CEO Hometown Favoritism in Corporate Environmental Policies

Abstract

We exploit within-firm variations in plant-level toxic releases to document the effect of managerial hometown favoritism on corporate environmental policies. We find that pollution intensity is 20% lower for plants near CEOs' hometowns, and this reduction is facilitated by waste management efforts such as source reduction, recycling, and energy recovery. Analyses using CEO turnover provide causal inference. Hometown emission reduction is stronger for poorly governed firms, and is significantly weakened following the 2003 dividend tax cut that mitigates agency conflicts. In addition, hometown emission reduction is most salient for firms with worse CSR performance or more financial constraints. Our findings reveal that CEOs' personal motives affect corporate pollution abatement, and this manifests as an agency problem.

Regulators and economists alike have long desired to understand the determinants of environmental pollution, and they have become increasingly aware of the vital role businesses play in environmental sustainability. An emerging literature seeks to uncover how the preferences of investors and capital market participants shape corporate environmental policies (Akey and Appel, 2019; Dyck, Lins, Roth, and Wagner, 2019; Krueger, Sautner, and Starks, 2020; Naaraayanan, Sachdeva, and Sharma, 2020; Shive and Forster, 2020). Arguably equally important are the characteristics and preferences of corporate insiders, particularly in regard to CEOs, who are the key figures responsible for firms' organization and operation. Yet, little is known regarding whether and how the preferences of CEOs map onto corporate environmental policies.[1]

Despite its importance, establishing the causal impact of managerial preferences on corporate environmental policies is empirically challenging. For one thing, it is difficult to elicit CEOs' intrinsic environmental preferences. Survey evidence ostensibly shows that almost all CEOs agree on the importance of sustainability issues, and they feel personally responsible laying out their company's core purpose and role in society (Winston, 2019). However, frequent pollution incidents and breaches of environmental laws suggest that CEOs' inherent preferences may differ from their public statements.[2] For another, there is an inconclusive debate about whether CEOs truly have a personal impact on corporate policies (e.g., Bertrand and Schoar, 2003), or it is rather the matching between firms and CEOs through the board that explains "managerial styles" (Fee, Hadlock, and Pierce, 2013). In this paper, we overcome these challenges by examining how CEOs' psychological attachment to their hometowns affects location-specific corporate environmental performance.

Psychological theories suggest that attachment to places offers people a "sense of belonging," and this attachment is incorporated into one's identity (Fullilove, 1996). Most people feel deeply attached to their hometown (Dahl and Sorenson, 2010), driving them to care for and proactively contribute to the well-being of their local community. Moreover, people generally have a stronger

[1]For studies that relate CEOs' preferences and ideologies to socially responsible corporate behaviors, see, e.g., Masulis and Reza (2015); Cronqvist and Yu (2017); Di Giuli and Kostovetsky (2014); and Duchin, Simutin, and Sosyura (2020).

[2]From 2000 onwards, U.S. environmental agencies investigated close to 200,000 non-compliance cases, representing a total of $800 billion in legal penalties for U.S. firms.

desire to maintain a positive image in their hometown and to engage in prosocial behaviors because local social ties make their deeds more salient and memorable (Relph, 1976). Research in environmental protection shows that attachment to a particular place encourages individual environmentally responsible behaviors (Vaske and Kobrin, 2001; Hernández, Martín, Ruiz, and Hidalgo, 2010). Based on the hypothesis that CEOs prefer to avoid exposing their hometowns and local residents to severe pollution, we predict that CEOs will more substantially internalize the externalities caused by corporate pollution, and hence curb firms' emissions near their hometowns.[3]

We utilize plant-level pollution data provided by the Toxic Release Inventory (TRI) from the U.S. Environmental Protection Agency (EPA) to examine the impact of hometown attachment on corporate pollution. Unlike generic firm-level ESG-related scores,[4] these granular plant-level pollution data allow a research design that alleviates the endogeneity concerns driven by firm–CEO matching. Because hometown attachment is specific to CEO–location pairs, we can compare, in the same firm-year, the toxic emissions of a company's plants close to the CEO's hometown relative emissions of other plants that are distant. This within-firm comparison enables us to isolate the effect of location-specific managerial preferences based on the geographical distribution of corporate emissions. Furthermore, TRI data allows us to make direct inferences about environmental abatement activities, connecting CEOs' personal preferences to resource allocation within the firm and substantiating the mechanisms that alter toxic emissions.

In a sample of Standard and Poor's (S&P) 1500 companies that release toxic substances into the environment, we find strong evidence that establishments located near the hometown of the parent firm CEO have a lower level of pollution intensity (defined as pollution per unit of production) than other plants of the same firm. Controlling for firm-by-time fixed effects, industry-by-time fixed effects, and location-by-time fixed effects, the pollution intensity from establishments located in a CEO's hometown state is about 20% lower than that of non-hometown plants.[5] This baseline result

[3]CEOs may also donate to philanthropic organizations tied to their hometowns as a substitute for reducing firms' pollution in their hometowns. However, as pointed out by Hart and Zingales (2016), when attempting to reduce pollution, companies have a natural efficiency advantage over individuals.

[4]There is also considerable disagreement across CSR ratings from different rating agencies (Berg, Koelbel, and Rigobon, 2020).

[5]Throughout this paper, we use *hometown plants* to refer to plants located in home state of the parent firm's

indicates that CEO hometown proximity is associated with better environmental performance by the firm's plants.

Importantly, the lower level of toxic release near CEOs' hometowns is not due to differences in production scale nor due to time-varying industry factors, because our regression controls for scale measures and plant industry-by-year fixed effects. Instead, hometown emission reduction is driven primarily by investing in more thorough waste management practices. We find that hometown plants implement more source-reducing abatement activities, such as material substitutions and process modifications, which reduce the creation of toxic waste from the production process. Furthermore, after toxic waste is generated, hometown plants also engage more intensively in further waste management practices, such as recycling and energy recovery, to offset the amount of eventual emission to the environment. Collectively, this set of results on abatement and waste management paints a more complete picture of the mechanisms through which hometown plants can achieve lower emissions.

A more nuanced alternative explanation for our main finding involves pollution considerations that are specific to firm-location pairs. For example, a firm in California might be subject to particularly heavy regulatory scrutiny and is thus forced to curb its emissions in that state. The company in turn appoints a Californian CEO who has connections to local politicians to assuage regulators. Parent–year fixed effects in our baseline regression specification are insufficient to rule out this alternative interpretation. To sharpen our identification, we identify a subsample of firms that experience CEO turnovers and perform a within-plant analysis. When a firm hires a new CEO who is not from the hometown state of her predecessor, this changes the proximity of the firm's plants to the CEO's hometown. Consistent with our main result, we find that plants experience a reduction in pollution intensity when their locations coincide with the incoming CEOs' hometown state. In the same vein, plants located near the outgoing CEO's hometown experience an increase in pollution intensity after the CEO turnovers.

Pollution abatement activities are costly for firms. Based on the latest survey jointly adminis-

CEO or within 100 miles of the parent CEO's hometown county.

tered by the EPA and the U.S. Census Bureau (EPA, 2005), U.S. manufacturers spent over \$26.57 billion on costs related to pollution abatement. This accounts for over 20% of manufacturing firms' total capital expenditure.[6] If these reductions in pollution intensity in CEO hometowns are driven by CEO personal preferences, such reductions are unlikely to be value optimizing for firms' shareholders. Since it is difficult to measure plant efficiency directly, we rely on an indirect method based on the argument that good corporate governance should dampen the relationship between plant pollution and CEO hometown proximity if such a policy is sub-optimal for the firm. We find evidence consistent with this conjecture. In a set of cross-sectional analyses, the negative effect of CEO hometown proximity on plant pollution is more pronounced for companies with poor governance measures and scant analyst coverage. This result is suggestive that the observed reduction in hometown pollution may not have occurred if CEOs maximized shareholder value alone. In other words, such pollution reduction activities represent a form of *hometown favoritism*.

To provide a causal interpretation of the role of governance in curbing inefficient hometown favoritism, we exploit the 2003 dividend tax cut as a quasi-natural experiment. The 2003 Tax Reform Act lowers the highest statutory dividend tax rate from 35% to 15%, one of the largest reforms of U.S. dividend tax rate. Prior studies show that firms with higher executive shareholding increased their dividend payouts after the tax reform. This suggests that principal-agency issues that held up earnings before the reform were mitigated by the reduction of dividend tax rate (Chetty and Saez, 2005; Brown, Liang, and Weisbenner, 2007; Chetty and Saez, 2010). Using the 2003 dividend cut as a setup that exogenously reduces the agency friction of firms with a high executive ownership, we compare the degree of hometown pollution reduction before and after the tax cut across companies.[7] We find that after the 2003 dividend tax cut, hometown plants belonging to parent firms with higher CEO ownership experience an increase in toxic emissions relative to the non-hometown plants of the same firm, suggesting a reduction in hometown favoritism. Thus, the results from this

[6]The 2005 survey was the latest survey available. In recent years, the sharp increase in abatement expenditures mandated by the stringent environment regulations is driving down overall toxic releases (Shapiro and Walker, 2018). It is likely that the 2005 survey offers a conservative estimate for current abatement costs.

[7]This setting is also utilized by Masulis and Reza (2015) and Cheng, Hong, and Shue (2020) to show the agency nature of certain corporate social responsibility activities.

quasi-natural experiment support the view that the lower pollution in CEOs' hometown plants arises from agency issues between shareholders and managers. In other words, CSR activities driven by managerial personal preferences are suboptimal for shareholders. However, one important caveat is that such CSR endeavors can in fact improve the welfare of outside stakeholders

While CEO hometown favoritism affects the geographical distribution of pollution emissions across firm's plants, it is unclear whether a CEO's location-specific prosocial preference affects a firm's aggregate environmental performance. For example, a CEO may increase the pollution emissions of non-hometown plants, thus offsetting the emission reduction in her hometown. In a set of firm-level analyses, we document that a firm generates less aggregate pollution for each unit of economic activity when the firm's headquarters is located in the CEO's home state or when a majority of the firm's business is concentrated in the home state of the CEO, measured as the fraction of the firm's establishments located in the CEO's home state. This finding not only corroborates the plant-level analyses, but also suggests that CEO hometown bias could affect firm-level aggregate environmental outcomes.

Finally, we examine the cross-sectional variation in CEOs' hometown favoritism. Our results suggest that the hometown pollution-reduction effect is more pronounced in firms with worse overall environmental performance. Our interpretation of these findings is that firms with poor environmental performance do not lag behind because their CEOs are unaware of environmental issues; instead, those CEOs selectively protect the environment near their hometown while deliberately withholding overall corporate pollution mitigation due to cost considerations. In addition, we also find that CEOs' hometown favoritism in environmental protection is more salient among financially constrained firms. Generally speaking, the cross-sectional results show that CEOs prioritize environmental protection in their hometown when cost considerations (e.g., limited financial resources) hinder firms' investments in ESG-related activities in other locations.

Our paper contributes to several strands of literature. First, it contributes to our understanding of the determinants of corporate social responsibility and environmental policies in particular. Bénabou and Tirole (2010) suggest that CSR activities may represent a shrewd business strategy that allows firms to "do well by doing good" or an agency issue initiated by managers. Despite its importance, direct evidence on insider-initiated CSR activities is limited. Masulis and Reza (2015) show that CEO charity preferences positively affect corporate philanthropy. Cheng, Hong, and Shue (2020) document that CSR activities are dampened when agency frictions between managers and shareholders are exogenously reduced. Many of extant studies measures managerial preferences at the personal level, and this hampers a causal interpretation of the impact of managers' preferences. Our paper utilizes hometown attachment to induce location-specific managerial preferences, thus we can saturate manager–firm selection bias using firm fixed effect models.

In terms of corporate environmental policies, previous studies have identified financial constraints (Cohn and Deryugina, 2018; Xu and Kim, 2021), ownership structure (Shive and Forster, 2020), local regulations (Bartram, Hou, and Kim, 2020), as well as legal liabilities (Akey and Appel, 2021) as determinants of corporate pollution. Our paper focuses on a more behavioral driver of corporate pollution. The reduction in hometown pollution can be seen as a form of insider-initiated CSR behavior and thus unlikely to be optimal for firm value.[8]

Second, the findings in this paper contribute to the literature on how hometown connections affect economic agents when making business decisions. For example, hometown CEOs are more likely to protect employees from their hometown from industry distress (Yonker, 2017a), spend more on R&D projects (Lai, Li, and Yang, 2020), and acquire companies located near their hometowns (Jiang, Qian, and Yonker, 2019).[9] Our paper shows that managerial hometown attachment motivates managers to internalize the corporate externalities generated by pollution emissions. Given the increasing global demand for corporations to take a more proactive role in addressing environmental problems, our paper sheds light on the potential of harnessing individual prosocial incentives in addressing environmental and other types of externalities.

This paper also relates to the broader literature on the impact of managerial styles (Bertrand

[8]For more research connecting CSR to corporate profitability, please refer to Margolis, Elfenbein, and Walsh (2009) and Kitzmueller and Shimshack (2012) for a comprehensive review, in addition to recent work such as Flammer (2015), Krüger (2015) and Ferrell, Liang, and Renneboog (2016).

[9]Other examples include banks opening branches near CEO hometowns (Lim and Nguyen, 2020) and credit analysts giving more generous ratings to issuers in their home states (Cornaggia, Cornaggia, and Israelsen, 2020).

and Schoar, 2003). Past studies show that many aspects of corporate policies can be explained by CEOs' preferences and beliefs that stem from their life experiences. These events include childhood experiences (Malmendier, Tate, and Yan, 2011; Duchin et al., 2020), early labor market experiences (Schoar and Zuo, 2017), disaster experiences (Bernile, Bhagwat, and Rau, 2017), and previous job experiences (Benmelech and Frydman, 2015; Dittmar and Duchin, 2016). We present evidence that CEO hometown origins also affect firm environmental policies.

I. Institutional Background and Data

A. Institutional Background

Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA) created the EPA's Toxic Release Inventory (TRI) Program. It specifies that chemicals covered by the TRI Program cause one or more of the following: (a) cancer or other chronic human health effects, (b) significant adverse acute human health effects, and (c) significant adverse environmental effects. The resultant list of chemicals contains over 600 individually listed chemicals and chemical categories, as well as the emission levels reported for each chemical, establishment, and year. Reporting is mandatory if an establishment has at least 10 employees, operates in a specific list of NAICS code, and emits one or more of a specified list of chemicals above certain quantity threshold.

To ensure the reporting quality of the TRI data, Section 1101 of Title 18 of the U.S. Code makes it a criminal offense to falsify information given to the U.S. government (including intentionally falsifying records maintained for inspection). Section 325(c) authorizes civil and administrative penalties for noncompliance with TRI reporting requirements. The EPA also conducts an extensive quality analysis of TRI reporting data and provides analytical support for enforcement efforts led by its Office of Enforcement and Compliance Assurance (OECA). The EPA first identifies TRI forms that contain potential errors, then contacts the facilities that submitted them. If the errors are confirmed, these facilities must then submit corrected reports.

In addition to monitoring toxic releases, the EPA also records information on facilities' engagements in various waste management activities. Panel (a) of Figure 1 provides an overview of firms' pollution abatement activities under two major categories: *pollution prevention* (also referred to as *source reduction*) and *post-production processes*. Pollution prevention reduces or eliminates the pollutants generated during the production process through practices such as modifying production processes, promoting the use of nontoxic or less toxic substances, and implementing conservation techniques. Post-production activities (including treatment, recycling, and disposal) are used to manage pollutants after their generation by the production process.

In Panel (b) of Figure 1, we decompose the cost categories for abatement expenditures according to the 2005 EPA Pollution Abatement Costs and Expenditures (PACE) survey summary for the manufacturing sector. Pollution abatement operating costs amounted to $20,677.6 million in 2005 across all industries, of which $2,848.4 million (14%) was attributed to capital depreciation. In contrast, the expenditures associated with energy, contract work, labor, and materials and supplies make up the vast majority (above 85%) of abatement costs. Furthermore, out of all new capital expenditures (a total of $128,325.2 million), only $5,907.8 million (4.6%) was attributed to pollution abatement capital expenditures. Perhaps contrary to conventional wisdom, pollution abatement does not rely heavily on capital investment and machinery. Instead, waste management is more significant along many dimensions of operations in modern corporations.

Panel (a) of Figure 2 shows the EPA's guidelines on waste management approaches. The EPA encourages facilities to first reduce or eliminate the use of TRI-listed chemicals and limit the creation of chemical waste through source reduction (i.e., pollution prevention) activities. Source reduction activities are ranked as the most effective method with the greatest benefit to the environment. For waste that is generated, the preferred management method is recycling (i.e., the reuse of discarded materials in the production of new products), followed by combustion for energy recovery and treatment (processes that eliminate toxic chemicals or neutralize its hazardous properties, such as incineration and oxidation). Finally, as a last resort, the chemical waste is released into the environment.

B. Toxic emission data

Our sample consists of plant-level toxic emission data from the TRI between 1992 and 2019. We focus on the total onsite toxic emissions (*Total Release*) from a plant in a given year in order to capture the negative footprint of firms' production activities on local environments and public health.[10]

Each year, facilities must report their newly implemented source reduction activities by selecting 47 codes that fall under eight broad categories. We retrieve information on plants' source reduction activities from the EPA's Pollution Prevention (P2) database. Appendix Table A3 displays the eight categories and their respective frequencies of adoption. *Good operating practices* (32.1%) and *process modifications* (20.2%) are consistently the most commonly reported categories of source reduction. These are followed by *spill and leak prevention* (15.2%), *raw material modifications* (10%), and *inventory control* (7.5%).

To assess plants' engagement in post-production waste management activities, we trace the percentage of total generated toxic waste (*Total Waste*) reduced through recycling, energy recovery and treatment, as well as the toxic waste released to the environment.[11] Panel (b) of Figure 2 showcases the relative importance of each waste management activity and the fraction of generated waste being released. During our sample period, a majority (over 65%) of the toxic chemicals produced ends up disposed into the environment. Treatment processes eliminated approximately 25% of the total toxic chemicals produced, while recycling (5.3%) and recovery (4.4%) account for the remaining fraction.

The TRI also contains the industry code, the location of each establishment, and the name for each establishment's ultimate parent firm, defined as the highest level corporation that owns at least 50% of voting shares. We then supplement the facility-level toxic release information from

[10] We choose onsite toxic emissions because our hypothesis emphasizes managers' incentive to reduce the *local* pollution. Some establishments ship some of their toxic chemicals (usually a small fraction) offsite, potentially far away from the polluting facilities, for further waste management or disposal.

[11] Suppose that after implementing source reduction practices, a plant still generates 5,000 pounds toxic chemicals. If recycling, energy recovery, and treatment each reduces the toxic waste by 1,000 pounds (20%), then 2,000 pounds of toxic chemicals (40% of total generated waste) is still released to the environment.

TRI with additional facility information from the National Establishment Time-Series (NETS) database. The NETS database provides plant-level longitudinal data, converted from Dun and Bradstreet (D&B) archival establishment data, that include measures of facility production scale such as the number of employees and the dollar amount of sales. We use the number of employees at a given establishment as our primary control for production scale.[12]

We obtain parent-level accounting information from the Compustat database, and we adopt the following procedure to link the TRI reports, NETS, and Compustat. First, we rely on the facility-level D&B numbers to link the TRI data to the NETS database, using a link provided in the TRI database. Second, we use an algorithm to match the name of the ultimate parent firm of each plant in the TRI database to its publicly traded parent in Compustat. Because parent names change across time in both the TRI database and Compustat, we use historical firm names from CRSP, supplemented by historical name and address information obtained from 10-K,10-Q, and 8-K filings using the SEC Analytical Package provided by the Wharton Research Data Service (WRDS) during the matching process. We remove common suffixes (e.g., "Corp.", "Incorporated", "LC", etc) before matching. To ensure the quality of the match, we manually check each link produced by the algorithm to further ensure its accuracy. Thus, we can identify the exact location of each establishment within a given parent firm.

C. CEO hometown data

After obtaining the list of Compustat parent firms linked to their plants in the EPA database, we proceed to identify the parent CEOs and their hometowns. We rely mainly on Execucomp to obtain CEO names. Because Execucomp includes only S&P 1500 firms, we supplement this list with CEO information from Capital IQ. We then locate the hometown of each of the included CEOs by identifying their birthplaces. Following previous studies (e.g., Bernile, Bhagwat, and Rau, 2017), we collect CEO birthplace information from various sources. We first search CEO names in two databases: the Marquis Who's Who and the Notable Names Database. If the birthplace

[12]Using the dollar amount of sales generates quantitatively similar results for all our analyses.

information of a given CEO is unavailable from either databases, we search for the CEO's name along with the company name using Google and utilize the relevant results. The Google search provides CEO hometown information from various sources, including local newspapers, LinkedIn, and school alumni information.

D. Summary statistics

Among the 1,585 unique parent firms in the intersection between Compustat and the TRI database, we successfully obtain reliable birthplace information for 949 CEOs hired by 709 firms.[13] After omitting any plants that lack the information needed for our regression analyses, the final sample contains 485 firms that hire 680 unique CEOs, and these are linked to 6,120 plants from the TRI database.

Table A2 reports the the list of SIC 2-digit industries that have the most plants in the final sample. Not surprisingly, industries that tend to generate more pollution have more plants in our sample. For example, *chemicals and allied products* contributes the highest number of plants. In Figure 3, we plot the the county-level number of CEO who appear in our sample. The figure shows a geographically widespread pattern of CEO hometowns, with some clustering in areas such as New York City or Cook County, Illinois. Wyoming is the only state that does not have a CEO in our sample.

Panel (a) of Figure 4 shows the geographic distribution of polluting plants in our sample. A total of 1,622 counties have polluting plants and are included in our analyses. There is a large geographic variation, with a few counties (e.g., San Francisco, California, or Cook County, Illinois) hosting many plants. To illustrate the volume of pollution at the plant level, we further calculate the average total toxic release for all plant–years in each county. We plot the results in Panel (b). The two figures show that the number of plants and the average plant pollution at the county level are non-overlapping, i.e., counties that contain many plants do not necessarily have higher plant-

[13]The rate of finding CEO hometowns is close to the rate reported in Bernile, Bhagwat, and Rau (2017), who find CEO birthplace information for 2,102 CEOs out of the 6,804 CEOs (30.9%) in the Execucomp database. Our sample universe is smaller to start with because we only include firms that operate in certain industries that appear in the TRI data.

level pollution levels, and vice versa. In addition, high-emission plants tend to show a dispersed geographical distribution.

Table I reports the summary statistics of the key variables for the final samples. Panel A shows that the average plant generates 1,402 thousand pounds of toxic chemicals, and releases 246 thousand pounds of waste into the environment. Waste management activities (i.e., recovery, recycle, treatment) reduce the amount of toxic wasted released to the environment by 34.9%, of which treatment accounts for 25.1%, recycling accounts for 5.3%, and recovery accounts for 4.4%.[14] The distribution of pollution amounts across plants is highly skewed. The average number of plant-level employees is 756.2, and the average number of unique chemicals used in each plant–year is 5.7. In our sample, 8.7% of the plants are located in their parent CEO's hometown states, 7.2% of the plants are located within 100 miles of the centroid of their parent CEO's hometown county, and 17.3% of the plants are located in the same state as the company's headquarters. Panel B reports the summary statistics of the firm sample constructed based on the plant sample in Panel A. The average firm emit 2,742 thousand pounds of waste and hires 7,462 employees. Roughly 10% of a company's plants are located in the CEO's hometown, and 26% of firm–years belong to firms that hire CEOs whose hometowns are located in the same state as the firm's headquarters.

II. Empirical Results

In this section, we first establish an empirical relationship between a plant's proximity to its CEO's hometown and the plant's pollution emission level. We then examine the methods of pollution reduction used by hometown plants. Furthermore, we investigate CEO turnover events, and we track the emissions of plants after their proximity to their parent CEO's hometown changes dramatically.

[14] A small fraction of plants with zero *Total Waste* produced do not have treatment, recycling, or recovery percentages.

A. Hometown favoritism and pollution intensity

In this subsection, we test our main hypothesis that plants produce less pollution when they are located near the hometown of their parent firm's CEO. We measure the hometown favoritism a CEO exhibits toward a specific plant using two dummy variables, *D(Hometown State)* and *D(≤ 100 miles)*. The former indicator equals one for plants located in their company CEOs' hometown states and zero otherwise. The latter indicator equal one for plants located within 100 miles of their company CEOs' hometown county. Our main regression model is

$$\begin{aligned} log(Total\ Release_{p,s,i,j,t}) = \alpha + \beta_1 Hometown\ Favoritism + \beta_2 D(HQ\ State) \\ + \beta_3 log(Employees) + \beta_4 Chemicals + FEs + \epsilon_{p,s,i,j,t}, \end{aligned} \tag{1}$$

where $log(Total\ Release_{p,s,i,j,t})$ is the volume of toxic wastes released in year t from plant p of parent firm i that operates in industry j and is located in state s.[15] *Hometown Favoritism* is either *D(Hometown Plants)* or *D(≤ 100 miles)*. To account for the scale and production-related differences between plants, we control for logarithm number of employees and the number of chemicals used at the plant level. Our key estimate is β_1, which captures the difference in pollution intensity (i.e., the pollution amount conditional on production scale) across hometown and non-hometown plants within the same firm–year. Standard errors are two-way clustered at the parent–year level and plant state–year level.

Table II presents our baseline findings on pollution intensity in managers' hometowns. The key explanatory variable is *D(Hometown State)* in columns (1) to (3) and *D(≤ 100 miles)* in columns (4) to (6). We allow for different sets of fixed effects to explore the variation within the different levels of observations. In columns (1) and (4), the regressions include only parent firm-by-year fixed effects, which capture any time-varying confounding factors at the parent company level, thus absorbing the potential selection issue between firms and CEOs. In columns (2) and (5), we additionally control for plant state-by-year fixed effects, which account for geographical

[15] In Appendix Table A4, we take an inverse hyperbolic sine transformation of the volume of toxic wastes and document quantitatively similar results.

shocks across states, such as changes in the stringency of local environmental regulations. In columns (3) and (6), we account for the full set of fixed effects, including plant industry-by-year fixed effects, which absorb shocks specific to the industry that local plants operate in. Thus, the model in columns (3) and (6) is highly saturated, and this is our preferred specification because it essentially compares plants close to or far from their CEO's hometown within the same parent firm–year and the same industry–year, while accounting for time-varying confounding factors in their various locations.

Across all specifications, we obtain negative coefficient estimates on the proximity of CEO hometowns, suggesting that plants near their CEOs' hometowns display lower pollution intensity. The coefficient estimates are statistically different from zero at the conventional level, and they are economically meaningful. Under our preferred specification in column (3), pollution intensity is approximately 20% lower (calculated as $e^{-0.220} - 1$) for plants located in their CEOs' hometown states than for other plants. Our baseline estimates (presented in Table II) support the view that managers' hometown favoritism, possibly driven by hometown attachment, drives firms to internalize more negative externalities in their CEOs' hometowns.

One possible alternative explanation that may confound our preferred interpretation of CEO hometown favoritism is that CEOs are more likely than the general population to grow up in areas with lower pollution, not because they allocate less pollution to their hometowns.[16] This is unlikely to explain our findings, however, as we control for plant state-by-year fixed effects to account for time-varying confounding factors at the local level. If local socioeconomic development or regulatory environments drive the level of local corporate pollution, then these factors should affect all plants in a location uniformly, irrespective of their proximity to their respective parent-firm CEO hometowns. In contrast, our results suggest that, given the same location at the same time, a plant has a lower level of pollution intensity if its firm's CEO was born nearby.

[16]Previous studies show that CEOs are more likely to come from wealthier families with more educated parents (Duchin, Simutin, and Sosyura, 2020), who may have more desire and resources to relocate to places with better environmental amenities. Furthermore, studies have shown that firms tend to locate their pollution activities in more disadvantaged areas with lower aggregate income (Banzhaf, Ma, and Timmins, 2019).

B. *Source reduction and other waste management activities*

Given the findings that hometown plants emit less toxic chemicals conditional on production scale, we next examine the channels through which CEOs can reduce pollution intensity in plants near their hometowns. There are several means at the CEOs' disposal. First, CEOs could invest in their hometown plants' source reduction efforts to reduce the total waste generated by their production processes. Second, hometown plants may be better equipped for waste management so they can utilize treatment, recycling, and waste recovery methods to release a smaller fraction of their total toxic waste into the environment. The evidence in this subsection shows that both channels are at work.

We first examine the plant-level implementation of source reduction activities, which are promoted by the EPA as the most effective way to prevent pollution. For each establishment–year, newly initiated source reduction activities are recorded for the chemicals reported. We count the number of cumulative source reduction activities adopted at the plant–chemical level, and we examine whether hometown plants implement more activities than non-hometown plants. Results using an OLS regression model are presented in Table III.

The dependent variable in Panel (a) of Table III is the cumulative number of source reduction activities. The coefficient estimate for *D(Hometown State)* suggests that hometown plants implement 0.197 more source reduction activities than other non-hometown plants within the same parent firm–year. This effect is significant at the 5% level and is also economically meaningful because it corresponds to 8.9% of the average number (2.22) of source reduction activities. Similar results are obtained in column (2), where we use the dummy variable *D($\leq$ 100 miles)* to measure CEOs' hometown favoritism. In Panel (b), we compare the *Total Waste* produced, and the results show that hometown plants generate around 14% less total waste than other plants, conditional on the amount of production. Overall, Table III provides clear evidence that managers reduce corporate pollution in their hometowns through investing in pollution reduction practices, giving hometown plants a greater comparative advantage to curb their generation of toxic waste relative to non-hometown plants.

At the same time, for the same amount of generated wastes, plants can limit their emission of toxic chemicals through various waste management activities. Thus, hometown plants may also choose to engage in other waste management activities to reduce the amount of hazardous wastes released to the environment. To this end, we calculate the fraction of wastes handled by each of the three approaches (i.e., treatment, recycling, and recovery) out of the total generated wastes, as well as the fraction of waste eventually released. We then examine whether the three types of waste management (i.e., recycling for reuse, energy recovery, and further treatment) prevent the emission of a larger fraction of generated toxic waste.

Table IV presents the results. We find that hometown plants conduct more waste management activities through recycling and energy recovery. Panel (a) shows that, relative to non-hometown plants, hometown plants exhibit a 1 percentage point (pp) higher fraction of emissions prevented due to the recycling or combustion (for energy recovery) of generated waste. As as result, hometown plants show a 1.74 pp reduction in total emitted waste (see column (4)). The pattern of offsetting toxic releases through recycling and recovery is amplified when we compare plants within a 100-mile radius of the CEO's hometown in Panel (b). This 3.25 pp reduction in emissions (via more recycling and energy recovery) corresponds to around 5% of the average percentage of total waste released into the environment.

So far, our results focuses on pollution intensity, defined as emissions per unit of production. Another potential channel through which CEOs can curb toxic emissions near their hometown is to influence the production scale. For example, CEOs can either cut production to reduce emissions directly, or they can adopt more advanced (and greener) technologies to increase productivity, with lower emissions being an unintended side effect. We explore this alternative in Appendix Table A5 by examining the level of economic activity at hometown plants, measured by the total employment and sales (in dollars). Across both measures, from columns (1) to (4), hometown plants display a about 10% more economic activity than non-hometown plants. Despite the fact that hometown plants receive more investment and maintain a larger scale, the estimates in columns (5) and (6) suggest that these plants do not appear to be more productive in terms of the amount of sales per employee. The results presented in Appendix Table A5 are consistent with the literature showing that CEOs favor employment and investment near their hometowns (Yonker, 2017a; Jiang et al., 2019), and they contradict the view that smaller production scale or higher productivity are channels for pollution reduction.

Taken together the results from Table III and IV, we conclude that a large portion of the pollution intensity reduction in hometown plants can be attributed to source reduction activities. Alternative waste management activities, such as recycling and recovery, also contribute to the overall emission reduction. Our findings also rule out the possibility that potentially new (and greener) capital investments, driven by CEO hometown favoritism, are fully responsible for pollution reduction. This is because source reduction and waste management activities are primarily not based on capital (as shown in Panel C of Figure 2). However, while additional abatement activities reduce local pollution, they also represent significant operational costs, thus they are unlikely to be optimal for the firm. In other words, CEOs devote more company resources to pollution abatement for hometown plants relative to the optimal level based on firms' costs–benefits analyses. We further explore the value implication for firms in the next section, where we connect our findings to agency problems.

C. Change in pollution around CEO turnovers

The fixed effects strategy in our baseline model removes all time-varying confounding factors at the firm level, the industry level, and the location level. However, this strategy cannot account for selection issues at the level of firm-by-location pairs. For example, firms that face more stringent environmental regulations in a state may hire a CEO from that state to help with regulatory compliance. To alleviate this endogeneity concern, we further exploit parent firms' managerial turnover events as shocks to plants' proximity to CEO hometowns and conduct a within-plant difference-in-differences (diff-in-diff) analysis. When a company experiences CEO turnover, and the newly hired CEO and the outgoing CEO are from different states, the firm's plants located in the hometown state of the new CEO will gain favoritism, while plants located in the hometown state of the previous CEO lose favoritism. Thus, as long as the timing of CEO turnover is not driven by factors associated with a future divergence in trends between affected plants and non-affected plants within the same parent firm, the plant-level analyses based on CEO turnovers help alleviate the more nuanced endogeneity concerns at the firm–location pair level.

To implement the test, we first identify a list of 155 firms that experienced CEO turnover during our sample period, and we further require that a CEO turnover event in a parent firm must lead one or more of its plants to change from a non-hometown plant to a hometown plant, or vice versa. In addition, interim CEOs (i.e., CEOs with tenure no longer than one year) are also removed from the turnover sample. Within each turnover firm, we distinguish two groups of affected plants: (a) the plants located in the hometown states of the outgoing CEOs and (b) the plants located in the hometown states of the incoming CEOs. For each turnover event, we rank all unaffected plants based on the absolute difference in pollution levels between these unaffected plants and the treated plant, and match up to five control plants from the same parent firm to the treated plants based on the absolute difference in pollution levels. We then separately perform the following regression at the plant level for the two groups of treated plants during the ten-year window surrounding the turnover events, while controlling for plant fixed effects, parent–year fixed effects, plant state–year fixed effects, and plant industry–year fixed effects:

$$\begin{aligned} Pollution_{p,i,s,t} = {} & \alpha + \beta_1 D(Treated\,Plant) * D(Post) + \beta_2 log(Employees) \\ & + \beta_3 \#Chemicals + \alpha_p + \alpha_{i,t} + \alpha_{j,t} + \alpha_{s,t} + \epsilon_{p,i,j,s,t}, \end{aligned} \tag{2}$$

where *D(Treated Plant)* is either *D(Hometown to nonhometown)* or *D(Nonhometown to Hometown)*. The former variable indicates plants located in the outgoing CEOs' hometown. The latter variable indicates plants located in the incoming CEOs' hometown. The coefficients on both indicators are absorbed by plant fixed effects. The variable *D(Post)* indicates post-turnover years for a matched treated–control pair. Plant fixed effects (α_p) allow us to control for any time-invariant plant characteristics and thus focus on the changes in hometown favoritism induced by

CEO turnover, alleviating the concern that our results might be driven by differences in the nature of businesses between hometown and non-hometown plants.[17]

Table V reports the results. The coefficients on *D(Treated Plant)* estimate the within-plant change in pollution level after a change in hometown status (i.e., whether a plant is located in the hometown state of its parent CEO) due to CEO turnover. In column (1), plants that change from a hometown plant to non-hometown plant experience a 51.4% (calculated as $e^{0.426} - 1$) increase in emission intensity. In column (2), we document a similar magnitude of the reduction in total waste emissions, and this reduction is associated with plants changing from non-hometown plants to hometown plants around CEO turnover events. We verify the parallel trend assumption that underlie the diff-in-diff analyses in both columns. The results reported in Appendix A6 show that for both types of treated plants, their pollution intensities share a similar trend with their respective control plants before CEO turnover occurs. Thus, the within-plant analyses show that turnover-induced changes in hometown status affect decisions related to toxic waste emissions, and this lends support to a causal interpretation of the impact of hometown favoritism on local pollution.

An alternative interpretation of the test based on CEO turnover is that some firm–location pair confounding factors are associated with CEO turnover. For instance, a firm may hire a local CEO from one state if it plans to improve its environmental performance in that state. However, this alternative view is difficult to reconcile with the result in column (1) of Table V because it is unlikely that a firm initiates a CEO turnover in order to emit more pollution in the outgoing CEO's hometown. To further assess the validity of this explanation, we examine whether the plant-level impact of CEO turnover is stronger among plants that are "important" to the parent firm. If parent firms change CEOs in response to geographical environmental considerations, they are more likely to do so in states that are central to the firms' operations. In Appendix A7, we measure the pre-turnover importance of a plant to a firm as the fraction of a firm's employees or sales from this plant, and we interact this measure with the two indicators for turnover-affected

[17] *D(HQ State)* is absorb by plant fixed effect in the regression.

plants. Turnover-induced changes in pollution intensity do not differ across plants in states that have varying relative operational importance to the firm, and plants in states that are not central to a firm's operation still display sharp changes in pollution around CEO turnover. The evidence supports the view that turnover events affect plant-level pollution through the channel of CEO hometown favoritism, rather than firms' location-specific business considerations.

III. Hometown pollution reduction as an agency problem

To the extent that CEOs reduce pollution in their hometown plants because they instill their personal preferences into corporate policy, the lower pollution intensity in CEO hometown plants is unlikely to be optimal for shareholder value, even though it may be desirable from the perspective of local residents (and the CEO). However, evaluating the optimality of hometown pollution reduction is challenging because it is difficult to empirically measure the corresponding changes in shareholder value. In this section, we adopt two strategies to connect our findings with agency problems: first, we examine whether the impact of hometown favoritism on plant pollution depends on the strength of corporate governance; second, we exploit the 2003 Tax Reform Act as an exogenous shock to CEOs' cost of pursuing private benefits using company resources.

If hometown pollution reduction is indeed sub-optimal from firms' perspective, managers in firms with better governance are less likely to implement value-decreasing policies than those in poorly governed firms, and we should expect more pronounced hometown pollution reduction among poorly governed (Yonker, 2017a). We first conduct a cross-sectional test to examine whether the strength of corporate government affects the degree of hometown favoritism on plant pollution. We utilize three governance measures: the G-index (governance index) from Gompers, Ishii, and Metrick (2003), the E-index (entrenchment index) from Bebchuk, Cohen, and Ferrell (2009), and analyst coverage (e.g., Irani and Oesch, 2013; Chen, Harford, and Lin, 2015). The G-index counts the incidence of 24 provisions that strengthen managerial takeover defenses or weaken shareholder rights. The E-index refines the G-index by considering six of the 24 provisions that are most detrimental to shareholder value.[18] Higher values on the G- or E-index indicates lower governance quality. We construct three dummy variables to indicate firms the lower governance quality: *D(High G-Index)*, *D(High E-Index)*, and *D(Low Analyst Coverage)*. We then include the interactions of the three dummy variables with *D(Hometown State)* in a regression on plant emissions:

$$\begin{aligned} log(Total\ Release_{p,s,i,j,t}) = \alpha + \gamma D(Hometown\ State) * LowGov + \beta_1 D(Hometown\ State) \\ + \beta_2 D(HQ\ State) + \beta_3 log(Employees) + \beta_4 Chemical\ Counts + FEs + \epsilon_{p,s,i,j,t} \quad (3) \end{aligned}$$

Under our hypothesis of sub-optimal hometown pollution reduction, we expect γ to be negative.

The results are reported in Table VI. Across all columns, the coefficient estimates for the interaction terms between the hometown plant indicator and the low governance quality indicator (γ) are significant and negative, indicating that total toxic releases are lower in plants near CEOs' hometowns, especially when firm governance is poor. These results suggest that the impact of hometown favoritism on local pollution is concentrated among firms with lower governance quality and firms that are less scrutinized by analysts. This is more consistent with the hypothesis that the reduction in toxic emissions in CEOs' hometown plants is unlikely to be efficient from the shareholders' perspective, and it is more likely to arise under agency issues between shareholders and managers.

The 2003 dividend tax cut While the above cross-sectional analyses is indicative of an agency-based view of hometown favoritism in corporate pollution, the results may be subject to the concern that corporate pollution decisions and governance are both endogenously determined. We assess whether managerial agency problems causally impact their incentives to reduce hometown

[18] The G-index is downloaded from the Institutional Shareholder Services (ISS) database and the E-index is obtained from Bebchuk et al. (2009) (`http://www.law.harvard.edu/faculty/bebchuk/data.shtml`). Both variables are available only between 1990 and 2006 due to changes in ISS survey methods in 2007, after which many provisions used to construct the two indices are either no longer available or have different definitions. Because governance indices are relatively stable within firms, we follow previous studies (e.g., Li and Li, 2018) to propagate the 2006 values to the result of our sample period.

emissions by exploiting a quasi-natural experiment that reduces the degree of agency frictions for a subset of companies. Specifically, we exploit the Jobs and Growth Tax Relief Reconciliation Act of 2003, which reduced the marginal federal dividend income tax rate from 35% to 15% for the recipients of most taxable dividends.[19]

The 2003 tax reform was proposed by President George W. Bush in January 7, 2003. It was largely unanticipated (Auerbach and Hassett, 2006). Although it was signed into law on May 28, it applied retroactively to January 1, 2003. Chetty and Saez (2005) and Brown, Liang, and Weisbenner (2007) document that firms with high executive ownership significantly increased their dividend payouts following the tax reform. Such differential increases in dividend payouts indicate that, before the tax cut, principal–agency conflicts prevented managers from efficiently returning capital to shareholders (Chetty and Saez, 2010). A lower dividend tax rate increases the value of dividend income to shareholding managers; therefore, this tax reform reduced the conflicts between principal and agents, and encouraged firms to maximize shareholder value.[20]

Building on the findings above, we hypothesize that if the relatively low corporate pollution near CEO hometowns represents managerial private benefits and is detrimental to shareholder value, the dividend tax cut will weaken CEOs' hometown favoritism. This prediction should be particularly true for CEOs who hold a relatively high ownership of the company, as the dividend cut increases shareholding managers' incentives to maximize firm value. If, on the other hand, hometown pollution reduction is optimal for shareholder value, we should expect managers to either maintain or intensify such behavior after the 2003 tax reform.

[19]The 2003 tax reform reduced the marginal tax rate on qualified and taxable dividends for individual taxpayers in the top 4 ordinary income tax brackets from 38.6 percent, 35 percent, 30 percent, and 27 percent to 15 percent, and for individual taxpayers in the bottom 2 ordinary income tax brackets from 15 percent and 10 percent to 5 percent. About 90% accrue to taxpayers in the top 4 income brackets. The 2003 tax reform also cut the top capital gain rate from 20 percent to 15 percent, and accelerated the legislated phase-in of individual ordinary income tax rate reduction, immediately reducing the top rate from 38.6 percent to 35 percent instead of waiting for it to drop to 37.6 percent in 2004 and 35 percent in 2006 (Yagan, 2015).

[20]In Appendix Table A8, we confirm the effect of CEO stock ownership on firms' responses to the 2003 dividend cut for both the full Compustat sample and our TRI-linked sample. Firms are significantly more likely to initiate or increase dividend payouts after the 2003 tax reform, and this effect is amplified by higher CEO stock ownership. Thus, the results validate the tax reform as an exogenous shock to managerial incentives and to corporate agency problems.

We test this prediction by performing the following triple-difference regression:

$$\begin{aligned} Log(Total\ Release)_{p,i,s,t} = {} & \alpha + \beta_1 D(Hometown\ State) + \beta_2 D(Hometown\ State) * D(Post\ 2003) \\ & + \beta_3 D(Hometown\ State) * \%\, CEO\ Ownership \\ & + \beta_4 D(Hometown\ State) * D(Post\ 2003) * \%\, CEO\ Ownership \\ & + Controls + FEs + \epsilon_{p,i,s,t}, \end{aligned} \tag{4}$$

where *D(Post 2003)* is a dummy variable that equals one for years after 2003, and *% CEO Ownership* is the number of stocks owned by a CEO in Execucomp over the total shares outstanding.[21] Controls include *Log(Employees)* and *Chemical Counts*, parent-by-year fixed effects, plant fixed effects, plant-industry fixed effects, and plant state-by-year fixed effects. The coefficient of interest is on the triple interaction term (β_3), which captures the within-plant impact of the dividend tax cut, conditional on firm CEOs' stock ownership.

Table VII reports the regression results. In both columns, the coefficient on *D(Hometown State)*% CEO Ownership* is positive, suggesting a lesser degree of hometown favoritism in pollution decision as CEO ownership increases. This is consistent with the predictions in Jensen and Meckling (1976) that CEO shareholding is negatively related to CEO consumption of private benefits. More importantly, the marginal impact of CEO ownership on curbing hometown favoritism more than doubles after the 2003 dividend tax cut, as indicated by the significantly positive coefficient on the triple interaction term *D(Hometown State)*D(Post 2003)*% CEO Ownership*. This is consistent with the agency-based interpretation of CEO hometown pollution reduction, which holds that dividend tax cuts increase a manager's costs of diverting corporate resources for personal reasons. This narrows the gap between hometown plants and non-hometown plants in terms of their respective pollution abatement activities as well as their pollution intensity.

Furthermore, we consider the possible nonlinear impact of the dividend tax cut on alleviating agency conflicts between managers and shareholders. As Cheng, Hong, and Shue (2020) argue, for

[21] The interaction between *D(Post 2003)* and *% CEO Ownership* is absorbed by parent–year fixed effects.

managers with either very low or very high levels of ownership, the increase in effective ownership brought by the Tax Reform Act has a weaker impact on the strength of managers' self-serving incentives. The former type of managers has very little equity ownership of the firm and little claim to dividends, while the latter group of managers has incentives that are already aligned with shareholders' interests absent the tax cut. In column (2), we additionally include in the regression the interaction terms with the squared term of *% CEO Ownership*. Consistent with the hypothesized nonlinear impact of the Tax Cut Reform, we document a positive coefficient estimate for the triple interaction term with *% CEO Ownership*^{2}. This suggests that the 2003 dividend tax cut played a lesser role in ameliorating agency-motivated hometown favoritism among firms that were less subject to agency conflicts before the tax cut.

Lastly, we substantiate the causal interpretation of the dividend tax cut by verifying the parallel trend assumption that underlies the quasi-natural experiment. Specifically, we set up a dynamic specification by replacing the *D(Post 2003)* dummy in Equation 4 with six year dummies, *D(Tax Reform*$_h$*)*, where h ranges from -3 to 3. The variable *Tax Reform*$_h$ represents h years since the 2003 tax. If h is negative, then the Tax Reform Act will take effect $-h$ years later. The year 2003 is indicated by $h = 0$, and it is omitted from the regression to form the benchmark year. The periods three years before 2003 and three years after 2003 are grouped into $h = -3$ and $h = 3$, respectively. We perform the dynamic regression with *Log(Total Release)* as the outcome variable, and we plot the regression coefficients for $D(Hometown\ State) * \%\ CEO\ Ownership * D(Tax\ Reform_h)$ in Figure 5. The plot shows that the coefficient estimates for the pre-2003 period interactions are all close to zero, and the impact of the Tax Reform Act becomes statistically significant in year 1 and remains persistent. Thus, the dynamic regression lends strong support for the parallel assumption that underlies this quasi-natural experiment.

IV. Cross-sectional Tests

In this section, we first examine whether having a hometown CEO affects the aggregate outcomes for firm-level environmental performances. We then examine cross-sectional variations in the impact of CEO hometown bias and, in particular, how this impact varies with firm-level financial constraints and general ESG profiles.

A. Firm-level consequences

Does a CEO's hometown preference influence pollution intensity at the parent level? The previous within-firm analyses document a strong impact of CEO hometown favoritism on the within-firm geographical distribution of corporate pollution. However, differences in pollution emissions across plants within a firm do not necessary imply changes in aggregate firm-level pollution. Because investments in abatement activities are costly, CEOs might increase pollution emissions in other plants within the parent firm to compensate for hometown pollution reduction. Under this scenario, the aggregate emissions of a company may be unchanged.

To empirically evaluate hometown CEOs' aggregate impact on corporate pollution, we construct two measures to capture the extent to which firm-level operations concentrate in CEO hometown states, and we correlate these measures with the total level of corporate pollution. First, because headquarters are the centers of core corporate activities, we follow previous studies (Lai, Li, and Yang, 2020) to define an indicator *D(Hometown in HQ)* that equals one when a firm hires a CEO whose hometown is in the corporate headquarters state. Second, we compute the fraction of plants located in CEO's hometown state among all plants of the parent firm: *Frac Hometown Plant*.[22] We then aggregate the plant-level pollution to the parent level and conduct the following regression at the firm level, controlling for firm industry–year and headquarters state–year fixed

[22] We also calculate a weighted average of *Frac Hometown Plant* by weighing each plant by its pollution amount and obtain consistent results.

effects:

$$log(Total\ Release_{i,j,s,t}) = \alpha + \beta_1 Local\ CEO\ + Controls_{i,t} + \alpha_{j,t} + \alpha_{s,t} + \epsilon_{i,j,s,t}, \quad (5)$$

where the dependent variable is the log amount of toxic release aggregated at the firm level. The variable *Local CEO* is proxied by *D(Hometown in HQ)* or *Frac Hometown Plant*. The control variables include *Log(Firm Employees)*, *Cash/Total Assets*, *CAPX/PPENT*, *Firm Tangibility*, and *Tobin's Q*. We also include firm industry-by-year and firm headquarters state-by-year fixed effects to account for industry- and state-specific shocks.

Table VIII shows the results from the firm-level regression. In column (1), the coefficient on *Frac Hometown Plant* suggests that firms with a higher proportion of plants in their CEOs' hometown states emit less toxic waste. In column (2), we replace *Frac Hometown Plant* with *D(Hometown in HQ)* and obtain consistent findings. In terms of economic magnitude, the log transformed amount of pollution is 0.660 lower for firms that hire CEOs from headquarter states, or 5.6% lower than the sample mean. Thus, these results suggest a lower emission intensity when there is a high overlap between the CEO's hometown state and the geographic footprints of firm pollution. However, we caution a causal interpretation about hometown CEOs and aggregate firm pollution emissions, given the potential endogenous matching between firms and local CEOs (Yonker, 2017b).

B. Hometown favoritism, overall firm CSR, and financial constraints

Does CEOs' hometown favoritism in regard to pollution reduction manifest among firms with poor overall environmental performance, or among firms that lack the financial flexibility to improve their environmental performance? The answer to this question may help shed some light on the underlying motives of corporate (dis)engagement in environmental protection. If the lower level of pollution near a CEO's hometown is accompanied by poor overall environmental performance or stringent financial constraints at the parent level, this result will lend further support to the view that CEOs selectively drives down pollution near their hometown. On the other hand, if the lower pollution level near the CEO's hometown is particularly salient for firms with better environmental performance or financially healthy firms, this would suggest that when firms spend more on CSR and environmental protection, CEOs tilt relatively more resources to their hometowns during the process.

We obtain data on parent-level measures of ESG ratings from the Kinder, Lydenberg, and Domini (KLD) database to empirically examine whether the effect of CEO hometown favoritism depends on parent-level ESG performance. Following Cronqvist and Yu (2017), among others, we create an ESG score by netting the strengths and concerns counts for a firm across the following six dimensions reported by KLD: *community*, *diversity*, *employee relations*, *environment*, *human rights*, and *product*.[23] We also separately count the strengths and concerns score for the *environment* dimension, and then construct two dummy variables, *D(Low KLD Score)* and *D(Low ENV Score)*, to indicate firms with below-median ESG and environmental scores, respectively. To capture parent firms' degree of financial constraint, we rely on the text-based measure from Bodnaruk, Loughran, and McDonald (2015) and the expected default frequency (EDF) provided by Moody's Analytics.[24] We then construct indicators based on each of the four measures and interact them with *D(Hometown State)* from Equation 1.

The regression results are listed in Table IX. The interaction terms of *D(Hometown State)* with *D(Low ESG Score)* and *D(Low ENV Score)* are both negative and economically sizable, suggesting that hometown favoritism in environmental performance is concentrated among firms with lower overall CSR and environmental ratings. Thus, these results suggest that poor ESG performance in many firms may not be explained by a lack of managerial awareness of social and environmental externalities generated by corporations, because managers in these firms are still attentive toward internalizing externalities in their hometowns. Rather, lower ESG spending in these firms might be due to deliberate cost–benefit considerations, i.e., the benefits of ESG spending accruing to

[23]Each strength count adds +1 to the CSR score and each concern count adds -1 to the score.

[24]We use the text-based measure from Bodnaruk et al. (2015) because its coverage has a large overlap with our sample period.

shareholders do not justify the costs of ESG engagement. In columns (3) and (4), we observe stronger evidence of hometown favoritism among financially constrained firms, suggesting that firm CEOs prioritize their hometown environment over other locations more when facing limited financial resources to act in an environmentally friendly way.

V. Conclusion

In this paper, we study the impact of managerial hometown preferences on corporate environmental policies. We find that plants located near parent firm CEOs' hometowns emit significantly less toxic chemicals than other plants within the parent firm–year. Using CEO turnover events at the parent firm level and controlling for local time-varying heterogeneity, we show that this finding is likely due to CEOs' preference for internalizing corporate externalities that affect their hometowns. CEOs reduce corporate pollution in their hometown by implementing more costly abatement activities. We also document that parent firms with operations concentrated in CEOs' hometowns generate less overall pollution than other firms.

Our paper provides evidence on pollution reduction activities that are driven by managerial personal preferences and are thus likely to be suboptimal for shareholders. The reduction in hometown plant emissions is more pronounced among firms with poor governance. On the other hand, our findings also suggest that managers' prosocial preferences can promote more environmentally friendly behaviors from the firm, helping to internalize the environmental externalities of the firm. Therefore, one must consider the balance between shareholder value and the environmental impact of firms.

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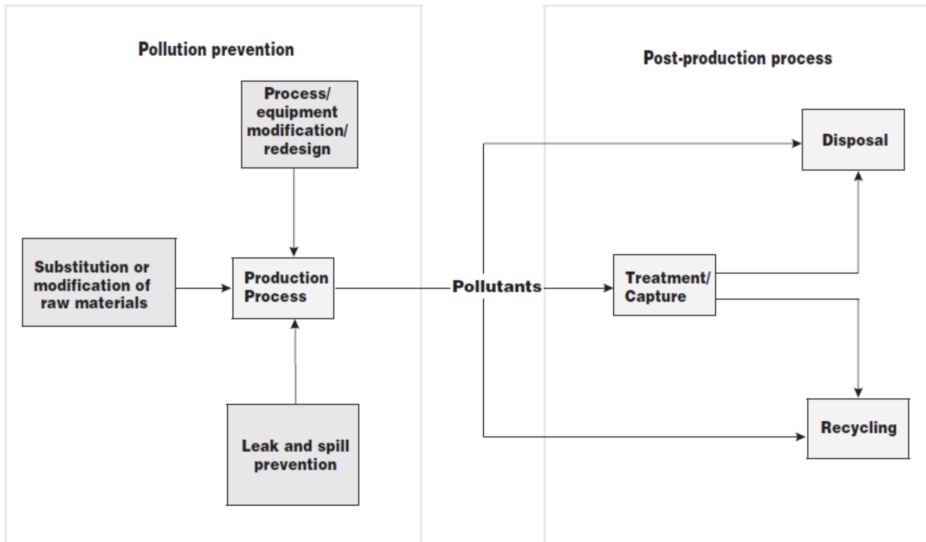
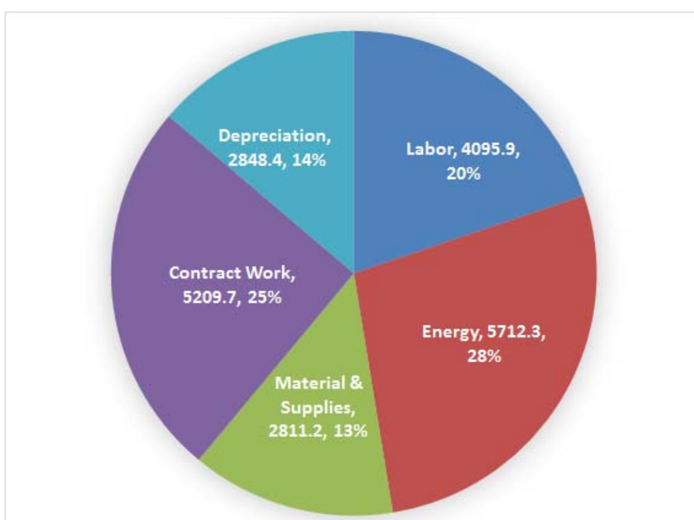
Figure 1: Waste management activities and Abatement Costs

This figure provides an overview of pollution abatement activities and related costs. Panel (a) illustrate the pollution abatement process under two main categories: pollution prevention and post-production process. In Panel (b) we decompose abatement costs and expenditures based on the Pollution Abatement Costs and Expenditures (PACE) survey in 2005 (the most recent available) conducted by the U.S. Census Bureau in the manufacturing sector.

(a) Pollution abatement process



(b) Abatement costs and expenditures ($mil)

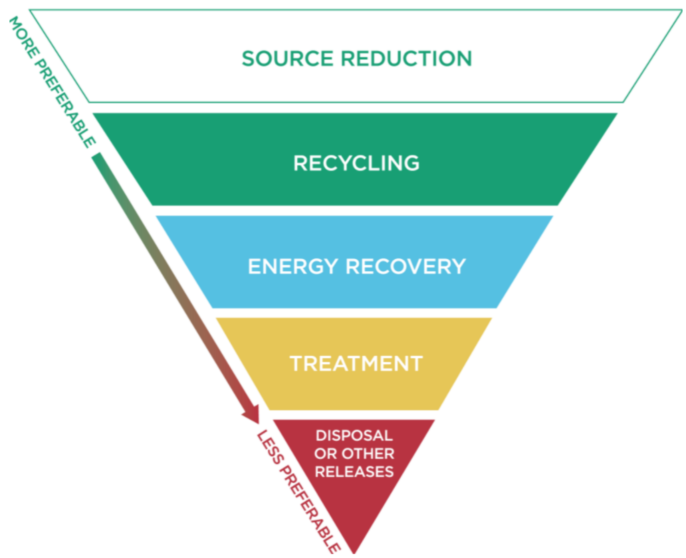


Source: Pollution Abatement Costs and Expenditures (PACE) 2005 survey

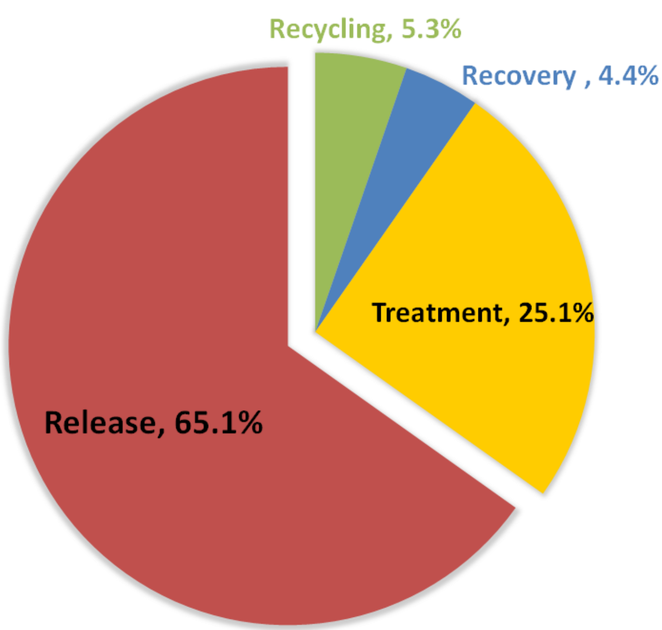
Figure 2: Waste Management Hierarchy and Intensity

This figure shows EPA's waste management hierarchy and their relative importance in reducing emission. In Panel (a), Waste management activities are ranked from the top of the inverted triangle to the bottom by EPA's preference. The most preferred approach includes source reduction (pollution prevention) activities that directly reduce the generation of toxic releases, followed by post-product processes such as recycling, energy recovery, and treatment. The least preferred approach is disposal or other release into the environment. Panel (b) shows the average percentage of generated waste that are eliminated by recycling, energy recovery, treatment, and released to the environment.

(a) Waste management hierarchy



(b) Waste management intensity



Source: United States Environmental Protection Agency

Figure 3: CEO's hometown counties

This figure shows the geographical distribution of the hometown counties where CEOs in our sample grow up. The sample includes 680 unique CEOs from 300 counties. The size of the circle grows with the number of CEOs in a given county.

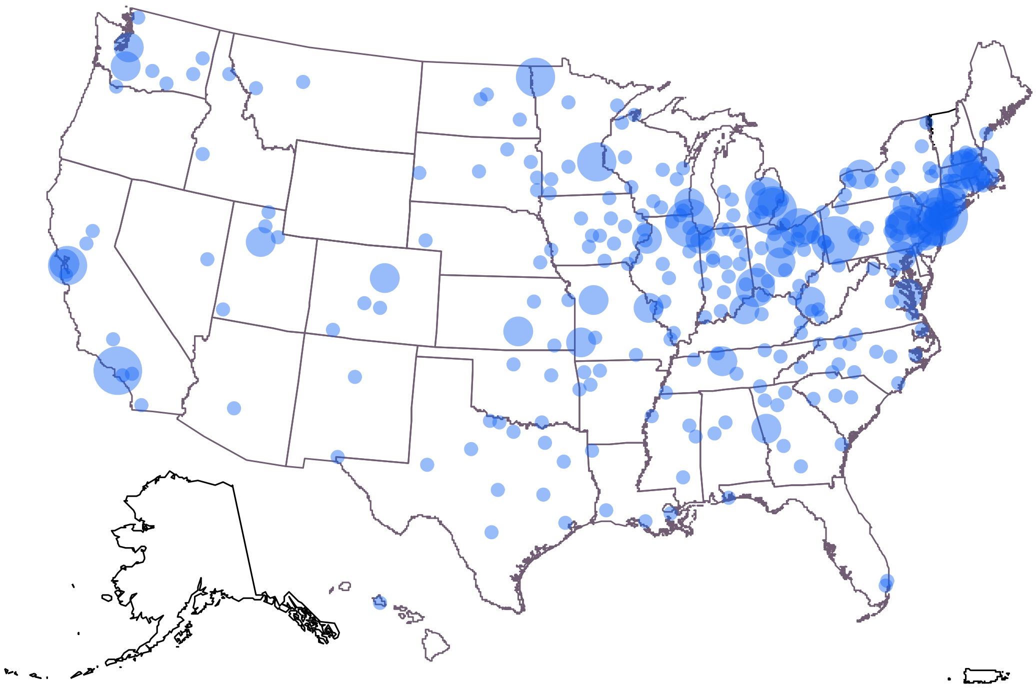
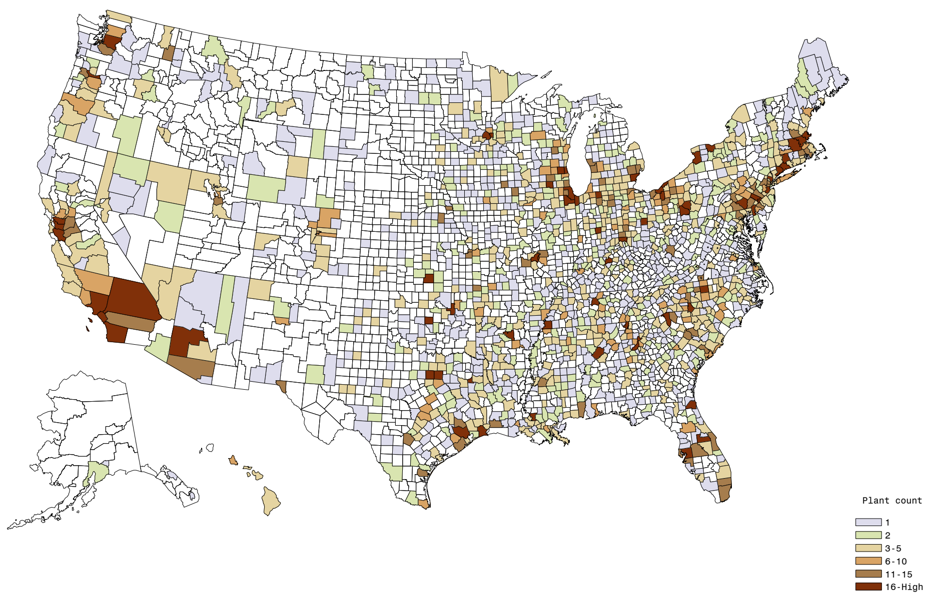


Figure 4: Distribution of emitting plants and emission level

This figure plots the county-level distribution of plants and levels of toxic releases. Panel (a) displays the number of polluting plants in our final sample for each county. Panel (b) displays the county-level average plant emission in pounds. Average plant emission is calculated as the mean of total toxic releases for all plant-years in a given county.

(a) County-level plant counts



(b) County-level average plant releases

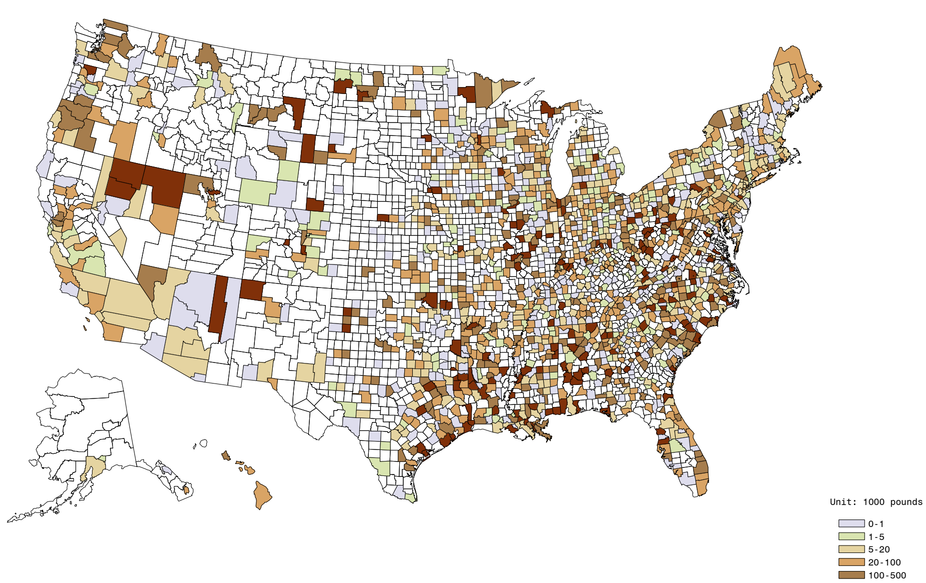


Figure 5: Dynamic impact of the 2003 Tax Reform Act on hometown favoritism

This figure shows the dynamic Diff-in-Diff estimation based on the 2003 dividend tax cut from the following regression:

$$
\begin{aligned}
Log(Total\ Release)_{p,i,s,t} = {} & \alpha + \beta_1 D(Hometown\ State) * D(Post\ 2003) \\
& + \beta_2 D(Hometown\ State) * \%CEO\ Ownership \\
& + \sum_{h=-3,\cdots,3+} \gamma_h D(Tax\ Reform_h) * \%CEO\ Ownership * D(Hometown\ State) \\
& + Controls + FEs + \epsilon_{p,i,s,t}
\end{aligned}
$$

h takes the value of -3,-2,-1,1,2, and 3+. Years before year -3 and after year 3 are lumped with year -3 and 3, respectively. Year 0 is 2003, when the Tax Reform Act was officially signed into law, and is also the benchmark year. Controls include the natural log of plant employees and the count of chemicals used. FEs include parent-by-year FEs, plant FEs, plant industry-year FEs, and plant state-by-year FEs. Point estimates and 95% confidence intervals are plotted for γ_h.

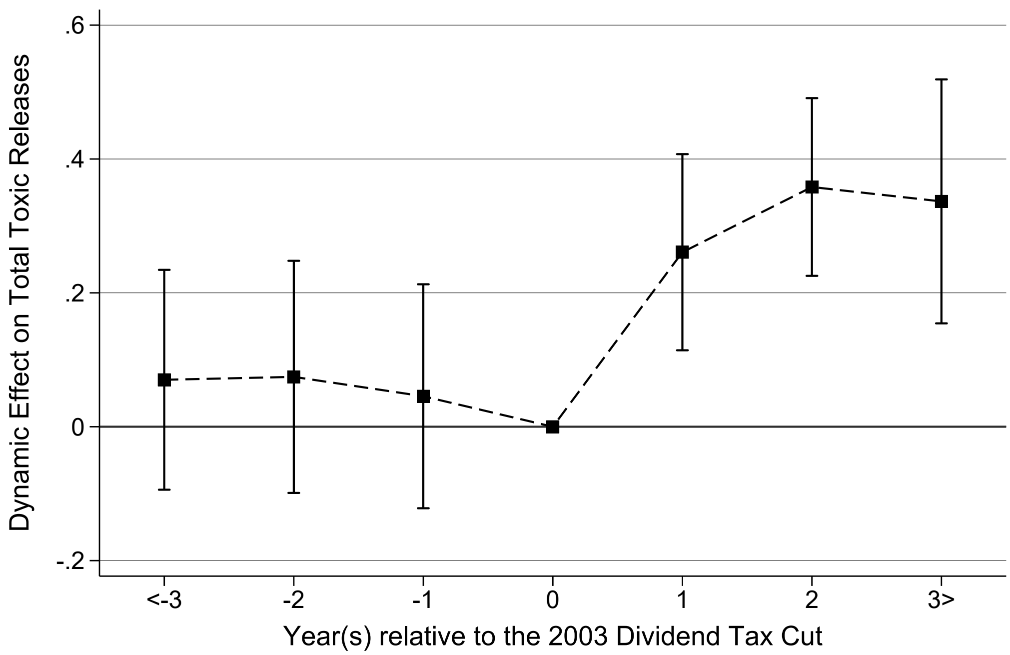


Table I: Summary Statistics

This table shows summary statistics for the sample of plants between 1992 and 2019 with non-missing variables in our main regression analyses. Continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Variable definitions are listed in Appendix A1.

Variable	N	Mean	Median	SD
Panel A: Plant-level Sample				
Total Release (1,000 pounds)	41633	246.092	6.037	787.617
Total Waste (1,000 pounds)	41633	1402.334	20.140	4847.177
Log(Total Release)	41633	7.706	8.706	4.543
Log(Total Waste)	41633	8.929	9.911	4.894
% Recycled	37842	5.341	0.000	20.351
% Recovery	37842	4.405	0.000	17.652
% Treatment	37842	25.117	0.000	37.462
% Waste Management	37842	34.873	0.000	42.120
% Release	37842	65.127	100.000	42.120
Employees	41633	756.152	300.000	1307.847
Chemical Counts	41633	5.676	3.000	6.138
D(Plant in Hometown)	41633	0.087	0.000	0.282
D(leq 100 miles)	41633	0.072	0.000	0.259
D(Plant in HQ)	41633	0.173	0.000	0.379
Panel B: Firm-level Sample				
Firm Total Release (1,000 pounds)	3564	2742.168	223.088	7626.129
Log(Firm Total Release)	3564	11.886	12.315	3.523
Firm Employees	3564	7443.135	2955.000	11361.757
Log(Firm Employees)	3564	7.780	7.992	1.840
Frac Hometown Plant	3564	0.097	0.000	0.198
D(Hometown in HQ)	3564	0.261	0.000	0.439
Cash/Total Assets	3564	0.070	0.039	0.080
CAPX/PPENT	3564	0.175	0.162	0.082
Firm Tangibility	3564	0.335	0.297	0.177
Tobin's Q	3564	1.667	1.424	0.802
G-index	2471	10.042	10.000	2.505
E-index	2380	2.530	3.000	1.328
ROA	3564	0.045	0.049	0.082
% CEO Ownership	2937	0.951	0.177	2.337
# Analyst Coverage	3564	10.677	9.000	8.987
KLD Score	1805	0.533	0.000	3.414
ENV Score	1805	-0.188	0.000	1.498
Text FC	2778	0.014	0.014	0.004
EDF	3285	0.823	0.126	3.210

Table II: Do managers pollute less in their hometowns?

This table reports the baseline results on whether firms pollute less in their CEOs' hometown plants. The sample include plant-year observations between 1992 and 2019. The dependent variable is the plant-level total toxic releases. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Total Release)					
	(1)	(2)	(3)	(4)	(5)	(6)
D(Hometown State)	-0.320***	-0.182**	-0.220***			
	(0.074)	(0.076)	(0.076)			
D($\leq$ 100 miles)				-0.423***	-0.225***	-0.312***
				(0.076)	(0.078)	(0.076)
D(HQ State)	-0.038	0.036	0.052	-0.045	0.027	0.048
	(0.053)	(0.054)	(0.054)	(0.052)	(0.052)	(0.052)
Log(Employees)	0.156***	0.150***	0.104***	0.157***	0.150***	0.105***
	(0.014)	(0.015)	(0.012)	(0.014)	(0.015)	(0.012)
Chemical Counts	0.362***	0.357***	0.354***	0.362***	0.357***	0.354***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Observations	41633	41633	41633	41633	41633	41633
Adjusted R^2	0.555	0.560	0.625	0.556	0.560	0.625
Parent-year FE	Y	Y	Y	Y	Y	Y
Plant state-year FE	N	Y	Y	N	Y	Y
Plant Industry-year FE	N	N	Y	N	N	Y

Table III: Hometown favoritism and source reduction

This table investigates the impact of hometown favoritism on plants' source reduction activities and total waste generation. In Panel (a), the dependent variable is the cumulative number of source reduction activities adopted at the chemical-level. In Panel (b), the dependent variable is the amount of total waste generated at the plant level. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and chemical-year in Panel (a) and by parent-year and plant state-year in Panel (b). ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Panel (a): Source Reduction Activities

Dependent variable	Source Reduction Activity Counts	
	(1)	(2)
D(Hometown State)	0.197**	
	(0.098)	
D($\leq$ 100 miles)		0.284**
		(0.138)
D(HQ State)	0.095	0.101
	(0.073)	(0.074)
Log(Employees)	0.053***	0.053***
	(0.016)	(0.016)
Log(Lagged Total Waste)	0.124***	0.124***
	(0.007)	(0.007)
Observations	187789	187789
Adjusted R^2	0.206	0.206
Parent-year FE	Y	Y
Chemical-year FE	Y	Y

Panel (b): Total Waste Generated

Dependent variable	Log(Total Waste)	
	(1)	(2)
D(Hometown State)	-0.130***	
	(0.050)	
D($\leq$ 100 miles)		-0.088*
		(0.051)
D(HQ State)	0.045	0.028
	(0.037)	(0.035)
Log(Employees)	0.087***	0.087***
	(0.011)	(0.011)
Chemical Counts	0.308***	0.308***
	(0.005)	(0.005)
Observations	41633	41633
Adjusted R^2	0.578	0.578
Parent-year FE	Y	Y
Plant state-year FE	Y	Y
Plant industry-year FE	Y	Y

Table IV: Hometown favoritism and waste management activities

This table investigates the impact of hometown favoritism on plants' waste management through recycling, energy recovery, treatment, and releases. The dependent variables measure the percentage of toxic waste processed by each approach. Thus, the dependent variables from column (1) to (4) sum to 100% for any given plant-year. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Panel (a): CEO hometown state plants

Dependent variables	% Recycled (1)	% Recovery (2)	% Treatment (3)	% Released (4)
D(Hometown State)	0.826**	0.891**	0.019	-1.740**
	(0.371)	(0.412)	(0.704)	(0.768)
D(HQ State)	-0.301	-0.199	-0.317	0.821
	(0.279)	(0.292)	(0.620)	(0.653)
Log(Employees)	-0.323***	0.087	0.365**	-0.129
	(0.079)	(0.081)	(0.145)	(0.157)
Chemical Counts	0.372***	0.265***	1.455***	-2.092***
	(0.032)	(0.030)	(0.052)	(0.059)
Observations	37705	37705	37705	37705
Adjusted R^2	0.251	0.316	0.338	0.371
Parent-year FE	Y	Y	Y	Y
Plant state-year FE	Y	Y	Y	Y
Plant industry-year FE	Y	Y	Y	Y

Panel (b): Plants within 100 Miles from CEO hometowns

Dependent variables	% Recycled (1)	% Recovery (2)	% Treatment (3)	% Released (4)
D($\leq$ 100 miles)	1.416***	1.212***	0.623	-3.253***
	(0.435)	(0.455)	(0.788)	(0.865)
D(HQ State)	-0.312	-0.199	-0.441	0.956
	(0.277)	(0.298)	(0.606)	(0.649)
Log(Employees)	-0.325***	0.097	0.346**	-0.116
	(0.079)	(0.082)	(0.146)	(0.156)
Chemical Counts	0.372***	0.267***	1.457***	-2.095***
	(0.032)	(0.030)	(0.052)	(0.059)
Observations	37614	37614	37614	37614
Adjusted R^2	0.251	0.316	0.337	0.370
Parent-year FE	Y	Y	Y	Y
Plant state-year FE	Y	Y	Y	Y
Plant industry-year FE	Y	Y	Y	Y

Table V: Differences-in-Differences analysis based on CEO turnovers

This table shows the Diff-in-Diff estimations at the plant-level based on CEO turnover events. We first select a group of firms with turnover events that shock plant-level measures of hometown favoritism, and identify treated plants, i.e., plants that change from being in CEO hometown states to being out of CEO hometown states (or vice versa). For each turnover, we rank all unaffected plants by the differences in pollution level between these unaffected plants and the treated plants. Lastly, we match each treated plant with up to five control plants with the smallest difference in pollution level relative to the treated plant. In column (1), the sample includes treated plants located in the hometowns of outgoing CEOs and their control plants. In column (2), the sample includes treated plants in the hometowns of incoming CEOs and their control plants. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variables	Log(Total Release)	
	(1)	(2)
D(Hometown to Nonhometown)*D(Post)	0.415**	
	(0.181)	
D(Nonhometown to Hometown)*D(Post)		-0.572**
		(0.264)
D(Post)	0.0503	0.0106
	(0.034)	(0.069)
Log(Employees)	0.0683	0.127**
	(0.089)	(0.061)
Chemical Counts	0.161***	0.223***
	(0.027)	(0.026)
Observations	4617	4684
Adjusted R^2	0.971	0.975
Parent-year FE	Y	Y
Plant state-year FE	Y	Y
Plant industry-year FE	Y	Y
Plant FE	Y	Y

Table VI: The impact of governance on hometown favoritism

This table investigates if the impact of hometown favoritism on local toxic release depends on parent firms' quality of corporate governance. *D(High G-index)* and *D(High E-index)* are indicators for parent firms with above median G-index and E-index, respectively, where a high G- or E-index suggests poor governance. *D(Low Analyst Coverage)* is a dummy variable that equals one if a parent firm has below median number of analyst coverage in a given year and zero otherwise. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Total Release)		
	(1)	(2)	(3)
D(Hometown State)	-0.195*	-0.060	-0.086
	(0.104)	(0.108)	(0.091)
D(Hometown State)*D(High G-index)	-0.259*		
	(0.135)		
D(Hometown State)*D(High E-index)		-0.531***	
		(0.132)	
D(Hometown State)*D(Low Analysts)			-0.275**
			(0.119)
D(HQ State)	0.093	0.183***	0.054
	(0.063)	(0.066)	(0.054)
Log(Employees)	0.106***	0.105***	0.104***
	(0.015)	(0.014)	(0.012)
Chemical Counts	0.350***	0.350***	0.354***
	(0.008)	(0.008)	(0.007)
Observations	30343	29418	41633
Adjusted R^2	0.640	0.639	0.625
Parent-year FE	Y	Y	Y
Plant state-year FE	Y	Y	Y
Plant industry-year FE	Y	Y	Y

Table VII: The effect of the 2003 dividend tax cut on hometown favoritism

This table presents the Diff-in-Diff test that exploit the 2003 Tax Reform Act as a shock to CEOs' private cost of hometown favoritism. *D(Post 2003)* is an indicator for years after 2003. *% CEO Ownership* is the fraction of shares owned by CEO over total shares outstanding, and *% CEO Ownership*^{2} is its squared term. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Total Release)	
	(1)	(2)
D(Hometown State)		
*D(Post 2003)	-0.242**	-0.304***
	(0.099)	(0.110)
D(Post 2003)% CEO Ownership	0.318***	0.639***
	(0.090)	(0.232)
*% CEO Ownership	0.130	0.226**
	(0.080)	(0.091)
D(Hometown State)	0.098	0.088
	(0.081)	(0.084)
D(HQ State)	-0.744***	-0.737***
	(0.176)	(0.176)
Log(Employees)	0.006	0.006
	(0.016)	(0.016)
Chemical Counts	0.239***	0.239***
	(0.010)	(0.010)
D(Hometown State)		
*% CEO Ownership^2		-0.009
		(0.012)
D(Post 2003)% CEO Ownership^2		-0.057**
		(0.024)
Observations	35789	35789
Adjusted R^2	0.905	0.905
Parent-year FE	Y	Y
Plant FE	Y	Y
Plant state-year FE	Y	Y
Plant industry-year FE	Y	Y

Table VIII: Parent level impact of hometown favoritism

This table reports the regression results of parent level toxic release using Equation 5. The dependent variable is the log value of one plus parent total toxic releases. *Frac Hometown Plant* is the fraction of plants located in the CEO's hometown states for a given parent firm. *D(Hometown in HQ)* is an indicator that equals one if a parent firm's headquarter state is also its CEO's hometown state and zero otherwise. Control variables include *Log(Firm Employees)*, *Cash/Total Assets*, *CAPX/PPENT*, *Firm Tangibility*, and *Tobin's Q*. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by industry-year and headquarter state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Total Release)	
	(1)	(2)
Frac Hometown Plant	-1.312***	
	(0.306)	
D(Hometown in HQ)		-0.660***
		(0.118)
Log(Firm Employees)	0.650***	0.638***
	(0.040)	(0.040)
Cash/Total Assets	-1.160	-1.401*
	(0.749)	(0.749)
CAPX/PPENT	-4.513***	-4.547***
	(0.777)	(0.783)
Firm Tangibility	4.125***	4.363***
	(0.507)	(0.496)
Tobin's Q	-0.306***	-0.308***
	(0.086)	(0.088)
Observations	3564	3564
Adjusted R^2	0.455	0.457
Parent industry-year FE	Y	Y
Headquarter state-year FE	Y	Y

Table IX: Hometown favoritism, overall firm CSR, and financial constraints

This table reports the regressions that examine how the impact of hometown favoritism on pollution reduction varies with parent firms' overall CSR performance and financial constraint. *D(Low KLD Score)* is a dummy variable for firm-years with below-median ESG performance, calculated by aggregating the strength and concern counts across six dimensions in the KLD data set: Community, diversity, employee relations, environment, human rights, and product. *D(Low ENV Score)* is a dummy variable for firm-years with below-median environmental performance, calculated as the strength and concern counts for the environmental dimension in the KLD data set. *D(High Text FC)* is an indicator for firm-years with above-median financial constraint measure defined in Bodnaruk et al. (2015). *D(High EDF)* is an indicator for firm-years with above-median expected default probability obtained from Moody's Analytics. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable		Log(Total Release)		
	(1)	(2)	(3)	(4)
D(Hometown State)	-0.041	0.019	-0.149	-0.075
	(0.134)	(0.173)	(0.117)	(0.096)
D(Hometown State)*D(Low CSR Score)	-0.378***			
	(0.145)			
D(Hometown State)*D(Low ENV Score)		-0.374**		
		(0.168)		
D(Hometown State)*D(Text FC)			-0.313**	
			(0.140)	
D(Hometown State)*D(High Default Risk)				-0.328**
				(0.136)
D(Hometown State)*D(Unfavorable Credit Rating)				
D(HQ State)	0.077	0.068	0.132**	0.088
	(0.070)	(0.071)	(0.060)	(0.057)
Log(Employees)	0.075***	0.075***	0.090***	0.116***
	(0.014)	(0.014)	(0.014)	(0.013)
Chemical Counts	0.380***	0.380***	0.353***	0.347***
	(0.008)	(0.008)	(0.007)	(0.007)
Observations	25517	25517	32656	37826
Adjusted R^2	0.666	0.666	0.640	0.618
Parent-year FE	Y	Y	Y	Y
Plant state-year FE	Y	Y	Y	Y
Plant industry-year FE	Y	Y	Y	Y

Appendix A.

Table A1: Variable Definitions

Plant-level variables	
Total Release	The amount of total onsite toxic release in 1,000 pounds
Total Waste	The amount of total generated toxic waste in 1,000 pounds
Log(Total Release)	The natural log of one plus *Total Release*
Log(Total Waste)	The natural log of one plus *Total Waste*
Abatement Counts	The cumulative number of abatement categories adopted at the chemical-level
% Recycled	The percentage of total waste reduced through recycling
% Recovery	The percentage of total waste reduced through energy recovery
% Treatment	The percentage of total waste reduced through treatment
% Release	The percentage of total waste released to the environment
% Waste Management	The percentage of total waste reduced by waste management activities
Employees	The number of employees at the plant-level
Chemical Counts	The count of distinct chemicals used by a plant
D(Hometown State)	An indicator for plants located in its parent CEO's hometown state
D($\leq$ 100 miles)	An indicator for plants located within 100 miles of its parent CEO's hometown county centroid
Firm-level variables	
Firm Total Release	The amount of firm-level total toxic release in 1,000 pounds aggregated across plants
Log(Firm Total Release)	The natural log of one plus the amount of firm-level total toxic release in 1,000 pounds aggregated across plants
[0.5em] Firm Employees	The number of parent employees aggregated across plants
Log(Firm Employees)	The natural log of one plus the number of parent employees aggregated across plants
Frac Hometown Plant	The fraction of plants located in the CEO's hometown states for a given parent firm
D(Hometown in HQ)	An indicator for parent firms with headquarters located in its CEO's hometown state
[0.5em] Cash/Total Assets	The ratio of cash and cash-equavalent securities to total book value of assets
CAPX/PPENT	The ratio of capital expenditure to net property, plants, and equipment
Firm Tangibility	The fraction of PPENT over total assets
Tobin's Q	(Total Asset + Common Shares Outstanding$\times$ Closing Price (Fiscal Year)-Common Equity - Deferred Taxes)/Asset
ROA	Net income over total assets
% CEO Ownership	The percentage of shares owned by CEO over total shares outstanding
G-index	The corporate governance index constructed by Gompers et al. (2003)
E-index	The entrenchment index inBebchuk et al. (2009)
# Analyst Coverage	The number of analysts following a firm
KLD Score	The aggregate strength and concern counts across six dimensions in the KLD data set
ENV Score	The strength and concern counts for the environmental dimension in the KLD data set
Text FC	The text-based financial constraint measure defined in Bodnaruk et al. (2015)
EDF	Expected default frequency obtained from Moody's Analytics
D(High G-index)	An indicator for firms with above-median value of the Governance index
D(High E-index)	An indicator for firms with above-median value of the Entrenchment Index
D(Low Analyst Coverage)	An indicator for firms with below-median value of number of analysts following
D(Low KLD Score)	An indicator for firms with below median KLD score
D(Low ENV Score)	An indicator for firms with below median environmental score
D(High Text FC)	An indicator for firms with above median text-based financial constraint measures in Bodnaruk et al. (2015)
D(High EDF)	An indicator for firms with above median expected default likelihood in Moody's Analytics

Table A2: Distribution of Plants Industry

This table shows the distribution of industries (defined at the 2-digit SIC code) for plants of Compustat firms with CEO hometown information between 1992 and 218. Only industries with top 20 number of plants are shown.

2-digit Code	Industry	# of Establishments
28	Chemicals and Allied Products	960
37	Transportation Equipment	569
34	Fabricated Metal Products	556
20	Food and Kindred Products	543
36	Electronic & Other Electrical Equipment & Components	481
35	Industrial and Commercial Machinery and Computer Equipment	452
33	Primary Metal Industries	413
30	Rubber and Miscellaneous Plastic Products	335
26	Paper and Allied Products	251
49	Electric, Gas and Sanitary Services	232
51	Wholesale Trade - Nondurable Goods	230
24	Lumber and Wood Products, Except Furniture	204
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	187
32	Stone, Clay, Glass, and Concrete Products	181
29	Petroleum Refining and Related Industries	164
25	Furniture and Fixtures	83
22	Textile Mill Products	74
27	Printing, Publishing and Allied Industries	72
39	Miscellaneous Manufacturing Industries	57
10	Metal Mining	27

Table A3: The frequency and category of source reduction activities

This table lists the eight broad categories of source reduction activities. Among chemical-year observations that implement the any of the abatement activities, we also calculate each category's frequency of implementation in the TRI database.

Source Reduction Category	Percent(%)
Good Operating Practices	32.09
Process Modifications	20.17
Spill and Leak Prevention	15.20
Raw Material Modifications	9.98
Inventory Control	7.48
Surface Preparation and Finishing	5.52
Cleaning and Degreasing	4.82
Product Modifications	4.74

Table A4: Baseline results with an inverse hyperbolic sine transformation of the pollution level

This table examines whether the baseline results hold when we take an inverse hyperbolic sine (IHS) transform the measure of total pollution amount. The sample include plant-year observations between 1992 and 2019. The dependent variable is the IHS-transformed plant-level total toxic releases. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	IHS(Total Release)					
	(1)	(2)	(3)	(4)	(5)	(6)
D(Hometown State)	-0.338***	-0.198**	-0.233***			
	(0.077)	(0.080)	(0.080)			
D($\leq$ 100 miles)				-0.443***	-0.237***	-0.332***
				(0.080)	(0.082)	(0.080)
D(HQ State)	-0.033	0.042	0.057	-0.040	0.031	0.053
	(0.056)	(0.056)	(0.057)	(0.055)	(0.054)	(0.055)
Log(Employees)	0.161***	0.155***	0.109***	0.162***	0.155***	0.109***
	(0.015)	(0.015)	(0.013)	(0.015)	(0.015)	(0.013)
Chemical Counts	0.370***	0.365***	0.362***	0.370***	0.365***	0.361***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Observations	41633	41633	41633	41633	41633	41633
Adjusted R^2	0.548	0.552	0.617	0.548	0.552	0.617
Parent-year FE	Y	Y	Y	Y	Y	Y
Plant state-year FE	N	Y	Y	N	Y	Y
Plant Industry-year FE	N	N	Y	N	N	Y

Table A5: Hometown plants and production scale

This table reports results on whether firms produce less in their CEOs' hometown plants. The sample include plant-year observations between 1992 and 2019. The dependent variable is the the plant-level employment in columns (1)-(2), sales in columns (3)-(4), and sales over employees in columns (5)-(6). The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Employment)		Log(Sales)		Sales/Employees	
	(1)	(2)	(3)	(4)	(5)	(6)
D(Hometown State)	0.101***		0.087**		0.002	
	(0.036)		(0.034)		(0.002)	
D($\leq$ 100 miles)		0.138***		0.112***		-0.002
		(0.036)		(0.034)		(0.002)
D(HQ State)	0.155***	0.158***	0.152***	0.156***	-0.006***	-0.005***
	(0.027)	(0.027)	(0.024)	(0.024)	(0.001)	(0.001)
Observations	41633	41633	41560	41560	41560	41560
Adjusted R^2	0.395	0.395	0.401	0.401	0.661	0.661
Parent-year FE	Y	Y	Y	Y	Y	Y
Plant state-year FE	Y	Y	Y	Y	Y	Y
Plant industry-year FE	Y	Y	Y	Y	Y	Y

Table A6: Dynamic impact of CEO turnover on plant-level pollution

This table shows the dynamic effect of CEO turnover on plant-level pollution estimated from the following equation:

$$log(Total\ Release_{p,s,i,j,t}) = \alpha + \beta_1 D(Treated\ Plant) * D(Turnover_{i,h}) + \beta_2 log(Employees) + \beta_3 Chemicals + \alpha_p + \alpha_{i,t} + \alpha_{s,t} + \alpha_{j,t} + \epsilon_{p,s,i,j,t}$$

where h = -2, -1, 0, 1, or 2. $D(Turnover_{i,h})$ indicates h years after CEO turnovers. If h is negative, then a CEO turnover will be initiated $-h$ years later. Years after year 2 are grouped into $D(Turnover_{i,2})$. Years before year -2 are treated as benchmark year. The regression is based on matched samples that include plants affected by parent firm CEO turnovers (plants located in the hometowns of either the outgoing CEOs or incoming CEOs). For each treated plant, we match up to five control plants with the closest total pollution level within the same parent firm. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Total Release)	
	(1)	(2)
D(Hometown to Nonhometown)*D(Turnover_-2)	0.0207	0.381
	(0.235)	(0.369)
D(Hometown to Nonhometown)*D(Turnover_-1)	0.212	-0.270
	(0.253)	(0.300)
D(Hometown to Nonhometown)*D(Turnover_0)	0.544**	0.0163
	(0.273)	(0.325)
D(Hometown to Nonhometown)*D(Turnover_1)	0.627***	-0.528
	(0.236)	(0.333)
D(Hometown to Nonhometown)*D(Turnover_2)	0.675***	-0.972***
	(0.247)	(0.375)
Log(Employees)	0.0749	0.131**
	(0.088)	(0.060)
Chemical Counts	0.160***	0.222***
	(0.027)	(0.026)
Observations	4617	4684
Adjusted R^2	0.971	0.975
Parent-year FE	Y	Y
Plant state-year FE	Y	Y
Plant industry-year FE	Y	Y
Plant FE	Y	Y

Table A7: Cross-sectional analyses of CEO turnovers based on the importance of hometown states

This table contains the results on if the impact of CEO turnovers on plant-level pollution is stronger for plants in states that are important to firms' business operations. The regression is based on matched samples that include plants affected by parent firm CEO turnovers (plants located in the hometowns of either the outgoing CEOs or incoming CEOs). For each treated plant, we match up to five control plants with the closest total pollution level within the same parent firm. *D(High EMP Plant)* and *D(High Sales Plant)* are indicators for plant with more than 10% of employees and sales within the parent firm during the three year before CEO turnovers. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by parent-year and plant state-year. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Dependent variable	Log(Total Release)			
	(1)	(2)	(3)	(4)
	Log(Total Release)	Log(Total Release)	Log(Total Release)	Log(Total Release)
D(Hometown to Nonhometown)*D(Post)	0.402*		0.383*	
	(0.233)		(0.221)	
D(Nonhometown to Hometown)*D(Post)		-0.631**		-0.484*
		(0.294)		(0.283)
D(Hometown to Nonhometown)*D(High EMP Plant)*D(Post)	0.212			
	(0.889)			
D(Nonhometown to Hometown)*D(High EMP Plant)*D(Post)		0.152		
		(0.332)		
D(Hometown to Nonhometown)*D(High Sales Plant)*D(Post)			0.226	
			(0.789)	
D(Nonhometown to Hometown)*D(High Sales Plant)*D(Post)				-0.283
				(0.333)
D(Hometown to Nonhometown)*D(High EMP Plant)	0.106			
	(1.257)			
D(Nonhometown to Hometown)*D(High EMP Plant)		-0.636		
		(0.814)		
D(Hometown to Nonhometown)*D(High Sales Plant)			0.857	
			(1.971)	
D(Nonhometown to Hometown)*D(High Sales Plant)				-0.546
				(0.459)
D(High EMP Plant)*D(Post)	-0.178	-0.147		
	(0.164)	(0.185)		
D(High Sales Plant)*D(Post)			-0.190	-0.180
			(0.126)	(0.171)
D(High EMP Plant)	0.791**	0.972**		
	(0.337)	(0.424)		
D(High Sales Plant)			0.454**	0.0574
			(0.192)	(0.241)
D(Post)	0.0702*	0.0362	0.0691*	0.0436
	(0.038)	(0.080)	(0.038)	(0.083)
Log(Employees)	0.0485	0.0445	0.0636	0.143**
	(0.092)	(0.068)	(0.090)	(0.063)
Chemical Counts	0.161***	0.221***	0.163***	0.222***
	(0.027)	(0.026)	(0.027)	(0.027)
Observations	4617	4684	4617	4684
Adjusted R^2	0.971	0.975	0.971	0.975
Parent-year FE	Y	Y	Y	Y
Plant state-year FE	Y	Y	Y	Y
Plant industry-year FE	Y	Y	Y	Y
Plant FE	Y	Y	Y	Y

Table A8: The impact of CEO stock ownership on corporate dividend payouts

This table reports the regressions that estimate the impact of CEO stock ownership on dividend payouts around the 2003 tax reform. Analyses are conducted for the full Compustat sample in panel (a) and the TRI linked sample in panel (b) for the period between 2000 and 2005. *D(Post 2003)* indicates years after 2002. *Initiation* is an indicator for firms that pay dividend in year *t* but not in year *t-1* (*t*). *Increase* is an indicator for firms that pay 20% more dividend in year *t* than in year (*t-1*). We also include two dividend payout ratios, calculated using income before extraordinary items (IB) and total assets as the denominators. Firm controls include *Log(Firm Employees)*, *Cash/Total Assets*, *CAPX/PPENT*, *Firm Tangibility*, *Tobin's Q*, and *ROA*. The fixed effects included in the regressions are denoted at the bottom of the table. Standard errors are clustered by firm. ***, **, and * indicate significance level and the 1%, 5%, and 10%, respectively.

Panel (a): Compustat Sample

Dependent variable	Initiation (%)	Increase (%)	Dividend/IB (%)	Dividend/Assets (%)
	(1)	(2)	(3)	(4)
D(Post 2003)* % CEO Ownership	0.307***	1.192***	0.199	0.042***
	(0.117)	(0.231)	(0.128)	(0.013)
D(Post 2003)	2.037***	5.022***	0.769***	0.152***
	(0.166)	(0.253)	(0.208)	(0.042)
% CEO Ownership	-0.181	-0.847***	-0.251*	-0.041***
	(0.118)	(0.210)	(0.135)	(0.013)
Observations	45579	45579	45570	44863
Adjusted R^2	0.046	0.239	0.599	0.414
Firm controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Panel (b): TRI Sample

Dependent variable	Initiation (%)	Increase (%)	Dividend/IB (%)	Dividend/Assets (%)
	(1)	(2)	(3)	(4)
D(Post 2003)*% CEO Ownership	0.686*	0.452	0.938*	0.062**
	(0.368)	(0.679)	(0.562)	(0.027)
D(Post 2003)	1.040**	7.059***	-1.931*	-0.068
	(0.509)	(1.344)	(1.127)	(0.061)
% CEO Ownership	-0.252	0.731	-0.136	-0.041
	(0.198)	(0.588)	(0.530)	(0.034)
Observations	2672	2672	2672	2672
Adjusted R^2	0.015	0.194	0.552	0.695
Firm controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y