; Omer et al., 2020) by examining whether directors' network helps them leverage information to improve their firm's environmental performance.

This chapter is organized as follows. In the next section, I review the literature and outline our main hypotheses. We present the datasets and explain how I combine them to perform our analysis in Section 3. Section 4 lays out the empirical models for both network formation and network influence studies. In the final section, I conclude and discuss the implications of our findings.

[1] Erel et al. (2021) study the director selection process from a different perspective. They use algorithms that rely on data on firms, current board members, and attributes of potential directors, to identify the quality of directors being considered for a given firm's board.

3.2 Related literature and hypotheses

The board of directors is a key component in corporate governance. Through their senior management advising and monitoring roles, the board contributes to the firm's strategic decision-making process and represents the interests of the shareholders. It has, therefore, a clear role to play in shaping a firm's environmental strategy, which can significantly impact the firm's value (Konar and Cohen, 2001; Eichholtz et al., 2010). A growing literature analyzes the links between board directors' characteristics and firms' environmental performance. My objective in this study is to contribute to this literature by examining the relationship between director appointment, director environmental record, and firm environmental performance.

3.2.1 Director selection process

Fama and Jensen (1983) were among the first to note that directors who are performing well on their monitoring and advising roles will be rewarded with additional board seats. Since then, there has been an extensive literature studying the relationship between director appointments and their performance (e.g., Brickley et al. 1999, Ferris et al. 2003, Fich and Shivdasani 2007). There is also evidence that companies seek a particular expertise or skill when hiring a new director. For example, Becher et al. (2017) find that, after a merger, the board of the acquiring firm changes substantially and that these adjustments reflect the firm's post-merger needs and skills upgrade.

Because environmental issues are now a major social concern, I am also interested in understanding whether good environmental performance is valued in the director labor market. In my setting, I consider all polluting industries in the USA and define a director's environmental performance (or record) based on the past environmental performance of the firms they are overseeing. Our conjecture is that, if fostering sustainability and reducing firms' negative environmental impact are becoming parts of companies' strategies, directors serving on companies' boards with good environmental performance are more likely to be appointed in the future.

Companies in polluting industries might also want to appoint directors with specific environmental skills. Recent results show that boards increasingly function through committees that focus on specific tasks, e.g., nomination of new directors, financial audits, or stainability. In line with the existing literature (Homroy and Slechten, 2019; Walls et al., 2012), I use director participation in a board committee focused on social or environmental issues as an observable measure of their environmental expertise. Our first two hypotheses are:

Testable hypothesis 1: Appointing a new candidate director or continuing with an existing candidate in period t depends on the candidate's past environmental performance (in period $t-1$).

Testable hypothesis 2: Companies are more likely to appoint directors who served on environmental committees.

I model the director appointment process using tools from network theory. I consider a network in which directors and firms are nodes. The appointment of a board member represents the formation of a link between a director and a firm. This chapter therefore focuses on directors' professional network, i.e. network formed by shared board directorates. Both professional and social networks have been shown to influence board characteristics and performance. For example, Kramarz and Thesmar (2013) provide evidence that CEO's social networks (i.e French elite institutions network and former high-ranking civil servants network) affect a firm's board composition and efficiency. Of particular interest for this chapter, Cashman et al. (2013) find that well-connected directors (i.e., directors serving on multiple boards) are more likely to obtain board appointments, while Cai et al. (2021) document that specific connections to the incumbent board significantly affect director appointments. Both studies suggest that the professional network matters for the probability to be appointed.

In contrast with Cashman et al. (2013) and Cai et al. (2021), who measure directors' connections using the concept of degree centrality, I use director and firm eigenvector centrality to measure the effect of the professional network on the probability to be appointed. Eigenvector centrality takes into account the importance of a node's first-degree connections. In other words, a director will be well-connected (i.e., have a high score for the eigenvector centrality) if they are connected to well-connected directors. In that respect, eigenvector centrality can be interpreted as a measure of director influence within the network.

Another important determinant of link formation in a network is homophily, i.e., the predominance of ties between similar individuals. The phenomenon of homophily has been identified in various types of relationships, including friendships (McPherson et al., 2001; Currarini et al., 2009) or work relations (Ibarra, 1995). When modeling the director network formation, I am investigating if homophily in environmental performance between the candidate and the existing board is associated with a higher probability of being appointed. This leads to our next hypothesis:

Testable hypothesis 3: Firms tend to appoint directors sharing more similarities (in terms of their environmental performance or their network centrality) with existing board members.

Given the size of my network, I use Bayesian estimation techniques similar to Christakis et al. (2020) and De Silva et al. (2022). The advantage of using this method, compared to a logistic regression (used in most papers studying director appointments), is that it allows us to continuously update posterior estimates of network parameters given prior information on link formation and network characteristics.

One point needs to be made. My analysis is based on the premises that directors represent shareholders and, if promoting good environmental performance positively affects a firm's value, shareholders might be interested in appointing directors with the appropriate set of skills or expertise. Shareholders typically do not nominate the directors who represent them. In most legal systems, the incumbent board nominates candidates, who are voted upon by the shareholders in a general meeting. There is evidence that shareholder votes have little impact on board elections (Bebchuk, 2003; Cai et al., 2009). However, Cai et al. (2009) also document that, even in uncontested elections, lower levels of director votes affect some corporate outcomes (e.g., lower "abnormal" compensation and higher levels of CEO turnover). Moreover, in recent years, activist shareholders have become increasingly successful in obtaining board seats in proxy contests (Zhang, 2021).

3.2.2 Directors network and environmental performance

Previous research on the relationship between firm environmental performance and board characteristics has focused on directors' legal expertise (De Villiers et al., 2011; McKendall et al., 1999), specific environmental expertise based on their roles, their presence in environmental sub-committees in other boards (Homroy and Slechten, 2019; Walls et al., 2012), or political and academic experience (Zhuang et al., 2018). Similarly, board orientation toward corporate social responsibility (CSR) issues, captured by the existence of a CSR-focused committee, significantly improves a firm's environmental performance (Dixon-Fowler et al., 2017; García Martín and Herrero, 2020).

Arguably, another important element for directors' monitoring and advising roles is their networks. Carpenter and Westphal (2001) suggest that social connections allow a director to learn about business practices more quickly than if he or she was forced to rely on secondary sources. Better-connected directors will have more opportunities to leverage their network to provide information and resources to advise the senior management. There is evidence of an association between board connections and a firm's value (Fracassi and Tate, 2012; Zona et al., 2018) or a firm's future performance (Larcker et al., 2013). Studies also indicate that board connections affect financial reporting quality (Omer et al., 2020), M&A transactions (Cai and Sevilir, 2012) or innovation (Chuluun et al., 2017). In the same spirit, board directors' networks can constitute a key element in improving a firm's environmental performance. Ortiz-de Mandojana et al. (2012) find that having a well-connected board tends to increase the probability of adopting proactive environmental strategies. Kassinis and Vafeas (2002) show that directors accumulate human capital from their multiple board affiliations, which leads to fewer environmental litigations.

My point of departure is that I am not only studying how well connected a director is, but also how 'toxic' their connections are. Compared to directors serving on the boards of firms with poor environmental performance, directors connected to 'clean' firms might have better access to relevant information about good environmental practices or new environmentally efficient technologies and waste management techniques (and their implementation costs), etc. My objective is to evaluate whether good environmental practices can spread through shared directorship. Therefore, besides testing whether well-connected firms have better environmental performance, I also consider a measure of the board's environmental record based on their connections with 'clean firms'. Specifically, a director environmental record is determined by the environmental performance of the other plants s/he was overseeing in the previous year. *Testable hypothesis 4: Board directors with good environmental records in other firms positively influence their focal firm's environmental performance.*

3.3 Environmental performance

I construct measures of environmental performance at the facility- and director-level from the DNT compiled in the second chapter using toxic releases as my key indicator. Summary statistics are presented in Table 3.1.

At the facility-level

The first facility-level measure of environmental performance is a dummy variable, *pollute*, which takes the value 1 in a given year if the facility reports a release of toxic chemicals above the reporting threshold to the TRI, and zero otherwise. As shown in Table 3.1, facilities with and without directors have similar probabilities to pollute (around 53%). Secondly, I use the facility's total toxic releases and total toxic waste managed through RRT in a given year. Facilities belonging to a firm with a board of directors release, on average, a larger amount of toxic chemicals, but the proportion of total toxic waste managed through RRT is very similar between the two groups (around 83%).

At the director-level

I use two different measures that depend on the past environmental performance of all the firms to which a director is connected. Note that, as mentioned earlier, I use the full network based on BoardEx data (and not only the network of directors and firms matched with the TRI data) to define directors' connections and compute the centrality measures. First, the director-level *pollution ratio* is constructed as the proportion of all the facilities overseen by a director that are releasing toxic chemicals in the environment. I then compute the *Board's average pollution ratio*, which is the average pollution ratio of the directors serving on the board overseeing a TRI-reporting facility. On average, the directors overseeing a TRI-reporting facility (column (2) of Table 3.1) have a pollution ratio of about 36%. That is, slightly more than one-third of all the facilities supervised by the members of this board (in other companies) are releasing toxic chemicals.

My next measure of directors' environmental performance is based on degree centrality (i.e., the number of direct links). Instead of using the degree centrality measure directly, I calculate the proportion of 'pollution links' relative to their total links, denoted as *relative pollution degree centrality.* I define 'pollution links' as the number of connections that a director has to firms that had at least one toxic-releasing facility in the previous year. This measure provides a director's overall environmental performance and captures a director's connections with the polluting firms relative to their connections with all companies.

Figures 3.1 and 3.2 illustrate how I compute our environmental performance measure using degree centrality. The Figures present a sub-network of the two most influential directors (determined by their eigenvector centrality measures) among all directors who are connected to at least one firm in the TRI dataset (green and brown nodes) in 2017. The blue nodes represent the other directors in the network. Firms in the network are characterized by their environmental performance based on the information from the TRI dataset. Brown nodes represent firms that have reported at least one toxic release, while green nodes represent firms without any toxic releases. In Figure 3.1, both directors have two 'pollution links' as they are connected to two firms with poor environmental performance. However, one director is serving on the board of three firms, while the other director is connected to seven firms. The director with seven connections will, therefore, be considered as having a better environmental performance.

Figure 3.1 only shows nodes that are no further than two edges from the most influential directors (red nodes). When allowing more distanced nodes in the graph, the size increases exponentially. Figure 3.2 includes all nodes that are within a distance of four from any of the two most influential directors. The number of nodes increases by 1,316, and the number of edges increases by 1,815 compared to Figure 3.1.

3.4 Empirical analysis

My empirical analysis is divided into two parts. I first examine how TRI-reporting firms appoint their board directors. In particular, I investigate whether firms value directors' past environmental performance when determining their suitability for the board. Second, I show how, once appointed, these board directors influence firms' environmental performance.

3.4.1 Director appointments

In the first part of my analysis, I study directors' network formation through the board appointment process. In each period, a firm j has the opportunity to form (or continue) a link with a director d and it will only form a connection if it is beneficial.[2] A link between j and d is established (or continues) if a firm appoints a director to its board (or renews a director on its board). Candidates are eligible to apply for and hold multiple positions simultaneously. A firm can appoint more than one director to its board and hiring decisions are independent of one another. Firms (or their board selection committee) make final decisions on their candidates and hire them simultaneously for a given year.

My dependent variable is equal to 1 if a firm, in time period (year) t, forms a link with a director and 0 otherwise. I assume that firms are aware of the shape of their current network but have no information with respect to its future shape. Below I describe the variables used in our empirical analysis and the methodology.

The firm's decision to appoint a director will depend on the existing links (network structure) and the director's attributes. I characterize the structure of the firm-director network with firm and director eigenvector centrality measures, which capture the network influence of both types of network participants. This set of measures is denoted by N. Other aspects of the network that might affect a firm-director match are board size or number of seats already held by a candidate. These aspects are however already captured by our centrality measure because they are highly correlated with firm and director influence. For this reason, I do not include board size or number of seats in our network formation models.

[2] As a result, directors are considered passive actors in our setting, exerting no decision power with respect to the link formation.

I consider different individual characteristics that could affect the probability that a firm forms a link with a director. First, I include the candidate director's pollution ratio and experience in environmental committees at time $t-1$ (testable hypotheses 1 and 2). The director's past pollution ratio captures a director's connections to polluting facilities (our measure of her/his environmental performance in other companies). The variable *candidate's past experience in environmental committees* is the log of the number of environment-related committee positions held by a director in the previous year. This is my measure of director expertise in environmental issues. I also include an interaction term between a candidate's past pollution ratio and a director's influence to investigate whether the importance of a candidate's environmental performance varies with her/his position in the network. This set of environmental characteristics is denoted by R. Other individual characteristics are likely to affect the probability to form a link between a firm and a director. I consider director market exposure, which is a proxy for director experience, and is computed as the number of years since a director's first appearance in the BoardEx data at a given time.[3] I also include a dummy variable, which is equal to 1 if the candidate director was a CEO in a different firm at time $t-1$. These other individual characteristics are denoted by D.

Finally, to test my prediction that firms appoint directors sharing more similarities with existing board members (hypothesis 3), I use the difference in a director's relative pollution degree centrality with respect to board members' average relative pollution degree centrality as our homophily measure. I consider two additional variables controlling for the similarities between the candidate director and the firm: 1) the difference in a director's pollution ratio with respect to the firm's pollution ratio (defined as the proportion of facilities owned by that firm which are releasing toxic chemicals), and 2) the difference in a director's influence and the firm's influence (eigenvector centrality). My conjecture is that an influential firm will prefer to hire a candidate who is more central in the network, and a 'clean' firm (with a low pollution ratio) might not be willing to hire a director with a poor environmental record due to reputation concerns. These three homophily measures are denoted by $g(N)$.

[3] A director's experience in the focal firm is another variable that might affect the probability that a firm continues a link with an existing director. However, it is highly correlated with market exposure.

One potential concern with my measures of environmental performance and homophily is that they could capture industry expertise. For example, directors currently serving on the board of chemical companies will have a greater exposure to polluting facilities and poorer environmental performance than directors in less polluting sectors. Other firms in the chemical industry might want to hire those directors for their expertise, rather than their similarities in terms of environmental performance. To address this issue, for all the directors matched with at least one TRI-reporting firm, I compute the number of TRI-reporting firms and the number of non-TRI-reporting firms in which a director serves as a board member. On average, a director is connected to three TRI-reporting firms and three non-TRI-reporting firms. Moreover, looking more closely at the TRI sectors only, a director is on average connected to TRI-reporting firms from four different sectors. Note that a firm can be in more than one sector.

Pool of candidates for the director network formation

It is not realistic to assume that all directors in BoardEx are potential candidates for all TRI-reporting firms in the network. Potential candidates have to be in the reach of this firm, which is determined by their position in the network. To identify potential pools of candidates, I take the following steps. First, for each TRI-reporting firm, I construct the maximum difference in the relative pollution degree centrality a director has had with its board from 2000 to 2017. Similarly, I measure the maximum difference between all the appointed directors' pollution ratios and the firm's pollution ratio during the sample period. Then, I consider all candidates that fall within either of these two maximum values as a potential candidate for a given board. Based on these cut-offs, I identify a possible 8,487,170 director-firm pairs for all TRI-reporting firms with directors for all years. On average, this corresponds to about 300 potential candidates per TRI-reporting firm in a given year. We use this sample in our network formation analysis.

Table 3.2 shows summary statistics for the variables used in the link formation analysis. Column 1 presents summary statistics for all 2,873 TRI-reporting firms with directors, while Column 2 provides information for 661 listed firms with directors. The data are for all potential directors matched with a given firm in a given year. On average, the unconditional probability of a director and a firm forming a direct link is 1.9%. The average candidate director's past pollution ratio indicates that 44.6% of the facilities overseen by candidates are reporting toxic releases. The average probability that a candidate has served on an environmental board committee is only 1%. Further, a candidate director's average market exposure in BoardEx is about 5.5 years.

Modeling network formation

I model the probability, $Pr(l_{d,j,t}|R_{d,t-1}, N_{d,j,t-1}, g(N_{d,j,t-1}), D_{d,t-1}; \theta_t)$, of a link $l_{d,j,t}$ established by firm j to director d at time t as a function of an unknown vector of parameters denoted by θ_t. I use observed data of the structure of the network, N, directors' environmental characteristics, R, other individual characteristics, D, and the homophily measures, $g(N)$, and we postulate a prior distribution for θ. Based on this information, we derive the posterior distribution for θ_t and calculate the probability of link formation for different values of $N_{d,j,t-1}$, $R_{d,t-1}$, $D_{d,t-1}$ and $g(N_{d,j,t-1})$.

I consider an empirical framework defining the probability of forming a link between firm j and director d at time t as:

$$ln\left(\frac{Pr(l_{d,j,t}|N_{d,j,t-1}, R_{d,t-1}, D_{d,t-1}, g(N_{d,j,t-1}); \theta_t)}{1 - Pr(l_{d,j,t}|N_{d,j,t-1}, R_{d,t-1}, D_{d,t-1}, g(N_{d,j,t-1}; \theta_t)}\right)$$
$$= \gamma + N^{'}_{d,j,t-1}\beta + \rho R_{d,t-1} + \delta D_{d,t-1} + (g(N_{d,t-1} - N_{j,t-1})'\Psi(g(N_{d,t-1} - N_{j,t-1}))) + \tau_t + \epsilon_{d,j,t} \tag{3.1}$$

where the term $(g(N_{d,t-1} - N_{j,t-1})'\Psi(g(N_{d,t-1} - N_{j,t-1})))$ is the disutility (cost) of having a difference in homophily between potential director candidates which relates to firm j in period $t-1$ (see Christakis et al. (2020) for a similar measure of homophily). Ψ is a diagonal matrix. The function g is a measure of homophily that is expressed as the absolute value of the difference in environmental performance and influence between director candidates and firms. I assume that the $\epsilon_{d,j,t}$ are independent across all j and d at a given time, t, and that they follow a logistic distribution.

Following Christakis et al. (2020) and De Silva et al. (2022), I use Bayesian estimation to obtain posterior distributions for each parameter based on prior information on link-formation choices. I exploit the latest developments in Markov-Chain-Monte-Carlo (MCMC) methods to generate different network-related posterior distributions. Specifically, I use a Bayesian MCMC technique based on a hybrid Metropolis-Hastings algorithm with Gibbs sampling updates to estimate our posterior mean and posterior standard deviations. In this way, one can search over the set of parameter estimates to find one that leads to the highest likelihood of getting a network distribution that looks similar to the observed network-related distribution.[4] Further, I take advantage of the full dataset instead of taking random draws from the samples.[5] I use uniform priors for the regression coefficients and an inverse-gamma prior with shape and scale parameters of 0.1 and 0.1 for the error variance. In all my Bayesian estimates, I use 10,000 iterations and omit the first 2,500 to mitigate possible start-up effects. However, one must verify the convergence of MCMC before making any inferential conclusions about the obtained results. In my exercise, I observe that the posterior distribution looks normal. Further, the kernel density estimates based on the first and second halves of the sample are very similar to each other and are close to the overall density estimate.

The Bayesian approach offers several advantages. First, it continuously updates posterior estimates given prior information on link formation and network characteristics. Second, the MCMC gives me the finite-sample properties of the resulting estimates rather than asymptotic approximations. Additionally, incorporating a non-parametric assumption on the posterior distribution makes the specification of the model more flexible and, hence, the results more robust (Li and Zheng, 2009).

Network formation results

Table 3.3 presents the means and credible intervals of the posterior distributions of my model parameters for all the TRI-reporting firms in my sample (Column 1) and for listed firms only (Column 2).[6] First, the candidate and firm network variables (influence measured by eigenvector centrality) play an important role in explaining link formation. In Columns 1 and 2, the mean of the posterior distribution of the director's influence is about 0.1 and the 95% credible interval lies strictly within a positive range of values, suggesting that firms tend to connect with influential directors. Similarly, influential firms tend to connect with more directors. This is not surprising as influential firms tend to have more

[4] Gelman (2004) provides a detailed description of the Bayesian method used in this paper.

[5] Note that this is computationally demanding. I use Lancaster University's High Performance Computer to estimate these Bayesian models.

[6] Note that I do not include a listed dummy (and its interactions with all other variables) in my director-firm level estimations because this dummy variable would be highly correlated with a firm's eigenvector centrality. Listed firms are usually large and, as a result, have larger boards (with more connections) and higher eigenvector centrality.

board members.

Further, the mean of the posterior distribution for a director's past pollution ratio is negative, and the 95% credible interval lies strictly within a negative range of values. This indicates that firms take candidates' past environmental record into account when evaluating their suitability for the board (consistent with hypothesis 1). The effect is stronger for listed firms, which is in line with previous research analyzing investor reactions to public disclosure of TRI. Khanna et al. (1998) show that listed firms in the chemical industry incurred statistically significant negative stock market returns following the publication of TRI data and that these losses had a significant impact on their subsequent toxic releases. It illustrates that listed companies might be more responsive to the increasing pressure to become environmentally responsible by hiring directors with a good environmental record. It is also interesting to note that the mean of the posterior distribution of a director's past pollution ratio interacted with the director's influence is strictly negative. Even though firms are more likely to appoint an influential director, they will refrain from doing so if this director has a poor environmental performance. Serving on an environment-related board committee increases the probability of being appointed as a board member (hypothesis 2).

Considering the homophily measures, my results are consistent with hypothesis 3. They indicate that an increase in the differences in a director's relative pollution degree centrality with respect to that of other existing board members decreases the probability of their being appointed as a board member. This probability is also lower when the differences in a director's pollution ratio and influence with respect to the firm increase. Beyond these results of interest to us, we can see that, as expected, exposure in the market and the candidate being a CEO in another company are positively associated with the probability of being appointed as a director.[7]

3.4.2 Director network influence on environmental performance

After discussing the determinants of network formation, I empirically investigate how the features of a network and a firm's boardroom characteristics affect the environmental performance of the facilities owned by this firm. When it comes to toxic production-related

[7] Considering the goodness of fit of the Bayesian estimates, the trace plot of the constant demonstrates good mixing. The posterior distribution of the constant is normal, as is expected for the specified likelihood and prior distributions. These figures are available upon request.

waste, firms can either release this waste into the environment (air, water or land), or use cleaner waste management practices, such as recycling. Directors make collective decisions regarding the firm's overall environmental strategy that will affect its waste management practices, which then determine the environmental performance of all its facilities. I model this relationship using the following regression equation:

$$y_{f,j,i,l,t} = \beta B_{j,t-1} + C'_{j,t-1}\gamma + F'_{f,t-1}\delta + \eta M_{i,t} + L'_{l,t}\phi + \alpha_f + \tau_t + \mu_{f,j,i,l,t} \tag{3.2}$$

where facility f belongs to firm j from industry i, in location l at time t. α_f is the industry-, facility- or firm-fixed effects or random effects (depending on the specification) that controls for time-invariant unobservable heterogeneity. τ_t is the time effect that controls for common time-varying effects (e.g. changes in regulation, public pressure...). $y_{f,j,i,l,t}$ is my measure of a facility's environmental performance. My main variable of interest is the board's past environmental performance (denoted by B), measured by the board's past average pollution ratio.[8] It indicates the average proportion of polluting facilities overseen by the members of the board in other companies in the last period.

I control for a series of board, firm and facility characteristics. C contains all firm-level and board-level variables; F controls for facility-level information. The variable *proportion of directors in environmental committees* captures directors' expertise in environmental issues. I also take into account diversity in terms of environmental records among the directors. To this end, we use directors' relative pollution degree centrality and define diversity in terms of environmental records as the board range (i.e. the difference between the maximum and minimum of the directors' relative pollution degree centrality). Diversity can affect a firm's environmental performance in two different ways: (1) a more diverse board may result in better firm's environmental performance if this diversity originates from exposure to different waste management practices in other companies (i.e. different expertises),[9] and (2) a more diverse board may result in lower environmental performance if this diversity reflects different opinions regarding environmental issues and increases the chance of conflicts among board members.[10]

[8] Note that my main results remain qualitatively the same if I use my other measure of director's environmental performance, i.e. relative pollution degree centrality.

[9] See Harjoto et al. (2015).

[10] Hoang et al. (2022) find that political polarization in the boardroom negatively affects a firm's environmental performance (measured by the environmental scores from MSCI ESG Research).

Additionally, I control for firm size proxied by the number of plants it owns in a given year, and a firm's influence in the market using the firm's eigenvector centrality. Following Khanna et al. (1998), I include a listed firm dummy to capture the fact that publicly traded companies might be more responsive to the increasing pressure to become environmentally responsible.[11] In the same spirit, I consider a BoardEx dummy, which is equal to 1 if the facility belongs to a firm present in the BoardEx data (i.e., a firm with a board of directors). Note that a firm in BoardEx can be listed or not With this dummy variable, my objective is to control that the effect of a board's average pollution ratio on the firm's environmental performance is not entirely driven by the fact that TRI-reporting firms in BoardEx are different from TRI-reporting firms without board information.

Further, summing up all facilities' toxic releases by industry, I construct an industry-level total releases per year (for the industries identified in the TRI data). I include total industrial toxic releases (M) as a control variable to capture industrial heterogeneity, since a firm's industry context affects its environmental management and performance (Hartmann and Vachon, 2018). The tract-level demographic characteristics (denoted by L) that could affect a facility's decisions regarding waste management practices, include median household income, minority ratio, college-education ratio, population density, and an indicator for facilities sited in a special tract. Regarding the geographical characteristics, I control for tracts that are part of an MSA, urban county, rural county, and coastal county, in addition to counties located along the border with Canada and Mexico.

Compared to most of the literature on firm environmental performance and board characteristics that rely on score-based environmental measures (e.g., KLD index) or environmental litigation, I am using a quantitative measure of pollution (based on TRI data) with much greater variation. I consider two measures of environmental performance at the facility level: the probability that this facility releases toxic chemicals in the environment and the total amount of toxic releases. I then examine a potential channel through which companies can reduce their facilities' chemical releases, i.e. other waste management practices (RRT).[12]

[11] In our facility- and board-level regressions, it is possible to use a listed dummy because observations are not at the director level, but collapsed at the firm or board level.

[12] The EPA also requires facilities to report their pollution prevention activities (P2). However, they are only required to provide a list of these activities without specifying the effect on toxic releases. Moreover, pollution prevention activities are considered more a long-term investment as they may require process

Facility-level probability of pollution

I first investigate whether board characteristics affect the probability that a facility reports a release to the TRI Program. Our dependent variable, $pollute_{f,i,j,l,t}$, takes the value 1 if facility f, belonging to firm j in sector i and located in tract l, releases any pollutants at time t; otherwise, it is 0.

I estimate equation (3.2), where $y = pollute$, using a simple probit model with time and industry fixed effects. Table 3.4 presents the marginal effects associated with the probit estimation. In Columns 1 and 3, I use the actual values of our environmental performance measures to compute the board's pollution ratio and range of board's relative pollution degree centrality. In Columns 2 and 4, I weigh each director's environmental performance measure by their calculated probability of being a member of the board in a given firm at a given time (using the posterior estimates for all firms in our sample from Table 3.3, Column 1). This allows me to address endogeneity concerns related to the use of the actual number of direct director-firm links in the facility-level environmental performance analysis.

My results for all facilities in Columns 1 and 2 indicate that poor directors' environmental performance leads to a significantly higher probability of future toxic releases at the facility level (consistent with hypothesis 4). For example, at the mean level of the board's average pollution ratio, the probability of polluting is 48.6 percent. This effect is consistent and stronger when I use the expected value of the board's average pollution ratio (Column 2).

As suggested by previous research, directors' expertise in environmental issues (proxied by their participation in environmental board committees) is negatively associated with the probability to pollute at the facility level. Having a diverse board is associated with a lower probability of pollution incidents. If the facility belongs to an industry reporting large amounts of toxic releases, then the facility has a higher probability of release in any given year. Listed firms or firms in BoardEx have a lower probability of polluting com-

modifications, equipment replacement, etc. It might, therefore, take more than one year to observe its effects on releases.

pared to non-listed/non-BoardEx firms. This is in line with my conjecture that listed firms will be more conscious about their environmental impacts because they are accountable to their shareholders. In Columns 3 and 4, I report the results for BoardEx facilities only. My main findings are very similar. In Table 3.5, I estimate these models with facility-level random effects. While the magnitude of the estimated marginal effects has decreased, the qualitative findings do not change.

Facility-level toxic releases

I then use the log of total toxic waste released at the facility level as our dependent variable and estimate equation (3.2) using a linear regression model. Tables 3.6 and 3.7 report the estimated results for all facilities and facilities that belong to a firm in BoardEx, respectively. In Columns 1 and 3, I include firm-level fixed effects while, in Columns 2 and 4, I control for facility-level unobservable heterogeneity by including facility-level fixed effects. Further, Columns 3 and 4 are estimated using the posterior estimates of the network formation analysis for all firms in my sample (Table 3.3, Column 1).[13]

In Table 3.8, I report the marginal effects at the means for all facilities (Panel A) and BoardEx facilities (Panel B). Having a board with a high average pollution ratio is associated with larger amounts of releases at the facility level. The marginal effect (the point estimate) indicates that at the mean level of the board's average pollution ratio, the total releases at a facility increase by 0.237. This point estimate is even stronger when I use the expected value of the board's average pollution ratio (Column 2).

In my dataset, many firms are not reporting any toxic releases in a given year. As a robustness check, I have left-censored the data for toxic releases per firm per year and estimated our empirical models using censored regression techniques. I present these results in Table 3.12 (for all facilities in Panel A and for BoardEx firms in Panel B). As a reference point, in Columns 1 and 4, I report linear regression results with industry controls. In Columns 2 and 5, I report the censored regression results. In Columns 3 and 6, I present another set of censored regression results with facility-level random effects controlling for facility-level unobservable heterogeneity. My qualitative results hold.

[13] Note that, while I cannot include the BoardEx dummy because it does not vary through time, I can use the listed dummy. This variable is not necessarily constant for an individual firm. Indeed, my sample covers 17 years of data and firms can be listed or delisted over time.

Facility-level toxic waste recovered, recycled, and treated

If a facility does not report toxic releases, it might be because they successfully manage their hazardous wastes through other waste management practices (RRT). To investigate the role played by the board of directors in the choice of waste management activities, I estimate the impact of the board's past environmental records in other companies on the proportion of total production-related toxic waste managed through RRT. My dependent variable is the log difference in the total toxic material recovered, recycled, and treated (RRT), and the total production-related toxic material managed by a facility. I estimate a linear regression model similar to equation (3.2). Results are presented in Table 3.9. In Columns 1 and 3, I include firm-level fixed effects while, in Columns 2 and 4, I control for facility-level unobservable heterogeneity by including facility-level fixed effects. As before, Columns 3 and 4 are estimated using the posterior estimates of the network formation analysis for all firms in my sample (Table 3.3, Column 1).

In line with my previous results, a board with a high average pollution ratio will have a smaller proportion of its toxic waste managed through RRT. This suggests that reductions in total toxic releases are not entirely driven by reductions in production. Firms also seem to change their waste management practices. The marginal effects at the mean are presented in Table 3.10. The marginal effect (the point estimate) indicates that at the mean level of the board's average pollution ratio, the proportion of toxic waste managed through RRT decreases by 0.081. This point estimate is consistent and even stronger when we use the expected value of the board's average pollution ratio (Column 2).

Environmental performance and institutional ownership

Recent evidence suggests that hedge funds or other institutional investors can affect environmental performance, through investor activism (Naaraayanan et al., 2021; Liang et al., 2022). To examine whether institutional ownership might drive our results, I obtain companies' shareholding information via Refinitiv Eikon and merge this information with our dataset using companies' tickers provided by BoardEx (listed companies only).[14] I

[14] Refinitiv (a subsidiary of London Stock Exchange Group) is one of the world's largest providers of financial markets data and infrastructure (`https://www.refinitiv.com/en/products/eikon-trading-software#`).

re-estimate equation (3.2), where my dependent variables are the log of total toxic releases or the log difference in the total toxic material recovered, recycled, and treated and control for the percentage of shares held by institutional investors (*Holdings by institutions*) and by strategic entities (*Holdings by Strategic Entities*). I have 517 unique companies' shareholding information from 2000 to 2017 (these firms do not necessarily have complete information for the entire period). Strategic entities can be companies, government agencies, individual investors, or insider investors. They do not buy shares for investment management purposes, but rather for strategic stakes (concentrated stock position or substantial equity position for enhancing acquisition, hedge, yield enhancement...). The category *Holdings by institutions* includes, among others, bank and trust, hedge fund, investment advisor, insurance company, pension fund, private equity, venture capital... There is a quarterly record for each company's ownership information in the database and I take the average values for each given year.

Table 3.13 reports the results for the log of total toxic releases (Columns 1 and 2) or the log difference in the total toxic material recovered, recycled, and treated (Columns 3 and 4). Results remain qualitatively the same. In particular, facilities overseen by directors with lower pollution ratios tend to release less toxic chemicals and have a higher proportion of waste managed through RRT. The shareholding variables are not significant. Note that the values of the *Board's average pollution ratio* coefficient are larger than in Tables 3.7 or 3.9. This is again in line with our conjecture that listed firms accountable to their shareholders may have more incentives to improve their environmental performance.

Environmental performance and ESG scores

The TRI data provide an objective and quantitative measure of a firm's environmental performance. However, it covers only one aspect of this environmental performance (toxic chemical waste). Most public companies are now evaluated by third-party providers on their environmental, social, and governance (ESG) performance in several dimensions. Most of these ESG scores are computed using information disclosed by companies through corporate social responsibility (CSR) or sustainability reports, annual reports, websites, and other public sources. In that respect, it might be more subjective than data on actual toxic chemical releases. Moreover, there are a number of companies that provide ESG scores and each of them uses their own methodology to compute these scores.

These ESG scores have been extensively used in the academic literature. Investors and other stakeholders are increasingly relying on these ratings as well. In addition, some studies have focused on the role of board directors in determining firms' ESG performance (e.g. Cucari et al. (2018), Harjoto and Wang (2020), and Rossi et al. (2021)). For this reason, I re-estimate our model (3.2) using ESG scores as a dependent variable. I download Thomas Reuters ESG scores from Refinitiv Eikon. These scores are only available since 2002 and I am able to obtain 446 unique listed firms' ESG scores for the period 2002 to 2017 (these firms do not necessarily have complete information for the entire period). I use Thomas Reuters ESG scores, along with their Environmental Pillar Scores, Social Pillar Scores, and Governance Pillar Scores. I also include the score on *Resource usage*, which is a category of the Environmental Pillar measuring a company's capacity to reduce the use of materials, and to find more eco-efficient solutions by improving supply chain management.

First, it is important to note that ESG scores and TRI data are not correlated, suggesting that they indeed capture different aspects of environmental performance. For example, the correlation between the total ESG score and total toxic releases is only 0.035, and the correlation with the Environmental Pillar score is -0.02. This is confirmed by the results presented in Table 3.14. I estimate equation (3.2), where my dependent variables are the total ESG scores (Column 1) and each of its components (Columns 2 to 5). I observe that a board's pollution ratio or the proportion of directors serving on environmental board committees have no significant impact on the total ESG score or on any of the components of the ESG scores. These results seem to suggest that ESG scores are not affected by directors' past environmental performance (in terms of toxic chemicals) or experience. The only exception is the Environmental component of the ESG score that is positively associated (at 10% level) with the presence of an environmental committee. Note that in all columns of Table 3.14, I control for ownership by institutions and strategic entities.[15] Further, the insignificant effect of directors' toxicity-related experiences on their firms' ESG scores indicates that directors' experience with one environmental issue does not improve their firms' ESG scores in other areas.

[15] As mentioned previously, there are many companies providing ESG scores. As a robustness check, I estimate the same models using ESG scores from Yahoo Finance (based on research from Sustainalytics, a global provider of ESG information for publicly listed firms). Results (available upon request) remain unchanged.

3.4.3 Effect of appointing a clean director

An underlying assumption of my empirical analysis is that a director hired in year $t-1$ is able to affect a firm's releases in year t. It is important to note that the waste management practices reported in the TRI data (energy recovery, recycling, and treatment of toxic waste) are activities that can be implemented on a relatively short-term basis as they can be carried out by specialized firms in the remediation industry (De Silva et al., 2021). These firms already have the knowledge (skilled workers) and specialization to carry out these tasks. However, to address the concern that decisions or advice from the board might take time to translate into releases reductions, I examine the evolution of a firm's environmental performance around the appointment of a new director (an event study-type analysis). Compared to the network formation discussion, this analysis allows me to distinguish the changes in environmental performance associated with a new appointment from the changes associated with variations in pollution measures of "continuing directors".

In this exercise, I consider the appointment of a new director as an event and denote the appointment's year as year zero. In my sample, I include only newly appointed directors who served on the board of their new firm for at least one year after the appointment. This corresponds to 10,716 directors matched with 2,085 firms (corresponding to 16,925 facilities). For each of the 143,672 unique director-facility pairs identified, I create a panel with two years prior to the event and, at most, four years after the event. This generates a panel of 848,475 observations. As an alternative specification, I consider only director-facility pairs for which the newly appointed director serves on the board for at least two years. This method identifies 127,428 unique director-facility pairs, generating a panel of 799,743 observations. The difference in the number of observations between the two specifications is explained by the turnover of board members: 15% of newly appointed directors leave their firm after just one year and only 51% of new directors serve on the board for more than 5 years. Using this data, I estimate the following panel regression model:

$$\begin{aligned} y_{f,d,j,i,l,t} =& \kappa\, Clean_{f,d,j,i,l,t} + E'_{f,d,j,i,l,t}\lambda + (Clean_{f,d,j,i,l,t} \times E_{f,d,j,i,l,t})'\theta \\ &+ C'_{j,t-1}\gamma + F'_{f,t-1}\delta + \eta M_{i,t} + L'_{l,t}\phi + \alpha_j + \tau_t + \epsilon_{f,j,i,l,t} \end{aligned} \tag{3.3}$$

where y is my dependent variable and represents the log of toxic waste released or the log difference in the total toxic material recovered, recycled, and treated (RRT), and the total production-related toxic material managed by a facility f in year t. *Clean* is a dummy variable that is equal to 1 if the newly appointed director has a past pollution ratio below 25%. A director is, therefore, considered as a clean director if less than 25% of the facilities he oversees are polluting facilities (i.e., report toxic releases to the TRI). E is a vector of dummy variables for every year after the appointment. C, F, M, and L represent the control variables at the firm-, facility-, industry-, and location-level. τ_t are time fixed-effects. By including firm-fixed effects (α_j), I control for unobservable firm heterogeneity and examine differences in pollution measures after the appointment of a clean director, taking out the mean effect.

I am primarily interested in the values of the coefficients κ and θ, which measure the effect on releases and RRT one year after the appointment and in the longer term (up to four years after appointment). The results in Table 3.11 indicate that a newly appointed clean director has a significant and immediate (one year after appointment) negative effect on total releases. The effect persists after one year, but its magnitude decreases over time. I observe the same pattern for toxic waste managed through RRT. Looking at Column 1, appointing a new director leads to an average increase in total releases of 9% after one year. However, if the appointed director is a clean director, then the facility total releases will be 58% lower than for a facility appointing a director with poor environmental performance. Column 3 suggests that appointing a new clean director increases the proportion of waste managed through RRT by 14% compared to a dirty director. I also estimate this model when a director is considered as clean when her/his past pollution ratio is less than 50%. The results (available upon request) are qualitatively the same, even though the magnitude of the coefficients is slightly lower.[16]

3.4.4 Unchanged board composition and information access

Another potential interpretation of my results is that firms' concerns about environmental issues drive both their environmental performance and their decisions to hire directors with good environmental records. To examine the likelihood of this interpretation, I re-

[16]For example the coefficient of the interaction term for one year after appointment drops from 58% to 46%.

duce my analysis to a subset of firms whose board composition did not change from the previous year. This restriction implies that the identity of the directors on the board remains unchanged but their environmental records (pollution ratio and relative pollution degree centrality), their influence, and their environmental expertise (proxied by their participation in environmental committees in other firms) may still vary. These changes could be due to these directors' being appointed or removed from other boards or changes in the environmental performance of other firms in the network.

Note that this restriction also allows us to control for other board characteristics that could affect a firm's environmental performance and do not vary for the boards included in my restricted sample (e.g. board size, gender ratio, directors education background...). By focusing on firms whose board composition did not change, I check that changes in a facility's environmental performance are not driven by these characteristics.

The results for this restricted sample are presented in Table 3.15. I estimate a linear model with facility-, or firm-level fixed effects, where the dependent variable is the log of the total amount of toxic waste released in the environment at time t (similar to equation (3.2)) for firms whose board composition did not change for at least two consecutive years. A higher board's average pollution ratio (at $t-1$) is still associated with larger amounts of toxic releases (at t).[17] In Table 3.16, I present the effects at the mean. The effect of average pollution ratio on total releases is even stronger than in Table 3.8 (with the full sample).

These results also support my conjecture that director networks affect firms' toxic releases through better access to information. In my restricted sample, any change in the board's average pollution ratio of firm j does not come from a new director being appointed in firm j but is driven by existing directors being appointed to/removed from other boards or by changes in environmental performance of the other facilities overseen by directors in firm j. By sitting on a larger number of boards with good environmental performance, directors from firm j are exposed to better environmental practices that they can bring to firm j to help improve its environmental performance.

[17]Note that the results for the range of boards' relative degree centrality and the proportion of directors serving on environmental committees do not hold. The effect is now positive, but not significant for the environmental committees variable. This is highly likely due to the fact that with the restricted sample, these variables do not vary a lot from one year to the other.

3.5 Conclusion

Given its central role in corporate governance, I examine how the board of directors helps shape a firm's environmental strategy. I first study the director appointment process using a network setting. In particular, I am interested in understanding if directors' environmental record, measured by the environmental performance of the firms they are overseeing, is a determinant of the probability of being appointed in another company. I use Bayesian techniques to obtain posterior distributions for each network parameter based on prior information on link-formation choices. I then estimate the impact of directors' characteristics (including their environmental records in other companies) on future firm environmental performance. Using the parameters estimated in the first step of my analysis, I am able to address endogeneity concerns related to the actual number of direct director-firm links.

I show that firms are more likely to appoint candidates who are similar (in terms of environmental performance and influence) to their existing board directors, but also candidates with a good environmental record. Interestingly, when a director becomes influential, poor environmental performance will reduce their probability of being appointed. Additionally, my study shows that directors' previous environmental performance affects their current facilities' environmental performance. Having directors with a good environmental performance on the board is associated with a lower probability of releasing toxic chemicals and a higher proportion of toxic waste managed through energy recovery, recycling, and treatment. To understand the dynamics of director appointment and improvement in firms' environmental performance, I perform an event-study type analysis in which we look at the evolution of a firm's environmental performance up to four years after the appointment of a director. My results confirm that the appointment of a *clean* director leads to a reduction in toxic releases and that the magnitude of the impact decreases over time.

Environmental sustainability is rising on the societal agenda. For example, the CEO of BlackRock said that BlackRock would exit certain investments that present a high sustainability-related risk' and move more aggressively to vote against management teams that are not making progress on sustainability (New York Times, 2020). Another striking example is the judgment from a district court in The Hague (Netherlands) that ordered Royal Dutch Shell to reduce its CO_2 emissions by 45% from 2019 levels in line with global climate goals (May 2021). This was the first time a court ruled that a large polluting company must comply with the Paris Climate Agreement. My analysis provides important insights on the role of corporate governance structure in internalizing these increasing environmental pressures. In particular, my results suggest that the market could exert pressure on influential directors to be "greener". This will have spillover effects as influential directors with good environmental records are more likely to be appointed and can then expand their environmental performance via their networks. Regulations such as the Companies Act 2006 in the UK, which make the directors accountable for the environmental impact of their firm, could be effective in promoting good environmental practices only if directors are able to have a significant impact on a firm's environmental strategy. My research provides evidence that this is the case and highlights the importance of director networks to enhance firms' environmental performance.

Figures

Figure 3.1: Directors' sub-network with a distance of 2 and environmental indicators

This graph shows a sub-network focusing on two directors among all directors who are connected to at least one TRI-reporting firm for the year 2017. I am representing all the nodes that are at a distance of at most two (two edges) from the two most influential directors (red nodes). The brown nodes represent polluting firms, and the green nodes represent clean firms. Blue nodes represent the other directors. Clean firms are defined as firms with no facilities releasing toxic chemicals above the TRI threshold for a given year. This sub-network includes nine firms–three polluting firms and six clean firms–with 69 directors. In our setting, directors' environmental performance will be a function of the past environmental performance of their connected firms. In this example, both directors have two 'pollution links' as they are connected to two polluting firms. However, one director serves on the board of three firms, while the other is connected to seven firms. The director serving on the board of seven firms will be considered as having a better environmental performance.

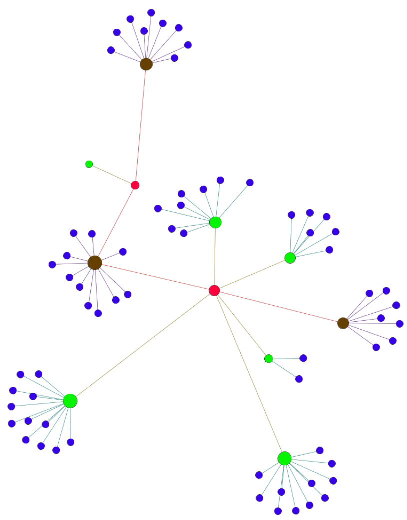
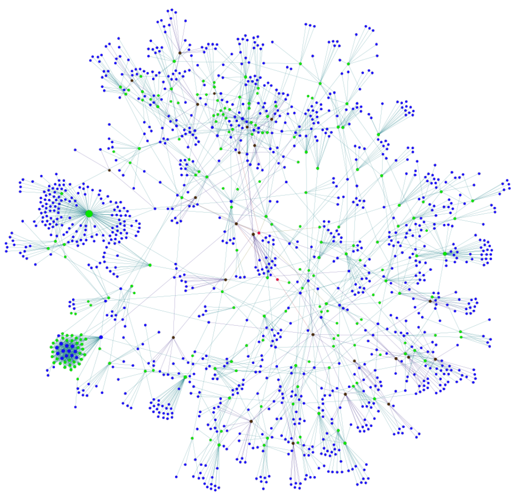


Figure 3.2: Directors' sub-network with a distance of 4 and environmental indicators

Figure 3.2 presents the sub-network of the two most influential directors (same directors as in Figure 3.1) among all TRI-related directors (represented by the red nodes) for the year 2017. Nodes' color notations are the same as in Figure 3.1. Compared to Figure 3.1, I expand the sub-network to include all the nodes at a distance of at most four from the two most influential directors. With this increase in distance, the number of nodes increases by 1,316, and the number of edges increases by 1,815. The comparison of Figures 3.1 and 3.2 provides some insight into the complexity and size of the network.



Tables

Table 3.1: Database on Director Network and Toxic Releases (DNT): 2001-2017

Variables	All	With directors	Without directors
Panel A: Sample Counts			
Total number of observations (facility level)	582,722	288,277	294,445
Number of unique firms	19,035	2,873	16,162
Number of unique facilities	40,990	18,927	22,063
Number of unique directors	17,224	17,224	0
Number of unique tracts (with at least one facility)	18,183	11,172	12,550
Panel B: Firm-level Statistics			
Board's average pollution ratio	0.049	0.359	0
	(0.179)	(0.293)	
Range of the board's relative pollution degree centrality	0.041	0.435	0
	(0.174)	(0.399)	
Firm's influence (10^{-4})	0.051	0.306	0
	(5.292)	(13.014)	
Firm has an environmental committee	0.004	0.023	
	(0.062)	(0.150)	
Proportion of directors in environmental committees	0.005	0.027	
	(0.049)	(0.118)	
Panel C: Facility-level Statistics			
Probability of polluting	0.532	0.530	0.534
	(0.499)	(0.499)	(0.499)
Total toxic releases by facility (in thousands of pounds)	121.538	151.602	92.105
	(4,214.303)	(2,212.775)	(5,509.371)
Total RRT by facility (in thousands of pounds)	612.145	793.167	434.914
	(12,532.12)	(949.263)	(14,917.53)
Facility belongs to a listed firm	0.183	0.370	0
	(0.387)	(0.483)	
Panel D: Facility-level Demographic and Geographic Characteristics			
Median household income	56,484.18	56,559.55	56,410.39
	(23,104.16)	(23,293.22)	(22,917.36)
Minority ratio	0.231	0.232	0.229
	(0.238)	(0.237)	(0.239)
College ratio	0.194	0.195	0.192
	(0.172)	(0.175)	(0.168)
Population density	1,422.282	1,225.626	1,614.818
	(2,538.237)	(2,156.295)	(2,850.125)
Probability of locating in a special tract	0.014	0.016	0.012
	(0.117)	(0.127)	(0.107)
Probability of a plant located in an MSA County	0.760	0.751	0.769
	(0.427)	(0.432)	(0.421)
Probability of a plant located in an urban County	0.222	0.231	0.214
	(0.416)	(0.421)	(0.410)
Probability of a plant located in a costal County	0.173	0.175	0.171
	(0.378)	(0.380)	(0.376)
Probability of being located in a Mexico border County	0.010	0.010	0.009
	(0.096)	(0.099)	(0.093)
Probability of being located in a Canada border County	0.042	0.038	0.046
	(0.200)	(0.191)	(0.209)

Standard deviations are in parentheses.

Table 3.2: Summary statistics of variables used in the network formation analysis: 2001 - 2017

Variable	Mean	
	All firms	Listed firms
	(1)	(2)
Probability of creating a link	0.019	0.026
	(0.137)	(0.160)
Candidate's past pollution ratio	0.446	(0.488)
	(0.386)	(0.368)
Candidate's influence	0.0002	0.0002
	(0.014)	(0.014)
Candidate's past pollution ratio × influence	0.0001	0.0001
	(0.009)	(0.010)
Candidate is a CEO in a different firm	0.092	0.089
	(0.289)	(0.285)
Candidate's past experience in environmental committees	0.010	0.011
	(0.115)	(0.117)
Market exposure in years (number of years in BoardEx)	5.545	5.935
	(4.506)	(4.578)
Firm's influence	0.0001	0.00003
	(0.0021)	(0.0014)
Difference in candidate's relative pollution degree centrality and	0.324	0.338
other board members average relative pollution degree centrality[a]	(0.299)	(0.249)
Difference in candidate's pollution ratio and firm's	0.322	0.323
pollution ratio[a]	(0.312)	(0.280)
Difference in candidate's influence and firm's influence[a]	0.0003	0.0003
	(0.014)	(0.015)

Standard deviations are in parentheses.
[a] The homophily measures are given in absolute values.

Table 3.3: Bayesian estimates of network formation parameters

Variable	Mean of the posterior distribution	
	All firms	Listed firms
	(1)	(2)
Candidate's past pollution ratio$_{t-1}$	-0.0009	-0.0149
	[-0.0113, -0.0006]	[-0.0154, -0.0144]
Candidate's influence$_{t-1}$	0.0978	0.0922
	[0.0947, 0.1009]	[0.0876, 0.0977]
Candidate's pollution ratio$_{t-1}\times$ influence$_{t-1}$	-0.0490	-0.0543
	[-0.05126, -0.0464]	[-0.0552, -0.0535]
Candidate is a CEO in a different firm$_{t-1}$	0.0015	0.0022
	[0.0012, 0.0019]	[0.0016, 0.0028]
Candidate's past experience in environmental committees$_{t-1}$	0.1681	0.2384
	[0.1669, 0.1693]	[0.2376, 0.2392]
Firm's influence$_{t-1}$	0.1190	0.3207
	[0.1176, 0.1203]	[0.3177, 0.3240]
Difference in candidate's relative pollution degree centrality and	-0.0287	-0.0450
other board members average relative pollution degree centrality$^{a}_{t-1}$	[-0.0291, -0.0284]	[-0.0457, -0.0443]
Difference in candidate's pollution ratio and firm's	-0.0472	-0.0754
pollution ratio $^{a}_{t-1}$	[-0.0475, -0.0469]	[-0.0760, -0.0748]
Difference in candidate's influence and firm's influence$_{t-1}$	-0.0663	-0.0702
	[-0.0685, -0.0637]	[-0.0727, -0.0671]
Log(Market exposure in years)	0.0020	0.0026
	[0.0019, 0.0022]	[0.0024, 0.0029]
Trend	Yes	Yes
Number of obs	8,487,170	3,173,029
Log marginal likelihood	4,954,608	1,352,932

95% Credible intervals are in parentheses.
[a] The homophily measures are given in absolute values.

Table 3.4: Pollution probabilities

Variable	Probability of polluting$_{ft}$			
	All facilities		BoardEx facilities	
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	0.486***		0.489***	
	(0.004)		(0.004)	
The range of the board's relative pollution degree centrality$_{j,t-1}$	-0.198***		-0.170***	
	(0.003)		(0.003)	
E[Board's average pollution ratio]$_{j,t}$		0.956***		0.962***
		(0.008)		(0.008)
E[The range of the board's relative pollution degree centrality]$_{j,t-1}$		-0.385***		-0.331***
		(0.006)		(0.007)
Firm's influence$_{j,t-1}$	0.340	0.261	-0.840	-0.912
	(1.465)	(1.464)	(1.447)	(1.446)
Log of total industrial toxic releases$_{i,t}$	0.100***	0.100***	0.104***	0.104***
	(0.004)	(0.004)	(0.005)	(0.005)
Facility belongs to a BoardEx firm$_{f,t}$	-0.112***	-0.113***		
	(0.002)	(0.002)		
Proportion of directors in environmental committees$_{j,t-1}$	-0.124***	-0.127***	-0.121***	-0.126***
	(0.006)	(0.006)	(0.006)	(0.006)
Facility belongs to a listed firm$_{f,t}$	-0.034***	-0.034***	-0.030***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.002)
Located in a special tract	Yes	Yes	Yes	Yes
MSA, Urban, and Costal County effects	Yes	Yes	Yes	Yes
Located in a county that border Mexico or Canada	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Observations	582,722	582,722	288,277	288,277
Wald χ^2	36,113	36,211	28,004	28,122
Log likelihood	-382,348	-382,305	-183,485	-183,434

Robust standard errors are in parentheses. Marginal effects are reported. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Pollution probabilities – with facility-level random effects

Variable	Probability of polluting$_{ft}$			
	All facilities		BoardEx facilities	
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	0.291***		0.288***	
	(0.004)		(0.004)	
The range of the board's relative pollution	-0.055***		-0.042***	
degree centrality$_{j,t-1}$	(0.003)		(0.003)	
E[Board's average pollution ratio]$_{j,t}$		0.573***		0.568***
		(0.008)		(0.008)
E[The range of the board's relative pollution		-0.109***		-0.084***
degree centrality]$_{j,t-1}$		(0.007)		(0.007)
Firm's influence$_{j,t-1}$	0.867	0.837	0.776	0.748
	(1.609)	(1.608)	(1.552)	(1.552)
Log of total industrial toxic releases$_{i,t}$	0.102***	0.102***	0.095***	0.095***
	(0.002)	(0.002)	(0.003)	(0.003)
Facility belongs to a BoardEx firm$_{f,t}$	-0.097***	-0.096***		
	(0.005)	(0.005)		
Proportion of directors in environmental	-0.087***	-0.093***	-0.075***	-0.082***
committees$_{j,t-1}$	(0.009)	(0.009)	(0.008)	(0.008)
Facility belongs to a listed firm$_{f,t}$	-0.033***	-0.033***	-0.032***	-0.031***
	(0.004)	(0.004)	(0.004)	(0.004)
Facility level random effects	Yes	Yes	Yes	Yes
MSA, Urban, and Costal County effects	Yes	Yes	Yes	Yes
Located in a county that border Mexico or Canada	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Observations	582,722	582,722	288,277	288,277
Wald χ^2	12,022	12,082	8,820	8,882
Log likelihood	-246,321	-246,286	-114,845	-114,810

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6: Regression results for total toxic releases - all facilities

Variable	Log of toxic releases$_{ft}$			
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	1.333***	1.581***		
	(0.140)	(0.125)		
The range of the board's relative pollution	-0.201**	-0.171**		
degree centrality$_{j,t-1}$	(0.086)	(0.082)		
E[Board's average pollution ratio]$_{j,t-1}$			2.620***	3.106***
			(0.275)	(0.245)
E[The range of the board's relative pollution			-0.392**	-0.330**
degree centrality]$_{j,t-1}$			(0.169)	(0.162)
Firm's influence$_{j,t-1}$	25.338	24.740	25.215	24.602
	(33.214)	(33.626)	(33.201)	(33.612)
Log of total industrial toxic releases$_{i,t}$	0.351***	0.269***	0.351***	0.269***
	(0.028)	(0.019)	(0.028)	(0.019)
Proportion of directors in environmental	-0.183	-0.167	-0.212	-0.201
committees$_{j,t-1}$	(0.289)	(0.281)	(0.294)	(0.287)
Facility belongs to a listed firm$_{f,t}$	-0.238*	-0.232*	-0.237*	-0.232*
	(0.128)	(0.128)	(0.128)	(0.128)
Firm effects	Yes		Yes	
Facility effects		Yes		Yes
Located in a special tract	Yes		Yes	
MSA, Urban, and Costal County effects	Yes		Yes	
Located in a county that border Mexico or Canada	Yes		Yes	
Time effects	Yes	Yes	Yes	Yes
Observations	582,722	582,722	582,722	582,722
R^2	0.462	0.725	0.462	0.725

Robust standard errors clustered by firms are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Regression results for total toxic releases - BoardEx facilities

Variable	Log of toxic releases$_{ft}$			
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	1.511***	1.748***		
	(0.137)	(0.126)		
The range of the board's relative pollution	-0.112	-0.093		
degree centrality$_{j,t-1}$	(0.083)	(0.079)		
E[Board's average pollution ratio]$_{j,t-1}$			2.968***	3.432***
			(0.269)	(0.247)
E[The range of the board's relative pollution			-0.216	-0.178
degree centrality]$_{j,t-1}$			(0.162)	(0.155)
Firm's influence$_{j,t-1}$	25.150	24.800	25.025	24.660
	(33.276)	(34.108)	(33.263)	(34.095)
Log of total industrial toxicity$_{i,t}$	0.384***	0.270***	0.384***	0.270***
	(0.036)	(0.032)	(0.036)	(0.032)
Proportion of directors in environmental	-0.179	-0.170	-0.214	-0.211
committees$_{j,t-1}$	(0.287)	(0.280)	(0.293)	(0.287)
Facility belongs to a listed firm$_{f,t}$	-0.271**	-0.277**	-0.271**	-0.277**
	(0.134)	(0.135)	(0.134)	(0.135)
Firm effects	Yes		Yes	
Facility effects		Yes		Yes
Located in a special tract	Yes		Yes	
MSA, Urban, and Costal County effects	Yes		Yes	
Located in a county that border Mexico or Canada	Yes		Yes	
Time effects	Yes	Yes	Yes	Yes
Observations	288,277	288,277	288,277	288,277
R^2	0.361	0.762	0.361	0.762

Robust standard errors clustered by firms are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.8: Marginal effects for total toxic releases

Variable	Log of toxic releases$_{ft}$			
	(1)	(2)	(3)	(4)
Panel A: All facilities				
Board's average pollution ratio$_{j,t-1}$	0.237***	0.281***		
	(0.025)	(0.022)		
The range of the board's relative pollution degree centrality$_{j,t-1}$	-0.043**	-0.037**		
	(0.019)	(0.018)		
E[Board's average pollution ratio]$_{j,t-1}$			0.237***	0.281***
			(0.025)	(0.022)
E[The range of the board's relative pollution degree centrality]$_{j,t-1}$			-0.043**	-0.036*
			(0.019)	(0.018)
Firm's influence$_{j,t-1}$	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Panel B: BoardEx facilities				
Board's average pollution ratio$_{j,t-1}$	0.543***	0.628***		
	(0.049)	(0.045)		
The range of the board's relative pollution degree centrality$_{j,t-1}$	-0.049	-0.041		
	(0.036)	(0.034)		
E[Board's average pollution ratio]$_{j,t-1}$			0.543***	0.628***
			(0.049)	(0.045)
E[The range of the board's relative pollution degree centrality]$_{j,t-1}$			-0.048	-0.039
			(0.036)	(0.034)
Firm's influence$_{j,t-1}$	0.0003	0.0003	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)

Robust standard errors clustered by firms are in parentheses. *** p$<$0.01, ** p$<$0.05, * p$<$0.1

Table 3.9: Regression results for toxic waste managed through RRT

Variable	Log $\left(RRT_{ft}/\text{total toxic waste}_{ft}\right)$			
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	-0.458***	-0.512***		
	(0.070)	(0.070)		
The range of the board's relative pollution	0.083*	0.077*		
degree centrality$_{j,t-1}$	(0.048)	(0.047)		
E[Board's average pollution ratio]$_{j,t-1}$			-0.899***	-1.005***
			(0.137)	(0.138)
E[The range of the board's relative pollution			0.155	0.143
degree centrality]$_{j,t-1}$			(0.094)	(0.092)
Firm's influence$_{j,t-1}$	-11.320	-10.971	-11.267	-10.915
	(14.816)	(15.103)	(14.819)	(15.106)
Log of total industrial toxic releases$_{i,t}$	-0.077***	-0.124***	-0.077***	-0.124***
	(0.012)	(0.014)	(0.012)	(0.014)
Proportion of directors in environmental	0.044	0.017	0.053	0.028
committees$_{j,t-1}$	(0.159)	(0.145)	(0.160)	(0.147)
Facility belongs to a listed firm$_{f,t}$	0.088	0.090	0.088	0.090
	(0.069)	(0.069)	(0.069)	(0.069)
Firm effects	Yes		Yes	
Facility effects		Yes		Yes
Located in a special tract	Yes		Yes	
MSA, Urban, and Costal County effects	Yes		Yes	
Located in a county that border Mexico or Canada	Yes		Yes	
Time effects	Yes	Yes	Yes	Yes
Observations	582,722	582,722	582,722	582,722
R^2	0.404	0.614	0.404	0.614

Robust standard errors clustered by firms are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.10: Marginal effects for toxic waste managed through RRT

Variable	Log $\left(RRT_{ft}/\text{total toxicity}_{ft}\right)$			
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	-0.081***	-0.091***		
	(0.012)	(0.012)		
The range of the board's relative pollution	0.018*	0.017*		
degree centrality$_{j,t-1}$	(0.010)	(0.010)		
E[Board's average pollution ratio]$_{j,t-1}$			-0.164***	-0.184***
			(0.025)	(0.025)
E[The range of the board's relative pollution			0.034	0.032
degree centrality]$_{j,t-1}$			(0.021)	(0.020)
Firm's influence$_{j,t-1}$	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Firm effects	Yes		Yes	
Facility effects		Yes		Yes

Robust standard errors clustered by firms are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.11: Effect of a clean director

Variable	Log of toxic releases$_{ft}$		Log $\left(\text{RRT}_{ft}/\text{total toxic waste}_{ft}\right)$	
	Minimum years after appointment		Minimum years after appointment	
	One	Two	One	Two
	(1)	(2)	(3)	(4)
Director's pollution ratio$_{d,t-1}\leq$ 0.25	-0.023***	-0.025***	0.013***	0.012***
	(0.007)	(0.009)	(0.004)	(0.005)
One year after$_{d,j,t}$	0.089***	0.085***	-0.028***	-0.027**
	(0.021)	(0.024)	(0.010)	(0.011)
One year after$_{d,j,t}\times$ director's pollution ratio$_{d,t-1}\leq$ 0.25	-0.578***	-0.548***	0.171***	0.162***
	(0.115)	(0.110)	(0.035)	(0.038)
Two years after$_{d,j,t}$	0.037***	0.035**	-0.008	-0.008
	(0.012)	(0.014)	(0.008)	(0.009)
Two years after$_{d,j,t}\times$ director's pollution ratio$_{d,t-1}\leq$ 0.25	-0.257***	-0.245***	0.069***	0.065***
	(0.060)	(0.060)	(0.021)	(0.022)
Three years after$_{d,j,t}$	0.016	0.014	0.001	0.001
	(0.010)	(0.012)	(0.006)	(0.006)
Three years after$_{d,j,t}\times$ director's pollution ratio$_{d,t-1}\leq$ 0.25	-0.165***	-0.156***	0.045***	0.042**
	(0.046)	(0.044)	(0.016)	(0.017)
Four years after$_{d,j,t}$	0.015*	0.013	-0.003	-0.003
	(0.008)	(0.009)	(0.004)	(0.004)
Four years after$_{d,j,t}\times$ director's pollution ratio$_{d,t-1}\leq$ 0.25	-0.114***	-0.108***	0.026**	0.024**
	(0.030)	(0.030)	(0.011)	(0.011)
Firm's influence$_{j,t-1}$	24.769	22.233	-28.232	-28.000
	(26.401)	(27.856)	(27.466)	(28.008)
Log of total industrial toxic releases$_{j,t}$	0.424***	0.429***	-0.052***	-0.053**
	(0.045)	(0.046)	(0.020)	(0.020)
Director is a CEO of a firm$_{d,t-1}$	-0.033	-0.028	0.004	0.004
	(0.032)	(0.031)	(0.015)	(0.015)
Proportion of directors in environmental	0.223	0.220	-0.136	-0.172
committees$_{j,t-1}$	(0.519)	(0.537)	(0.215)	(0.224)
Facility belongs to a listed firm$_{f,t}$	-0.010	0.003	-0.001	0.007
	(0.162)	(0.161)	(0.080)	(0.079)
Firm effects	Yes	Yes	Yes	Yes
Located in a special tract	Yes	Yes	Yes	Yes
MSA, Urban, and Costal County effects	Yes	Yes	Yes	Yes
Located in a county that border Mexico or Canada	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Observations	848,475	799,743	848,475	799,743
R^2	0.332	0.331	0.213	0.211

Robust standard errors clustered by firms are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.12: Censored linear regression results for total releases

Variable	Log of toxic releases$_{ft}$					
	OLS	Censored		OLS	Censored	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All facilities						
Board's average pollution ratio$_{j,t-1}$	3.640***	3.921***	3.178***			
	(0.211)	(0.033)	(0.049)			
The range of the board's relative pollution degree centrality$_{j,t-1}$	-1.311***	-1.522***	-0.406***			
	(0.223)	(0.028)	(0.048)			
E[Board's average pollution ratio]$_{j,t-1}$				7.151***	7.706***	6.254***
				(0.414)	(0.064)	(0.096)
E[The range of the board's relative pollution degree centrality]$_{j,t-1}$				-2.557***	-2.961***	-0.793***
				(0.437)	(0.055)	(0.095)
Firm's influence$_{j,t-1}$	-21.588	-11.377	27.053	-22.032	-11.919	26.747
	(22.169)	(12.100)	(21.310)	(22.242)	(12.100)	(21.310)
Log of total industrial toxic releases$_{i,t}$	0.241***	1.063***	2.446***	0.241***	1.064***	2.445***
	(0.030)	(0.033)	(0.029)	(0.030)	(0.033)	(0.029)
Facility belongs to a BoardEx firm$_{f,t}$	-0.662***	-0.875***	-0.783***	-0.663***	-0.878***	-0.784***
	(0.151)	(0.019)	(0.094)	(0.151)	(0.019)	(0.094)
Proportion of directors in environmental committees$_{j,t-1}$	-0.802**	-1.023***	-1.398***	-0.831**	-1.057***	-1.492***
	(0.401)	(0.051)	(0.127)	(0.395)	(0.051)	(0.127)
Facility belongs to a listed firm$_{f,t}$	-0.133	-0.200***	-0.361***	-0.131	-0.201***	-0.360***
	(0.148)	(0.021)	(0.054)	(0.148)	(0.021)	(0.054)
Facility level random effects			Yes			Yes
Observations	582,722	582,722		582,722	582,722	
R^2	0.129			0.128		
Log likelihood		-1.252e+06	-994,239		-1.252e+06	-994,224
Uncensored observations		310,227	289,967		310,227	289,967
Panel B: BoardEx facilities						
Board's average pollution ratio$_{j,t-1}$	3.572***	3.877***	3.193***			
	(0.205)	(0.033)	(0.048)			
The range of the board's relative pollution degree centrality$_{j,t-1}$	-1.096***	-1.287***	-0.299***			
	(0.216)	(0.029)	(0.047)			
E[Board's average pollution ratio]$_{j,t-1}$				7.020***	7.622***	6.284***
				(0.403)	(0.066)	(0.094)
E[The range of the board's relative pollution degree centrality]$_{j,t-1}$				-2.138***	-2.502***	-0.582***
				(0.424)	(0.057)	(0.092)
Firm's influence$_{j,t-1}$	-29.880	-20.459*	26.593	-30.259	-20.936*	26.295
	(21.448)	(12.200)	(20.648)	(21.499)	(12.198)	(20.648)
Log of total industrial toxic releases$_{i,t}$	0.264***	1.077***	2.311***	0.264***	1.077***	2.309***
	(0.032)	(0.045)	(0.040)	(0.032)	(0.045)	(0.040)
Proportion of directors in environmental committees$_{j,t-1}$	-0.742*	-0.982***	-1.277***	-0.784*	-1.031***	-1.376***
	(0.411)	(0.052)	(0.124)	(0.405)	(0.053)	(0.124)
Facility belongs to a listed firm$_{f,t}$	-0.102	-0.160***	-0.381***	-0.100	-0.160***	-0.380***
	(0.140)	(0.021)	(0.054)	(0.139)	(0.021)	(0.054)
Facility level random effects			Yes			Yes
Observations	288,277	288,277	288,277	288,277	288,277	288,277
R^2	0.168			0.168		
Log likelihood		-616,794	-478,834		-616,963	-478,818
Uncensored observations	152,861	152,861	152,861	152,861	152,861	152,861

Robust standard errors clustered by firms are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.13: Regression results for total releases and RRT

Variable	Log of toxic releases released$_{ft}$		Log of $\left(\frac{\text{RRT}}{\text{total toxic waste}}\right)_{ft}$	
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	3.180***		-1.108***	
	(0.403)		(0.244)	
The range of the board's relative pollution degree centrality$_{j,t-1}$	0.027		0.028	
	(0.213)		(0.131)	
E[Board's average pollution ratio]$_{j,t-1}$		6.183***		-2.153***
		(0.800)		(0.478)
E[The range of the board's relative pollution degree centrality]$_{j,t-1}$		0.074		0.025
		(0.420)		(0.259)
Firm's influence$_{j,t-1}$	-27.333***	-27.780***	21.183	21.399
	(4.817)	(4.836)	(14.577)	(14.632)
The firm has an environmental committee$_{j,t-1}$	0.021	0.015	-0.028	-0.026
	(0.057)	(0.058)	(0.037)	(0.038)
Log of total industrial toxicity$_{i,t}$	0.239***	0.239***	-0.094***	-0.094***
	(0.045)	(0.045)	(0.032)	(0.032)
Holdings by institutions$_{i,t}$	-0.002	-0.002	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.002)
Holdings by strategic entities$_{i,t}$	-0.003	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Facility effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
Observations	89,961	89,961	89,961	89,961
R^2	0.780	0.780	0.610	0.610

This table reports the OLS regression results for all facilities. The dependent variable is the log of total toxic Robust standard errors clustered by firms are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.14: Regression results for total releases and ESG scores

Variable	Log of ESG Score				
	Total	Environmental	Social	Resource use	Governance
	(1)	(2)	(3)	(4)	(5)
Panel A: Without expected values					
Board's average pollution ratio$_{j,t-1}$	0.004	0.071	-0.041	0.213	-0.051
	(0.099)	(0.352)	(0.086)	(0.464)	(0.120)
The range of the board's relative pollution	0.023	0.056	0.006	0.125	-0.035
degree centrality$_{j,t-1}$	(0.048)	(0.178)	(0.048)	(0.231)	(0.086)
Firm's influence$_{j,t-1}$	0.883	38.296	4.453	13.563	-14.280
	(8.778)	(24.856)	(10.263)	(18.601)	(12.875)
The firm has an environmental committee$_{j,t-1}$	0.000	0.136*	0.003	0.085	-0.026
	(0.022)	(0.080)	(0.037)	(0.077)	(0.039)
Log of total industrial toxicity$_{i,t}$	0.003	-0.017	0.005	0.003	0.010
	(0.009)	(0.026)	(0.009)	(0.030)	(0.011)
Holdings shares	Yes	Yes	Yes	Yes	Yes
Facility effects	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes
Observations	55,082	55,082	55,082	55,082	55,082
R^2	0.766	0.722	0.749	0.716	0.566
Panel B: With expected values					
E[Board's average pollution ratio]$_{j,t-1}$	0.010	0.126	-0.070	0.410	-0.095
	(0.194)	(0.686)	(0.165)	(0.907)	(0.231)
E[The range of the board's relative pollution	0.028	-0.006	-0.005	0.159	-0.073
degree centrality]$_{j,t-1}$	(0.095)	(0.349)	(0.093)	(0.457)	(0.171)
Firm's influence$_{j,t-1}$	0.924	38.552	4.483	13.746	-14.276
	(8.740)	(25.079)	(10.232)	(18.405)	(12.898)
The firm has an environmental committee$_{j,t-1}$	-0.000	0.134*	0.003	0.082	-0.026
	(0.022)	(0.080)	(0.037)	(0.078)	(0.039)
Log of total industrial toxicity$_{i,t}$	0.003	-0.017	0.005	0.003	0.010
	(0.009)	(0.026)	(0.009)	(0.030)	(0.011)
Holdings shares	Yes	Yes	Yes	Yes	Yes
Facility effects	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes
Observations	55,082	55,082	55,082	55,082	55,082
R^2	0.766	0.722	0.749	0.716	0.566

This table reports the OLS regression results for all facilities. The dependent variable is the log of total toxic Robust standard errors clustered by firms are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.15: Regression results for total releases - firms with same boards

Variable	Log of toxic releases$_{ft}$			
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	2.653***	2.671***		
	(0.221)	(0.233)		
The range of the board's relative pollution	0.469***	0.462***		
degree centrality$_{j,t-1}$	(0.070)	(0.073)		
E[Board's average pollution ratio]$_{j,t-1}$			5.189***	5.224***
			(0.444)	(0.468)
E[The range of the board's relative pollution			0.937***	0.925***
degree centrality]$_{j,t-1}$			(0.135)	(0.142)
Firm's influence$_{j,t-1}$	14.212	15.578	14.111	15.473
	(32.957)	(34.368)	(32.999)	(34.413)
Log of total industrial toxic releases$_{i,t}$	0.359***	0.184***	0.359***	0.184***
	(0.043)	(0.028)	(0.043)	(0.028)
Proportion of directors in environmental	0.273	0.277	0.211	0.215
committees$_{j,t-1}$	(0.221)	(0.225)	(0.239)	(0.244)
Facility belongs to a listed firm$_{f,t}$	-0.079	-0.081	-0.080	-0.082
	(0.116)	(0.123)	(0.116)	(0.122)
Firm effects	Yes		Yes	
Facility effects		Yes		Yes
Located in a special tract	Yes		Yes	
MSA, Urban, and Costal County effects	Yes		Yes	
Located in a county that border Mexico or Canada	Yes		Yes	
Time effects	Yes	Yes	Yes	Yes
Observations	173,528	173,528	173,528	173,528
R^2	0.354	0.791	0.354	0.791

Robust standard errors clustered by firms are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.16: Marginal effects for total releases - firms with same boards

Variable	Log of toxic releases$_{ft}$			
	(1)	(2)	(3)	(4)
Board's average pollution ratio$_{j,t-1}$	1.238***	1.246***		
	(0.103)	(0.109)		
The range of the board's relative pollution	0.234***	0.230***		
degree centrality$_{j,t-1}$	(0.035)	(0.036)		
E[Board's average pollution ratio]$_{j,t-1}$			1.232***	1.241***
			(0.106)	(0.111)
E[The range of the board's relative pollution			0.238***	0.235***
degree centrality]$_{j,t-1}$			(0.034)	(0.036)
Firm's influence$_{j,t-1}$	0.0001	0.0002	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Firm effects	Yes		Yes	
Facility effects		Yes		Yes
Observations	173,528	173,528	173,528	173,528
R^2	0.352	0.795	0.352	0.795

Robust standard errors clustered by firms are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Chapter 4

Board Networks, Corporate Political Donations, and Environmental Performance

4.1 Introduction

In the United States, the political environment is becoming more polarized (The Guardian, 2019). Due to the rising polarization, support for protecting environmental quality, once viewed as "a uniting issue", is now significantly divided along party lines (Harring and Sohlberg, 2017; Dunlap, 2019). In the US, the Republican Party has long been criticised to be climate deniers (The Guardian, 2015). The Republican-led Supreme Court limited the US Environment Protection Agency's power to regulate against greenhouse gas emissions in 2022 (Financial Times, 2022g). Earlier nine Republican attorneys-general accused BlackRock, the world largest asset manager, of prioritizing climate "activism" over fiduciary duty to their state pension funds (Financial Times, 2022i). The State Financial Officers Foundation, the Republican treasurers' group is taking an anti-ESG (Environment, Social and Governance) stance while some 13 treasurers of Democratic states signed a joint letter stressing that investments need to be made "for the long term" (Financial Times, 2022a). In the private sector, an anti-ESG exchange trade fund (ETF) was launched and attracted $315 millions in less than a month (Financial Times, 2022b). There is the argument that firms maximizes their profits at the expense of more morally preferable alternatives. However, there is increasing evidence showing a positive impact of adopting environmentally friendly practices on corporate financial performance (Manrique and Martí-Ballester, 2017; Yue et al., 2020; Abate et al., 2021; Xiong, 2021). Therefore, it is rational for firms to conduct environmentally friendly practices as part of their profit maximization efforts.

The rapidly increasing spending in recent US election and the rising involvement of large donors in particular donors with corporate connections does not only reflect the polarizing US politics, but also fuels the process (La Raja and Schaffner, 2015). The 2020 election was the most expensive election in American history. Presidential and congressional candidates spent a total of almost $14 billion, around four times the total amount spent in 2000. In recent years, candidates for state and federal offices have raised substantially more than in the past (Davidson et al., 2021). Most of these expenses are made up of campaign donations. The share of large donations in the total value of donations has been increasing every election. According to data from OpenSecrets (2020), large donations accounted for 71% of total fundraising in 2018. An important issue with these large contributions is that they originate from individuals, who are linked to companies (CEOs, members of the board of directors, etc.). Increase in their political donations indicate they are more politically active.

This chapter studies potential consequences of the observed polarization of US politics on firms' decision making, in particular environmental strategies, by taking an empirical approach and using multiple sources of data. I use the database, DNTP, compiled in the second chapter, which records business network, facilities' toxic release, geographic and demographic information, directors' characteristics and environmental performances along with political donation and ideology information between 2000 and 2014. I study two questions: 1) how political ideology affects companies' environmental performance in terms of toxic releases; 2) how political ideology affect director appointments. I make the following three major contributions to the existing literature.

First, I contribute to the broader study about corporate political donations. There has been a body of literature studying corporate political strategy. Having greater influence can help firms and/or individuals to influence regulation changes to benefit them (or harm them less). In the financial market, Correia (2014) finds that politically connected firms are less likely to face a Securities and Exchange Commission (SEC) enforcement action and they face lower penalties when prosecuted. Making political donations is one of the most obvious ways to gain political access. Bertrand et al. (2020) show that grants given to charitable organizations located in a congressional district increase when its representative obtains seats on committees that are of policy relevance to the firm associated with the foundation. Ovtchinnikov and Pantaleoni (2012) present evidence showing individuals make political contributions strategically by targeting politicians with power to affect their economic well-being. There are other external factors determining corporate political strategy. Economic performance is closely related to a firm's performance and a firm's performance will affect its political strategy (Mathur and Singh, 2011; Hui et al., 2008; Goldman et al., 2009; de Figueiredo Jr and Edwards, 2007). Gulen and Myers (2021) find out that violation rates for these facilities are significantly lower than those in non-battleground states, suggesting regulators treat the battleground states favourably. Muttakin et al. (2021) examine the association between a country's electoral system and greenhouse gas(GHG) emission intensity of firms and find that companies operating in countries using majoritarian electoral systems, where corporations have a relatively low influence on election outcomes, are associated with lower GHG emission intensity than those in proportional electoral systems.

The returns of political donations has been analyzed to distinguish the motives behind political donations. There have been mixed findings. Some literature points out there is no evidence supporting the investment view.[1] For example, Aggarwal et al. (2012) find that a $10,000 increase in donations is associated with a reduction in annual excess returns of 7.4 basis points, showing no evidence supporting donations represent investment in political capital. On the other hand, some studies have shown that making political donations helps to improve corporate performances. Titl and Geys (2019) find that donating firms receive more small contracts allocated under less regulated procurement procedures, face less competition in more regulated and open procurement procedures, and tend to win with bids further above the estimated cost of the procurement contract. Regarding the environment related regulatory risk, Heitz et al. (2021) examine whether the EPA selectively enforces regulation for politically connected firms and found no difference in EPA investigations between politically connected and unconnected firms. Brown et al. (2015) link tax-specific PAC support to tax-specific outcomes, providing an economic link for the observed contribution-return relation documented by Cooper et al. (2010) and provided evidence of an incremental effect of tax-specific lobbying for firms that develop stronger relationships with tax policymakers via PAC support.

While the existing literature focuses on how political donations are used to influence

[1]Refer investment view to Tobin (1958) and Hall and Wayman (1990)

regulations and policy making, this chapter has an empirical approach that enables us to focus on ideology-driven motive. The use of the TRI Program provides us with a unique opportunity to concentrate on the effect of political ideology, since the US EPA has not changed reporting thresholds and chemical listed in the TRI Program between 2002 and 2011 (De Silva et al., 2021). The US EPA did not changed reporting thresholds and chemicals listed in the TRI Program between 2002 and 2011, only made minor changes to the chemical list.[2] In addition, the TRI Program does not involve any penalty as long as firms report their toxic releases as requested, which means that companies do not have enough motivation to use political donations to affect the Program. Therefore, there is no correlation between toxic releases reported under the TRI Program and a firm's political donation strategy.

Second, this chapter contributes to the literature of studying the effect of political ideology in shaping environment-related policies. In this field, some existing studies focus on the public sector by studying how a government's political ideology shapes its country's policies including environment-related policy (e.g. Bjørnskov (2005), Mian et al. (2010), and Wang et al. (2022)). Left-leaning politicians have claimed to have the most comprehensive pro-environmental agenda (e.g. Carter (2009) and Clements (2014)). Similarly for ordinary populations, right-leaning individuals seem to be less supportive of environmental policies than left-leaning individuals (e.g. Dunlap (1975), Samdahl and Robertson (1989), Whittaker et al. (2005), Greenhill et al. (2014), and Hamilton and Saito (2015)). Further, there has also been a growing literature studying the effect of political ideology within private organizations (including companies). For example, Gupta et al. (2017) introduce the concept of organizational political ideology based on employee's political donations, and found companies' adoption of socially responsible practices is influenced by organizational ideologies, above and beyond executive ideology. However, not all employees are equal, some business individuals are more influential and play more significant roles in shaping companies' policies and political ideology. For example, Unsal et al. (2016) find CEOs' political orientation determines her/his firm's political behavior and firms with Republican leaning CEOs tend to lobby more bills and spend more money. In this chapter, I focus on companies' political ideology instead of particular personnel's political ideology. This is because Bonica (2016a) points out that corporate elites' political donation strategies are

[2]The EPA added 16 chemicals to the list in 2011 and added, reinstated and expanded three main compounds between 2016 and 2019.

not necessarily in line with their companies.[3]

To study the effect of political ideology, I estimate how a firm's political ideology influences its facilities' toxic releases, toxic management and ESG scores by using a simple linear technique. The firm's political ideology is measured by a firm's relative donations to the Republican party. A firm's relative donation to the Republican party is the proportion of total political donations made by the given firm that is given to the Republican candidates. However, organizational political ideology is only one dimension of a firm's political ideology. Hoang et al. (2020) show polarization in the boardroom worsens companies' environmental performance; therefore, I create diversity measures to measure a given firm's boardroom political diversity and the difference between the firm itself and its directors. I also take into account the effect of the local political effect on facilities' environmental performance and create a dummy variable to identify whether a county is a Republican or Democratic county based on its voting pattern, along with other factors that have shown by the existing literature to have significant impacts on companies' environmental performances. My results show that a firm with a higher relative donations for the Republicans tends to release more toxic chemicals to the environment. This finding implies that political ideology has an effect on shaping firms' environmental strategies and Republican-leaning firms have poorer environmental performances in terms of toxic releases.

Third, I also study the effect of political ideology in network formation, since political activities can be affected by social networks. For example, Bond (2007) show that club and school ties play a significant part in corporate political donations in Britain. Director appointment can be modelled as network formation, as once a director is appointed to a firm, this director forms close connections with the firm and its other board directors. There has been extensive literature on how companies appoint their directors based on various factors. Director appointments are made based on candidates' performance records (Brickley et al., 1999; Ferris et al., 2003; Fich and Shivdasani, 2007), while some directors are appointed for particular expertise (Becher et al., 2017), including environment related expertise (Walls et al., 2012; Homroy and Slechten, 2019). Moreover, the pre-existing network structure also plays a role in business appointment. Kramarz and Thesmar (2013) provide evidence showing CEO's social networks affect her/his firm's board composition

[3] Corporate elites includes directors and executives

and efficiency while Cashman et al. (2013) find that well-connected directorship candidates are more likely to be appointed and Cai and Sevilir (2012) showed having connections to the incumbent board members significantly help to obtain board positions. In addition, a major determinant of network formation is homophily, i.e., the predominance of ties between companies and directors who share similarities. Westphal and Zajac (2013) and Kogut et al. (2014) find that existing directors tend to favor colleagues who have more similarities on major demographic characteristics. However, the literature on the role of political ideology played in director appointment is very limited. Board members are expected to make decisions on corporate political spending in line with corporate strategies, policies, and values and also to mitigate risks (Bagley et al., 2015). Therefore, it is important to study the role of political ideology in appointing board directors.

To study the effect of political ideology in appointing directors, I follow a similar method in Chapter 3. In addition to the homophily measures created in the previous chapter, I create politics-related homophily measures between candidates and firms by using the CF-scores obtained in the DNTP database. My findings show that board directors are more likely to appoint someone who shares similar political ideology, explaining how the business world becomes more politically polarized. Further, the inclusion of network formation study enables me to endogenize the effect of directors' environmental experience and political ideology.

This chapter is organized as follows. In the next section, I present how I construct political ideology measures from the DNTP. Section 3 lays out the empirical models and presents the results. In the final section, I conclude and discuss the implications of my findings.

4.2 Measures for environmental performance and political ideology

I keep all measures from Chapter 3, and construct political ideology measures for firms and directors. Summary statistics are presented in Table 4.1.

4.2.1 Environmental Performance and Network Influence (R)

At director-level, *pollution ratio* is the ratio of the total number of polluting facilities relative to the total number of plants which s/he is a board director in the previous year; and *relative dirty degree centrality* is obtained by computing the proportion of 'toxic links' relative to her/his total links. Note that, *polluting facility* is defined as a facility that reports any toxic releases to the TRI Program and toxic link is defined as the link where a director is appointed to a firm that has one or more polluting facilities. In addition, I use eigenvector centrality measure to capture a firm's and a director's network influence.

4.2.2 Politics related measures (P)

In addition to the CF-scores already included in the DNTP dataset, I create firms' political ideology measures based on their donation records. The first political ideology measure is a dummy variable, *no donation*, which takes the value 1 in a given year if the firm and its board director makes no political contribution at all, and zero otherwise. As shown in Table 4.1, 98.7% of firms along with their directors make no political donations. However, for firms with 3 or more directors, this proportion reduces to 83.8%. The second political ideology measure, *relative donation for Republicans*, is the proportion of the given firm's donation to the Republican Party relative to its total political donations. The average donation for Republicans by firms is approximately $\$15,704.04$ and the average relative donation for Republicans by firm is approximately 0.142. Figure 4.3 shows that relative donation to the Republicans is slightly higher than relative donation to the Democrats on average while the proportion of politically active firms is increasing over time. Further, in Figure 4.1, we can see that although firms' CF scores seem to be correlated with their relative donations for the Republicans, there are many outliers suggesting the opposite. This could be caused by event-driven political donations that firms only make donations strategically in respond to some certain events and do not make donations when there is no event. Since it has been noted by many scholars that political donation is a noisy proxy (Baron et al., 2021). In the spirit of Lee et al. (2014), I take the moving averages of 2-year election cycle in the hope of eliminating the possibility that political donations made by firms might not clearly reflect their organizational political orientation. Taking the moving averages enables to mitigate the effects of strategic donations and reduce the noise of particular political events (e.g. elections). In addition, I also create a dummy variable, *Republican-leaning firm*, which equals 1 in a given year if the firm's *relative donation for Republicans* is greater than 0.5, and 0 if otherwise.

Then I create two politically diversity measures. The first measure is *diversity in directors' CF-scores*. This is computed from difference between the largest CF-score and the small CF-score among the board members. I focus on a reduced sample of firms with more than 2 directors when studying political ideology diversity. The average of *diversity in directors' CF-scores* for firms with more than 2 directors are 0.480. The second diversity measure is the *difference between board directors' average CF-scores and their firms' CF-scores*. The average difference for firms with more than 2 directors is 0.116 in this reduced sample. Figure 4.4 shows the change in political diversity over time. We can see that diversity in directors' political ideology and difference between firms' and CEO's agenda are increasing over time, while difference between firms' and boards' CF-scores is decreasing.

Besides firms' and directors' political measures, I also create a local political measure for facilities. This measure, *Republican county*, is a dummy variable that identifies whether a county is Republican or Democratic county based on its voting results in Presidential elections. Approximately 58.5% of facilities are located in Republican counties in the reduced sample of firms with 3 or more directors.[4]

4.3 Empirical Analysis

I empirically study how political ideology and contribution affect firms' environmental performance of the facilities owned by the given firms. This chapter also focuses on toxicity related performance, including releasing toxic waste to the environment (air, water and/or land) and using clean waste management practices (RRT). Directors make collective decisions regarding their firms' environmental strategies that determine all their facilities' individual toxicity related performances. I examine if environmental strategies are affected by firms' political ideology.

[4]Around 56.9% of facilities are located in Republican counties in the DNTP.

I model this relationship using the following regression equation:

$$y_{f,j,i,l,t} = B^{'}_{j,t-1}\beta + P^{'}_{j,t-1}\zeta + C^{\prime}_{j,t-1}\gamma + F^{'}_{f,t-1}\delta + \eta M_{i,t} + L^{'}_{l,t}\phi + \alpha_f + \tau_t + \mu_{f,j,i,l,t}, \quad (4.1)$$

where facility f belongs to firm j from industry i, in location l at time t. α_f is the industry-, facility- or firm-level fixed effects or random effects (depending on the specification) and τ_t is the time effect. $y_{f,j,i,l,t}$ is my measure of a facility's environmental performance.

My focus is firm's political ideology related characteristics (denoted by P). I include the measures, *no donation*, *relative donation for Republicans* by firms, and *Republican-leaning firm* for studying the role of political ideology in affecting firms' environmental performance. *No donation* identifies the effect of a firm's political involvement, while *relative donation for Republicans* and *Republican-leaning firm* identify the effect of a firm' political ideology. The political ideology diversity measures, *diversity in directors' CF-scores* and *difference in firms' and board's CF-scores*, are used to study the effect of political ideology. Further, I estimate my model using the reduced sample of only firms with 3 or more directors.

Further, the board's past environmental performance (denoted by B) is included.[5] *The board's past average pollution ratio* is the average proportion of polluting facilities overseen by the members of the board in other firms in the last period. *The range of relative pollution degree centrality* captures the diversity in terms of directors' environmental records. I include the number of facilities it owns in a given year, and a firm's influence in the market using the firm's eigenvector centrality to control for firms' size. Following Khanna et al. (1998), I include a dummy to identify the fact that publicly trade companies might be more responsive to the increasing pressure to become environmentally responsible. More importantly, I use the industrial total releases to control the industry factor. Industries do not only affect firms' production nature that determine how likely the firms release toxicity, but also affect firms' external regulatory environment. Some industries are more dependent on policy makers than others, for example, the defence industry is more dependent compared with the technology industry as the major clients for the defence industry is the government. The demographic and geographical characteristics (denoted by L) of a facility's location could affect its decisions on waste management practices. Regarding

[5]More details are provided in Chapter 3.

the demographic characteristics, we control for median household income, minority ratio, college education ratio, population density. Regarding the geographical characteristics, we control for tracts that are part of an MSA, urban county, rural county, and coastal county, a border with Canada or Mexico, in addition to counties located in a special tract. I also control for facility-level unobservable heterogeneity by including facility-level fixed effects.

To address the endogenous concerns related to the use of the actual number of direct director-firm links, I follow a similar approach used in Chapter 3 by analyzing network formation. I follow the same step in the previous chapter to create a pool of candidates. Summary statistics for this pool are presented in Table 4.2. I define the probability of forming a link between firm j and director d at time t as:

$$ln\left(\frac{Pr(l_{d,j,t}|N_{d,j,t-1},R_{d,t-1},D_{d,t-1},g(N_{d,j,t-1});\theta_t)}{1-Pr(l_{d,j,t}|N_{d,j,t-1},R_{d,t-1},D_{d,t-1},g(N_{d,j,t-1};\theta_t)}\right)$$
$$=\gamma+N_{d,j,t-1}^{'}\beta+\rho R_{d,t-1}+\delta D_{d,t-1}+(g(N_{d,t-1}-N_{j,t-1})'\Psi(g(N_{d,t-1}-N_{j,t-1})))+\tau_t+\epsilon_{d,j,t} \tag{4.2}$$

where the term $(g(N_{d,t-1}-N_{j,t-1})'\Psi(g(N_{d,t-1}-N_{j,t-1})))$ is the disutility (cost) of having a difference in homophily between potential director candidates which relates to firm j in period $t-1$ (see Christakis et al. (2020) for a similar measure of homophily). Four homophily measures denoted by g include three measures created in Chapter 3 and one new political ideology measure.[6] The political ideology measure is the difference in a candidate's CF-scores and board's CF-scores. I use a Bayesian MCMC technique based on a hybrid Metropolis-Hastings algorithm with Gibbs sampling updates to estimate the posterior mean and posterior standard deviations. Then using the results, I re-estimate Equation 4.1 with expected values.

Director appointment

Table 4.3 presents the means and credible intervals of the posterior distributions of my model parameters. Column 1 presents results for all the TRI-reporting firms in our sample without consideration of political ideology, Column 2 presents results for all the TRI-

[6]The homophily measures obtained from Chapter 3 are: 1) the difference in a director's relative pollution degree centrality with respect to board members' average relative pollution degree centrality, 2) the difference in a director's pollution ratio with respect to the firm's pollution ratio, and 3) the difference in a director's influence and the firm's influence.

reporting firms with considering political ideology, and Column 3 presents results for politically active firms only. First, the candidate and firm network variables (influence measured by eigenvector centrality) play an important role in explaining link formation. In all 3 columns, the mean of the posterior distribution of the director's influence is above 0.1 and the 95% credible interval lies strictly within a positive range of values, suggesting that firms tend to connect with influential directors. Similarly, influential firms tend to connect with more directors. This is not really surprising as influential firms tend to have bigger boards.

Further, the mean of the posterior distribution for a director's past pollution ratio is negative, and the 95% credible interval lies strictly within a negative range of values. This indicates that firms take candidates' past environmental record into account when evaluating their suitability for the board. The effect is stronger for politically active firms. It illustrates that politically active companies might be more responsible by hiring directors with a good environmental record. It is also interesting to note that the mean of the posterior distribution of a director's past pollution ratio interacted with the director's influence is strictly negative. Even though firms are more likely to appoint an influential director, they are reluctant to do so if this director has a poor environmental performance.

Considering the homophily measures, my results indicate that an increase in the differences in a director's relative pollution degree centrality with respect to that of other existing board members decreases the probability of their being appointed as a board member. This probability is also lower when the differences in a director's pollution ratio and influence with respect to the firm increase. In addition, when considering the difference in political ideology, I also find that firms tend to appoint candidates who share similar political ideology with their existing board members. This finding helps to explain how businesses become more politically polarized.

Beyond these results of interest to me, we can see that, as expected, exposure in the market and the candidate being a CEO in another firm are positively associated with the probability of being appointed as a director. Listed firms tend to appoint more directors as listed firms tend to be larger than those private ones on average. Finally, serving on an environment-related board committee increases the probability of being appointed as a board member.

In Table 4.4, I re-estimate my model on the sample of firms with 3 or more directors and the results do not vary significantly. Firms are still more likely to appoint candidates with better environmental records, more experience, and/or greater influence. Similarly, firms do not welcome candidates with great influence but poor environmental record. In addition, it is also shown that candidates who served as CEOs or environmental committee members in other companies are more likely to be appointed as board directors. For homophily measures, it is generally consistent that firms tend to appoint candidates with more similarities including political ideology to their boards; however, for politically ideology, politically active firms with 3 or more directors tend to diverse their boards' political ideology.

4.3.1 Facility-level toxic releases

I first investigate if a firm's political ideology play a role in its facilities' future environmental performance by estimating Equation 4.1 using log of total toxic waste released as our dependent variable. The result is presented in Table 4.5. The results in Columns 1 and 2 are obtained by using *relative donation for Republicans* as the key political ideology indicator for firms, while the results in Columns 3 and 4 use *Republican-leaning firm* as the firms' political ideology identifier. Because of inclusion of political diversity measures, I only use the sample of firms with 3 or more directors. In Columns 1 and 3, I only use the lagged values for politics related measures; while I use the moving averages of 2 year politics related measures in Columns 2 and 4.

The results shown in Table 4.5 imply that being politically unaffiliated (i.e. making no political donation at all) has no statistically significant effect on firms' environmental performance. However, when a firm donates a greater proportion to the Republicans (indicating leaning more towards the Republican party), it tends to perform worse in terms of its toxic releases. From Columns 3 and 4, it is clear to see that Republican leaning firms tend to have poorer environmental performance (i.e. release more toxic chemicals to the environment). Since directors have the responsibility of monitoring companies' political activities and executives have the power to manage their sponsoring PACs, firms' relative donation for Republicans can be seen as the combination of firms' and their boards' political ideology. These findings are in line with Figure 4.1 and 4.2 where firms and boards with positive CF-scores (i.e. Republican-leaning firms) seem to have higher probabilities of polluting more than firms and boards with negative CF-scores (i.e. Democratic-leaning firms) do. When a firm has a board of more diverse directors in terms of their political ideology measured by CF-scores, it tends to have better environmental performances; however, such effect is statistically insignificant. Similarly the effect of difference in board's and firm's CF-scores is also statistically insignificant.

Regarding environmental measures, the results are consistent with my previous findings in Chapter 3. When board directors have better environmental records and connect to cleaner network, their firms are likely to perform better regarding toxic releases. The diversity in terms of environmental performance among board directors is also shown to have a positive effect on firm's environmental performance that increasing the diversity helps to lower toxic wastes. Further, the effects of environmental performance related measures are significant at 99% confident level, while the effect of *relative donation for Republicans* is significant at 95% confident level. This indicates that firms' and boards' environmental experiences have more determining impacts on firms' environmental performances.

To address endogeneity concerns related to directors' appointments, I re-estimate Equation 4.1 using the expected values computed based on the network formation results from Table 4.3. The results are consistent with my previous results using the actual values. In Table 4.6, firms with greater relative donations to the Republicans are likely to release more toxic chemicals (shown in Columns 1 and 2) In line with this relationship, *Republican-leaning firms* are expected to have higher toxic releases (shown in Columns 3 and 4). The effects of diversity in directors' CF-scores and difference in board's and firm's CF-scores remain statistically insignificant.

Overall, all my results indicate that when firms make more donations to the Republican Party relatively (i.e. lean more towards the Republican Party), they tend to release more toxic chemical to the environment. There is no significant impact of having a more diverse board or appointing a director who shares different political ideology with the firm on the firm's environmental performance. However, even with consideration of political ideology, directors' and firms' previous environmental performance records play a more significantly role of determining firms' environmental performance, further emphasizing my findings in Chapter 3.

4.3.2 Facility-level toxic waste recovered, recycled, and treated

Due to the limitation and nature of some industries, some facilities are unavoidable to release some hazardous wastes during their production. Under such circumstance, it is important to notice these facilities' efforts regarding how they manage their toxic wastes. To investigate the role played by board directors' political ideology in the waste management activities, I estimate how the toxic chemical management (RRT) is affected by their board's political activities and/or ideology. My dependent variable is the log difference in the total toxic wastes recovered, recycled, and treated, and the total production-related toxic wastes released by a facility. I estimate a linear regression model similar to Equation 4.1. The results are presented in Table 4.7. Columns 1 and 2 show the results estimated using *relative donation for Republicans* and Columns 3 and 4 show the results estimated using *Republican leaning firm*. The effect of firms' political ideology (i.e. *relative donation for Republicans* and *Republican leaning firm*) on their environmental performance is statistically insignificant. Diversity in directors' political ideology and difference in directors' and firms' political ideology still play no significant role in shaping firms' RRT performance where political ideology is measured by CF-scores. As before, I also re-estimate the model using the posterior estimates of the network formation analysis for all firms in our sample. The results are shown in Table 4.8 which has a similar table structure as Table 4.7. The effects of firms' political ideology and all political diversity related measures on firms' toxic releases remains statistically insignificant.

In line with my previous results, board directors' environmental records play a much more significant role in determining their firms' RRT practices shown by results in both Tables 4.7 and 4.8. When board directors have better environmental records, their firms tend to perform more RRT activities. Diversity among board directors would also help to increase the volume of toxic wastes treated while the difference between a firm's and its board directors' CF-scores would lower the volume of treated wastes. However, none of these politics-related coefficients is statistically significant. This implies that politics play no significant role in promoting firms' environmentally friendly activities.

4.3.3 Environmental, Social and Governance (ESG) Scores and institutional holdings

In additon to toxicity-related measures, I also include ESG in my analysis. Nowadays, many public companies are now evaluated by third-party institutions on their environmental, social and governance (ESG) performance in multiple dimensions. This study uses Thomas Reuters ESG scores obtained via Eikon. I estimate a linear regression model similar to Equation 4.1 using firms overall ESG scores along with their environmental scores, resource scores, social scores and governance scores. The results obtained by using actual values are presented in Table 4.9 and the results obtained by using expected values computed from the posterior estimates of the network formation analysis are presented in Table 4.10. Results from two tables do not have any significant difference.

Donating a greater proportion to the Republican Party (i.e. having a higher relative donation to the Republicans) tends to lower a firm's overall ESG score along with its Environment score, Resource score and Social score. Increasing diversity in directors' political ideology would help to improve a firm's Environmental score, Resource score and Social scores. In addition, firms with greater influence measured by their eigenvector centrality tend to have better Environment scores and Resource scores. However, CEO's political ideology has significant impacts on a firm's Environment score, Social score and Governance score. A firm with a Republican-leaning CEO is likely to have better Governance score but poorer Environment score and Social score. The results imply that political ideology plays a significant role in determining a firm's ESG scores. Please note, as suggested in Chapter 3, the toxicity management and the ESG scores represent firms' environmental performance from different aspects.

4.4 Conclusion

Given the increasing polarization of US politics, I examine how political ideology shapes firms' environmental strategies. In this study, I use both CF-scores and relative donation as political ideology indicators of firms and directors. For firms especially, relative donation is a more straightforward and better measure for political ideology. As stated previously, firms do not have investment driven incentive to use political donations to influence the TRI Program since the Program has been generally consistent and does not involve penalty related to environmental performance. Any relationship between political donation and toxicity-related performance can only be explained by political ideology. Further, by using 2 year moving averages, I can mitigate the effect of strategic political donation while using CF-scores is unable to do so.

I study the roles of political ideology in director appointments and shaping firms' environmental strategies. I first study the director appointment process using a network setting. In particular, I am interested in understanding if a director candidate's political ideology, measured by CF-scores, is a determinant of her/his chance probability of being appointed. I use Bayesian techniques to obtain posterior distributions for each network parameter based on prior information on link-formation choices. The results show that firms are more likely to appoint candidates who are similar (in terms of environmental performance, influence and political ideology) to their existing board directors.

Further, I study the role of political ideology played in shaping firms' environment related policies. I estimate my models using both actual values and expected values computed using the posterior estimates of the network formation analysis. Using the parameters estimated in the first step of our analysis enables me to address endogeneity concerns related to the actual number of direct director-firm links. My analysis shows that firms with greater relative donation for Republicans are more likely to have poorer environmental performance; however, political ideology has no significant impact on the toxicity management (i.e. RRT). Besides toxicity related performance, political ideology is shown to play a significant part in determining a firm's overall ESG along with its Environment score, Resource score, Social score and Governance score separately.

Overall, my results are in line with my results from Chapter 3. Although political ideology has a significant impact on firms' environmental performance, directors' and firms' previous environmental performance records and networking have more significant roles. Directors once again are proven to have determinant impacts on their firms' toxicity related performance. Their environmental experiences and network positions are shown to have more significant impacts compared with political ideology. When directors have better environmental performance records and/or connect to other firms and directors with better records, they can help to improve their firms' environmental strategies. However, policy makers, especially politicians, need to step in to stop the polarizing trend and get back to science-driven policy making.

Figures

Figure 4.1: Comparison between firms' CF scores and relative donations for Republicans

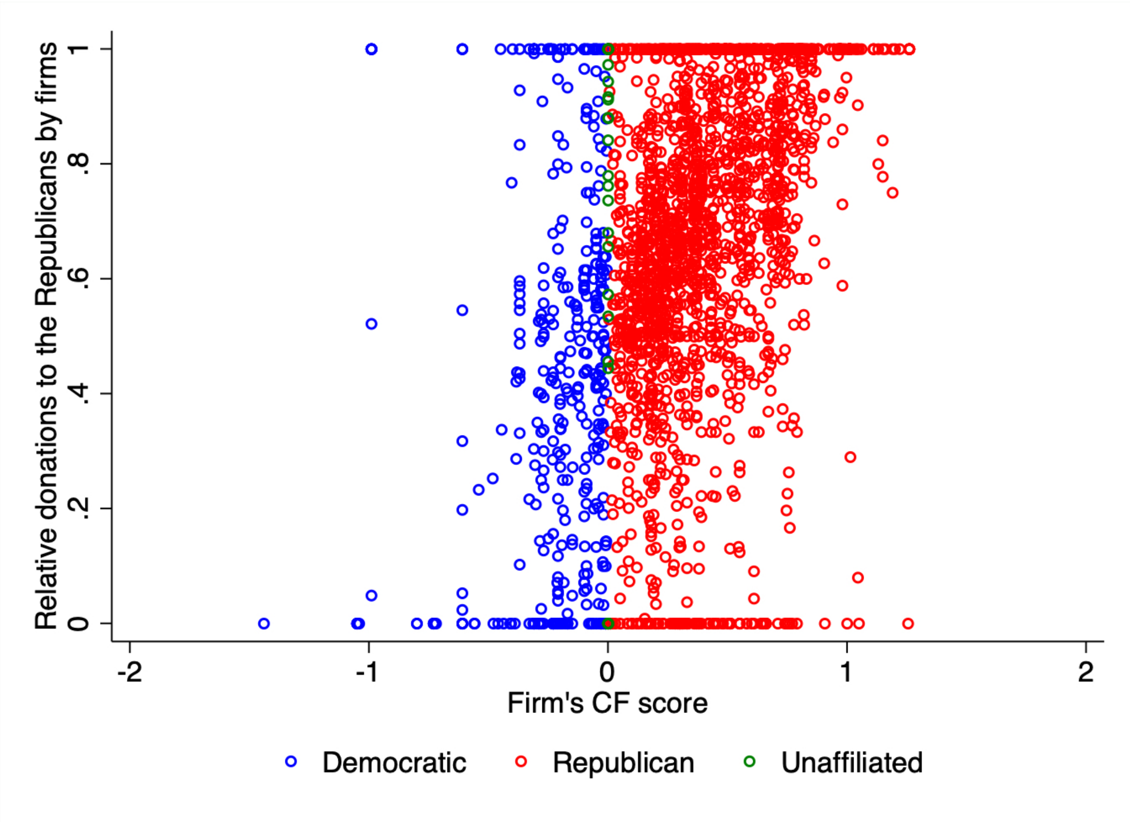


Figure 4.2: Comparison between boards' CF scores and toxicity released by firms

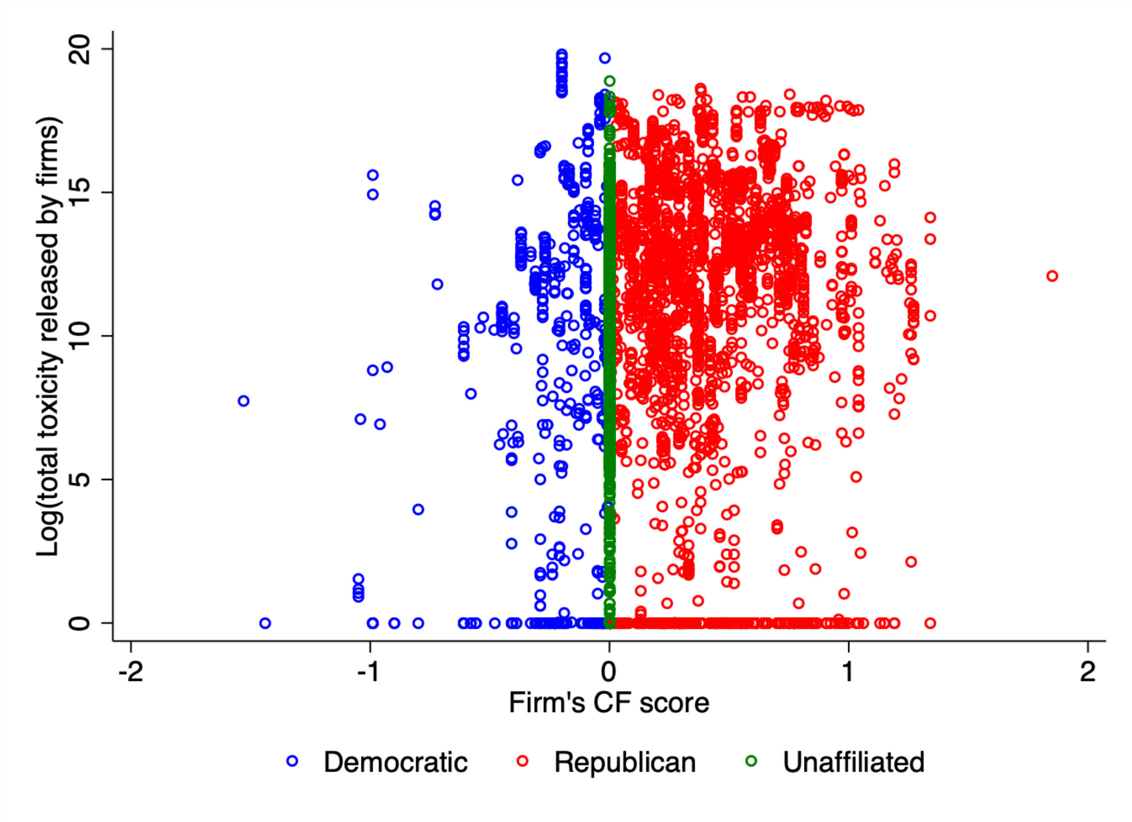


Figure 4.3: Relative donations by firms over time

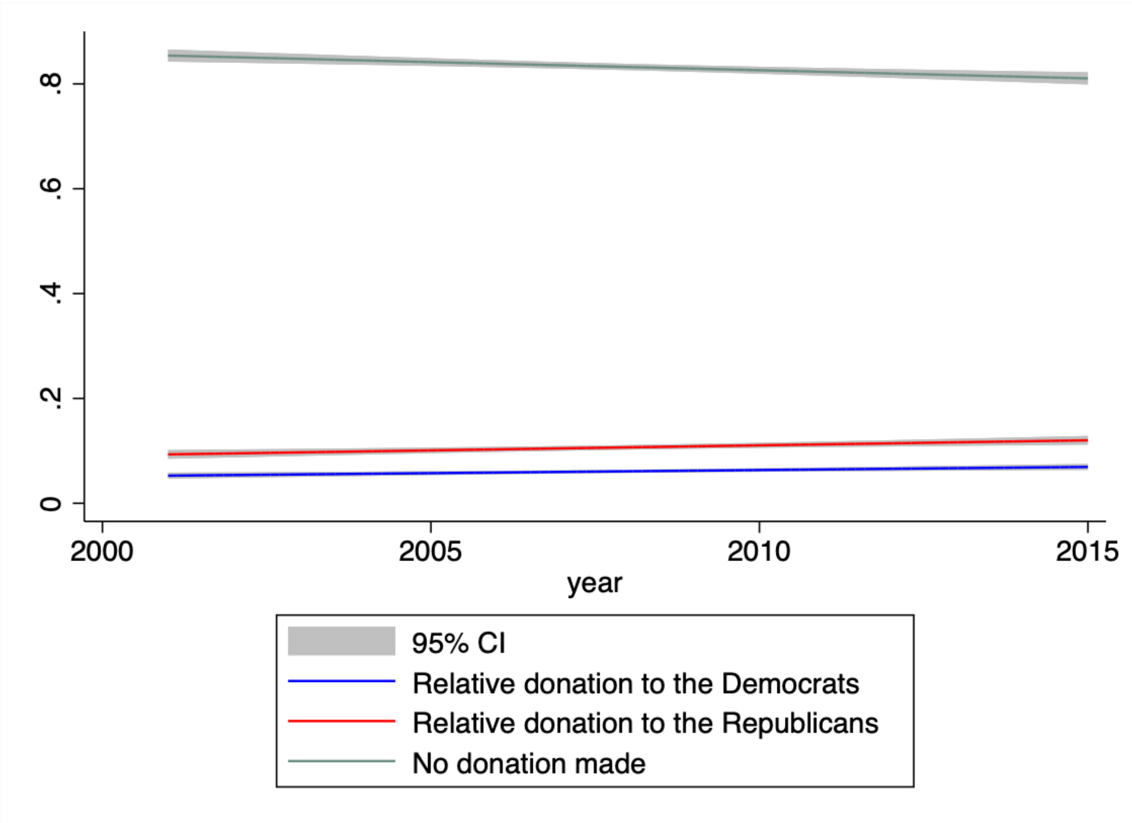
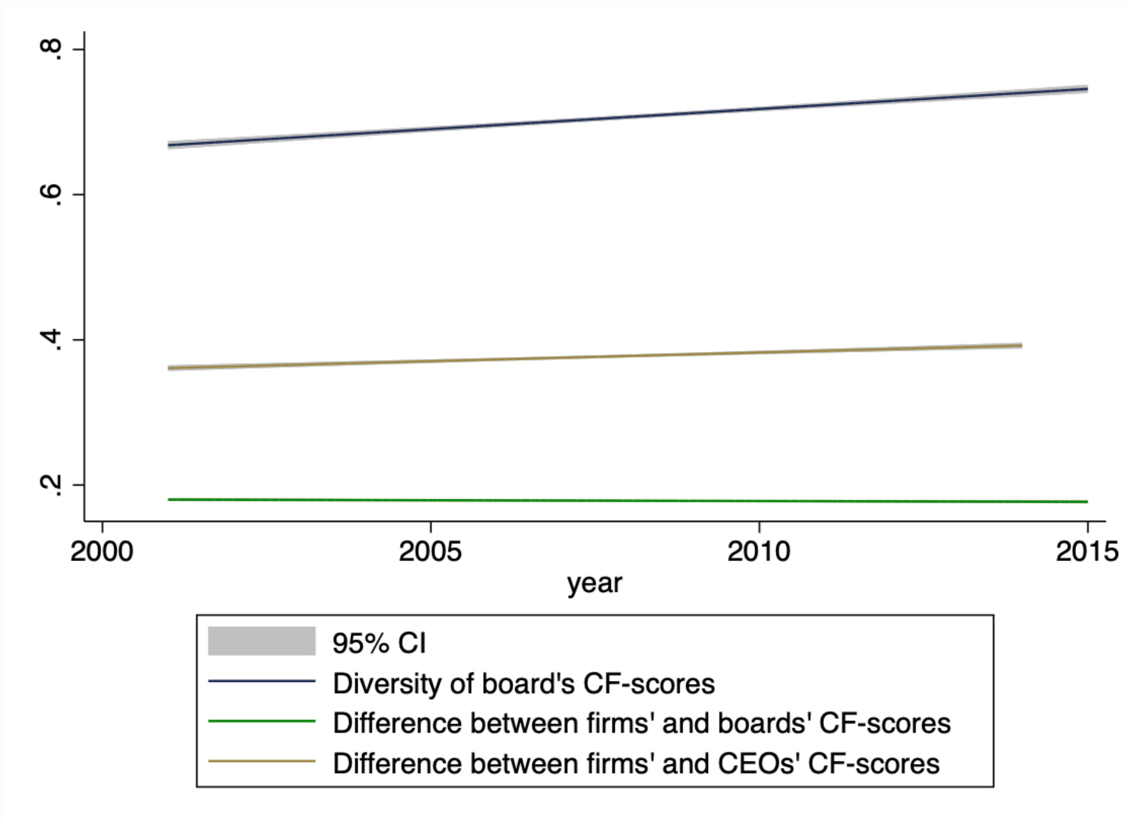


Figure 4.4: Political diversity over time



Tables

Table 4.1: Database on Director Network, Toxic Releases and Politics (DNTP): 2001-2014

Variable	All firms	Firms with 3 or more directors
Panel A: Sample Counts		
Total number of observations (facility level)	514,764	138,677
Number of unique firms	18,787	1,416
Number of unique facilities	40,509	12,177
Panel B: Firm-level statistics		
No donation made	0.987	0.838
	(0.113)	(0.365)
Relative donation to the Republicans	0.009	0.103
	(0.080)	(0.260)
Board's average pollution ratio	0.049	0.469
	(0.179)	(0.303)
The range of the board's relative pollution degree centrality	0.041	0.610
	(0.173)	(0.316)
Diversity in directors' CF-scores	0.030	0.480
	(0.187)	(0.558)
Difference in board's and firm's CF-score	0.013	0.116
	(0.088)	(0.183)
Firm's influence (10^{-4})	0.027	0.787
	(5.428)	(21.515)
Publicly listed	0.033	0.504
	(0.178)	(0.500)
Firm's CF scores	0.006	0.071
	(0.066)	(0.213)
CEO's CF scores	0.0001	0.0002
	(0.003)	(0.012)
Board's CF scores	0.007	0.049
	(0.007)	(0.106)
Number of facilities	2.245	10.199
	(7.565)	(19.470)
Panel C: Facility-level statistics		
Probability of polluting	0.535	0.505
	(0.499)	(0.500)
Total toxic releases by facility	123,039.2	170,025.2
	(4,047,159)	(2,748,379)
Total RRT by facility	592,915.9	610,475.6
	($1.03 * 10^7$)	(5,983,524)
Panel D: Facility-level demographic statistics		
Median household income	55,693.27	56,541.83
	(22,379.63)	(22,668.51)
Minority ratio	0.231	0.229
	(0.239)	(0.236)
College ratio	0.208	0.198
	(0.173)	(0.176)
Population density	1,417	1,250
	(2,528)	(2,216)
Probability of locating in a Republican state	0.569	0.585
	(0.495)	(0.492)

Standard deviations are in parentheses.

Table 4.2: Summary statistics for network formation analysis: 2001 - 2014

Variable	Mean	
	All firms	Politically active firms
	(1)	(2)
Probability of creating a link	0.019	0.026
	(0.138)	(0.160)
Director's past pollution ratio	0.445	(0.478)
	(0.383)	(0.378)
Director's influence	0.0002	0.0003
	(0.014)	(0.015)
Director's past pollution ratio × director's influence	0.0001	0.0002
	(0.009)	(0.010)
Firm's influence	0.0001	0.00003
	(0.002)	(0.004)
Difference in director's relative pollution degree centrality respect to	0.320	0.334
other board members average relative pollution degree centrality[a]	(0.297)	(0.256)
Difference in director's pollution ratio respect to firm's	0.326	0.320
pollution ratio[a]	(0.311)	(0.284)
Difference in director's influence and firms's influence[a]	0.0003	0.0005
	(0.014)	(0.016)
Difference in candidate's CF score and board's CF score	0.129	0.155
	(0.264)	(0.246)
Market exposure in years (number of years in BoardEx)	4.858	4.965
	(3.789)	(3.767)
Listed firms	0.366	0.524
	(0.482)	(0.499)
Candidate is a CEO of a different company	0.094	0.095
	(0.292)	(0.293)
Candidate's past experience in environmental committee	0.011	0.014
	(0.119)	(0.135)
Politically active firms	0.272	1
	(0.445)	

The homophily measures are given in absolute values.
Standard deviations are in parentheses.

Table 4.3: Bayesian estimates of network formation parameters

Variable	Mean of the posterior distribution		
	All firms		Politically active firms
	(1)	(2)	(3)
Candidate's past pollution ratio$_{i,t-1}$	-0.0009	-0.0021	-0.0121
	[-0.0113, -0.0006]	[-0.0024, -0.0019]	[-0.0126, -0.0116]
Candidate's influence$_{i,t-1}$	0.0978	0.0946	0.1379
	[0.0947, 0.1009]	[0.0937, 0.0956]	[0.1366, 0.1391]
Candidate's past pollution ratio × her/his influence$_{i,t-1}$	-0.0490	-0.0482	-0.0293
	[-0.0513, 0.0464]	[-0.0492, -0.0473]	[-0.0308, -0.0280]
Candidate is a CEO in a different firm$_{i,t-1}$	0.0015	0.0017	0.0038
	[0.0012, 0.0019]	[0.0014, 0.0020]	[0.0033, 0.0044]
Candidate's past experience in environmental committees$_{i,t-1}$	0.1681	0.1679	0.2821
	[0.1669, 0.1693]	[0.1674, 0.1684]	[0.2797, 0.2850]
Firm's influence$_{j,t-1}$	0.1190	0.1708	0.0965
	[0.1176, 0.1203]	[0.1702, 0.1713]	[0.0942, 0.0991]
Listed firms$_{j,t-1}$		0.0124	0.102
		[0.0123, 0.0126]	[0.0097, 0.0106]
Difference in candidate's relative pollution degree centrality respect	-0.0287	-0.0292	-0.0444
to other board members average relative pollution degree centrality$_{i,j,t-1}$	[-0.0291, -0.0284]	[-0.0295, -0.0289]	[-0.0452, -0.0434]
Difference in candidate's pollution ratio respect to firm's	-0.0472	-0.0475	-0.0711
pollution ratio$_{i,j,t-1}$	[-0.0475, -0.0469]	[-0.0478, -0.0472]	[-0.0719, -0.0704]
Difference in candidate's influence and firm's influence$_{i,j,t-1}$	-0.0663	-0.0667	-0.1061
	[-0.0685, -0.0637]	[-0.0678, -0.0657]	[-0.1079, -0.1045]
Difference in candidate's CF score and board's CF score$_{i,j,t-1}$		-0.0034	-0.0012
		[-0.0038, -0.0031]	[-0.0021, -0.0003]
Log(Market exposure in years)$_{i,t-1}$	0.0020	0.0019	0.0037
	[0.0019, 0.0022]	[0.0018, 0.0021]	[0.0034, 0.0041]
Trend	Yes	Yes	Yes
Number of obs	8,487,170	8,487,170	2,260,641
Log marginal likelihood	4,954,608	4,963,154.40	997,734.80

Confident intervals in parentheses

Table 4.4: Bayesian estimates of network formation parameters with only firms with 3 or more directors

Variable	Mean of the posterior distribution		
	All firms		Politically active firms
	(1)	(2)	(3)
Candidate's past pollution ratio$_{i,t-1}$	-0.0127	-0.0138	-0.0205
	[-0.0141, -0.0133]	[-0.0141, -0.0134]	[-0.0212, -0.0199]
Candidate's influence$_{i,t-1}$	0.1134	0.1113	0.1376
	[0.1109, 0.1163]	[0.1108, 0.1118]	[0.1348, 0.1400]
Candidate's past pollution ratio × her/his influence$_{i,t-1}$	-0.0471	-0.0456	-0.0185
	[-0.0484, -0.0458]	[-0.0463, -0.0449]	[-0.0219, -0.0147]
Candidate is a CEO in a different firm$_{i,t-1}$	0.0021	0.0021	0.0045
	[0.0016, 0.0026]	[0.0016, 0.0025]	[0.0035, 0.0053]
Candidate's past experience in environmental committees$_{i,t-1}$	0.2161	0.2167	0.2991
	[0.2147, 0.2175]	[0.2161, 0.2173]	[0.2967, 0.3015]
Firm's influence$_{j,t-1}$	0.0801	0.1089	0.0718
	[0.0783, 0.0815]	[0.1074, 0.1103]	[0.0599, 0.0829]
Listed firms$_{j,t-1}$		0.0045	0.0049
		[0.0042, 0.0047]	[0.0045, 0.0054]
Difference in candidate's relative pollution degree centrality respect	-0.0443	-0.0444	-0.0566
to other board members average relative pollution degree centrality$_{i,j,t-1}$	[-0.0449, -0.0437]	[-0.0449, -0.0439]	[-0.0577, -0.0556]
Difference in candidate's pollution ratio respect to firm's	-0.0682	-0.0679	-0.0796
pollution ratio$_{i,j,t-1}$	[-0.0687, -0.0677]	[-0.0684, -0.0675]	[-0.0804, -0.0789]
Difference in candidate's influence and firm's influence$_{i,j,t-1}$	-0.0841	-0.0801	-0.1082
	[-0.0896, -0.0786]	[-0.0820, -0.0783]	[-0.1118, -0.1043]
Difference in candidate's CF score and board's CF score$_{i,j,t-1}$		-0.0010	0.0063
		[-0.0015, -0.0004]	[0.0052, 0.0074]
Log(Market exposure in years)$_{i,t-1}$	0.0016	0.0016	0.0035
	[0.0014, 0.0018]	[0.0014, 0.0017]	[0.0031, 0.0039]
Trend	Yes	Yes	Yes
Number of observations	5,146,412	5,146,412	1,758,427
Log marginal likelihood	2,324,465.7	2,324,967.2	696,321

Confident intervals in parentheses

Table 4.5: Results for total releases of firms with 3 or more directors

Variable	Log of total release$_{j,t}$			
	1 year	2 years	1 year	2 years
	(1)	(2)	(3)	(4)
No political donations$_{j,t-1}$	-0.053	-0.035	-0.051	-0.076
	(0.075)	(0.100)	(0.073)	(0.099)
Relative donation to the Republicans$_{j,t-1}$	0.140**	0.226**		
	(0.066)	(0.094)		
Republican-leaning firm$_{j,t-1}$			0.126**	0.119**
			(0.058)	(0.058)
Board's average pollution ratio$_{j,t-1}$	0.862***	0.823***	0.861***	0.823***
	(0.054)	(0.058)	(0.054)	(0.058)
The range of the board's relative pollution degree centrality$_{j,t-1}$	0.106***	0.102***	0.107***	0.101***
	(0.016)	(0.017)	(0.016)	(0.017)
Diversity in directors' CF-scores$_{j,t-1}$	-0.036	-0.043	-0.036	-0.044
	(0.028)	(0.028)	(0.028)	(0.028)
Difference in board's and firm's CF-scores$_{j,t-1}$	0.020	0.026	0.020	0.027
	(0.026)	(0.025)	(0.025)	(0.025)
Firm's influence$_{j,t-1}$	0.021	0.021	0.021	0.021
	(0.026)	(0.027)	(0.026)	(0.027)
Log of total industrial toxic releases$_{j,t-1}$	0.181***	0.170***	0.181***	0.171***
	(0.030)	(0.029)	(0.030)	(0.029)
Publicly listed$_{j,t}$	-0.169*	-0.178*	-0.178*	-0.183*
	(0.103)	(0.105)	(0.101)	(0.104)
CEO's lagged CF scores$_{j,t-1}$	-0.192	-0.215	-0.083	-0.274*
	(0.182)	(0.155)	(0.191)	(0.144)
Log of median household income$_{j,t}$	0.356***	0.308**	0.355***	0.309**
	(0.129)	(0.124)	(0.129)	(0.124)
Minority ratio$_{j,t}$	0.148	0.206	0.147	0.200
	(0.286)	(0.280)	(0.286)	(0.280)
College ratio$_{j,t}$	-0.320	-0.303	-0.322	-0.293
	(0.295)	(0.295)	(0.296)	(0.295)
Log of population density$_{j,t}$	0.155	0.156	0.154	0.157
	(0.125)	(0.120)	(0.125)	(0.120)
Republican county$_{j,t}$	-0.034	-0.048	-0.034	-0.048
	(0.057)	(0.057)	(0.057)	(0.057)
Facility effect	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	138,018	127,963	138,018	127,963
R^2	0.803	0.813	0.803	0.813

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6: Results for total releases of firms with 3 or more directors (estimated with expected values)

Variable	Log of total release$_{j,t}$			
	1 year	2 years	1 year	2 years
	(1)	(2)	(3)	(4)
No political donations$_{j,t-1}$	-0.062	-0.042	-0.059	-0.083
	(0.076)	(0.101)	(0.075)	(0.100)
Relative donation to the Republicans$_{j,t-1}$	0.143**	0.223**		
	(0.067)	(0.094)		
Republican-leaning firm$_{j,t-1}$			0.129**	0.116**
			(0.057)	(0.058)
E(Board's average pollution ratio)$_{j,t-1}$	0.862***	0.823***	0.862***	0.823***
	(0.056)	(0.060)	(0.056)	(0.060)
E(The range of the board's relative pollution degree centrality)$_{j,t-1}$	0.110***	0.106***	0.110***	0.106***
	(0.016)	(0.017)	(0.016)	(0.017)
E(Diversity in directors' CF-score)s$_{j,t-1}$	-0.004	-0.014	-0.004	-0.014
	(0.025)	(0.024)	(0.025)	(0.024)
E(Difference in board's and firm's CF-scores)$_{j,t-1}$	0.003	0.013	0.005	0.014
	(0.027)	(0.024)	(0.026)	(0.025)
Firm's influence$_{j,t-1}$	0.021	0.021	0.021	0.021
	(0.027)	(0.028)	(0.027)	(0.028)
Log of total industrial toxic releases$_{j,t-1}$	0.181***	0.170***	0.181***	0.170***
	(0.030)	(0.029)	(0.030)	(0.029)
Publicly listed$_{j,t}$	-0.174*	-0.184*	-0.183*	-0.189*
	(0.103)	(0.104)	(0.101)	(0.104)
CEO's lagged CF scores$_{j,t-1}$	-0.143	-0.174	-0.031	-0.232
	(0.181)	(0.155)	(0.190)	(0.144)
Log of median household income$_{j,t}$	0.356***	0.309**	0.356***	0.310**
	(0.129)	(0.124)	(0.129)	(0.124)
Minority ratio$_{j,t}$	0.148	0.206	0.147	0.200
	(0.286)	(0.280)	(0.286)	(0.280)
College ratio$_{j,t}$	-0.320	-0.305	-0.322	-0.295
	(0.295)	(0.295)	(0.295)	(0.294)
Log of population density$_{j,t}$	0.154	0.155	0.152	0.155
	(0.125)	(0.120)	(0.125)	(0.120)
Republican county$_{j,t}$	-0.033	-0.047	-0.034	-0.048
	(0.058)	(0.057)	(0.057)	(0.057)
Facility effect	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	138,018	127,963	138,018	127,963
R^2	0.803	0.813	0.803	0.813

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7: Results for RRT of firms with 3 or more directors

Variable	Log(toxicity recovered/total toxicity)$_{j,t}$			
	1 year	2 years	1 year	2 years
	(1)	(2)	(3)	(4)
No political donations$_{j,t-1}$	0.077*	0.088	0.070*	0.058
	(0.040)	(0.059)	(0.039)	(0.058)
Relative donation to the Republicans$_{j,t-1}$	0.052	0.064		
	(0.041)	(0.051)		
Republican-leaning firm$_{j,t-1}$			0.026	-0.002
			(0.031)	(0.029)
Board's average pollution ratio$_{j,t-1}$	-0.300***	-0.291***	-0.300***	-0.291***
	(0.029)	(0.031)	(0.029)	(0.031)
The range of the board's relative pollution degree centrality$_{j,t-1}$	-0.040***	-0.041***	-0.040***	-0.041***
	(0.011)	(0.011)	(0.011)	(0.011)
Diversity in directors' CF-scores$_{j,t-1}$	0.021	0.025	0.022	0.026
	(0.017)	(0.016)	(0.017)	(0.016)
Difference in board's and firm's CF-scores$_{j,t-1}$	0.009	0.003	0.010	0.003
	(0.017)	(0.015)	(0.017)	(0.015)
Firm's influence$_{j,t-1}$	-0.011	-0.016	-0.011	-0.016
	(0.015)	(0.019)	(0.015)	(0.019)
Log of total industrial toxic releases$_{j,t-1}$	-0.083***	-0.079***	-0.083***	-0.079***
	(0.022)	(0.021)	(0.022)	(0.021)
Publicly listed$_{j,t}$	0.054	0.055	0.052	0.055
	(0.064)	(0.066)	(0.064)	(0.066)
CEO's lagged CF scores$_{j,t-1}$	0.323*	0.317**	0.339*	0.313**
	(0.179)	(0.158)	(0.178)	(0.156)
Log of median household income$_{j,t}$	-0.191**	-0.175*	-0.191**	-0.175*
	(0.092)	(0.091)	(0.092)	(0.091)
Minority ratio$_{j,t}$	0.035	0.059	0.035	0.058
	(0.218)	(0.214)	(0.218)	(0.214)
College ratio$_{j,t}$	-0.076	-0.126	-0.075	-0.121
	(0.222)	(0.226)	(0.222)	(0.226)
Log of population density$_{j,t}$	-0.172*	-0.184*	-0.172*	-0.183*
	(0.102)	(0.100)	(0.102)	(0.100)
Republican county$_{j,t}$	-0.005	-0.001	-0.006	-0.001
	(0.040)	(0.041)	(0.040)	(0.041)
Facility effect	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	138,018	127,963	138,018	127,963
R^2	0.649	0.665	0.649	0.665

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.8: Results for RRT of firms with 3 or more directors (estimated with expected values)

Variable	Log(toxicity recovered/total toxicity)$_{j,t}$			
	1 year	2 years	1 year	2 years
	(1)	(2)	(3)	(4)
No political donations$_{j,t-1}$	0.076*	0.087	0.069*	0.056
	(0.040)	(0.059)	(0.039)	(0.058)
Relative donation to the Republicans$_{j,t-1}$	0.058	0.068		
	(0.040)	(0.052)		
Republican-leaning firm$_{j,t-1}$			0.028	-0.000
			(0.030)	(0.029)
E(Board's average pollution ratio)$_{j,t-1}$	-0.300***	-0.291***	-0.300***	-0.291***
	(0.029)	(0.031)	(0.029)	(0.032)
E(The range of the board's relative pollution degree centrality)$_{j,t-1}$	-0.043***	-0.044***	-0.043***	-0.044***
	(0.011)	(0.011)	(0.011)	(0.011)
E(Diversity in directors' CF-score)s$_{j,t-1}$	0.010	0.013	0.010	0.013
	(0.016)	(0.015)	(0.016)	(0.015)
E(Difference in board's and firm's CF-scores)$_{j,t-1}$	-0.004	-0.004	-0.002	-0.003
	(0.019)	(0.017)	(0.019)	(0.017)
Firm's influence$_{j,t-1}$	-0.011	-0.016	-0.011	-0.016
	(0.015)	(0.019)	(0.015)	(0.019)
Log of total industrial toxic releases$_{j,t-1}$	-0.082***	-0.079***	-0.082***	-0.079***
	(0.022)	(0.021)	(0.022)	(0.021)
Publicly listed$_{j,t}$	0.056	0.059	0.054	0.058
	(0.064)	(0.066)	(0.064)	(0.066)
CEO's lagged CF scores$_{j,t-1}$	0.312*	0.305*	0.329*	0.299*
	(0.183)	(0.161)	(0.182)	(0.159)
Log of median household income$_{j,t}$	-0.192**	-0.176*	-0.192**	-0.176*
	(0.093)	(0.091)	(0.093)	(0.091)
Minority ratio$_{j,t}$	0.036	0.060	0.035	0.058
	(0.218)	(0.214)	(0.218)	(0.214)
College ratio$_{j,t}$	-0.075	-0.125	-0.075	-0.120
	(0.222)	(0.226)	(0.222)	(0.226)
Log of population density$_{j,t}$	-0.172*	-0.184*	-0.172*	-0.183*
	(0.102)	(0.100)	(0.102)	(0.100)
Republican county$_{j,t}$	-0.005	-0.001	-0.006	-0.001
	(0.040)	(0.041)	(0.040)	(0.041)
Facility effect	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	138,018	127,963	138,018	127,963
R^2	0.649	0.665	0.649	0.665

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Results for ESG with 3 or more directors (estimated with 2 year moving averages)

Variable	ESG (1)	Environment (2)	Resource (3)	Social (4)	Governance (5)
No political donations$_{j,t-1}$	-0.036	-0.198*	-0.223	-0.072	0.044
	(0.044)	(0.111)	(0.138)	(0.061)	(0.056)
Relative donation to the Republicans$_{j,t-1}$	-0.135**	-0.423***	-0.500**	-0.143**	-0.023
	(0.057)	(0.154)	(0.232)	(0.070)	(0.086)
Board's average pollution ratio$_{j,t-1}$	-0.008	-0.009	0.024	-0.005	-0.021
	(0.021)	(0.084)	(0.108)	(0.016)	(0.025)
The range of the board's relative pollution degree centrality$_{j,t-1}$	0.008	0.031	0.012	0.003	-0.011
	(0.009)	(0.026)	(0.031)	(0.009)	(0.018)
Diversity in directors' CF-scores$_{j,t-1}$	0.019	0.124**	0.102	0.022	-0.044*
	(0.023)	(0.062)	(0.063)	(0.023)	(0.024)
Difference in board's and firm's CF-scores$_{j,t-1}$	0.049	0.080	0.132	0.052*	0.067**
	(0.032)	(0.080)	(0.080)	(0.027)	(0.030)
Firm's influence$_{j,t-1}$	0.000	0.001**	0.001**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of total industrial toxic releases$_{j,t-1}$	0.002	-0.019	-0.004	0.005	0.009
	(0.010)	(0.029)	(0.032)	(0.009)	(0.013)
Publicly listed$_{j,t}$	0.183**	0.068	0.505	0.102	0.482**
	(0.083)	(0.643)	(0.550)	(0.170)	(0.220)
CEO's lagged CF scores$_{j,t-1}$	-0.052	-0.332**	-0.334	-0.196**	0.207**
	(0.064)	(0.138)	(0.230)	(0.092)	(0.092)
Log of median household income$_{j,t}$	0.005	0.057	0.008	-0.013	-0.032
	(0.025)	(0.071)	(0.086)	(0.031)	(0.032)
Minority ratio$_{j,t}$	0.025	-0.060	-0.195	0.014	0.029
	(0.049)	(0.156)	(0.180)	(0.056)	(0.073)
College ratio$_{j,t}$	-0.016	-0.202	-0.092	0.015	0.141
	(0.094)	(0.399)	(0.442)	(0.113)	(0.144)
Log of population density$_{j,t}$	-0.005	-0.082	-0.139	-0.003	0.017
	(0.022)	(0.078)	(0.092)	(0.023)	(0.026)
Republican county$_{j,t}$	-0.021	-0.069	-0.045	-0.021	0.016
	(0.014)	(0.062)	(0.063)	(0.016)	(0.023)
Firm effect	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Observations	42,731	42,731	42,731	42,731	42,731
R^2	0.759	0.716	0.715	0.746	0.544

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.10: Results for ESG of firms with 3 or more directors (estimated with expected values and 2 year moving averages)

Variable	ESG (1)	Environment (2)	Resource (3)	Social (4)	Governance (5)
No political donations$_{j,t-1}$	-0.045	-0.223*	-0.237*	-0.084	0.047
	(0.044)	(0.114)	(0.143)	(0.062)	(0.055)
Relative donation to the Republicans$_{j,t-1}$	-0.138**	-0.439***	-0.522**	-0.147**	-0.024
	(0.058)	(0.151)	(0.228)	(0.070)	(0.087)
E(Board's average pollution ratio)$_{j,t-1}$	-0.004	0.002	0.038	0.001	-0.021
	(0.021)	(0.085)	(0.109)	(0.016)	(0.023)
E(The range of the board's relative pollution degree centrality)$_{j,t-1}$	0.005	0.021	0.004	0.000	-0.013
	(0.009)	(0.024)	(0.030)	(0.009)	(0.018)
E(Diversity in directors' CF-scores)$_{j,t-1}$	0.032	0.169***	0.171***	0.042**	-0.041
	(0.021)	(0.059)	(0.066)	(0.021)	(0.026)
E(Difference in board's and firm's CF-scores)$_{j,t-1}$	0.016	0.031	0.108	0.014	0.051*
	(0.018)	(0.062)	(0.079)	(0.022)	(0.028)
Firm's influence$_{j,t-1}$	0.000	0.001**	0.001**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of total industrial toxic releases$_{j,t-1}$	0.001	-0.020	-0.005	0.005	0.009
	(0.010)	(0.029)	(0.032)	(0.009)	(0.013)
Publicly listed$_{j,t}$	0.186**	0.192	0.591	0.109	0.401**
	(0.082)	(0.607)	(0.520)	(0.168)	(0.203)
CEO's lagged CF scores$_{j,t-1}$	-0.026	-0.236	-0.211	-0.162*	0.205**
	(0.059)	(0.175)	(0.245)	(0.088)	(0.095)
Log of median household income$_{j,t}$	0.003	0.046	-0.001	-0.016	-0.029
	(0.025)	(0.070)	(0.085)	(0.030)	(0.033)
Minority ratio$_{j,t}$	0.025	-0.057	-0.190	0.014	0.029
	(0.050)	(0.156)	(0.178)	(0.056)	(0.074)
College ratio$_{j,t}$	-0.012	-0.190	-0.072	0.021	0.146
	(0.093)	(0.395)	(0.435)	(0.110)	(0.147)
Log of population density$_{j,t}$	-0.005	-0.079	-0.134	-0.003	0.017
	(0.022)	(0.077)	(0.092)	(0.022)	(0.027)
Republican county$_{j,t}$	-0.019	-0.067	-0.041	-0.019	0.017
	(0.014)	(0.062)	(0.063)	(0.016)	(0.023)
Firm effect	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Observations	42,731	42,731	42,731	42,731	42,731
R^2	0.758	0.717	0.717	0.745	0.542

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5

Conclusion

In this thesis, I study how firms' environmental strategies are formed. To study this question, I compile the Database on Director Network, Toxic Releases and Political Activities as a general resource for the study of director network development in relationship with corporate environmental activities and political activities. The database contains key information from six independent sources: 1) the Toxics Release Inventory (TRI) Program, 2) the BoardEx database, 3) the US Census, 4) Bonica (2016b)'s DIME, 5) the data for the US Senate, House and Presidential elections' results from MIT Election Data and Science Lab (Data and Lab, 2017b,a, 2018), and 6) institutional holding information and ESG scores via Eikon.

Then I use the compiled database to study the role of directors' environmental performance records. I examine how directors are appointed to firms' board and find that firms are more likely to appoint candidates who are similar to their existing board directors, but also candidates with a good environmental record. Interestingly, although influential directors are preferable, poor environmental performance will reduce their probabilities of being appointed. Additionally, my study shows that directors' previous environmental performance affects their current facilities' environmental performance. Having directors with a good environmental performance on the board is associated with a lower probability of releasing toxic chemicals and a higher proportion of toxic waste managed through energy recovery, recycling, and treatment. To understand the dynamics of director appointment and improvement in firms' environmental performance, I perform an event-study type analysis in which I look at the evolution of a firm's environmental performance up to four years after the appointment of a director. My results confirm that the appointment of a clean director leads to a reduction in toxic releases and that the magnitude of the impact decreases over time.

Besides environmental records, political ideology also plays a significant part in shaping firms' environmental policies. When firms have greater relative donations for Republicans, they have higher probabilities of releasing more toxic chemicals to the environment. To address potential endogenous concerns, I also include network formation analysis. The analysis finds candidates with similar political ideology are more likely to be appointed and helps to explain the political polarization trend in the business world. Besides toxicity related performance, political ideology is shown to play a significant part in determining a firm's overall ESG along with its Environment score, Resource score, Social score and Governance score separately. Firms with Republican leaning ideology tends to have lower overall ESG scores, Environment scores, Resource scores, and Social scores. As shown in the third chapter, toxicity related performance and ESG scores/Environment scores represent firms' environmental performance from different aspects. Therefore, it would be irresponsible to draw any firm conclusion on how political ideology affects a firm's ESG scores only based on this thesis.

My findings help to understand how firms' environmental policies are shaped and provide policy implications regarding some of the key factors that affect firms' environment-related decisions. On the one hand, this thesis has shown that firms are making active efforts to improve environmental performances by appointing *clean* directors. The higher probability of being appointed may provide an incentive for director candidates to improve their environmental performances. On the other hand, political polarization brings a negative effort on promoting sustainable growth that the Republican-leaning ideology attributes more toxic releases. There are two important policy implications behind my findings. First, business individuals like board directors are playing an important role in shaping their firms' environmental policies. To accelerate the transition to a clean economy, policy makers can target influential business individuals by creating more incentives and providing more information on latest environment-related development (e.g. subsidies, new technology development). Second, political polarization is undermining the efforts in promoting sustainable growth. It is important for policy makers to depolarize the political environment. Otherwise, we may see an increasing role played by political ideology in shaping firms' environmental policies. This is particularly bad with polarized Republican-leaning firms.

However, there are some limitations to this study. The major limitation to this study is data availability. Some board directors' characteristics (e.g. gender, education backgrounds, wages), which have been shown by some literature to have effects on environmental performances, are not taken into account in this study due to the limitation of data sources. The board director network is not complete, as directors from small and low-profile private firms are likely missing in the BoardEx database. Further, this study only captures the networks of board directors alone, while the directors can also be influenced via other social network channels (e.g. family connection, neighbourhood, alumni network and etc.). Moreover, since toxic releases are only one of many dimensions of environmental performances, we need further evidence to apply the findings from this study to other environmental issues, such as climate change.

For future research, as mentioned previously in Chapter 2, I would use the database compiled in this study to study other issues relating to environment, network and politics (e.g. the development of political ideology within board director networks). In addition, social media is blamed for inflaming political polarization (The Hill, 2021) and there has been extensive literature using networks on social media, especially Twitter, to study political polarization.[1] While, this study helps to explain political polarization in the business world by analyzing the director network formation. This implies that political polarization can also be fueled by traditional social networks other than social media. Therefore, in order to have a more complete understanding of today's political polarization, more study on the role of traditional social networks in political polarization could be done.

Overall, this study shows that firms' environmental strategies are influenced by directors' environmental performance records, network positioning, and firms' political ideology. Directors with good environmental records help to improve their firms' environmental performances. In addition, firms who have "cleaner" network positioning tend to have better performances. Network positioning is determined by how firms appoint their board directors. A firm can make its network positioning "cleaner" by appointing directors with better environmental records and/or retaining its board directors who are joining cleaner firms. The network formation analyses show firms are more willing to appoint influential

[1] For example, Conover et al. (2011), Gruzd and Roy (2014), Borge-Holthoefer et al. (2015), and Kearney (2019).

candidates who have better environmental performance records and share more similarities. Further, political ideology also has an impact that Republican-leaning firms tends to release more toxic chemicals, though it is not as significant as the other two factors. Therefore, from this study, we can see that firms are improving their environmental performances by actively appointing directors with good records, but such effort can be undermined by the polarized Republican ideology.

Bibliography

Abate, G., Basile, I., and Ferrari, P. (2021). The level of sustainability and mutual fund performance in europe: An empirical analysis using esg ratings. *Corporate Social Responsibility and Environmental Management*, 28(5):1446–1455.

Adams, M. and Hardwick, P. (1998). An analysis of corporate donations: United kingdom evidence. *Journal of management Studies*, 35(5):641–654.

Aggarwal, R. K., Meschke, F., and Wang, T. Y. (2012). Corporate political donations: Investment or agency? *Business and Politics*, 14(1):1–38.

Alazzani, A., Hassanein, A., and Aljanadi, Y. (2017). Impact of gender diversity on social and environmental performance: evidence from malaysia. *Corporate Governance: The International Journal of Business in Society*, 17(2):266–283.

Ansolabehere, S., De Figueiredo, J. M., and Snyder Jr, J. M. (2003). Why is there so little money in us politics? *Journal of Economic perspectives*, 17(1):105–130.

Aranson, P. H. and Hinich, M. J. (1979). Some aspects of the political economy of election campaign contribution laws. *Public Choice*, 34(3):435–461.

Armstrong, C. S. and Larcker, D. F. (2009). Discussion of "the impact of the options backdating scandal on shareholders" and "taxes and the backdating of stock option exercise dates". *Journal of Accounting and Economics*, 47(1-2):50–58.

Bagley, C. E., Freed, B., and Sandstrom, K. (2015). A board member's guide to corporate political spending. *Harvard Business Review*, 30.

Baron, H., Blair, R., Choi, D. D., Gamboa, L., Gottlieb, J., Robinson, A. L., Rosenzweig, S., Turnbull, M., and West, E. A. (2021). Can americans depolarize? assessing the effects of reciprocal group reflection on partisan polarization.

Bebchuk, L. A. (2003). The case for shareholder access to the ballot. *The Business Lawyer*, pages 43–66.

Becher, D. A., Walkling, R. A., and Wilson, J. I. (2017). Board changes and the director labor market: The case of mergers. *Working Paper, Drexel University.*

Berrone, P. and Gomez-Mejia, L. R. (2009). Environmental performance and executive compensation: An integrated agency-institutional perspective. *Academy of Management Journal*, 52(1):103–126.

Bertrand, M., Bombardini, M., Fisman, R., and Trebbi, F. (2020). Tax-exempt lobbying: Corporate philanthropy as a tool for political influence. *American Economic Review*, 110(7):2065–2102.

Bizjak, J., Lemmon, M., and Whitby, R. (2009). Option backdating and board interlocks. *The Review of Financial Studies*, 22(11):4821–4847.

Bjørnskov, C. (2005). Does political ideology affect economic growth? *Public Choice*, 123(1):133–146.

Bond, M. (2007). Elite social relations and corporate political donations in britain. *Political Studies*, 55(1):59–85.

Bonica, A. (2014). Mapping the ideological marketplace. *American Journal of Political Science*, 58(2):367–386.

Bonica, A. (2016a). Avenues of influence: on the political expenditures of corporations and their directors and executives. *Business and Politics*, 18(4):367–394.

Bonica, A. (2016b). Database on ideology, money in politics, and elections: Public version 2.0 [computer file]. *Stanford, CA: Stanford University Libraries.* https://data.stanford.edu/dime.

Borge-Holthoefer, J., Magdy, W., Darwish, K., and Weber, I. (2015). Content and network dynamics behind egyptian political polarization on twitter. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pages 700–711.

Brickley, J. A., Linck, J. S., and Coles, J. L. (1999). What happens to CEOs after they retire? New evidence on career concerns, horizon problems, and CEO incentives. *Journal of Financial Economics*, 52(3):341–377.

Brown, J. L., Drake, K., and Wellman, L. (2015). The benefits of a relational approach to corporate political activity: Evidence from political contributions to tax policymakers. *The Journal of the American Taxation Association*, 37(1):69–102.

Buttel, F. M. and Flinn, W. L. (1978). The politics of environmental concern: The impacts of party identification and political ideology on environmental attitudes. *Environment and Behavior*, 10(1):17–36.

Cai, J., Garner, J. L., and Walkling, R. A. (2009). Electing directors. *The Journal of Finance*, 64(5):2389–2421.

Cai, J., Nguyen, T., and Walkling, R. A. (2021). Director Appointments: It Is Who You Know. *The Review of Financial Studies*, forthcomming.

Cai, Y. and Sevilir, M. (2012). Board connections and M&A transactions. *Journal of Financial Economics*, 103(2):327–349.

Carpenter, M. A. and Westphal, J. D. (2001). The strategic context of external network ties: Examining the impact of director appointments on board involvement in strategic decision making. *Academy of Management journal*, 44(4):639–660.

Carter, N. (2009). Vote blue, go green? cameron's conservatives and the environment. *The Political Quarterly*, 80(2):233–242.

Cashman, G. D., Gillan, S. L., and Whitby, R. J. (2013). Human and social capital in the labor market for directors. In *Advances in Financial Economics*. Emerald Group Publishing Limited.

Chinn, S., Hart, P. S., and Soroka, S. (2020). Politicization and polarization in climate change news content, 1985-2017. *Science Communication*, 42(1):112–129.

Christakis, N., Fowler, J., Imbens, G. W., and Kalyanaraman, K. (2020). An empirical model for strategic network formation. In Graham, B. and Áureo de Paula, editors, *The Econometric Analysis of Network Data - Chapter 6*, pages 123–148. Academic Press.

Chuluun, T., Prevost, A., and Upadhyay, A. (2017). Firm network structure and innovation. *Journal of Corporate Finance*, 44:193–214.

Clements, B. (2014). Political party supporters' attitudes towards and involvement with green issues in britain. *Politics*, 34(4):362–377.

CNN (2021). Activist investor ousts at least two Exxon directors in historic win for pro-climate campaign. https://edition.cnn.com/2021/05/26/business/exxon-annual-meeting-climate-oil/index.html. Accessed: 2021-05-27.

Cohen, L., Frazzini, A., and Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, 116(5):951–979.

Coles, J. L., Daniel, N. D., and Naveen, L. (2008). Boards: Does one size fit all? *Journal of Financial Economics*, 87(2):329–356.

Conover, M., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., and Flammini, A. (2011). Political polarization on twitter. In *Proceedings of the international aaai conference on web and social media*, volume 5, pages 89–96.

Cooper, M. J., Gulen, H., and Ovtchinnikov, A. V. (2010). Corporate political contributions and stock returns. *The Journal of Finance*, 65(2):687–724.

Correia, M. M. (2014). Political connections and sec enforcement. *Journal of Accounting and Economics*, 57(2-3):241–262.

Cucari, N., Esposito de Falco, S., and Orlando, B. (2018). Diversity of board of directors and environmental social governance: Evidence from italian listed companies. *Corporate Social Responsibility and Environmental Management*, 25(3):250–266.

Currarini, S., Jackson, M. O., and Pin, P. (2009). An economic model of friendship: Homophily, minorities, and segregation. *Econometrica*, 77(4):1003–1045.

Daily Main (2022a). DeSantis pulls $2BN from woke BlackRock in largest anti-ESG divestment by any Republican state - as Biden encourages 401ks to invest in the underperforming funds. https://www.dailymail.co.uk/news/article-11490899/Florida-pulls-2-bln-BlackRock-largest-anti-ESG-divestment.html. Accessed: 2022-12-11.

Daily Main (2022b). Republicans introduce bill to crack down on ESG guidelines at NASA and the Pentagon that would require contractors to publish emissions data and targets. https://www.dailymail.co.uk/news/article-11539423/Republicans-launch-bill-crack-ESG-guidelines-used-investment-firms.html. Accessed: 2022-12-11.

Data, M. E. and Lab, S. (2017a). U.S. House 1976–2020.

Data, M. E. and Lab, S. (2017b). U.S. Senate 1976–2020.

Data, M. E. and Lab, S. (2018). County Presidential Election Returns 2000-2020.

Davidson, R. H., Oleszek, W. J., Lee, F. E., Schickler, E., and Curry, J. M. (2021). *Congress and its members*. cq Press.

Davis, G. F. (1996). The significance of board interlocks for corporate governance. *Corporate Governance: An International Review*, 4(3):154–159.

de Figueiredo Jr, R. J. and Edwards, G. (2007). Does private money buy public policy? campaign contributions and regulatory outcomes in telecommunications. *Journal of Economics & Management Strategy*, 16(3):547–576.

De Silva, D. G., Gertsberg, M., Kosmopoulou, G., and Pownall, R. A. (2022). Evolution of a Dealer Trading Network and its Effects on Art Auction Prices. *European Economic Review*.

De Silva, D. G., Hubbard, T. P., and Schiller, A. R. (2016). Entry and exit patterns of "Toxic" firms. *American Journal of Agricultural Economics*, 98(3):881–909.

De Silva, D. G., McComb, R. P., Schiller, A. R., and Slechten, A. (2021). Firm behavior and pollution in small geographies. *European Economic Review*, 136:103742.

De Villiers, C., Naiker, V., and Van Staden, C. J. (2011). The effect of board characteristics on firm environmental performance. *Journal of Management*, 37(6):1636–1663.

Dixon-Fowler, H. R., Ellstrand, A. E., and Johnson, J. L. (2017). The role of board environmental committees in corporate environmental performance. *Journal of Business Ethics*, 140(3):423–438.

Dunlap, R. E. (1975). The impact of political orientation on environmental attitudes and actions. *Environment and behavior*, 7(4):428–454.

Dunlap, R. E. (2019). Partisan polarization on the environment grows under trump.

Dunlap, R. E. and McCright, A. M. (2008). A widening gap: Republican and democratic views on climate change. *Environment: Science and Policy for Sustainable Development*, 50(5):26–35.

Eichholtz, P., Kok, N., and Quigley, J. M. (2010). Doing well by doing good? Green office buildings. *American Economic Review*, 100(5):2492–2509.

Elmagrhi, M. H., Ntim, C. G., Elamer, A. A., and Zhang, Q. (2019). A study of environmental policies and regulations, governance structures, and environmental performance: The role of female directors. *Business Strategy and the Environment*, 28(1):206–220.

Erel, I., Stern, L. H., Tan, C., and Weisbach, M. S. (2021). Selecting directors using machine learning. *The Review of Financial Studies*, 34(7):3226–3264.

Fama, E. F. and Jensen, M. C. (1983). Separation of ownership and control. *The Journal of Law and Economics*, 26(2):301–325.

Ferris, S. P., Jagannathan, M., and Pritchard, A. C. (2003). Too busy to mind the business? monitoring by directors with multiple board appointments. *The Journal of Finance*, 58(3):1087–1111.

Fich, E. M. and Shivdasani, A. (2007). Financial fraud, director reputation, and shareholder wealth. *Journal of Financial Economics*, 86(2):306–336.

Fich, E. M. and Shivdasani, A. (2012). Are busy boards effective monitors? In *Corporate governance*, pages 221–258. Springer.

Financial Times (2022a). Anti-ESG ETF gets off to a roaring start. `https://www.ft.com/content/a8ce3918-59c3-4bca-8832-2a475a2c1124`. Accessed: 2022-09-20.

Financial Times (2022b). BlackRock denies Republican claims of climate 'activism'. `https://www.ft.com/content/a4af6919-b1cc-4c15-b17c-46186fddbd4c`. Accessed: 2022-09-20.

Financial Times (2022c). BlackRock warns it will vote against more climate resolutions this year. `https://www.ft.com/content/4a538e2c-d4bb-4099-8f15-a28d0fefcea2`. Accessed: 2022-12-11.

Financial Times (2022d). Fusion energy breakthrough by US scientists boosts clean power hopes. `https://www.ft.com/content/4b6f0fab-66ef-4e33-adec-cfc345589dc7`. Accessed: 2022-12-11.

Financial Times (2022e). High energy prices attract investors back to UK fossil fuel small caps. `https://www.ft.com/content/c6c5a378-7563-4a15-adeb-592607130a10`. Accessed: 2022-12-11.

Financial Times (2022f). IEA forecasts fossil fuel demand will peak this decade. https://www.ft.com/content/1fd06f38-ec60-4043-bcdd-adcba8beb006. Accessed: 2022-12-11.

Financial Times (2022g). US Supreme Court curbs EPA's power to regulate greenhouse gas emissions. https://www.ft.com/content/b69f0a4d-a9d8-4a2d-b891-2f3c142f66ac?emailId=62bdb199a16a430023b3cfb0&segmentId=3d08be62-315f-7330-5bbd-af33dc531acb. Accessed: 2022-06-30.

Financial Times (2022h). Vanguard quits climate alliance in blow to net zero project. https://www.ft.com/content/48c1793c-3e31-4ab4-ab02-fd5e94b64f6b. Accessed: 2022-12-11.

Financial Times (2022i). Why the future of ESG is at a crossroads. https://www.ft.com/content/cc846f88-727c-4843-92a8-790bab816d0e. Accessed: 2022-09-20.

Fisher, J. (1994). Why do companies make donations to political parties? *Political Studies*, 42(4):690–699.

Fracassi, C. and Tate, G. (2012). External networking and internal firm governance. *The Journal of Finance*, 67(1):153–194.

García Martín, C. J. and Herrero, B. (2020). Do board characteristics affect environmental performance? A study of EU firms. *Corporate Social Responsibility and Environmental Management*, 27(1):74–94.

Gelman, A. (2004). Parameterization and Bayesian Modeling. *Journal of the American Statistical Association*, 99(466):537–545.

Goldman, E., Rocholl, J., and So, J. (2009). Do politically connected boards affect firm value? *The review of financial studies*, 22(6):2331–2360.

Gordon, S. C., Hafer, C., and Landa, D. (2007). Consumption or investment? on motivations for political giving. *The Journal of Politics*, 69(4):1057–1072.

Greenhill, M., Leviston, Z., Leonard, R., and Walker, I. (2014). Assessing climate change beliefs: Response effects of question wording and response alternatives. *Public Understanding of Science*, 23(8):947–965.

Gruzd, A. and Roy, J. (2014). Investigating political polarization on twitter: A canadian perspective. *Policy & internet*, 6(1):28–45.

Gulen, H. and Myers, B. W. (2021). The selective enforcement of government regulation: Battleground states, state regulators, and the epa. *State Regulators, and the EPA (June 30, 2021).*

Gupta, A., Briscoe, F., and Hambrick, D. C. (2017). Red, blue, and purple firms: Organizational political ideology and corporate social responsibility. *Strategic Management Journal*, 38(5):1018–1040.

Gupta, A., Nadkarni, S., and Mariam, M. (2019). Dispositional sources of managerial discretion: Ceo ideology, ceo personality, and firm strategies. *Administrative Science Quarterly*, 64(4):855–893.

Hall, R. L. and Wayman, F. W. (1990). Buying time: Moneyed interests and the mobilization of bias in congressional committees. *American political science review*, 84(3):797–820.

Hamilton, L. C. and Saito, K. (2015). A four-party view of us environmental concern. *Environmental Politics*, 24(2):212–227.

Harjoto, M., Laksmana, I., and Lee, R. (2015). Board diversity and corporate social responsibility. *Journal of Business Ethics*, 132(4):641–660.

Harjoto, M. A. and Wang, Y. (2020). Board of directors network centrality and environmental, social and governance (esg) performance. *Corporate Governance: The international journal of business in society*, 20(6):965–985.

Harring, N. and Sohlberg, J. (2017). The varying effects of left–right ideology on support for the environment: Evidence from a swedish survey experiment. *Environmental Politics*, 26(2):278–300.

Hartmann, J. and Vachon, S. (2018). Linking environmental management to environmental performance: The interactive role of industry context. *Business Strategy and the Environment*, 27(3):359–374.

Hassan, T. A., Hollander, S., Van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202.

Heitz, A., Wang, Y., and Wang, Z. (2021). Corporate political connections and favorable environmental regulatory enforcement. *Management Science*.

Hillman, A. J., Cannella, A. A., and Paetzold, R. L. (2000). The resource dependence role of corporate directors: Strategic adaptation of board composition in response to environmental change. *Journal of Management studies*, 37(2):235–256.

Hillman, A. J. and Dalziel, T. (2003). Boards of directors and firm performance: Integrating agency and resource dependence perspectives. *Academy of Management Review*, 28(3):383–396.

Hoang, T., Ngo, P. T., and Zhang, L. (2020). Polarized corporate boards. *Available at SSRN 3747607*.

Hoang, T., Ngo, P. T., and Zhang, L. (2022). Polarized corporate boards. *Available at SSRN 3747607*.

Homroy, S. and Slechten, A. (2019). Do Board Expertise and Networked Boards Affect Environmental Performance? *Journal of Business Ethics*, 158(1):269–292.

Hui, C., David, P., and Ya-Wen, Y. (2008). Corporate lobbying and financial performance. Technical report, Working Paper 2010.

Ibarra, H. (1995). Race, opportunity, and diversity of social circles in managerial networks. *Academy of Management Journal*, 38(3):673–703.

Ibrahim, N. A. and Angelidis, J. P. (1995). The corporate social responsiveness orientation of board members: Are there differences between inside and outside directors? *Journal of business Ethics*, 14(5):405–410.

Ilhan, E., Krueger, P., Sautner, Z., Starks, L. T., et al. (2019). Institutional investors' views and preferences on climate risk disclosure. Technical report, Swiss Finance Institute Swiss, Switzerland.

Jensen, M. C. and Murphy, K. J. (1990). Performance pay and top-management incentives. *Journal of political economy*, 98(2):225–264.

Kang, E. (2008). Director interlocks and spillover effects of reputational penalties from financial reporting fraud. *Academy of Management Journal*, 51(3):537–555.

Kassinis, G. and Vafeas, N. (2002). Corporate boards and outside stakeholders as determinants of environmental litigation. *Strategic Management Journal*, 23(5):399–415.

Kearney, M. W. (2019). Analyzing change in network polarization. *New Media & Society*, 21(6):1380–1402.

Khanna, M., Quimio, W. R. H., and Bojilova, D. (1998). Toxics release information: A policy tool for environmental protection. *Journal of Environmental Economics and Management*, 36(3):243–266.

Kogut, B., Colomer, J., and Belinky, M. (2014). Structural equality at the top of the corporation: Mandated quotas for women directors. *Strategic Management Journal*, 35(6):891–902.

Konar, S. and Cohen, M. A. (2001). Does the market value environmental performance? *Review of Economics and Statistics*, 83(2):281–289.

Kramarz, F. and Thesmar, D. (2013). Social networks in the boardroom. *Journal of the European Economic Association*, 11(4):780–807.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.

La Raja, R. and Schaffner, B. (2015). *Campaign finance and political polarization: When purists prevail*. University of Michigan Press.

Larcker, D. F., So, E. C., and Wang, C. C. (2013). Boardroom centrality and firm performance. *Journal of Accounting and Economics*, 55(2-3):225–250.

Larcker, D. F., So, E. C., Wang, C. C., et al. (2010). *Boardroom centrality and stock returns*. Citeseer.

Lee, J., Lee, K. J., and Nagarajan, N. J. (2014). Birds of a feather: Value implications of political alignment between top management and directors. *Journal of Financial Economics*, 112(2):232–250.

Li, T. and Zheng, X. (2009). Entry and competition effects in first-price auctions: theory and evidence from procurement auctions. *The Review of Economic Studies*, 76(4):1397–1429.

Liang, H., Sun, L., and Teo, M. (2022). Responsible hedge funds. *Review of Finance*, 26(6):1585–1633.

Liao, L., Luo, L., and Tang, Q. (2015). Gender diversity, board independence, environmental committee and greenhouse gas disclosure. *The British accounting review*, 47(4):409–424.

Longo, S. B. and Baker, J. O. (2014). Economy "versus" environment: The influence of economic ideology and political identity on perceived threat of eco-catastrophe. *The Sociological Quarterly*, 55(2):341–365.

Lu, J. and Herremans, I. M. (2019). Board gender diversity and environmental performance: An industries perspective. *Business Strategy and the Environment*, 28(7):1449–1464.

Manrique, S. and Martí-Ballester, C.-P. (2017). Analyzing the effect of corporate environmental performance on corporate financial performance in developed and developing countries. *Sustainability*, 9(11):1957.

Mathur, I. and Singh, M. (2011). Corporate political strategies. *Accounting & Finance*, 51(1):252–277.

McKendall, M., Sánchez, C., and Sicilian, P. (1999). Corporate governance and corporate illegality: The effects of board structure on environmental violations. *The International Journal of Organizational Analysis*, 7(3):201–223.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27(1):415–444.

Mian, A., Sufi, A., and Trebbi, F. (2010). The political economy of the us mortgage default crisis. *American Economic Review*, 100(5):1967–98.

Muttakin, M. B., Mihret, D. G., and Rana, T. (2021). Electoral system, corporate political donation, and carbon emission intensity: Cross-country evidence. *Business Strategy and the Environment*, 30(4):1767–1779.

Naaraayanan, S. L., Sachdeva, K., and Sharma, V. (2021). The real effects of environmental activist investing. *European Corporate Governance Institute–Finance Working Paper*, (743).

Omer, T. C., Shelley, M. K., and Tice, F. M. (2020). Do director networks matter for financial reporting quality? evidence from audit committee connectedness and restatements. *Management Science*, 66(8):3361–3388.

OpenSecrets (2020). 2020 election to cost $14 billion, blowing away spending records. https://www.opensecrets.org/news/2020/10/cost-of-2020-election-14billion-update/. Accessed: 2021-08-15.

Ortiz-de Mandojana, N., Aragón-Correa, J. A., Delgado-Ceballos, J., and Ferrón-Vílchez, V. (2012). The effect of director interlocks on firms' adoption of proactive environmental strategies. *Corporate Governance: An International Review*, 20(2):164–178.

Ovtchinnikov, A. V. and Pantaleoni, E. (2012). Individual political contributions and firm performance. *Journal of Financial Economics*, 105(2):367–392.

Pearce, D. (2002). An intellectual history of environmental economics. *Annual review of energy and the environment*, 27(1):57–81.

Rossi, M., Chouaibi, J., Chouaibi, S., Jilani, W., and Chouaibi, Y. (2021). Does a board characteristic moderate the relationship between csr practices and financial performance? evidence from european esg firms. *Journal of Risk and Financial Management*, 14(8):354.

Samdahl, D. M. and Robertson, R. (1989). Social determinants of environmental concern: Specification and test of the model. *Environment and behavior*, 21(1):57–81.

Schnattschneider, E. (1960). The semi-sovereign people. *New York: Holt, Reinhart and Winston.*

Semadeni, M., Chin, M., and Krause, R. (2022). Pumping the brakes: Examining the impact of ceo political ideology divergence on firm responses. *Academy of Management Journal*, 65(2):516–544.

The Guardian (2015). The Republican Party stands alone in climate denial. https://www.theguardian.com/environment/climate-consensus-97-per-cent/2015/oct/05/the-republican-party-stands-alone-in-climate-denial. Accessed: 2023-02-25.

The Guardian (2019). Political polarisation over climate crisis has surged under Trump. https://www.theguardian.com/environment/2019/oct/11/political-polarisation-climate-crisis-trump. Accessed: 2021-09-15.

The Hill (2021). Social media making political polarization worse: report. https://thehill.com/policy/technology/

571747-social-media-making-political-polarization-worse-report/. Accessed: 2022-12-11.

Titl, V. and Geys, B. (2019). Political donations and the allocation of public procurement contracts. *European Economic Review*, 111:443–458.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: journal of the Econometric Society*, pages 24–36.

Unsal, O., Hassan, M. K., and Zirek, D. (2016). Corporate lobbying, ceo political ideology and firm performance. *Journal of Corporate Finance*, 38:126–149.

Verba, S., Schlozman, K. L., and Brady, H. E. (1995). *Voice and equality: Civic voluntarism in American politics*. Harvard University Press.

Walls, J. L., Berrone, P., and Phan, P. H. (2012). Corporate governance and environmental performance: Is there really a link? *Strategic Management Journal*, 33(8):885–913.

Wang, Q.-J., Feng, G.-F., Wang, H.-J., and Chang, C.-P. (2022). The influence of political ideology on greenhouse gas emissions. *Global Environmental Change*, 74:102496.

Westphal, J. D. and Zajac, E. J. (2013). A behavioral theory of corporate governance: Explicating the mechanisms of socially situated and socially constituted agency. *Academy of Management Annals*, 7(1):607–661.

Whittaker, M., Segura, G. M., and Bowler, S. (2005). Racial/ethnic group attitudes toward environmental protection in california: is "environmentalism" still a white phenomenon? *Political Research Quarterly*, 58(3):435–447.

Xiong, J. X. (2021). The impact of esg risk on stocks. *The Journal of Impact and ESG Investing*, 2(1):7–18.

Yue, X.-G., Han, Y., Teresiene, D., Merkyte, J., and Liu, W. (2020). Sustainable funds' performance evaluation. *Sustainability*, 12(19):8034.

Zhang, S. (2021). Directors' career concerns: Evidence from proxy contests and board interlocks. *Journal of Financial Economics*, 140(3):894–915.

Zhuang, Y., Chang, X., and Lee, Y. (2018). Board Composition and Corporate Social Responsibility Performance: Evidence from Chinese Public Firms. *Sustainability*, 10(8):2752.

Zona, F., Gomez-Mejia, L. R., and Withers, M. C. (2018). Board interlocks and firm performance: Toward a combined agency–resource dependence perspective. *Journal of Management*, 44(2):589–618.