Synergy or Redeployment?

Examining Environmental Spillovers in Multi-Unit Firms

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Abstract

We study how environmental regulation affecting one unit impacts sibling units belonging to the same firm. A resource reallocation perspective suggests shifting pollution activities from regulatory-constrained units to unconstrained sibling units. In contrast, the forced adoption of pro-environmental practices in the regulated units may have positive spillovers on sibling units if cleaner operating practices are adopted all across the firm. Examining this theoretical tension, we find evidence of both logics. More importantly, we demonstrate that multi-unit firms face a trade-off between pollution reallocation and knowledge sharing about pro-environmental practices. Consistent with this trade-off, we report that firms that redeploy pollution are less likely to share best environmental practices. Overall, our findings indicate that on average multi-unit firms have weaker environmental performance having 44% higher excess emissions than single-unit firms, especially those that prioritize redeploying polluting activities within the firm over sharing pro-environmental practices.

1. Introduction

Multi-unit firms facing environmental pressures in a subset of their establishments have two options unavailable to single-unit firms. They can leverage their relative size advantages to invest in developing better environmental practices that can be spread across all units more efficiently. Alternatively, they can shift pollution activities from affected to unaffected units. The former option suggests that multi-unit firms enjoy better environmental performance overall, while the latter option would lead to the opposite conclusion. How multi-unit firms choose to react is crucial in determining how environmental pressures in one unit are transferred to other units through within-firm spillovers.

Similarly, the Strategic Management literature has identified two main logics for resource-based diversification strategies that grant multi-unit firms a corporate advantage: resource redeployment and resource sharing. The resource-sharing logic refers to intra-temporal economies of scope driven by firms simultaneously sharing the same indivisible resource (i.e., knowledge) across distinct product lines (Teece, 1980; Rumelt, 1982; Markides & Williamson, 1994; Helfat & Eisenhardt, 2004; Zhou, 2011). In contrast, the resource-redeployment logic refers to inter-temporal economies of scope derived from the flexibility of transferring resources from one business unit or product line to another to maximize resource productivity (Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010; Wu 2013; Sakhartov & Folta, 2014; Dickler & Folta, 2020; Giarratana & Santaló, 2020, Dickler, Folta, Giarratana, & Santaló, 2022). This paper investigates the implications of these two different logics by examining the distinct environmental performance of business units belonging to the same firm. Ultimately, our analysis sheds light on how multi-unit firms may experience environmental performance advantages or disadvantages relative to single-unit firms.

The U.S. Clean Air Act (CAA) provides an ideal context to analyze how environmental regulation affecting one unit of a firm impacts sibling units within the same company because it varies across both time and geographical areas. It imposes stricter regulations on air quality in certain geographical areas, creating pressure for businesses located in those areas to improve their environmental performance. This makes it costlier for these businesses to emit pollutants compared to units located in unregulated areas.

While a resource redeployment perspective would suggest shifting costly pollution activities from regulated units to others, the adoption of cleaner operating technologies in the regulated units may have positive spillovers on other units if such knowledge is shared within the multi-unit firm. We exploit the exogenous variation coming from the CAA and the granularity of the Toxic Release Inventory (TRI) data from the U.S. Environmental Protection Agency (EPA) to test the richer implications of both sources of corporate advantage.

Previous literature has pointed toward a trade-off between organizing for resource redeployment (i.e., flexibility), versus organizing for simultaneously sharing resources (i.e., synergies), and the consequences for firm financial performance (Helfat & Eisenhardt, 2004; Sakhartov & Folta, 2014; Morandi Stagni, Giarratana & Santalo, 2020). This stream of research has identified a tension such that when firms organize for flexibility and thus redeployment of non-scale free resources, they have difficulties benefitting from synergies coming from sharing scale-free resources. This study investigates this theoretical tension in the context of environmental performance measured by toxic emissions of all business units belonging to the same firm. We find empirical evidence consistent with this trade-off: Firms that redeploy pollution from some units to others are those that tend to have less diffusion of pro-environmental practices and are less environmentally efficient. Specifically, whereas on average units with regulated siblings are 41%-45% more likely to adopt so-called source reduction activities (SRAs) if regulated siblings do so, for those units belonging to firms heavily relying on pollution redeployment within the firm the increased propensity to adopt SRAs drops to 8% at best and ranges 2% only. Consistently, while unregulated units increase their environmental efficiency in the presence of regulated siblings, for units owned by firms that heavily redeploy polluting activities, environmental efficiency is reduced. Finally, mimicking the established approach to determine excess value in diversified firms (e.g., Berger & Ofek, 1995), our empirical results indicate that multi-unit firms on average environmentally underperform their single-unit counterparts with 44.03% higher excess emissions. This effect is particularly pronounced for multi-unit firms that emphasize redeploying polluting activities within the firm over sharing pro-environmental practices.

Overall, our study makes three key contributions to the literature. First, we are contributing to the Corporate Strategy literature advancing our understanding of how a firm's multiple units interact within a single firm to create corporate advantage (Penrose, 1959; Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010; Sakhartov & Folta, 2014). In particular our findings emphasize that multi-unit firms face a trade-off between two drivers of corporate advantage, i.e., benefits from synergies and benefits from the flexibility to redeploy (Sakhartov & Folta, 2014; Morandi Stagni et al., 2020). This trade-off implies that firms have to choose between one of the two diversification logics instead of pursuing both of them simultaneously.

Second, we contribute to the work examining the determinants of firm environmental performance (e.g., Bansal, 2005; Berrone & Gomez-Mejia, 2009; Doshi, Dowell, and Toffel, 2013; Flammer, 2013, 2015) by theorizing and empirically demonstrating how a unit's affiliation within the corporate firm may impact its environmental performance. Our results highlight that units in multi-unit firms respond differently to institutional pressures than standalone units, and institutional pressures are especially effective for firms with the ability to share resources between the different units they operate. In contrast, multi-unit firms that emphasize redeployment strategies can counteract institutional pressures to improve environmental performance.

Third, we add to the literature on how firm environmental capabilities shape corporate strategies, including diversifying market entries (Diestre & Rajagopalan, 2011) and acquisitions (Berchicci, Dowell, & King, 2012; Berchicci et al., 2017). Our study emphasizes the importance of corporate strategy to understand the generation of firm environmental capabilities in the first place and how this generation is related to inter- and intra-temporal scope economies as well as characteristics of the corporate structure associated with each type of corporate advantage.

Finally, our study also contributes to the literature on general regulatory spillovers, particularly the literature that has investigated environmental spillovers and the so-called California effect (Vogel, 1995).

We demonstrate how environmental regulation in one jurisdiction can have spillovers in other unregulated locations. Our study is related to papers by Gibson (2019) and Rijal and Khanna (2020) that report how the regulation of a plant increases emissions at unregulated plants within the same firm. However, our study examines the trade-off between benefitting from synergies to reduce pollution across units within the same firm and benefiting from the flexibility to redeploy pollution to where it is less costly, not considered in previous work.

2. Theory and Hypotheses

2.1 Background: The Clean Air Act

The paper utilizes the regulatory framework of the U.S. Clean Air Act (CAA) to examine the environmental regulations in the United States. Under the CAA, it is mandatory to maintain minimum air quality levels in any given geographical area in the U.S. The Environmental Protection Agency (EPA) monitors the concentration of six air pollutants, including carbon monoxide, ground-level ozone, lead, nitrogen oxides, particulate matter, and sulfur dioxide, to ensure air quality standards are met. The EPA classifies separate nonattainment or attainment designations for each of the criteria pollutants in every U.S. county annually, based on whether the ambient concentration exceeds its regulated level or not. Counties that exceed the federal standard for a relevant pollutant are designated as “not in attainment”. It is essential to note that the CAA categorizes U.S. counties into pollutant-specific nonattainment and attainment areas, meaning that different counties can have different attainment levels for different pollutants. For instance, Orange County (CA) was in nonattainment for ground-level ozone and particulate matter in 2021 but maintained the air quality standards for sulfur dioxide, whereas Peoria County (IL) surpassed ambient concentration for sulfur dioxide but was in attainment for ground-level ozone and particulate matter. As a result, emitters of a pollutant in counties that are "not in attainment" for that focal pollutant are subject to stricter restrictions than emitters in "attainment" counties. Both EPA and state authorities enforce such restrictions. The enforcement instruments include buying pollution offsets from existing firms, cap-and-trade and tradable credit programs, and withdrawal of highway funds for areas that fail to develop adequate plans to attain and maintain air quality standards. Importantly, Section 113 of the CAA authorizes substantial fines for firms violating emission-related requirements, which in the case of Toyota Motor amounted to $180 million in 2021 (Tabuchi, 2021).

2.2 General Firm Reactions to Environmental Pressures

Our research pertains to the literature examining how firms react to pressures to improve their environmental performance, which can originate from various sources, such as legislation, stakeholders, economic opportunities, and ethical considerations (e.g., Bansal & Roth, 2000; Bansal, 2005). Scholars investigating firms' responses to institutional pressures imposed by regulators have widely recognized the importance of legislation in promoting improved environmental performance (e.g., Henriques & Sadorsky, 1996; Reid & Toffel, 2009; Darnall, Henriques, & Sadorsky, 2010; Kock, Santalo, & Diestre, 2012; Weigelt & Shittu, 2016). Although firms have discretion when operating within institutional constraints, sanctions and loss of legitimacy for non-compliance with these regulations threaten the firm's resources (DiMaggio & Powell, 1983; Oliver, 1991; Scott, 1987). It is well-established that specific mandatory regulations have led to a reduction in firms' environmental impacts (see Aragòn-Correa, Marcus, & Vogel (2020) for a recent review). The debate, however, centers on the impact of such regulations on firms' access to resources, their operating costs, and their flexibility, resulting in two prevailing perspectives on how firms subject to environmental regulation may react to the pressures exerted.

First, firms might invest more in developing new pollution-reducing technologies when subject to stringent policies (e.g., King & Lenox, 2001; Porter & van der Linde, 1995). Such investments might enhance the competitiveness of firms if they lower overall production costs, as cleaner technologies lead to higher productivity, input savings, improved legitimacy, and innovations, which over time offset regulatory costs. Many studies support the view that environmental regulations can indeed encourage the development of pollution-reducing technologies (e.g., Jaffe & Plamer, 1997; Darnall et al., 2010; Berrone, Fosfuri, Gelabert, & Gomez-Mejia, 2013; Aghion, Dechezleprêtre, Hemous, Martin, & Van Reenen, 2016).

Second, instead of substantive changes to environmental strategies reducing their pollution, international firms, in particular, might respond to mandatory environmental regulations by moving their pollution to countries that have weak environmental standards and enforcement (e.g., Birdsall & Wheeler, 1992; Eskeland & Harrison, 1997, Taylor, 2005). For instance, firms may modify their supply chains, shifting their production of cleaner products to comply with U.S. standards while importing more polluting products from countries with less stringent environmental regulations to bypass U.S. pollution standards (Rugman & Verbeke, 1998; Li & Zhou, 2017). Despite these clear theoretical predictions, the empirical evidence on the so-called pollution haven hypothesis is mixed. While some studies have found the expected negative relationship between environmental stringency and foreign direct investment (e.g., Li & Zhou, 2017, Barrett, 2017; Berry, Kaul, & Lee, 2021), others have reported no relationship (e.g., Eskeland & Harrison, 2003; Millimet & List, 2004), and still others have demonstrated a positive link (e.g., Friedman, Gerlowski, & Silberman, 1992; Christmann, 2004).

2.3 Multi-unit Firms' Responses to Environmental Pressures

This section details why compared to their single-unit counterparts, multi-unit firms have more alternatives when reacting to the environmental pressures that go beyond the ones described above. The Strategic Management literature submits that corporate advantage obtains from at least two major sources. First, multi-business firms can benefit from simultaneously sharing resources among their business, i.e., "intra-temporal" economies of scope, and second, they can benefit from the flexibility to redeploy resources from one business to another, i.e., "inter-temporal" economies of scope (Penrose, 1959; Teece, 1980; Rumelt, 1982; Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010; Sakhartov & Folta, 2014).

Drawing on these different sources of scope economies is relevant when studying multi-unit firms' reactions to environmental pressures, as it highlights the options a firm could exercise when one of its units operates in an area "not in attainment". First, they might exploit their additional flexibility coming from the potential to internally reallocate resources across units in their portfolio (Folta, Helfat, & Karim, 2016). Some empirical work establishes that multi-unit firms can exploit opportunities across their portfolio, whether it be by redeploying labor (e.g., Tate & Yang, 2015; Belenzon & Tsolmon, 2016; Santamaria, 2022), capital (e.g., Lovallo, Brown, Teece, & Bardolet, 2020; Morandi Stagni et al., 2020), plants (e.g., Sohl & Folta, 2021), or retail shelf-space (e.g., Giarratana & Santaló, 2020). Such adaptations seem to help in retrenching or expanding revenues in response to demand changes (e.g., Dickler & Folta, 2020; Miller & Yang, 2016) and allow multi-unit firms to benefit more from uncertainty than their single-unit counterparts (Dickler et al., 2022).

In a similar fashion, multi-unit firms can exploit opportunities within their portfolio by redeploying resources and production from units with stricter regulatory requirements (i.e., not in attainment) towards unrestricted units (i.e., in attainment). This is consistent with extant resource redeployment literature submitting that non-scale free resources subject to opportunity costs are moved within the firm to maximize their return (Levinthal & Wu, 2010, Wu, 2013) and the empirical evidence described directly above. Environmental regulations faced by a unit increase production costs for products requiring the use of the regulated pollutant. Therefore, production resources can be moved to other unrestricted geographical locations within the firm that have lower production costs. In fact, prior work in environmental economics has already established that firms try to evade stricter environmental regulations by redeploying pollution to less restricted plants (e.g., Gibson, 2019; Rijal & Khanna, 2020). Thus, in line with the above arguments and prior research, we hypothesize:

H1: Firms with units in restricted areas will shift pollution-related activities towards units operating in unrestricted areas, i.e., unrestricted units with restricted sibling units will pollute more.

As noted earlier, prior research has argued that scale-free resources often form the basis for resource sharing because they do not have capacity constraints and their value does not diminish when applied to more than one use (Levinthal & Wu, 2010). A unit operating in a stricter regulatory environment may acquire specific knowledge about how to operate in a more environmentally friendly manner and make several adjustments to reduce pollution. For example, units can adopt pollution-reducing practices including changes in production, operation, raw material use, or technological modifications (King & Lenox, 2002; Berchicci et al., 2012; Dutt & King, 2014; Berchicci, Dutt, & Mitchell, 2019). Whereas all these practices reduce the waste produced, they are costly to develop. If a unit is part of a multi-unit firm, the costs and benefits of pollution-reducing investments can potentially be spread across all units of the firm. Multi-unit firms, therefore, have a stronger economic incentive to invest in obtaining knowledge about pollution reduction than focused firms (e.g., McWilliams & Siegel, 2001; Kang, 2013).

In addition, such pro-environmental investments have been shown to elicit favorable reactions from key stakeholders such as stronger demand from customers, greater motivation and loyalty from employees, more positive assessments by investors, and a more favorable reputation among regulators and other stakeholders that can be leveraged across several different products and markets (e.g., Kang, 2013; Seo, Luo, & Kaul, 2021). Together, the knowledge obtained, and better environmental practices discovered may have positive spillovers in other businesses inside the same firm (Miller, Fern, & Cardinal, 2007; Berchicci et al., 2017). As technological knowledge is a scale free resource that can be used simultaneously by all units within the same firm at no extra cost (Levinthal and Wu, 2010), the created synergies will reduce pollution. In line with the rationale around benefits of resource sharing in multi-unit firms, we further hypothesize:

H2: Firms with units in restricted areas will share the knowledge gained about pollution-reducing practices with sibling units, i.e., unrestricted units with restricted sibling units adopting pollution-reducing practices will also adopt pollution-reducing practices.

2.4 Trade-offs in Multi-unit Firms' Responses to Environmental Pressures

Theoretical arguments in H1 and H2 highlight two opposing forces that determine whether stricter environmental regulations in one part of a company will have a positive or negative impact on pollution in other, unaffected areas of the organization. Moreover, existing work in Corporate Strategy has pointed out a trade-off between organizing for resource sharing versus organizing for resource redeployment (Helfat & Eisenhardt, 2004; Sakhartov & Folta, 2014; Morandi Stagni et al., 2020). This stream of research has identified a tension, such that returns from redeploying non-scale free resources compromise benefits from contemporaneously sharing scale-free resources (Levinthal & Wu, 2010, Sakhartov & Folta, 2014). There are several sources of tension in this trade-off.

Centralized coordination versus autonomy: In a multi-unit firm that shares a scale-free resource across distinct units, centralized coordination is necessary (Hill & Hoskisson, 1987; Hitt & Hoskisson, 1988; Zhou, 2011). For instance, if a unit acquires knowledge or a capability that could be successfully applied in another unit, a connection between units is necessary to encourage and facilitate knowledge transfer. Previous studies have systematically documented that the optimal organization for synergies requires active coordination and operating control mechanisms (Hill & Hoskisson, 1987; Markides & Williamson, 1996; Zhou, 2011). Linkages across units are associated with increases in the horizontal information managed by corporate headquarters, and therefore, managing synergies requires nonzero coordination costs (Hoskisson & Hitt, 1988; Rawley, 2010; Zhou, 2011). Typically, this results in larger corporate headquarters, including cross-business teams such as product management committees and liaison personnel (Collis, Young & Goold, 2007; Gupta & Govindarajan, 1986).

In contrast, the corporate advantage stemming from the flexibility to redeploy resources does not require any centralized coordination, except for a centralized authority that can transfer resources from one unit to another. After the resources are redeployed, the units managing them can enjoy full autonomy to independently maximize results without coordination or dependence on central authority choices (Helfat & Eisenhardt, 2004). Rather than cooperation and coordination between firm units, strategies that prioritize resource redeployment require organizational arrangements that emphasize competition between units (Hill, Hitt & Hoskisson, 1992).

Unit-level operating controls versus financial controls: The degree of organizational centralization also has implications for the unit's mechanisms of control. Centralized coordination means that the focal unit cannot be fully accountable for its results, which restricts to what extent unit managers' compensation can be linked to individual units' financial results. When firms are organized for synergies, executive compensation at the unit level has to rely on operating controls and subjective modes of evaluating performance (Govindarajan and Fisher 1990; Hill et al., 1992). Performance evaluation of units and their managers in decentralized firms oriented towards the redeployment of resources is fundamentally different. For example, Helfat and Eisenhardt (2004) describe how top executives at Omni Corporation, a Fortune 100 high-technology company, regularly redeployed resources by using a routine in which corporate headquarters identified businesses that had declining growth in margins and sales as well as resources that could be moved to entirely new related businesses with more attractive prospects. Thus, compared to when firms are organized for redeploymen, when attempting to optimize synergetic-driven performance, corporate headquarters needs to assess unit performance on a larger number of criteria: some subjective criteria like the degree of cooperation with other units along with objective measures like capacity utilization or labor productivity (Hill et al., 1992).

Overall, the optimal organizational structure for resource sharing is significantly different from the one required for emphasizing resource redeployment. As a result, multi-unit firms must decide which structure to adopt. This decision implies the existence of a trade-off. Multi-unit firms that excel in resource redeployment may fail to exploit synergy opportunities, while those that have perfected synergetic benefits may lag in exploiting resource redeployment opportunities. In this context, we hypothesize that:

H3a: Firms with units shifting pollution-related activities towards units operating in unrestricted areas will adopt fewer pollution-reducing practices in their unrestricted units.

H3b: Firms with units shifting pollution-related activities towards units operating in unrestricted areas will become less environmentally efficient in their unrestricted units.

3. Empirical Analysis

3.1 Sample

The ideal setting to test our hypothesis would be one in which (1) *redeployment* of pollution activities from regulated to unregulated units and (2) *knowledge sharing* through the adoption of pollution-reducing activities can be observed, which will allow us to (3) *estimate a trade-off* between the two corporate strategies. The U.S. manufacturing industry provides such a setting with access to detailed data on plant-level pollution and respective pollution-reducing activities, the corporate structure in which the focal plant operates, and an exogenous shock that increases the cost of polluting for some plants in the corporate portfolio but not for others.[1]

To test our predictions, we have collected data from various sources. First, we gathered data from the U.S. Government Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database, which has been providing annual plant-chemical-level information on the generation, management, and release of chemicals since 1987. Reporting is mandated by law and chemical generation and release information is not restricted to firms choosing to respond to voluntary questionnaires. Thus, the TRI is based on the population of establishments in the U.S. with 10 or more full-time employees that produce, process or use any listed chemical during a calendar year. Accordingly, firms self-report detailed information on the generation, management, and release of over 600 toxic chemicals. Although there is the potential for misreporting, EPA inspections mitigate this issue, and firms intentionally misreporting emissions may face criminal or civil penalties (Gibson, 2019; Xu & Kim, 2022). Additionally, de Marchi and Hamilton (2006) found that 95% of facilities reported information accurately, further strengthening the reliability of these data. The TRI data provides information not only on chemical releases through the ground, air, and water but also on related chemical-level "source reduction" activities (SRAs). Such practices reduce hazardous substances released into the environment before recycling, treatment, or disposal through cost-effective changes in production, operation, and raw materials use in accordance with the 1990 Pollution Prevention Act (Berchicci et al., 2019). Examples of SRAs include equipment or technology modifications, process or procedure modifications, reformulation or redesign of products,

[1] Our empirical approach complements work drawing on COMPUSTAT Firm and Business Segment databases used extensively in research on diversified firms and resource redeployment in particular (e.g., Dickler & Folta, 2020, Morandi Stagni et al., 2020; Dickler et al., 2022). Note that the TRI database provides more granular data that is on plant level, meaning that firms can operate multiple plants in the same industry segment (i.e., four-digit SIC code), which we control for in our empirical analyses.

substitution of raw materials, and improvements in housekeeping, maintenance, training, or inventory control (Berchicci et al., 2019).

We leverage a quasi-natural experiment that closely aligns with the ideal setting described above to test our hypotheses. Specifically, we rely on a key regulatory component of the Clean Air Act (CAA) that designates counties as attainment or nonattainment with respect to the National Ambient Air Quality Standards (NAAQS) on a yearly basis. The EPA monitors air quality and regulates different pollutants in specific counties based on ambient concentrations set out in the NAAQS. Counties with pollution levels above the NAAQS threshold for a certain chemical are considered regulated (i.e., nonattainment), while those with pollution levels below the threshold are considered unregulated (i.e., attainment). Firms operating polluting plants in nonattainment counties face more stringent regulations and emission restrictions than those in attainment counties. For example, new or modified sources of emissions in nonattainment areas must be offset by reductions in emissions from existing sources, and firms in nonattainment counties have to engage in cap-and-trade and tradable credit programs while being subject to substantial fines for violating stricter emission-related requirements. Within any non-attainment county, only polluting plants are regulated, and only if they emit the specific pollutant for which the county is in violation. The EPA Green Book provides data on the implementation of NAAQS and county attainment status, which we summarize in Table 1.

[Insert Table 1 about here.]

Finally, we combine the dataset on plants' generation, management, and release of chemicals and the attainment status of their location with the National Establishment Time Series (NETS) database using the identifiers provided by Dun and Bradstreet. This allows us to clearly identify the ultimate owner of all plants and the respective sibling plants that comprise a firm. Moreover, additional plant-level data such as plant-level sales and employees enable us to control for plant characteristics that may influence the emission of chemicals. In summary, this provides us with nearly complete coverage of manufacturing establishments' economic activity across the U.S. Following previous studies, we excluded data from 1987 to 1990 due to a change in the TRI reporting guidelines in 1991 (King & Lenox 2001, 2002; King et al. 2005; Doshi et al. 2013) and rely on data from 1991 to 2019.

3.2 Measures

3.2.1 Independent variables

In this study, the main predictor variable is "*regulated sibling*", which indicates the presence of a sibling plant within a company's portfolio that (a) operates in a county with pollution levels above the NAAQS threshold for a certain chemical and (b) emits that regulated chemical in a given year. Essentially, this variable is dependent on whether emissions of specific chemicals were restricted in a county or not. However, determining whether a chemical is impacted by the CAA can be difficult because most toxic chemicals do not clearly contribute to the six criteria pollutants regulated by the CAA (i.e., carbon monoxide, ground-level ozone, lead, nitrogen oxides, particulate matter, and sulfur dioxide). Because of the absence of such definitive classifications, Online Appendix A1 details the statistical approach we rely on to determine which chemical emissions are impacted by the CAA, i.e., significantly reduced in the year after the restriction was in place, and which are not. Based on this mapping "*regulated sibling*", is set to 1 if the focal plant has at least one sibling plant operating in a non-attainment county and emitting the focal regulated chemical. The average unregulated plant in the sample has a 70.7% likelihood of having a regulated sibling, and an average firm manages 6.19 regulated plants and 6.47 distinct regulated chemicals, as shown in Table 2.

When testing our second hypothesis, an alternative predictor variable is used. In particular, "*regulated sibling adopted SRA*" takes on a value of 1 if, in addition to being regulated, at least one sibling has further adopted a SRA and zero otherwise. As shown in Table 2, the probability that a regulated sibling has adopted a SRA is 31.7% on average.

[Insert Table 2 about here.]

3.2.2 Dependent variables

The main dependent variable is the plant's industry- and location-*adjusted emissions* of each focal chemical. We focus on emissions through air since the CAA only regulates air emissions.[2] To calculate this variable, we take the log of a plant's emissions in pounds for each chemical, as done in prior research (e.g., Gibson, 2019; Xu & Kim, 2022). We adjust a focal plant's emissions by comparing them to emissions reported by single-plant firms operating in the same two-digit SIC industry and U.S. state for the same chemical, such that for chemical *c* at time *t* adjusted emissions for plant *i* are computed using equation (1):

$$Adjusted\ emissions_{cit} = \ln(emissions_{cit}/sales_{cit}) - \ln\left(\sum_{j=1}^{n} \frac{emission_{cjt}^{sp}}{sales_{cjt}^{sp}}/n\right) \tag{1}$$

Where *n* is the number of single-plant firms operating in the same two-digit SIC industry and state as plant *i* at time *t*. Moreover $emission_{cjt}^{sp}$ and $sales_{cjt}^{sp}$ represent emissions and sales of single-plant firm *j* that operate in same industry and state as plant *i* at time *t*. Note that whereas redeployment of polluting activities towards a focal plant increases its total air emissions (Greenstone, 2002, 2003; Bento et al., 2015; Gibson, 2019; Xu & Kim, 2022), adjusting for general emission trends in the industry and in the local area helps to rule out confounding effects that could either mask or overstate the true effects of within-firm pollution redeployment.

The second hypothesis suggests that knowledge on environmentally-friendly production practices is shared among plants belonging to the same firm. Therefore, we predict that unregulated plants are more likely to adopt SRAs to enhance environmental efficiency through cost-effective changes in production, operation, or raw materials use, if one of their sibling plants is subject to stricter environmental regulations through the CAA and has already adopted SRAs. The *probability of SRA adoption*, specific to a focal

[2] One might be concerned about substitution effects across different release media impacting our analyses. We address this concern in section 4 “Robustness checks” by rerunning analyses using *total releases* through air, land, and water instead of *air emissions* whenever appropriate and results remain qualitatively the same (see Online Appendix A2).

chemical, is 11.5% for an average plant in our sample. It is worth noting that unlike toxic emissions and chemical waste management, the reporting of SRAs is voluntary.

We investigate Hypothesis 3 by introducing an additional measure that captures the potential effects of knowledge-sharing activities on a plant's ability to manage a focal chemical in a more environmentally friendly way. Following King and Lenox (2000, 2001), we use a production function to estimate a plant's environmental efficiency, which reflects its capacity to control and reduce pollution compared to similar facilities. Specifically, we estimate the relationship between plant size (sales), industry (four-digit SIC code), and chemical emissions within each year using standard ordinary least squares regression. Unlike King and Lenox (2000, 2001), who aggregate TRI data to the plant or firm level, we conduct our analysis at the chemical level, allowing us to evaluate changes in emissions resulting from knowledge-sharing and implemented solutions for each chemical at each plant. This approach, similar to Dutt and King (2014) and Berchicci et al. (2017), offers a more precise understanding of changes in environmental efficiency for each chemical over time and does not require assigning weights to chemicals of different types, such as using "human toxicity potential factor" (HTP) (Hertwich, Mateles, Pease, & McKone, 2001) or "reportable quantities" (RQ) (King and Lenox, 2000) when aggregating chemical emissions. We calculate the annual plant-chemical-level environmental performance as the standardized residual, or deviation, between observed and predicted emissions based on the following production function estimated by year, chemical, and industry:

$$l\,n(Emissions_{cit}) = \alpha_{cj} + \beta_{1cj}\ln(sales_{it}) + \beta_{2cj}\ln(sales_{it})^2 + \varepsilon_{cit} \qquad (2)$$

Where $l\,n(Emissions_{cit})$ is predicted air emissions of chemical *c* in plant *i*, in year *t*, *sales* reflect plant-level sales, and α_{cj}, β_{1cj}, and β_{2cj} are the estimated coefficients for chemical *c* and sector j. Thus, if a plant emits more of a focal chemical than predicted for its sales and industry, it will have a positive residual and a lower environmental efficiency. Thus, to ease interpretation, environmental performance is reverse coded by multiplying the residuals with -1 so that more positive values reflect higher environmental efficiency relative to similar facilities in the same industry. To further scrutinize that this dependent variable indeed captures efficiency changes due to knowledge sharing within multi-plant firms and no other confounding industry or local effects, we apply a similar adjustment as for *adjusted emissions*. Specifically, the average environmental efficiency for the same chemical reported by single-plant firms operating in the same two-digit SIC industry and the same state is subtracted from a focal plant's environmental efficiency to arrive at our third dependent variable, *adjusted environmental efficiency* as depicted in the equation (3):

$$Adjusted\ environmental\ efficiency_{cit} = Environmental\ efficiency_{cit} - \sum_{i=1}^{n} \frac{Environmental\ efficiency_{cit}^{sp}}{n}. \tag{3}$$

3.2.3 Control variables

We control for several chemical-level, plant-level, and firm-level factors that may influence plants' generation, management, and release of chemicals as reflected in our dependent variables. Firstly, we control for the *number of facilities* within a firm to consider the effect of firm size and scope. Secondly, we include *plant chemical experience*, which represents the number of years a specific plant has reported a particular chemical to the EPA under the TRI program. Thirdly, we account for the *number of chemicals* that a plant uses during production in a given year. Additionally, depending on the regression specification, we include logged *total releases* (through air, land, and water), the *number of regulated plants* within a firm for a particular chemical, and *firm size* (logged number of employees) as additional controls.

3.3 Analysis of main effects in firm reactions to environmental pressures

3.3.1 Empirical methodology

Our empirical approach aims to test the hypotheses that multi-plant firms are incentivized to engage in certain corporate strategies when they have a regulated plant in their portfolio. Specifically, we hypothesize that these firms will (1) reallocate emissions to unregulated plants, (2) share knowledge about source reduction activities across unregulated plants, and (3) face a trade-off between these two strategies. To test these hypotheses, we take advantage of the CAA as an exogenous shock that creates variation in the attainment status of plants emitting specific pollutants. This variation occurs based on whether a plant is located in a county that is above the pollution threshold and designated as "not in attainment," versus a county below the threshold and designated as "in attainment," both before and after the respective county has been designated.[3]

To estimate our model, we employ ordinary least squares (OLS) regressions for panel data, incorporating a comprehensive set of fixed effects. Firstly, we account for time-invariant observed and unobserved plant characteristics such as maximum capacity or technological capability by including plant fixed effects. Secondly, to control for omitted factors that are tied to industries and years or time-varying heterogeneity across industries, such as regulatory change, technological progress, or tariff changes, we include fixed effects for industry (four-digit SIC code) and year. Additionally, we incorporate chemical-fixed effects to control for broader chemical-related factors, such as chemical-specific and time-invariant differences in the production process or disposal of chemicals. The combined set of fixed effects allows us to account for numerous (un-)observable, time-invariant factors at the plant or chemical level, as well as industry-specific events and time trends that could influence both pollution and efficiency gains.

Consistent with prior research (Gibson, 2019), we focus our analyses on a sample of facilities meeting the following criteria: (a) not regulated by the CAA, i.e., designated as "in attainment," (b) belonging to a multi-plant firm, and (c) emitting chemicals that are potentially regulated by the CAA. Our reasoning is that if multi-plant firms indeed reallocate polluting activities away from regulated plants (Greenstone, 2002, 2003; Bento et al., 2015; Gibson, 2019; Xu & Kim, 2022), unregulated sibling plants will experience pollution spillovers, resulting in increased emissions. This effect is in line with our first prediction that firms are redeploying pollution activities inside the firms toward where it is most cost effective (H1):

$$Adjusted\ emissions_{cit} = \alpha \quad + \beta \quad regulated\ sibling_{cit} \ + P_i + C_c + T_t + \varepsilon_{cit} \quad (4)$$

[3] Existing literature has accumulated substantial evidence on county-level attainment status being exogenous (Henderson, 1996; Becker and Henderson, 2000, Greenstone, 2002; Auffhammer, Bento, and Lowe, 2011; Gibson, 2019) alleviating concerns around anticipatory effects.

Where and P_i, C_c and T_t are plant, chemical, and year fixed effects. We expect estimates of β to be positive if multi-plant firms are indeed reallocating polluting activities from regulated to unregulated plants where pollution is less costly. Conversely, more stringent environmental regulations create incentives for innovation and the adoption of cleaner alternatives in production, operation, and raw materials use (Jaffe & Plamer, 1997; Darnall et al., 2010; Berrone et al., 2013; Aghion et al., 2016). Therefore, having a sibling plant that is not only regulated by the CAA but also implemented the respective SRAs for a particular chemical increases the likelihood of the focal plant adopting SRAs for that chemical. We test this second prediction using the following specification:

$$SRA\ adoption_{cit} = \alpha \quad + \gamma \quad regulated\ sibling\ adopts\ SRA_{cit} + P_i + C_c + T_t + \varepsilon_{cit} \quad (5)$$

Estimates of γ are expected to be positive if multi-plant firms are indeed sharing knowledge about SRAs developed and implemented in regulated plants with their unregulated sibling plants. In other words, having a sibling plant that developed and implemented SRAs for a specific chemical is expected to increase the likelihood of the focal plant also adopting SRAs for that chemical.

3.3.2 Sample descriptives

Table 2 provides descriptive statistics at the chemical-plant level. There are 241,554 observations that satisfy our sample restriction criteria, namely (a) not regulated by the CAA, (b) belonging to a multi-plant firm, and (c) chemicals potentially regulated by the CAA with non-missing air emission data. As adjustments described in Equations (1), (2), and (3) require emissions and sales data, the variables *adjusted emissions*, *environmental efficiency*, and *adjusted environmental efficiency* have a lower number of observations, also because of missing data from single-plant firms. It is worth noting that only 11.5% of the observations in our sample adopt a SRA, whereas 70.7% of all sample observations have at least one sibling plant regulated by the CAA. Overall 31.7% of all observations have regulated siblings that adopt SRAs.

Figure 1 depicts the emissions and the probability of SRA adoption of our unregulated sample plants relative to their regulated counterparts over time. Panel A of this univariate analysis reveals that regulated plants have lower emissions than unregulated ones, which is consistent with existing evidence on the effectiveness of the CAA in improving ambient air quality (e.g., Henderson, 1996; Becker & Henderson, 2000, Greenstone, 2002, 2003). Interestingly, while unregulated plants have higher emissions overall, their emissions decrease in the presence of at least one regulated sibling, but remain higher if there is no regulated sibling plant in the company at all. Panel B suggests similar trends, with unregulated plants exhibiting a higher probability of adopting SRAs when they have at least one regulated sibling that has adopted SRAs, compared to those without such sibling plants. Together, these findings provide initial evidence of knowledge spillover effects from regulated plants to unregulated ones, resulting in lower emissions and greater probability of adopting SRAs.

[Insert Figure 1 about here.]

3.3.3 Results for main effects in firm reactions to environmental pressures

Table 3 presents the multivariate analysis. Model 1 displays the impact of our control variables indicating that chemical emissions increase with facilities' experience in terms of the generation, management, and release of a focal chemical, as well as the number of chemicals the plant uses. Model 2 present the results pertaining to our first hypothesis and indicates that having a *regulated sibling* is associated with a 14.13% increase in emissions ($\beta = 0.1413$, p-value = 0.015). This finding supports our prediction that production/pollution activities are redeployed within a firm following regulation, and is consistent with existing evidence that production is typically reallocated away from newly regulated industries or areas to other locations (Henderson 1996, Greenstone 2002, Walker 2011, 2013; Gibson, 2019; Bartram, Hou, and Kim, 2022).

[Insert Table 3 about here.]

Table 3 also presents the results pertaining to our second hypothesis, predicting that unregulated plants are more likely to adopt SRAs if they have a sibling plant that is regulated by the CAA and has adopted a SRA. In examining the effects of control variables, Model 3, which uses a linear probability model, indicates that SRA adoption probability increases with a plant's experience, and the total amount of air, water, and land releases the plant reports with regard to the focal chemical. Further, in line with our expectations, plants in our sample are more likely to adopt SRAs if they have at least one *regulated sibling plant that has adopted SRAs* (β = 0.0428, p-value = 0.000). Given that the sample mean of SRA adoption is 0.115, this implies a marginal effect of around 37%. These results provide initial support for our second hypothesis and suggest that knowledge sharing in multi-plant firms has positive spillover effects from regulated to unregulated plants.

3.4 Analysis of trade-off between firm reactions to environmental pressures

3.4.1 Empirical methodology

Our final hypothesis predicts a trade-off between the two corporate strategies analyzed in the previous section. Specifically, we argue that firms that shift pollution-related activities from regulated plants towards plants operating in unrestricted areas will be less likely to adopt SRAs (H3a) and become less environmentally efficient (H3b) in such unrestricted plants. To test these predictions, we create a plant-level measure for pollution redeployment from regulated plants to unregulated plants in our sample. However, we cannot directly observe whether a plant engages in absorbing pollution from regulated plants. Thus, we develop a method to estimate which plants experience a larger increase in emission as a result of having a regulated sibling. For this, we run individual plant regressions using the functional form displayed in equation (4). Hence, we can estimate the impact of having a regulated sibling for each plant on *adjusted emissions* using the same sample of unregulated plants belonging to multi-plant firms and control variables as in Table 3. Adjusting a focal plant's emissions by emission for the same chemical reported by single-plant firms operating in the same year, industry, and local area allows for a comparison of different chemicals emitted by the same plant. Each plant-level regression has, on average, 19.96 observations and considers all of the plant's chemical emissions potentially regulated by the CAA. Based on the size of these individual plant-level coefficients β for "*regulated sibling*" we built a classification of plants that strongly absorb pollution redeployed from other sibling plants. We defined "*redeployer50*" ("*redeployer90*") as an indicator variable equal to "1" for plants that redeploy/absorb pollution with coefficients of β above the sample median (the 90th percentile), and "0" otherwise. Note that the two indicator variables derived this way capture how much an unregulated plant is changing its emissions directly in response to having a regulated sibling, which is different from a plant's general changes in emissions over time.

To test the trade-off between redeployment and knowledge sharing, we run regressions to estimate the following two equations:

$$SRA\ adoption_{cit} = \alpha + \beta\ regulated\ sibling\ adopts\ SRA_{cit} +$$

$$\gamma\ regulated\ sibling\ adopts\ SRA_{cit} * Redeployment_i + P_i + C_c + T_t + \varepsilon_{cit} \quad (6)$$

$$Environmental\ Efficiency_{cit} = \alpha + \beta\ regulated\ sibling\ adopts\ SRA_{cit} +$$

$$\gamma\ regulated\ sibling\ adopts\ SRA_{cit} * Redeployment_i + P_i + C_c + T_t + \varepsilon_{cit} \quad (7)$$

Where $Redeployment$ takes the value of either "Redeployer50" or "Redeployer90". Note that both equations include controls for plant, county, and year fixed effects, denoted as $P_i, C_c,$ and T_t, respectively, whereas plant fixed effects absorb the main effect of the pollution $Redeployment_i$ variable. According to Hypothesis 3, we expect γ, the coefficient of the interaction term, to be negative—meaning that if a regulated sibling adopts a SRA, the likelihood that the focal plant also adopts a SRA is lower for those firms that heavily redeploy polluting activities.

3.4.2 Results for a trade-off between firm reactions to environmental pressures

This section ascertains whether firms indeed face a trade-off between redeploying pollution to where it is less costly—increasing emissions in unregulated plants—and sharing knowledge about environmentally efficient production. The results are presented in Table 4, which includes four models, the first two of which use the *probability of SRA adoption* as the dependent variable, and the other two use *adjusted environmental efficiency*. The main predictor variables are "*regulated sibling adopts SRA*", "*redeployer50*" ("*redeployer90*"), and their interactions.

[Insert Table 4 about here.]

The results show that having a *regulated sibling adopting a SRA* increases the likelihood of the focal plant adopting a SRA by 41%-45% compared to the sample mean.[4] However, this effect decreases for plants with high levels of redeployment, dropping to just 8% using the coefficients of Model 1 or to 2% using Model 2.[5] Models 3 and 4 corroborate this finding. The positive main effect implies that adoption of SRAs by siblings increases focal plant environmental efficiency ($\beta = 0.0246$ and $\beta = 0.0201$ respectively); although these coefficients are measured with noise and have relatively high p-values (p-value = 0.093 in Model 3 and p-value = 0.156 in Model 4). Moreover, the positive effect of sibling adoption of SRAs on focal plant environmental efficiency is undermined by redeployment. Specifically, the results suggest that firms that heavily redeploy pollution in response to regulation experience a decrease in the environmental efficiency of their plants of 3.54% in Model 3 (0.0246-0.0600 = -0.0354) and 8.34% in Model 4 (0.0201-0.8540 = -0.8339) when sibling plants adopt a SRA.

3.4.3 Mechanism behind the trade-off

This section investigates the mechanisms that may elucidate the trade-off between pollution redeployment and environmental knowledge sharing. We examine the extent to which a focal firm centralizes the management of their toxic waste to shed light on this phenomenon. Our data for this analysis is derived from the TRI form R section 3, which identifies the name and job title of the certifying officials responsible for verifying the information submitted for each chemical. We use this information to deduce the number of plants that a focal certifying official is responsible for, with a higher number indicating a more centralized structure. Our sample reveals that, on average, certifying officials report data for 1.89 facilities, representing 25.59% of all facilities in the firm. Additionally, the probability of an unrestricted plant sharing a certifying official with at least one regulated sibling is 29.38%.

[4] Since the sample mean of adopting a SRA is 0.115 then the likelihood of adopting a SRA by a focal plant increases by 45% using the coefficient of Model 1 (0.0522/0.115) and 41% using the coefficient of model 2 (0.0475/0.115).
[5] For Model 1 (0.0522-0.0425)/0.115 = 0.08 and for Model 2 (0.0475-0.0451)/0.115 = 0.02.

[Insert Table 5 about here.]

Consistent with our hypotheses, we anticipate that the effects of knowledge sharing will be more pronounced in centralized organizational structures, while redeployment effects will be more significant in decentralized ones. To investigate this idea, we conduct a subsample analysis by dividing our sample of unregulated plants into two groups: centralized (i.e., plants that share a certifying official with at least one sibling plant) and decentralized (i.e., plants that do not). Table 5 shows the results of these analyses. Several noteworthy observations can be made. First, as evidenced by the negative -38.62% effect size in the centralized subsample (Model 1: β = -0.3862, p-value = 0.102), the redeployment effect, as reported in Table 3, is largely driven by firms with a decentralized organizational structure. Hence, the redeployment effect is strongly positive in the decentralized subsample, with an effect size of 15.60% (Model 2: β = 0.1560, p-value = 0.008). Second, the knowledge-sharing effect is much stronger in the centralized subsample (Models 3 and 5) than in the decentralized ones (Models 4 and 6). Specifically, unregulated plants operating in centralized firms are four times more likely to adopt SRAs in response to a regulated sibling adopting SRAs (Model 3: β = 0.1312, p-value = 0.000) than those in decentralized firms that do not share a certifying official (Model 4: β = 0.0330, p-value = 0.000). Finally, the gains in environmental efficiency of unregulated plants that have regulated siblings vary meaningfully between the two subsamples, with a more substantial increase in efficiency in centralized firms (β = 0.0550, p-value = 0.247) than in decentralized ones (β = 0.0049, p-value = 0.732). The difference in coefficients across centralized firms sharing a certifying official and decentralized ones that do not is significantly different from zero for all three outcome variables (Welch-test of difference in coefficients with p-value = 0.000).

3.5 Excess environmental performance analysis

3.5.1 Empirical methodology

In this section, we aim to investigate whether the benefits of redeployment or synergy outweigh each other in determining the environmental performance of multi-plant firms relative to single-plant firms. As discussed in the previous sections, multi-plant firms may have lower environmental performance due to their flexibility to redeploy polluting activities within the firm to less costly locations, while their environmental performance may be enhanced due to their ability to share knowledge about pro-environmental practices between their plants. In the following, we determine whether one logic prevails over the other and thus, grants multi-plant firms in our sample a superior or inferior environmental performance compared to single-plant firms.

Building off of prior work that examines the excess financial performance of diversified firms (e.g., Berger & Ofek, 1995), a measure for excess environmental performance is developed. Specifically, we compute *excess emissions* for both multi-plant and single-plant firms by taking the natural logarithm of the ratio between a firm's actual emissions for a given pollutant and its imputed emissions. The imputed emissions of a firm are calculated as the sum of imputed emissions of its plants, which are obtained by multiplying the plant's sales by the median emission-to-sales multiplier of single-plant firms that emit the same pollutant in the same industry and state.

$$Excess\ emissions_{\ cjt} = \ln\left(\frac{Emissions_{\ cjt}}{Imputed\ emissions_{\ cjt}}\right) \qquad (8)$$

$$Imputed\ emissions_{\ cjt} = \sum_{i=1}^{n} sales_{cit} * \text{median}\left(\frac{Emissions_{cit}^{sp}}{Sales_{cit}^{sp}}\right) \qquad (9)$$

Lower *excess emissions* indicate better environmental performance of the firm. In our sample, which combines multi-plant and single-plant firms, the average excess emissions are negative at -0.4346, indicating that our sample firms emit less than single-plant firms in the same state and industry, on average. Univariate analyses reveal that the mean (median) excess emission of multi-plant firms are significantly lower at -0.9725 (-0.9099) than those of single-plant firms, which have mean (median) excess emissions of -0.0944 (0). This observation may be attributed to the considerable difference in firm size between single- and multi-plant firms, which leads to differences in scale economies.

In multivariate analyses controlling for such size differences, we test whether multi-plant firms enjoy excess environmental performance over single-plant firms. In the first step, we regressed excess emissions on an indicator variable "*multi-plant*", which takes the value of "1" for firms operating more than one plant and "0" otherwise. In the subsequent steps, we focused on examining differences across multi-plant firms that emphasize knowledge sharing about pro-environmental practices. Specifically, we developed a measure to capture "*sales of efficient plants*" as the fraction of firm sales generated by plants with environmental efficiency above the 75th percentile for a given chemical in a given year. Our sample of single- and multi-plant firms shows that an average of 11.66% of firm sales are generated by highly environmentally efficient plants. In addition to the *number of regulated plants* in the firm per focal chemical, we also included *firm size* (logged number of employees), and control variables from Table 3, which were aggregated on chemical-firm level.

3.5.2 Results for excess environmental performance in multi-unit firms

Table 6 presents regressions that test determinants of excess emissions for 731,533 chemical-firm-years, which includes both multi-plant (283,416) and single-plant firms (448,117). In all models, single-plant firms serve as the reference group, and just as multi-plant firms, they might be regulated by the CAA or not. The results from the baseline model suggest that excess emissions decrease with the average number of chemicals used by the firm and firm size, while increasing with the number of regulated plants within the firm and the firm's experience in using the chemical. Model 2 demonstrates that, once controlling for firm size effects, multi-plant firms in our sample have an average of 44.03% higher excess emissions (β = 0.4403, p-value = 0.000) and therefore pollute more than their single-plant counterparts.

[Insert Table 6 about here.]

Next, Models 3 and 4 compare excess emissions in multi-plant firms that emphasize sharing of pro-environmental practices across plants relative to single-plant firms that, by default, cannot share knowledge. As expected, excess emissions are reduced for firms with a higher proportion of sales generated by highly efficient plants (Model 3: β = -1.9904, p-value = 0.000). Interestingly, this effect is more pronounced for multi-plant firms operating such highly efficient plants with the additional opportunity of knowledge sharing (Model 4: β = -1.8826, p-value = 0.000), yielding an overall reduction in excess emissions relative to single-plant firms of 125.29%. These results suggest that some multi-plant firms leverage their organizational scope for pro-environmental practice diffusion.

However, the main results in Model 2 suggest that on average, multi-plant firms do not leverage their organizational scope for pro-environmental practice diffusion. Instead, the differences in excess emissions are driven by those multi-plant firms that follow a redeployment strategy to combat regulatory pressures to reduce pollution. Specifically, multi-plant firms with a focus on pollution redeployment have 14.28% to 20.16% higher excess emissions than single-plant firms (Model 5: $\beta = 0.1428$, p-value = 0.000; Model 7: $\beta = 0.2016$, p-value = 0.000). Further analysis using the number of "redeployer50" ("redeployer90") plants the firm operates generates consistent results. Overall, the evidence in Table 6 suggests that while on average, multi-plant firms underperform their single-plant counterparts, this is driven by multi-plant firms emphasizing pollution redeployment in response to regulatory pressures for cleaner production. In contrast, multi-plant firms that intensively leverage pro-environmental practices across multiple plants within the firm outperform single-plant firms in terms of environmental performance.

The above results suggest differences in environmental performance between single- and multi-plant firms because of multi-plant firms' ability to evade regulatory pressures through redeployment. This ability to internally shift pollution activities to where it is cheapest, however, should largely disappear once multi-plant firms are deprived of the respective payoffs, i.e., when *all* of their plants are subject to regulatory constraints by the CAA. To explore this possibility, we examine a subsample of 20.26% (148,023 observations) of our original dataset, wherein we limit the analysis to plants that are regulated by the CAA. We anticipate that the significant environmental performance advantage of single-plant firms over their multi-plant counterparts documented in Model 2 of Table 6 will dissipate. Consistent with this expectation, we find that in this subsample, "*multi-plant*" is no longer a meaningful predictor of excess emissions. The magnitude of the coefficient decreases by half, and the p-value suggests that the null hypothesis cannot be rejected (Model 9: $\beta = 0.2227$, p-value = 0.233).

4. Robustness checks

Our primary analyses consider air emissions because the CAA only regulates air emissions, but not other release media. However, there may be concerns regarding substitution effects between different release media, such as air, land, and water, which could affect our findings (Greenstone, 2003). It should be noted conceptually that substituting certain pollutants released through the air with others released through water and/or land could be difficult, as it may require changes not only in input materials but also in production processes. Even if substitution across release media occurred, it would generally work against detecting air pollution redeployment towards unregulated plants. To address these concerns empirically, we conducted additional analyses using *adjusted total releases*, which is the sum of chemicals released through air, land, and water, adjusted in the same way as *adjusted emissions* in equation (1). The results in Table 3 remained qualitatively unchanged. Additionally, we reanalyzed excess environmental performance using total releases instead of air emissions in equations (8) and (9), which yielded similar results to those in Table 6. These findings are not reported here to conserve space, but they are available in Online Appendix A2.

Our main analysis is on plant-chemical-year level. To provide additional evidence for the knowledge-sharing mechanism through SRA adoption proposed in Hypotheses 2 and 3a, we conducted a more detailed analysis at the plant-chemical-year-*SRA* level. Since there are 49 distinct SRA categories in our sample, we expanded every observation in our original dataset 48 times, resulting in a significantly larger sample size of 8,276,400 observations. In this enlarged sample, the likelihood of plants adopting a specific SRA for a given chemical is only 0.26%, and we created a binary variable indicating whether a *regulated sibling plant adopted the same exact SRA* for any type of chemical in a given year (mean = 1.89%). Together, this alternative sample differs from our original sample in that it is significantly larger, has many more zero values for the dependent variable "*probability of SRA adoption*" as well as the main predictor "*regulated sibling adopted same SRA*", but allows us to capture the nuances behind the knowledge sharing mechanism documented in our main analysis as it considers SRA variation. We re-estimated the results in Table 3 Model 3 and 4, Table 4 Model 1 and 2, and Table 5 Model 3 and 4 and obtained similar results (not reported here to conserve space but available from the Online Appendix A3). In particular, plants are more likely to adopt a focal SRA if they have at least one regulated sibling plant that has adopted the exact same SRA ($\beta = 0.0241$, p-value = 0.000). Given that the sample mean of SRA adoption is 0.0026 in this enlarged sample, this implies a much stronger marginal effect of around 927%.

When testing the trade-off between knowledge sharing and resource redeployment akin to Table 4, the direct effect of "*regulated sibling adopted same SRA*" on "*probability of SRA adoption*" is again positive and significant as in our main analysis. The interaction effect with "*redeployer50(90)*", however, lacks statistical significance. This is likely due to the fact that estimating an interaction effect of two variables that are heavily zero inflated, with "*regulated sibling adopted same SRA*" having a sample mean of only 0.019 and "*redeployer50(90)*" of 0.2091 (0.1003), is problematic. Finally, our main results in Table 5, Models 3 and 4 are confirmed using this enlarged sample. Specifically, unregulated plants operated in centralized firms are 2.65 times more likely to adopt the exact same SRAs in response to having a regulated sibling adopting the focal SRAs ($\beta = 0.0577$, p-value = 0.000) than those in decentralized firms not sharing a certifying official ($\beta = 0.0218$, p-value = 0.000).

To further scrutinize our findings on firms that face a trade-off between sharing knowledge about pro-environmental practices and redeploying pollution to less costly areas, we conducted additional robustness checks. In our primary analysis in section 3.4.1, we determined whether a plant is a "*Redeployer50(90)*" based on its emissions of *all* types of chemicals in a given year. This method indicates whether a plant significantly increases its emissions in response to having a regulated sibling during the entire sample period. In other words, a focal plant is either always or never a "*Redeployer50(90)*" plant, independent of the type of chemical analyzed, similar to a plant fixed effect. However, it is possible that a focal plant might absorb the pollution of regulated sibling plants heavily for some chemicals, but not for others. As a result, a single plant could have varying values for "*Redeployer50(90)"* depending on the chemical studied. To address this issue, we reanalyzed the data in section 3.4.1 using plant-*chemical*-level regressions, with an average of 12.13 observations per regression (as opposed to 19.96 in the primary analysis), to determine chemical-specific "*Redeployer50(90)*" plants. This approach, which employs more detailed data but fewer observations per plant-chemical combination, produces results that are very similar to those presented in Table 4. The findings from this analysis are not included here to save space but are available in Online Appendix A4.

Finally, to alleviate concerns regarding a potential look-ahead bias in our analysis, we implement a method to account for plants' capabilities to absorb pollution redeployed from sibling plants developing over time. Specifically, we limit the sample period for determining "*redeployer50(90)*" plants to the years 1991-2009, and assume that plants become "*redeployer50(90)*" only during later years in our sample. We then use these data and associated indicators to analyze the subsequent years of 2010-2019, thereby effectively avoiding the potential for using information still unknown in earlier periods. The results from this analysis, available in Online Appendix A4, are consistent with those reported in Table 4, thus providing further support for the robustness of our findings.

5. Discussion

In this paper, we investigate the environmental performance of multi-unit firms and analyze a crucial trade-off between knowledge sharing about pro-environmental practices within the firm and the internal relocation of pollution to units where the cost of pollution is lower. By exploring this tension, we not only document evidence of both sources of corporate scope advantages but also demonstrate that firms that redeploy pollution are less inclined to share their best environmental practices. Our findings suggest that multi-unit firms generally have weaker environmental performance compared to single-unit firms, particularly those that prioritize the redeployment of polluting activities within the firm instead of sharing pro-environmental practices.

Our findings extend recent work in Corporate Strategy that has separately examined increasingly nuanced sources of corporate advantage, i.e., benefits from simultaneously sharing resources versus benefits from the flexibility to redeploy them (Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010; Sakhartov & Folta, 2014). However, the interplay between these two drivers of corporate advantage remains understudied (Sakhartov and Folta, 2014; Morandi Stagni et al., 2020). Our findings emphasize that the organizational structure of a firm is a crucial boundary condition that determines the benefits derived from a specific source of corporate advantage. While centralized structures facilitate synergetic benefits from knowledge sharing, decentralized structures are necessary to reap the advantages of resource redeployment. Hence, this trade-off implies that multi-unit firms have to choose between one of the two diversification logics, for example when designing their organizational structure, instead of pursuing both of them simultaneously. Together, the empirical evidence we provide thus addresses the challenges in earlier research of empirically capturing the benefits of internal resource redeployment as compared to resource sharing while accounting for firms' organizational structure. This has important implications for corporate managers, who must consider this trade-off between scaling pro-environmental practices developed in one unit across multiple units within the firm or redeploying polluting activities to where they are least costly to perform. For example, our finding that environmental regulation prompts greater knowledge sharing among units operated in centralized (rather than decentralized) firms might encourage managers to re-evaluate the importance of corporate structure for achieving environmental as well as financial performance goals.

This paper reveals a potential trade-off between resource redeployment and the development of new capabilities within firms. Prioritizing resource redeployment to address specific problems may divert attention away from developing knowledge and addressing broader challenges, such as improving environmental efficiency. Conversely, our findings may suggest a trade-off between the development of redeployment capabilities and other sector-specific capabilities, considering the concept of "redeployment capability" introduced by Dickler et al. (2022). Ultimately, our research highlights the importance of balancing resource redeployment and capability development to achieve organizational goals effectively. By shedding light on this trade-off, we aim to encourage further investigation into the optimal allocation of resources and capabilities within firms, which could enhance organizational performance in various contexts.

Further, this study adds to existing work on the determinants of firm environmental performance (e.g., Bansal, 2005; Berrone & Gomez-Mejia, 2009; Doshi et al., 2013; Flammer, 2013, 2015). Our focus on firm-level drivers (being part of a multi-unit firm), in combination with institutional-level ones (receiving regulatory pressures for environmental improvement), sheds light on the influence of organizational structure on the effectiveness of pollution reduction and prevention programs. Specifically, our findings demonstrate that units within multi-unit firms respond differently to institutional pressures compared to standalone units, and that institutional pressures are more effective for multi-unit firms that can leverage resource sharing among different units. Conversely, multi-unit firms that prioritize resource redeployment strategies can counteract institutional pressures to improve environmental performance. For policymakers designing such pollution reduction and prevention programs, our results therefore suggest that a program's effectiveness depends in part on the organizational structure of the firms targeted. For instance, industries with a high proportion of single-unit firms may be more responsive to such programs due to their lack of flexibility to evade them, whereas multi-unit firms may be better equipped to scale investments in cleaner practices across their different units. By understanding and anticipating these differences across organizational structures, regulators can improve the efficiency and effectiveness of their programs.

Furthermore, our study adopts the "more integrated approach" called for by prior research on the importance of examining interaction effects between institutional pressures and firm characteristics for environmental sustainability outcomes (Aguilera, Aragon-Correa, Marano, & Tashman, 2021: p. 1488). Our theoretical framework and empirical analysis contribute to the literature on regulatory spillovers and environmental spillovers (Peukert et al., 2020; Vogel, 1995), and provide a foundation for further investigation into the relationship between organizational structure and environmental performance.

5.1 Implications for future research

Our research suggests several promising directions for future studies. Although our analysis covers a diverse range of industries and geographic locations spanning nearly three decades, our results may not be generalizable to regulatory contexts beyond the United States. For instance, multi-unit firms operating in the European Union (EU) might face greater or lesser challenges in responding to comparable regulatory pressures by redeploying resources across national borders than their U.S. counterparts. In addition, differences in knowledge-sharing potential across units may be amplified or mitigated by cross-country variations in institutional contexts (e.g., Kogut & Zander, 2004; Jensen & Szulanski, 2004; Ambos & Ambos, 2009). We therefore encourage future research to replicate our findings in diverse institutional and regulatory settings, utilizing, for instance, the European Pollutant Release and Transfer Register (E-PRTR) and comparing environmental regulations across EU member states.

While we believe that our study offers a novel approach to capturing the role of centralization and decentralization in firms' decision-making around chemical releases, there are limitations to the decision-making power that certifying officials have over individual plants or company-wide. Given that our results suggest that a firm's organizational structure can impact the prioritization of redeploying polluting activities within the firm versus sharing pro-environmental practices, future research could explore alternative proxies for different forms of organizing that capture decision rights at multiple levels of the firm hierarchy. One potential avenue to obtain more granular data on task allocation, decision power, incentives, and information provision related to firms' environmental strategies is the Carbon Disclosure Project (CDP) database.

6. Conclusion

Whereas existing literature in Strategic Management has speculated about a trade-off between organizing for resource redeployment versus organizing for synergies when it comes to financial performance in multi-unit firms (e.g., Sakhartov & Folta, 2014; Morandi Stagni et al., 2020), our study sets out to empirically investigate this theoretical tension in the context of firm environmental performance measured by toxic emissions of all units belonging to the same firm. Our findings suggest that multi-unit firms in our sample are able to leverage both types of corporate advantage, but are faced with a significant trade-off between pollution redeployment and knowledge sharing surrounding pro-environmental practices. Consistent with this trade-off, this study shows that firms that prioritize pollution redeployment are less likely to share the best environmental practices, and have weaker environmental performance than single-unit firms.

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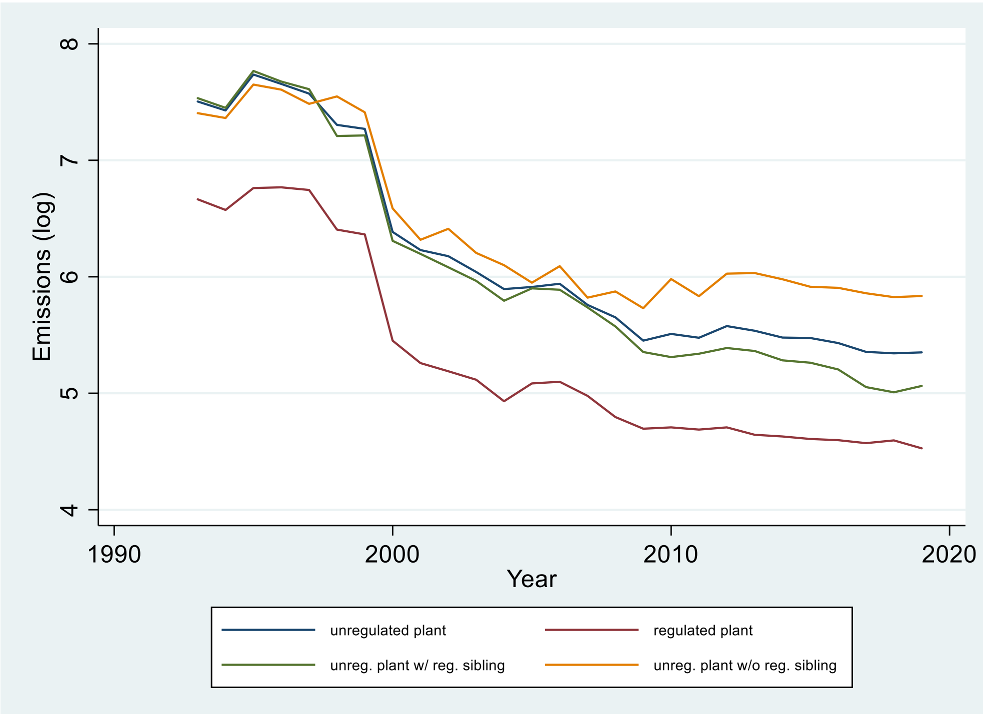
Figure 1: Sample descriptives

Panel A: Emissions of regulated and unregulated plants with and without regulated sibling plants



Panel B: Source reduction activities (SRAs) adopted for regulated and unregulated plants with and without regulated sibling plants adopting SRAs

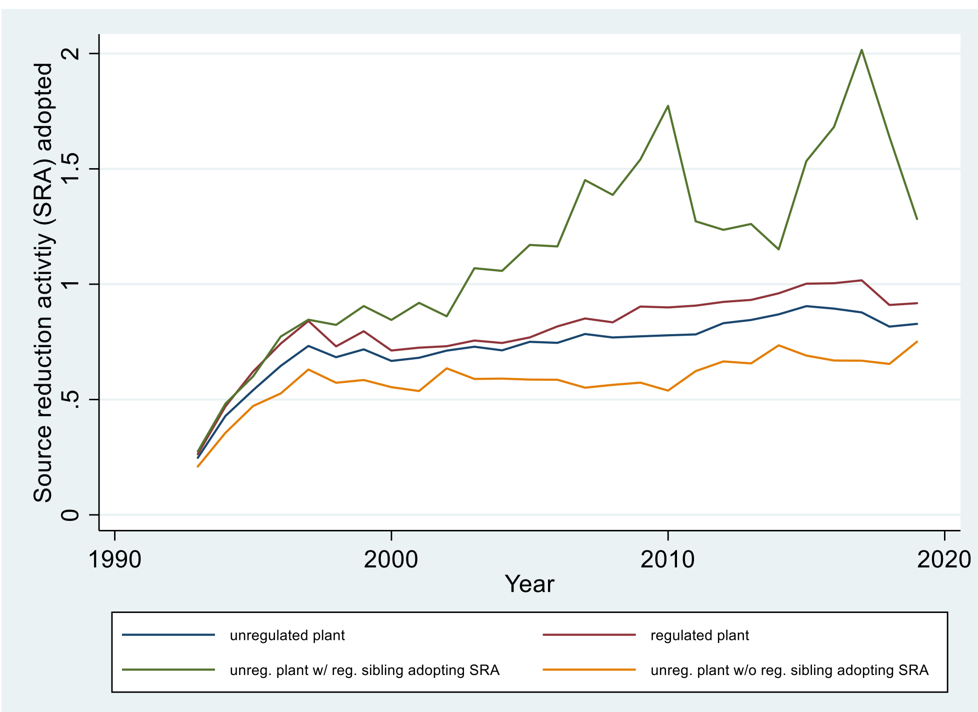


Table 1: Clean Air Act (CAA)-regulated US counties by U.S. states during entire sample period (1991-2019)

State/Territory	Abbr.	# counties not in attainment	# counties	% counties not in attainment
Alabama	AL	7	67	10.45%
Alaska	AK	3	29	10.34%
Arizona	AZ	9	15	60.00%
Arkansas	AR	1	75	1.33%
California	CA	45	58	77.59%
Colorado	CO	17	64	26.56%
Connecticut	CT	8	8	100.00%
Delaware	DE	3	3	100.00%
District of Colombia	DC	1	1	100.00%
Florida	FL	8	67	11.94%
Georgia	GA	29	159	18.24%
Hawaii	HI	0	5	0.00%
Idaho	ID	6	44	13.64%
Illinois	IL	16	102	15.69%
Indiana	IN	33	92	35.87%
Iowa	IA	2	99	2.02%
Kansas	KS	1	105	0.95%
Kentucky	KY	18	120	15.00%
Louisiana	LA	18	64	28.13%
Maine	ME	11	16	68.75%
Maryland	MD	15	24	62.50%
Massachusetts	MA	14	14	100.00%
Michigan	MI	29	83	34.94%
Minnesota	MN	10	87	11.49%
Mississippi	MS	1	82	1.22%
Missouri	MO	9	115	7.83%
Montana	MT	10	56	17.86%
Nebraska	NE	1	93	1.08%
Nevada	NV	5	17	29.41%
New Hampshire	NH	5	10	50.00%
New Jersey	NJ	21	21	100.00%
New Mexico	NM	3	33	9.09%
New York	NY	31	62	50.00%
North Carolina	NC	24	100	24.00%
North Dakota	ND	0	53	0.00%
Ohio	OH	42	88	47.73%
Oklahoma	OK	0	77	0.00%
Oregon	OR	11	36	30.56%

Pennsylvania	PA	49	67	73.13%
Rhode Island	RI	5	5	100.00%
South Carolina	SC	2	46	4.35%
South Dakota	SD	0	66	0.00%
Tennessee	TN	21	95	22.11%
Texas	TX	29	254	11.42%
Utah	UT	9	29	31.03%
Vermont	VT	0	14	0.00%
Virginia	VA	37	133	27.82%
Washington	WA	8	39	20.51%
West Virginia	WV	13	55	23.64%
Wisconsin	WI	14	72	19.44%
Wyoming	WY	4	23	17.39%

Table 2: Descriptive statistics for sample on plant-chemical level

	Mean	SD	P5	Median	P95	N
Total air emissions	36,785.710	295,505.641	0.000	670.000	120,000.000	241,554
Total air emissions (log)	6.103	3.891	0.000	6.509	11.695	241,554
Adjusted emissions	-2.040	3.781	-8.397	-1.900	3.972	172,425
Environmental efficiency	-0.064	0.950	-1.495	-0.076	1.471	193,847
Adj. environmental efficiency	-0.083	1.176	-1.937	-0.102	1.842	122,771
SRA adopted	0.115	0.319	0	0	1	241,554
Regulated sibling	0.707	0.455	0	1	1	241,554
Regulated sibling adopted SRA	0.317	0.465	0	0	1	241,554
Number of facilities	17.655	21.092	2.000	9.000	69.000	241,554
Number of chemicals	11.988	13.159	2.000	8.000	34.000	241,554
Plant chemical experience	9.435	6.780	1.000	8.000	23.000	241,554
Plant sales (log)	17.440	1.782	14.489	17.538	20.131	241,088

Table 3: Main results for plant-chemical-level emissions and probability of SRA adoption

DV:	Adjusted emissions		Probability of SRA adoption	
	(1)	(2)	(3)	(4)
Regulated sibling		0.1413**		
		(0.0580)		
Regulated sibling adopted SRA				0.0428***
				(0.0058)
Number of facilities	-0.0029	-0.0039**	0.0001	-0.0003
	(0.0020)	(0.0020)	(0.0002)	(0.0002)
Number of chemicals	0.0127	0.0122	-0.0005	-0.0006
	(0.0108)	(0.0106)	(0.0007)	(0.0007)
Plant chemical experience	0.0883***	0.0883***	0.0023***	0.0023***
	(0.0065)	(0.0065)	(0.0004)	(0.0004)
Total releases			0.0044***	0.0044***
			(0.0006)	(0.0006)
Constant	-2.9819***	-3.0605***	0.0784***	0.0727***
	(0.1318)	(0.1401)	(0.0108)	(0.0109)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Chemical FE	YES	YES	YES	YES
Plant FE	YES	YES	YES	YES
N	171,312	171,312	171,312	171,312
R^2	0.450	0.450	0.474	0.476

Note: Using OLS and a sample of unregulated plants, i.e., plants "in attainment" under the CAA, *adjusted emissions* (Models 1 and 2) and *probability of SRA adoption* (Models 3 and 4) are regressed on indicator variables for whether at least one of their sibling plants is regulated, i.e., "not in attainment" (Models 1 and 2) and has adopted a SRA (Models 3 and 4). Given the binary outcome variable in Models 3 and 4, a linear probability model is used. Fixed effects are included as indicated but not reported to conserve space. Standard errors clustered by plants are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Trade-off analysis

Dependent Variable:	Probability of SRA adoption		Adjusted environmental efficiency	
	(1)	(2)	(3)	(4)
Regulated sibling adopted SRA	0.0522***	0.0475***	0.0246*	0.0201
	(0.0066)	(0.0063)	(0.0146)	(0.0142)
Regulated sibling adopted SRA * Redeployer50	-0.0425***		-0.0600*	
	(0.0144)		(0.0359)	
Regulated sibling adopted SRA* Redeployer90		-0.0451***		-0.0854*
		(0.0133)		(0.0471)
Number of chemicals	-0.0006	-0.0006	-0.0050*	-0.0050*
	(0.0007)	(0.0007)	(0.0026)	(0.0026)
Plant chemical experience	0.0023***	0.0023***	-0.0282***	-0.0282***
	(0.0004)	(0.0004)	(0.0027)	(0.0028)
Number of facilities	-0.0003	-0.0003	-0.0006	-0.0006
	(0.0002)	(0.0002)	(0.0006)	(0.0006)
Total releases	0.0044***	0.0044***		
	(0.0006)	(0.0006)		
Constant	0.0710***	0.0718***	0.2570***	0.2576***
	(0.0110)	(0.0110)	(0.0406)	(0.0406)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Chemical FE	YES	YES	YES	YES
Plant FE	YES	YES	YES	YES
N	169,991	169,991	121,734	121,734
R^2	0.475	0.475	0.309	0.309

Note: Using OLS and a sample of unregulated plants, i.e., plants "in attainment" under the CAA, *probability of SRA adoption* (Models 1 and 2) and *adjusted environmental efficiency* (Models 3 and 4) are regressed on indicator variables for whether at least one of their sibling plants is regulated, i.e., "not in attainment and has adopted a SRA as well as their interaction with indicators for whether the focal plant is a plant prone to redeploying pollution (*redeployer50(90)*), in response to having a regulated sibling. Given the binary outcome variable in Models 1 and 2, a linear probability model is used. Fixed effects are included as indicated but not reported to conserve space. Standard errors clustered by plants are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Exploring the mechanism behind the trade-off: Centralized vs. decentralized firms

	Adjusted emissions		Probability of SRA adoption		Adjusted environmental efficiency	
	Central	Decentral	Central	Decentral	Central	Decentral
	(1)	(2)	(3)	(4)	(5)	(6)
Regulated sibling	-0.3862	0.1560***				
	(0.2360)	(0.0587)				
Regulated sibling adopts SRA			0.1312***	0.0330***	0.0550	0.0049
			(0.0256)	(0.0057)	(0.0475)	(0.0142)
Number of chemicals	0.0202	0.0129	-0.0015	-0.0005	-0.0075	-0.0051**
	(0.0159)	(0.0107)	(0.0014)	(0.0007)	(0.0059)	(0.0026)
Plant chemical experience	0.0682***	0.0910***	0.0027***	0.0023***	-0.0257***	-0.0294***
	(0.0101)	(0.0066)	(0.0006)	(0.0004)	(0.0040)	(0.0028)
Number of facilities	0.0156**	-0.0043**	0.0004	-0.0003	-0.0078***	-0.0005
	(0.0069)	(0.0021)	(0.0009)	(0.0002)	(0.0026)	(0.0006)
Total releases			0.0037***	0.0045***		
			(0.0010)	(0.0006)		
Constant	-2.6630***	-3.1197***	0.0765***	0.0728***	0.2970***	0.2748***
	(0.1793)	(0.1422)	(0.0161)	(0.0110)	(0.0714)	(0.0413)
Welch's t-test (p-value)	(1) – (2)	-556.889 (0.000)	(3) – (4)	931.894 (0.000)	(5) – (6)	215.603 (0.000)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Chemical FE	YES	YES	YES	YES	YES	YES
Plant FE	YES	YES	YES	YES	YES	YES
N	60,092	161,279	60,109	161,317	43,194	114,488
R^2	0.502	0.453	0.571	0.478	0.371	0.308

Note: Using OLS and a sample of unregulated plants, *adjusted emissions* (Models 1 and 2), *probability of SRA adoption* (Models 3 and 4), and *adjusted environmental efficiency* (Models 5 and 6) are regressed on indicator variables for whether the focal plant has at least one regulated sibling (adopting an SRA). Given the binary outcome variable in Models 3 and 4, a linear probability model is used. Models 1, 3, and 5 indicate results for plants operated in centralized firms (i.e., sharing a certifying official) whereas models 2, 4, and 6 are estimated based on plants in decentralized firms (i.e., not sharing a certifying official). Fixed effects are included as indicated but not reported to conserve space. Standard errors clustered by plants are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Excess emission analysis

DV: Excess emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Multi-plant		0.4403***		0.6297***	0.6099***	0.6242***	0.6172***	0.6268***	0.2227
		(0.0544)		(0.0533)	(0.0541)	(0.0533)	(0.0536)	(0.0533)	(0.1866)
Sales from efficient plants			-1.9904***	-1.6674***	-1.6671***	-1.6670***	-1.6671***	-1.6670***	
			(0.0257)	(0.0242)	(0.0242)	(0.0242)	(0.0242)	(0.0242)	
Multi-plant*Sales of efficient plants				-1.8826***	-1.8947***	-1.9085***	-1.8952***	-1.9004***	
				(0.0737)	(0.0738)	(0.0743)	(0.0740)	(0.0741)	
Redeployer50 firm					0.1428**				
					(0.0586)				
# of Redeployer50 plants						0.1622***			
						(0.0417)			
Redeployer90 firm							0.2016***		
							(0.0704)		
# of Redeployer90 plants								0.1991***	
								(0.0632)	
Number of regulated plants	0.0597***	0.0587***	0.0690***	0.0788***	0.0781***	0.0767***	0.0782***	0.0775***	0.4891***
	(0.0143)	(0.0142)	(0.0144)	(0.0147)	(0.0147)	(0.0146)	(0.0146)	(0.0146)	(0.0782)
Number of chemicals	-0.0171***	-0.0171***	-0.0167***	-0.0167***	-0.0166***	-0.0166***	-0.0166***	-0.0166***	-0.0145**
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0059)
Firm experience	0.0362***	0.0369***	0.0352***	0.0362***	0.0360***	0.0358***	0.0360***	0.0359***	0.0466***
	(0.0022)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0043)
Firm size	-0.4445***	-0.4861***	-0.4385***	-0.4848***	-0.4857***	-0.4875***	-0.4859***	-0.4865***	-0.5729***
	(0.0193)	(0.0207)	(0.0184)	(0.0197)	(0.0196)	(0.0195)	(0.0196)	(0.0195)	(0.0330)
Constant	1.7895***	1.8387***	1.9890***	2.0013***	2.0039***	2.0018***	2.0035***	2.0011***	1.4340***
	(0.1091)	(0.1114)	(0.1047)	(0.1062)	(0.1059)	(0.1057)	(0.1060)	(0.1057)	(0.1676)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Chemical FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	731,533	731,533	731,533	731,533	731,533	731,533	731,533	731,533	148,023
R^2	0.320	0.321	0.353	0.357	0.357	0.358	0.357	0.358	0.450

Note: The dependent variable is "*excess emissions*" and OLS is used in all models. Fixed effects are included as indicated but not reported to conserve space. Standard errors clustered by firms are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1