Engaging Supply Chains in Environmental Initiatives: Adoption and Information Sharing

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Abstract

This dissertation consists of three papers that analytically and empirically explore how to better engage firms and supply chains in environmental sustainability initiatives. Together, these papers contribute to the understanding of mechanisms and choices associated with the adoption of environmental initiatives, and to the understating of how environmental information acquisition and sharing affects decisions to adopt environmental initiatives.

In the first paper, *Energy Efficiency: Picking Up the Twenty-Dollar Bill*, we employ a game-theoretic model to analyze organizational barriers to adopting capital energy efficiency initiatives. We find that operating managers under-propose energy efficiency projects because the lack of expertise in energy efficiency increases project due diligence costs, causing such projects to be under-adopted by senior management compared to other capital projects yielding comparable economic benefits. We also find that firm-level environmental goals and partnerships with technology providers are more effective than subsidies in increasing the adoption of energy efficiency projects because they directly address managers' reluctance to propose such projects.

In the second paper, *Engaging Supply Chains in Climate Change*, we theorize and hypothesize on several factors that motivate suppliers to share climate change information with buyers when buyers request it. We test our hypotheses using data from the Carbon Disclosure Project's Supply Chain Program. We find evidence that suppliers are more likely to share this information when requests from buyers are more prevalent, when buyers appear committed to using the information, when suppliers belong to more profitable industries, and when suppliers are located in countries with greenhouse gas regulations.

In the third paper, *The Supply Chain Impact of Environmental Labeling Decisions*, we use analytical models to analyze two questions retailers face when contemplating the adoption of environmental labels: (1) Should the retailer choose an information label or a seal of approval label, and (2) Does the environmental performance of the product depend on the party in the supply chain making this decision? We find that the suitable label type depends on demand uncertainty, consumer perception, and costs to obtain labels. Also, in the majority of realistic scenarios, the retailer prefers a higher environmental performance level than the supplier.

Contents

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The following authors contributed to Chapter 3: Professor David Simchi-Levi and Cristian Figueroa.

Listing of figures

For my parents.

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1

Introduction

1.1 Operations and the Environment

Research at the intersection of operations management and environmental management has been growing rapidly in the past several years. Issues about climate change and the environment add novel dimensions to traditional operational decisions [8, 42]. Most fundamentally, operational decisions are subjected to additional *constraints* limiting energy usage, waste, and environmental externalities such as pollution and carbon emissions, and are evaluated with additional *performance measures* associated with the environment. Because of the scope and the nature of environmental issues, operational decision-makers also face unique challenges in the following ways: (1) operational decision-makers need to take into account a wider set of stakeholders, such as regulators, institutional investors, and non-profit organizations; (2)

operational decision-makers need to acknowledge and manage indirect and unclear financial benefits associated with environmental initiatives due to evolving consumer perception and regulations, and (3) because of the life-cycle nature of environmental performance measurement, decision-makers need to be aware that operational decisions have significant environmental repercussions on other members in the supply chain. These issues are explored in my dissertation.

1.2 Overview of dissertation research

In three chapters, my dissertation analytically and empirically explores how to better engage firms and supply chains in environmental sustainability initiatives.

Chapter 2, titled *Energy Efficiency: Picking Up the Twenty-Dollar Bill*, examines organizational barriers to energy efficiency initiatives and analyzes mechanisms that can be used to increase the adoption of energy efficiency initiatives. Although numerous studies have shown that energy efficiency initiatives can simultaneously generate positive economic benefits (i.e., returns) for and reduce the environmental impact of a firm, many firms continue to under-invest in such win-win opportunities. We use a game-theoretic model to illustrate how a firm's capital budgeting process can be a barrier to adopting energy efficiency projects despite their attractive economic benefits. We study three mechanisms used to promote the adoption of energy efficiency projects: firm-level environmental goals, governmental subsidies, and partnerships with technology providers.

We find that the two-level decision-making structure of the capital budgeting process and high due diligence costs—due to a lack of expertise in energy efficiency—cause such projects to be under-adopted compared to other capital projects yielding comparable economic benefits that involve more familiar technologies. In the capital budgeting process, an operating manager must decide to propose a project, and then the senior management decides whether to implement the project. Because an energy efficiency project is typically outside the scope of the firm and thus the manager's expertise, the manager incurs a higher cost of effort to perform due diligence for the project and thus is less likely to propose the project. We also found that environmental goals and partnerships with technology providers are more effective than subsidies in increasing adoption of energy efficiency projects because they directly address the manager's reluctance to propose an energy efficiency project. However, environmental goals lower the firm's overall payoff and partnerships with technology providers introduce operational complexity. Governmental subsidies that increase projects' economic benefits indirectly affect the manager's decision to propose the project, and thus are less effective for increasing the adoption of energy efficiency projects.

Chapter 3, titled *Engaging Supply Chains in Climate Change*, examines how to incentivize members of the supply chain to adopt an environmental initiative on sharing climate change information. Suppliers are increasingly being asked to share information about their vulnerability to climate change and their strategies to reduce greenhouse gas emissions. Their responses vary widely. We theorize and empirically identify several factors associated with suppliers being especially willing to share this information with buyers, focusing on attributes of the buyers seeking this information and of the suppliers being asked to provide it. We test our hypotheses using data from the Carbon Disclosure Project's Supply Chain Program, a collaboration of multinational corporations requesting such information from thousands of suppliers in 49 countries.

We find evidence that suppliers are more likely to share this information when requests from buyers are more prevalent, when buyers appear committed to using the information, when suppliers belong to more profitable industries, and when suppliers are located in countries with greenhouse gas regulations. We find evidence that these factors also influence the comprehensiveness of the information suppliers share and their willingness to share the information publicly. For a buyer looking to incentivize its suppliers to share their climate change information, there are two different levers it can use: demonstrating the buyer's commitment to use the suppliers' shared information through supplier score cards and procurement policies, and reaching out to work with other buyers to request climate change information from the suppliers. Also, the need to invest in these levers depends on the suppliers' industry and country contexts. For example, if a supplier is in a profitable industry, the supplier is already likely to share its climate change information, and thus it is less necessary for the buyer to invest in these levers.

Chapter 4, titled *The Supply Chain Impact of Environmental Labeling Decisions*, examines the choices facing a retailer adopting an initiative on environmental labeling. As environmental performance gains significance as a differentiating feature of a firm's products, many retailers are considering the use of labels to communicate the environmental performance of their offered products more easily to consumers, and have begun to measure and control their suppliers' environmental performance. However, little is known about how decisions regarding these labels affect supply chain behaviors and environmental performance. We use game theoretic models to analyze two important questions facing a retailer contemplating adoption of environmental labels: (1) What type of environmental labels should the retailer choose, and (2) Does the environmental performance of the product depend on the party in the supply chain making this decision? To answer the first question, we focus on two types of widely used environmental labels: information labels (e.g., the Carbon Trust's footprint labels), which communicates the level of environmental performance, and seal of approval labels (e.g., Green Seal Certification), which assert that the product has good environmental performance according to the labeling organization's standard. To answer the second question, we analyze decisions made under three models: (1) the Supplier-Choice model, in which the supplier makes the decision about the environmental performance of the product that it supplies to the retailer, (2) the Retailer-Choice model, in which the retailer chooses the environmental performance of the product for the supplier, and (3) the Benchmark model, in which a vertically integrated supply chain chooses the environmental performance that maximizes the supply chain profit.

We find that when there is no uncertainty in product demand, the retailer, the supplier, and the vertically integrated firm prefer the same optimal level of environmental performance. However, this alignment breaks down in the presence of demand uncertainty. In the majority of realistic scenarios, the retailer prefers a higher environmental performance level than the supplier, thus the retailer faces reduction in payoff when leaving environmental performance decisions to the supplier. Moreover, these results confirm anecdotal observations that retailers, rather than suppliers, are crucial enablers of environmental labeling initiatives. We also expect that seal of approval labels will be more prevalent in the scenarios in which (1) there is more uncertainty in product demand, (2) the product's environmental performance is more difficult for consumers to interpret, (3) the additional cost to acquire seal of approval labels is lower, and (4) the retailer can persuade the supplier to share part of the additional cost to acquire the label.

1.3 Contributions

My dissertation builds upon and contributes to two main streams of literature at the intersection of operations management and environmental management.

Firstly, dissertation contributes to the understanding of mechanisms and choices associated with the adoption of environmental initiatives. A decision to adopt an environmental initiative is often not only about economic returns, but also about risk mitigation and corporate philosophy. Such a decision usually faces challenges in the form of uncertain economic benefits due to evolving trends and changing perceptions of stakeholders [67, 69, 150]. Like other new paradigms, environmental initiatives also need to compete with firms' status quo and established core capabilities.

The three chapters of my dissertation examine the complex dynamic of adopting environmental initiatives in diverse contexts. Chapter 2 provides an analytical framework to explain intra-firm mechanisms that become barriers to adopting environmental initiatives that lie outside the firm's core capabilities, and explores mechanisms to overcome these barriers. Chapter 3 goes beyond the scope of an individual firm to provide a framework and hypotheses on how suppliers consider the uncertain costs and benefits of adopting an environmental initiative. Whereas Chapters 2 and 3 focus on the mechanisms leading up to the adoption of environmental initiatives, Chapter 4 provides an analytical framework to help understand the effects of different adoption choices on the environmental performance and economic benefits of firms, with particular focus on environmental labeling.

My dissertation also builds upon and contributes to the literature on environmental information sharing and acquisition and, in particular, on how such information affects decisions to adopt environmental initiatives. In operations management, most research on information sharing in supply chains has focused on sharing operational parameters such as demand forecasts and inventory levels to mitigate supply chain disruptions [37, 89]. The scant research on sharing other types of information has largely focused on management system standards such as ISO 9001 and ISO 14001 [e.g., 41, 93, 107] and on codes of conduct governing workplace conditions [e.g., 98, 140, 163].

Chapter 2 examines how the lack of information about an environmental initiative and the high cost of acquiring this information play an important role in explaining the under-adoption of environmental initiatives that are outside the firm's core capabilities. Chapter 2 also examines how different mechanisms to bolster the adoption of such initiatives address this high cost of information acquisition: by changing organizational priorities to render this cost less important, by bolstering the initiative's economic benefits in order to offset this cost, or by reducing or taking away this cost via partnership. The contextual focus of Chapter 3 is on environmental information sharing between a supplier and a buyer. Chapter 3 also theorizes–and empirically shows–how the costs and benefits of environmental information can be perceived by supply chain partners. The contextual focus of Chapter 4 is on environmental information sharing between upstream supply chain and end consumers through labels. This chapter also contributes to understanding how environmental information affects consumer demand and the retailer's choices in adopting environmental labels.

Although my dissertation focuses largely on environmental initiatives, many of the contributions made by this dissertation can be applied more widely to other types of initiatives that involve similar dynamics to those of environmental initiatives, such as initiatives about workers' health and safety or nutritional quality of foods.

Two economists are walking down a sidewalk and see what looks like a twenty-dollar bill. As one bends down to pick it up, the other says, "Don't bother—if it were a real twenty, someone else would have picked it up by now."

Old economists' joke

2

Energy Efficiency: Picking Up the Twenty-Dollar Bill

In 2008, the McKinsey Global Institute published a report with a striking conclusion that seven gigatons of annual CO_2 emissions could be abated at negative cost (i.e., it would be profitable to reduce CO_2 emissions) using various technologies that were currently available or would be available in the near future [12]. The majority of these abatement solutions are energy efficiency related, such as insulation improvements, using fuel-efficient vehicles, and improving water-heating and air-conditioning systems. Moreover, the highest percentage (39%) of the lowest-cost abatement solutions belong to the industrial sector [12]. The findings of the McKinsey study are supported by various other studies that document the existence of profitable energy efficiency opportunities that firms fail to exploit [4, 21, 48, 50, 60]. In this paper, we examine whether energy efficiency opportunities are undiscovered "twenty-dollar bills on the ground" that firms fail to pick up despite their simultaneous benefits to the business and the environment. We focus on industrial energy efficiency projects available to firms because, as discussed above, they represent the largest unexploited area. Since these energy efficiency projects generally require capital investments by firms, we call these projects capital energy efficiency projects.

To ground our discussion, we use waste-heat recovery (WHR) as an example of such capital energy efficiency projects that are under-adopted despite large positive economic and environmental benefits. Waste heat is generated in a production process, usually by way of fuel combustion or chemical reaction, and then released into the environment even though it can still be used as an energy source [20, 143]. Waste heat from industrial processes can be found in various forms, such as hot liquid, exhaust gas, waste steam, or radiation from equipment surfaces. Waste heat can be recovered in several ways; for example, it can be cycled back for use in production processes such as preheating, or it can be used to turn turbines to generate electricity. WHR has large positive economic and environmental benefits: using electricity-generating options that recycle waste heat provides a savings of \$5-\$50 per ton to avoid CO_2 emissions. Thus, 25 gigatons of CO_2 over the next 50 years can be eliminated using WHR with savings to society of \$200 to \$700 billion [33]. Despite the economic and environmental benefits of WHR, evidence suggests that many firms do not implement WHR when it is feasible and profitable. In a 2008 survey of companies in Arkansas, only 23% of firms with self-identified potential for combined heat and power, a common power-generation application of WHR, have followed through with concrete initiatives [111].

Our field work indicated that the capital budgeting process is a significant obstacle for implementing capital energy efficiency projects. To understand how capital energy efficiency projects fare in this process, we study decision-making in the capital budgeting process. For fair comparison, we concentrate on the scenario in which the energy efficiency project is competing for capital with other projects of the same project category and economic benefits (i.e., returns).

We show that a critical decision-making step occurs before the eventual project selection by the senior management team: the decision by the operating manager to invest effort in finding out about the project's outcome to perform due diligence for the project. Because energy efficiency projects often fall outside the core capabilities of the firm and thus impose a higher cost of effort on the manager, these projects are systematically under-proposed, leading to under-adoption. The key insight is that even if the economic benefit (i.e., return) of the project does not prevent it from being implemented, the lack of expertise, and thus the high due diligence cost, at the operating manager level prevents the project from being appropriately vetted and proposed.

This insight is critical for assessing the effectiveness of three commonly used mechanisms for encouraging energy efficiency adoption: setting an environmental goal within the firm, receiving a governmental subsidy, and partnering with a technology provider. We find that setting an environmental goal within the firm and partnering with a technology provider—mechanisms that directly overcome the manager's reluctance to invest effort in evaluating the energy efficiency project—are the most effective. Additionally, since these mechanisms affect the outcome of the capital budgeting process, we also show the impact of these mechanisms on the overall payoff of the firm.

When the firm sets an internal environmental goal, it explicitly communicates to the manager that energy efficiency projects are valued by the firm and thus will likely be selected in the capital budgeting process. The environmental goal causes projects without environmental benefits to be considered as less attractive, and increases the adoption of energy efficiency projects, even when the economic benefits of energy efficiency projects are less attractive then those of competing projects. The environmental goal induces the manager proposing an energy efficiency project to exert more effort. However, it dampens the efforts of other managers who may have otherwise proposed projects that have higher economic returns but do not advance the environmental goal. Thus, although the environmental goal increases the implementation of energy efficiency projects, it comes at a cost — the opportunity cost of not implementing other projects and the cost resulting from the other managers' disincentive to exert effort.

Subsidies that increase the economic benefits of energy efficiency projects (e.g., carbon credits from Kyoto Protocol's Clean Development Mechanism or sustainable source credits from generating electricity using recovered energy like waste heat) work indirectly through the project's higher economic benefit (i.e., project return) to induce the manager to exert effort. We find that energy efficiency project adoption increased only if these subsidies exceed a threshold level. Moreover, the threshold depends not only on the return of the project, but also on the manager's cost of effort and the other projects competing in the capital budgeting cycle. Our results further complicate the already murky assessment of *additionality*. A project meets the additionality criterion if it would not have been implemented without the subsidy. This is problematic because many of the factors that determine whether an energy efficiency project meets the additionality criterion are unobservable to the regulator. Moreover, these factors differ across firms and across different capital planning cycles. These results suggest that a more effective form of subsidies is one that directly overcomes the high due diligence cost incurred by operations managers, such as subsidies related to free energy audits, which provide free expertise in energy audits.

Another mechanism for increasing energy efficiency project adoption is for the host firm to partner with a specialized technology provider to evaluate and implement energy efficiency projects. The technology provider can benefit from learning effects over several similar projects. The host firm increases its operational scope by bringing in third-party expertise. Although this solves the capability issue, the firm must coordinate with another organization that will be operating within its facility. A critical issue is how the gains from energy efficiency should be split between the host firm and the technology provider. We find that there is a non-monotonic effect: if the host firm captures too few gains, the project would not be profitable, however, if it were to capture too much, that would dampen the technology provider's effort level.

Although our model and results aim to explain the under-adoption of capital energy efficiency projects, the insights from this work can also be applied to explain the under-adoption of other knowledge-based process improvement projects such as new investments in process technologies like automation and lean manufacturing [30, 31, 70]. Similarly, mechanisms to promote adoption, such as subsidies and firm-level environmental goals, can be modified to increase adoption of other knowledge-based process improvement projects.

The chapter is structured as follows. Section 2.1 is the literature review. In Section 2.2, we illustrate the capital budgeting process used as the basis for our analysis. In Section 2.3, we present the central model, and in Section 2.4 we analyze the project adoption decisions in light of this model. In Section 2.5, we consider three mechanisms for increasing implementation of energy efficiency projects. We discuss some extended results and the generalizability of our work in Section 2.6, and conclude in Section 2.7. All proofs are in Appendix A.

2.1 Literature Review

This paper builds on and contributes to two main streams of literature: (1) literature on the *efficiency gap* between the optimal and the actual levels of adoption of energy efficiency projects [79], as evidenced by profitable energy efficiency opportunities that are left unexploited [4, 21, 48, 50, 60], and (2) literature on the capital budgeting process. Our paper also builds upon the literature on energy service companies (ESCOs) and managing knowledge-based process improvement projects.

A significant body of work has examined the efficiency gap at the market level, and its causes have been attributed to both market and non-market failures. Several studies focus on identifying and quantifying the costs of the efficiency gap [77, 81, 94], identifying appropriate rates of returns for energy efficiency projects [135], policy intervention [62, 63, 79], and modeling individuals' and firms' interactions with the market in the decision to adopt energy efficiency technologies [78, 80]. Reviews of this literature can be found in Jaffe and Stavins [79, 80], Gillingham et al. [62], and Brown [21].

Some of these studies focus on similar mechanisms to ours in explaining the under-adoption of energy efficiency projects, such as misaligned incentives, the unobserved cost of learning about energy efficiency improvement options, and uncertainty in the payback [80]. However, whereas those studies apply these mechanisms at the market level, we apply them at the intra-organizational level, which allows us to investigate how these mechanisms affect the probability that firms will implement energy efficiency projects through the capital budgeting process.

A number of conceptual and empirical studies have also analyzed the efficiency gap at the organizational level. In particular, they examined organizational and behavioral barriers to energy efficiency adoption, including bounded rationality, moral hazard [48], low visibility and strategic priority of these projects [49, 121], the lack of internal operations management processes for these projects [1], and the low priority of these projects within the capital budgeting process [49, 119]. Related studies demonstrated that adoption of energy efficiency projects is more likely when they appear earlier in the list of recommendations, need lower managerial effort [105], and when their benefits are communicated in terms of loss of profit associated with failure to adopt these initiatives [106]. In a broader context of selecting R&D and process improvement projects, it has been shown that there is a gap between technically optimal and actual selection outcomes [71, 72]. Underfunding of process improvement projects despite positive returns has been attributed to organizational priority and resource allocation processes that favor product development projects over process development projects [30, 31, 70].

Those studies, like ours, focus on organizational barriers to project adoption, and some have also explored the capital budgeting process as a cause for under-adoption. However, to the best of our knowledge, our work is the first to examine how project characteristics, the decision-making process of operating managers in the capital-budgeting process, and organizational priorities work together to affect the firm's decision to adopt energy efficiency projects.

Our work builds upon and contributes to the literature on the capital budgeting process and, in particular, the relationship between the capital budgeting process and the manager's effort level. Lederer and Raith [88] also examines the selection of projects in the capital budgeting process. However, they focus on how the project's risk affects the manager's unobserved effort level after project investment, whereas we focus on how the cost of due diligence affects the manager's effort prior to proposing a project to senior management. Our extensive conversations with industry managers about the capital budgeting process also revealed that the process combines structured optimization—i.e., variants of linear and integer programming in corporate finance [19]—and a political process [17], which our study incorporated.

Our discussion of partnerships with technology providers builds upon the concept of energy service companies (ESCOs) [15, 46, 152, 153] and contributes to this literature by providing a modeling framework to illustrate how ESCOs can increase the adoption of capital energy efficiency projects. Our discussion of partnerships with technology providers also builds upon the literature on managing knowledge-based process improvement projects [e.g., 30, 31] and contributes to this literature by providing an alternative model of how external knowledge accumulates and is leveraged to enable adoption of process improvement projects.

2.2 Capital Budgeting Process

Although technical solutions for energy efficiency projects are often available and their environmental benefits often documented, our field work and findings from several surveys indicate that organizational barriers often prevent adoption of capital energy efficiency projects. In particular, these projects are often stymied in the firm's capital budgeting process [32, 111]. In this section, we describe the capital budgeting process used as a basis for our model development. This process is derived from formal text and from extensive conversations with industry managers.

The objective of the capital budgeting process is to allocate capital resources to projects that operationalize the firm's business strategy. It is a complex interaction between operating managers and senior management. There are three key components in the capital budgeting process: the project characteristics, senior management's decision criteria (i.e., the objective), and the operating manager's decision criteria.

Project characteristics. A project is evaluated based on its category and its economic benefit. There are several different project categories [17, 19, 73], and energy efficiency projects are generally considered to be *strategic* projects for new products and platforms, or *cost-reduction* projects, which include upgrading equipment or process improvement to enhance the performance of existing operations[1]. A project's economic benefit (i.e., project return) is represented by its net present value (NPV).

Senior management's decision criteria. Senior management selects the combination of projects that maximizes the sum of NPVs, keeping in mind the total budget for the planning cycle and the project categories. Because of their upside potential, strategic projects are often given priority over cost-reduction projects. Projects within the same category are compared.

Operating manager's decision criteria. A critical decision-making stage occurs before senior management can decide which projects to implement: a manager at the operating level must decide to champion the project by proposing it to senior management. It requires due diligence effort to obtain more information about the project's NPV and, for a project the manager actually proposes, significant political capital to guide a project through the capital budgeting process. In fact, because the effort required is quite high, managers typically do not propose projects unless they are fairly certain they will be implemented [32, 87]. Because the financial criteria are quite clear, and because there is typically a significant amount of information flowing informally

[1]Other project categories are *compliance* projects, which are required by law (e.g., EPA or OSHA regulations), *continuing operations*, which are replacements of equipment to maintain current operations and are often mandatory, and *capacity expansion* of existing business.

throughout the firm, the manager can usually assess which projects are more likely to be implemented [17].

In the model and analysis of energy efficiency project adoption that follows, we focus on comparing capital energy efficiency projects to other projects which (1) have the same economic benefits (NPVs) and (2) are in the same project category. Although capital energy efficiency projects may also face barriers to adoption due to a less attractive NPV profile or due to the nature of the project category they fall under—which we cover in Section 2.6—the analysis below shows that capital energy efficiency projects are under-adopted even when they are not at a disadvantage in terms of economic benefits.

2.3 Model

We use a stylized model to represent a firm's capital budgeting process. There are two managers, $i = 1, 2$, each of whom can propose a capital project to the senior management team. The senior management team selects which project(s) to implement, possibly choosing one, both, or neither project. The ex-ante *outcome* of project i is a high (H) payoff $r_i > 0$ with probability $\frac{1}{2}$, and a low (L) payoff $-k_i < 0$ with probability $\frac{1}{2}$, where $k_i > r_i$. These outcomes can be interpreted as possible NPVs (i.e., economic benefits or returns) of the project under different operating or market conditions. The uncertainty of the outcome reflects the managers' incomplete information about technology performance and future market conditions. For example, the outcome of a WHR project depends on the amount and quality of waste heat that is available, the long-term operational outlook of the plant, and—if the recovered waste heat is used for electricity generation—the projected price of electricity. This is information that should be uncovered during the due diligence process for assessing the project.

Managers' effort. Each manager performs a due diligence process on his or her project before deciding whether to propose it. In performing due diligence, manager i can exert effort $e_i \in [0, 1]$ to obtain better information on which outcome is more likely. This effort could be in the form of dedicating headcount to a project or engaging a consultant. The information obtained is captured in a signal θ_i, which has an ex-ante probability of being high (h) or low (l) with equal probability. The informativeness of the signal depends on the manager's effort level:

$$\Pr(\theta_i = h|H, e_i) = \Pr(\theta_i = l|L, e_i) = \frac{1 + e_i}{2},$$

which implies

$$\Pr(\theta_i = h|L, e_i) = \Pr(\theta_i = l|H, e_i) = \frac{1 - e_i}{2}.$$

Using Bayes' Rule, the probability of each outcome, given signal θ_i and effort e_i, is:

$$\Pr(H|\theta_i = h, e_i) = \frac{1 + e_i}{2} \qquad \Pr(L|\theta_i = h, e_i) = \frac{1 - e_i}{2}$$
$$\Pr(L|\theta_i = l, e_i) = \frac{1 + e_i}{2} \qquad \Pr(H|\theta_i = l, e_i) = \frac{1 - e_i}{2}$$

Although higher effort results in a better signal, effort is costly. Manager i's cost of effort is $\frac{d_i e_i^2}{2}$, where $d_i > 0$ depends on the manager's know-how and the capability of the firm. We make the following assumption regarding the transparency of the cost structure, effort, and signals.

Assumption 1 *Parameters r_i, k_i, and d_i are common knowledge, and θ_i and e_i are observable by everyone, $i = 1, 2$.*

Assumption 1 is consistent with the capital budgeting process described by Bower [17] as a political process with information flowing informally throughout the organization.

Throughout the chapter, we will use π (with appropriate subscripts) to denote the payoff of the managers and Π to denote the payoff of the firm. We assume that the manager is paid a fixed salary. His reward for pursuing the project comes in the form of recognition and is proportional to the success of the project. Thus, the expected net payoff of manager i if his project is implemented depends on his effort level and the expected payoff of the project:

$$\mathbb{E}(\pi_i(e_i)|h) = \gamma\left[\left(\frac{1+e_i}{2}\right)r_i - \left(\frac{1-e_i}{2}\right)k_i\right] - \frac{d_i e_i^2}{2}, \quad (2.1)$$

$$\mathbb{E}(\pi_i(e_i)|l) = \gamma\left[\left(\frac{1-e_i}{2}\right)r_i - \left(\frac{1+e_i}{2}\right)k_i\right] - \frac{d_i e_i^2}{2}. \quad (2.2)$$

We assume without loss of generality that $\gamma = 1$. The payoff of manager i if his project is not implemented, regardless of signal θ_i, is:

$$\pi_i(e_i) = -\frac{d_i e_i^2}{2}.$$

PROJECT SELECTION BY SENIOR MANAGEMENT. If manager i's project is implemented, the expected payoff of the firm depends on the manager's effort and the revealed signal:

$$\mathbb{E}(\Pi_i|h, e_i) = \left(\frac{1+e_i}{2}\right)r_i - \left(\frac{1-e_i}{2}\right)k_i \quad (2.3)$$

$$\mathbb{E}(\Pi_i|l, e_i) = \left(\frac{1-e_i}{2}\right)r_i - \left(\frac{1+e_i}{2}\right)k_i \quad (2.4)$$

Let $\mathbb{E}\Pi_i$ be the expected payoff of the firm from project i if project i is implemented. Senior management selects among the proposed capital projects to maximize the expected payoff of the firm, subject to a capital budget of B. Let the capital cost of project i be b_i. Senior management's decision is denoted by $\mathbf{x} = (x_1, x_2)$, where $x_i = 1$ if project i is selected by senior management for implementation and $x_i = 0$ if it is rejected. If manager i does not propose his project, $x_i = 0$ by default. Thus the senior management teams solves:

$$\max_{x_1, x_2} \mathbb{E}\Pi_1 x_1 + \mathbb{E}\Pi_2 x_2$$
$$\text{subject to } b_1 x_1 + b_2 x_2 \leq B$$
$$x_1, x_2 \in \{0, 1\}$$

In the case that the two projects compete for capital dollars and the two projects give the same positive expected payoff to the firm, we assume a tie-breaking rule where senior management randomizes between the projects with equal probability.

Timing of the game. Project opportunities arise asynchronously throughout the firm's planning cycle; therefore, the managers' decisions to commit effort occur asynchronously. Thus, we model the managers as acting sequentially in their decisions to commit effort. Either manager could commit first with equal probability. The following timing assumes manager i commits effort first, $i = 1$ or 2.

1. Manager i chooses effort e_i.
2. Manager $j \neq i$ chooses effort e_j, after observing e_i.
3. Signals θ_i and θ_j are revealed, then managers i and j decide whether to propose their projects.
4. The senior management team decides to implement one of the following options: (i) no project, (ii) project 1 only, (iii) project 2 only, (iv) projects 1 and 2.

Because senior management can choose not to implement any project and receive a payoff of zero, manager i will not propose his project if the expected payoff to the firm is negative. In practice, managers will adjust their efforts as they observe each other's effort. We simplify this process by allowing each manager to choose effort only once. However, since either manager is equally likely to go first, neither manager has an ex-ante advantage because of timing. We also make the following technical assumptions to ensure that there is an interior solution for effort level (i.e., $e_i \in (0,1)$) that will give managers positive expected payoff (otherwise, managers will never exert any effort), and that managers do not gain by exerting effort $e_i > 1$.

Assumption 2 $\frac{4}{5}k < r_i < d_i < k, i = 1, 2.$

2.4 Analysis of Project Adoption Under Capital Budgeting Process

We first analyze the straightforward case. When the capital budget is big enough so that both projects can be implemented, or when the budget constraint clearly eliminates one of the two projects, each manager's effort level is independent of the other's effort. The following lemma presents the results of this case.

Lemma 1 *If $b_1 + b_2 \leq B$, the managers exert the same effort level, $e_i^* = \frac{r_i+k_i}{4d_i}$, $i = 1, 2$, and each project is implemented with probability $\frac{1}{2}$. If $b_1 \leq B$ and $b_2 > B$, manager 1 exerts effort $e_1^* = \frac{r_i+k_i}{4d_i}$ and his project is implemented with probability $\frac{1}{2}$. Manager 2 exerts zero effort and his project is never implemented.*

Since managers are not competing against each other for capital, their effort levels are independent. If the manager's capital cost is lower than the budget constraint, he chooses his effort level to maximize his payoff knowing that his project will be selected as long as his signal is high. We see from Lemma 1 that neither manager has an inherent advantage.

Henceforth, we consider the more interesting case where the two managers compete for capital dollars, i.e., $b_1 + b_2 > B$ and $b_1, b_2 \leq B$.

2.4.1 Symmetric Managers and Projects

We consider the optimal effort levels and project selection decisions in the benchmark case where managers and projects are symmetric. That is, we assume $d_1 = d_2 = d$, $r_1 = r_2 = r$, and $k_1 = k_2 = k$. We define the following functions:

$$f_i(e_i) = \frac{r_i - k_i}{8} + \left(\frac{r_i + k_i}{8}\right) e_i - \frac{d_i e_i^2}{2} \quad (2.5)$$

$$g_i(e_i) = \frac{r_i - k_i}{4} + \left(\frac{r_i + k_i}{4}\right) e_i - \frac{d_i e_i^2}{2}. \quad (2.6)$$

These functions represent manager i's expected payoff when the probability of his project being selected for implementation given e_i is, respectively, $\frac{1}{4}$ and $\frac{1}{2}$. It is straightforward to show that $f_i(e_i)$ and $g_i(e_i)$ attain their global maxima at $e^*_{f_i} \equiv \frac{r_i+k_i}{8d_i}$ and $e^*_{g_i} \equiv \frac{r_i+k_i}{4d_i}$, respectively. For each manager i, we also define e''_{g_i} to be the effort level such that $g_i(e''_{g_i}) = f_i(e^*_{f_i})$. Note that $g_i(e_i) > f_i(e_i)$ for all e_i, thus $e''_{g_i} > e^*_{g_i}$. Note also that because of Assumption 2, $g_i(1) < 0$ and thus $e''_{g_i} \in (0, 1)$. Assuming symmetric managers and projects implies $f_i(\cdot) = f_j(\cdot) = f(\cdot)$ with corresponding global optimizer $e^*_f = \frac{r+k}{8d}$, and similarly $g_i(\cdot) = g_j(\cdot) = g(\cdot)$ with corresponding global optimizer $e^*_g = \frac{r+k}{4d}$. Moreover, $e''_{g_i} = e''_{g_j} = e''_g$. Let manager $i = 1$ or 2 be the first to commit effort (i.e., be the first mover) and let manager $j \neq i$ be the second mover.

The following proposition shows that neither manager has an ex-ante advantage.

Proposition 1 *If the probability of either manager committing effort first is $\frac{1}{2}$, each manager's project is implemented with probability $\frac{3}{8}$. No project is implemented with probability $\frac{1}{4}$.*

This result arises from our assumption that each manager could move first with equal probability because project opportunities arise at random times. Thus, neither manager has an inherent advantage. However, given a particular order of effort commitment, there is second-mover advantage. The first mover manager, manager i, plays weak (low effort) because he knows that manager j can observe

i's effort and respond by increasing his own effort in order to increase the expected payoff of project j enough so it will be selected by senior management. Therefore, manager i exerts low effort because he expects his project to be selected if and only if $\theta_i = h$ and $\theta_j = l$, i.e., with probability $\frac{1}{4}$. This is formalized in the following corollary.

Corollary 1 *Suppose manager i moves first. The optimal effort levels are $e_i^* = e_f^*$ and $e_j^* = e_g^*$. Project i is implemented with probability $\frac{1}{4}$, project j is implemented with probability $\frac{1}{2}$, and no project is implemented with probability $\frac{1}{4}$. There is a second-mover advantage.*

2.4.2 Energy Efficiency Projects and Asymmetric Costs of Effort

Evaluating or implementing an energy efficiency project requires technical expertise. Energy efficiency capital projects often fall outside the core capability or the scope of the firm. In fact, for most firms, energy production is an activity that is outsourced to a utility company. Firms typically do not have a large number of staff members, if any, who are dedicated to work on energy efficiency programs [111, 121]. Therefore, evaluating or implementing a complex energy efficiency capital project can be quite challenging and require high cost of effort from the operating manager proposing the project, simply because the firm does not have the in-house capability to do it. We henceforth assign manager 1 to be the manager with the opportunity to propose the energy efficiency project, and we assume that his cost of effort is higher than manager 2, $d_1 > d_2$. The projects are otherwise symmetric, i.e, $r_1 = r_2 = r$ and $k_1 = k_2 = k$. The following proposition shows that with higher cost of effort, the energy efficiency project is less likely to be implemented.

Proposition 2 *If $d_1 > d_2$, project 1 (energy efficiency) is implemented with probability $\frac{1}{4}$, project 2 is implemented with probability $\frac{1}{2}$, and no project is implemented with probability $\frac{1}{4}$. Compared to Proposition 1, when the cost of effort is symmetric, the energy efficiency project is less likely to be implemented and project 2 is more likely to be implemented.*

One of two cases could occur. If manager 1 (energy efficiency) moves first, "first-mover disadvantage" (Corollary 1) causes a higher cost of effort and further increases his disadvantage. Therefore, the equilibrium outcome is the same as in Corollary 1. If manager 1 moves second and has a higher cost of effort, he loses his second-mover advantage, and his project is implemented with low probability $\frac{1}{4}$. However, manager 2's equilibrium effort is higher than what is presented in Corollary 1 because he needs to exert more effort to overcome manager 1's second-mover advantage. Regardless of the magnitude of manager 1's effort cost disadvantage, manager 2's project is more likely to be implemented and manager 1 always exerts low effort ($e_1^* = e_{f_1}^*$). Thus, because energy efficiency is out of the scope of manager 1's expertise, *the manager's higher cost of effort systematically puts the energy efficiency project at a disadvantage*. Even when the firm's payoff from implementing the energy efficiency project is the same as the competing project, the energy efficiency project is less likely to be implemented.

2.5 Mechanisms for Increasing Implementation of Energy Efficiency Projects

In this section, we examine three mechanisms that can increase the implementation of energy efficiency projects: (1) setting an environmental goal within the firm, (2) receiving a governmental subsidy, and (3) partnering with a technology vendor to implement a solution. We will use WHR as a specific example to ground our discussion in this section.

2.5.1 Setting an Environmental Goal within the Firm

Firms are increasingly including environmental goals as part of their strategic mission. For example, Alcoa incorporated sustainability into its strategic mission by setting a CO_2 intensity improvement goal of 30% by 2020 and 35% by 2030, using a 2005 baseline. CEMEX considers leadership in sustainable construction a key strategy—one of its goals is to reduce CO_2 emissions per ton of cement by

25% by 2015, compared to a 1990 baseline [34, 35]. We consider the impact of setting an emissions-reduction goal on the capital project selection process. In effect, another criterion is added to the senior management team's consideration at the project selection stage. This criterion is manifested as an additional constraint in senior management's optimization problem:

$$\begin{aligned}
&\max_{x_1, x_2} \mathbb{E}\Pi_1 x_1 + \mathbb{E}\Pi_2 x_2 \\
&\text{subject to} \\
&b_1 x_1 + b_2 x_2 \leq B \\
&a_1 x_1 + a_2 x_2 \geq A \\
&x_1, x_2 \in \{0, 1\},
\end{aligned}$$

where A is the emissions-reduction goal and a_i represents the emissions reduction by project i. Because the WHR project is more environmentally beneficial by nature, we have $a_1 > a_2$.

The following proposition shows that if WHR competes with a project that does not reduce emissions, the environmental goal shifts the project selection outcome to favor WHR.

Proposition 3 *If $a_1 > A > a_2$, the effort levels are $e_1^* = e_{g_1}^*$ and $e_2^* = 0$. Manager 1's project (WHR) is implemented with probability $\frac{1}{2}$ and no project is implemented with probability $\frac{1}{2}$.*

Compared to Proposition 2, setting an internal environmental goal increases the probability of implementing WHR from $\frac{1}{4}$ to $\frac{1}{2}$. When the emissions reduction goal A is set sufficiently high, the environmental goal can increase the relative attractiveness of the WHR project by eliminating the feasibility of the non-WHR project. The only reason WHR would not be selected is if it does not meet the budget constraint. However, the firm's expected payoff decreases by setting the environmental goal, as shown in the following corollary.

Corollary 2 *Compared to when there is no internal environmental goal, manager 1 (WHR) exerts higher effort, manager 2 exerts lower effort, and the expected payoff of the firm is lower. The firm's expected opportunity cost of setting an internal environmental goal is* $\frac{r-k}{8} + \frac{r+k}{8}\left(e^*_{f_1} + e''_{g_1} + e^*_{g_2} - 2e^*_{g_1}\right) > 0$.

Setting a concrete goal and directly measuring the environmental impact increases the probability of WHR implementation. Manager 1 (who proposes the WHR project) increases his effort level because he expects his project to be selected. Therefore, he increases his own expected payoff by increasing his due diligence effort. However, the firm's expected payoff decreases because imposing the emissions goal reduces the incentive of the other manager. Both managers know manager 1's project will be selected if θ_1 is high, so manager 2 reduces his effort.

To summarize, the firm achieves the objective of increasing the probability of implementing energy efficiency projects by introducing an environmental goal. Because the environmental goal can eliminate the competing non-WHR project from senior management's consideration, the WHR project can be implemented even when its economic benefit or return (e.g., its NPV or payback period) is less attractive than the competing non-WHR project, which has smaller environmental benefits. With an environmental goal, the firm decreases its expected payoff by (1) choosing an energy efficiency project that may have an inherently lower return than an alternate project unless the environmental benefits can be monetized, and (2) introducing an agency problem that reduces the losing manager's effort level. Although firms are aware of the first effect, as there can often be a tradeoff when choosing between two capital projects, our results show that firms should also consider how additional criteria such as an environmental goal could affect the organizational dynamics within the firm.

2.5.2 Subsidizing Energy Efficiency Projects

A subsidy augments the energy efficiency benefits and allows the manufacturer to monetize some of the environmental benefits created by recovering waste heat.

The regulator can subsidize energy efficiency projects in a number of ways. A subsidy for WHR could be in the form of carbon emission avoidance credits or Renewable Energy Certificates (RECs), which are traded on a per kilowatt-hour basis [74, 146]. We study how a subsidy that increases the return of WHR projects affects the capital project selection process. Without the subsidy, the return of project 1 is the same as the return of project 2, i.e., $r_1 = r_2 = r$, as assumed in previous sections. With a subsidy, let the return of project 1 (WHR) be higher than project 2, i.e., $r_1 > r_2 = r$. We assume as before that $d_1 > d_2$ and that the subsidies do not affect the capital requirement of the project. We also assume that Assumption 2 is still satisfied after the subsidy is applied.

The following proposition shows that the subsidy needs to be higher than a threshold level in order to increase the probability of WHR implementation.

Proposition 4 *There exists* $\hat{r}_1 > r_2$ *such that for* $r_1 > \hat{r}_1$*, the probability that WHR is implemented increases from* $\frac{1}{4}$ *to* $\frac{1}{2}$.

Recall from Proposition 2 that the waste heat manager has an inherent disadvantage because energy efficiency is outside the scope of his expertise, thus, his cost of effort is higher. In order to compensate for the higher cost, the return of the project must be sufficiently high. The following proposition shows that, unlike the internal environmental initiative, a subsidy increases the firm's expected payoff.

Proposition 5 *Any level of subsidy* $r_1 > r_2$ *increases the firm's expected payoff.*

It is intuitive that a subsidy helps the firm. However, combining the results of Propositions 4 and 5 implies that projects implemented in the $r_1 \in (r_2, \hat{r}_1)$ payoff range would have been implemented even without the subsidy. Therefore, the subsidy dollars increase the expected payoff of the firm, but do not change the firm's decision-making outcome to increase the probability of WHR. This result has significant implications for the carbon credit *additionality* debate. The additionality criteria stipulates that carbon credits should only be given for projects that would otherwise not have been implemented. The result shows that subsidy dollars would be given to projects that do not meet the additionally criterion. Moreover, since $\hat{r}_1$ depends on r_2, d_1, and d_2, the threshold level of the subsidy depends on the costs of effort of the managers and the characteristics of the competing project—all are dimensions that are opaque to the regulator. The firm could use this information asymmetry to its advantage to claim additionality, or the regulator could refuse to acknowledge a legitimate organizational hurdle to implementing WHR projects.

Although the firm's expected payoff is always higher with a subsidy, the firm's expected payoff does not monotonically increase in r_1. Specifically, there is a step decrease in the expected payoff of the firm at $r_1 = \hat{r}_1$.

Corollary 3 *There exist $r_1' < \hat{r}_1$ and $r_1'' > \hat{r}_1$ such that the firm's expected payoff when $r_1 = r_1'$ is greater than its payoff when $r_1 = r_1''$.*

When $r_1 > \hat{r}_1$, the outcome of the capital budgeting process changes in favor of the WHR project. When r_1 is just above $\hat{r}_1$, manager 2 reduces his effort relative to when r_1 is just below $\hat{r}_1$ because he knows it is unlikely his project will be implemented, but manager 1 increases his effort because his project is more likely to be implemented. However, manager 1 exerts a lower effort level as the winning manager than manager 2—this is the main driver of the decrease in the firm's expected payoff at $r_1 = \hat{r}_1$. Manager 1's optimal effort level is sufficiently lower than manager 2's optimal effort level even when weighted by a higher subsidized payoff, the expected payoff of the firm is still lower when manager 1 wins. For $r_1 \neq \hat{r}_1$, the expected payoff of the firm increases in r_1. The effect of a subsidy on the firm's expected payoff is illustrated in the following numerical example (Figure 2.5.3).

Numerical Example. The following numerical example illustrates the effect of a subsidy on the managers' effort levels and the firm's expected payoff. Let

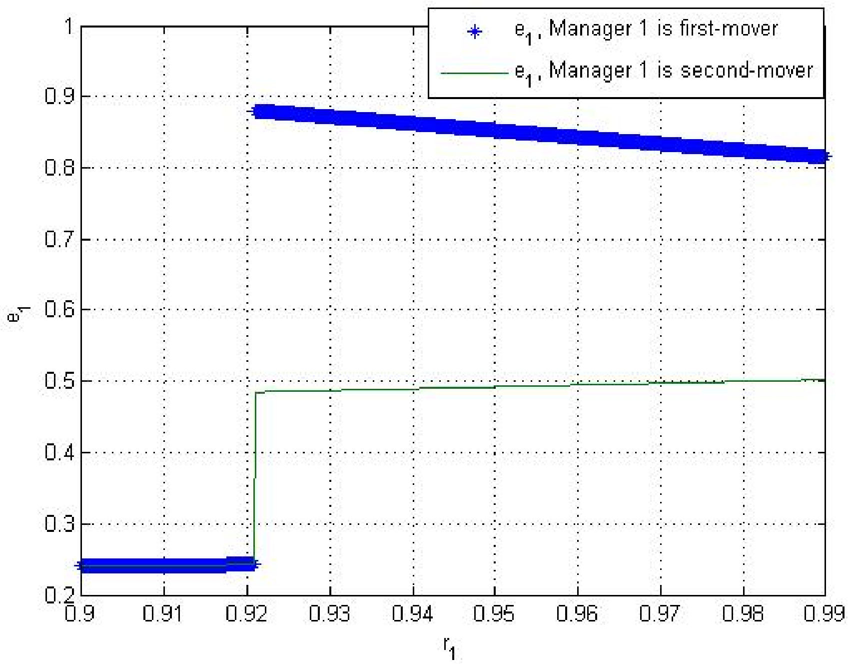

Figure 2.5.1: *Optimal effort levels of manager 1 (WHR) as a function of subsidy levels* $r_1 \in (r_2, d_1) = (0.90, 0.99)$, $k = 1$, $r_2 = 0.90$, $d_1 = 0.99$, *and* $d_2 = 0.95$. *Note that* $\hat{r}_1 = 0.921$, *the threshold subsidy level above which the probability that the energy efficiency project is implemented increases from* $\frac{1}{4}$ *to* $\frac{1}{2}$.

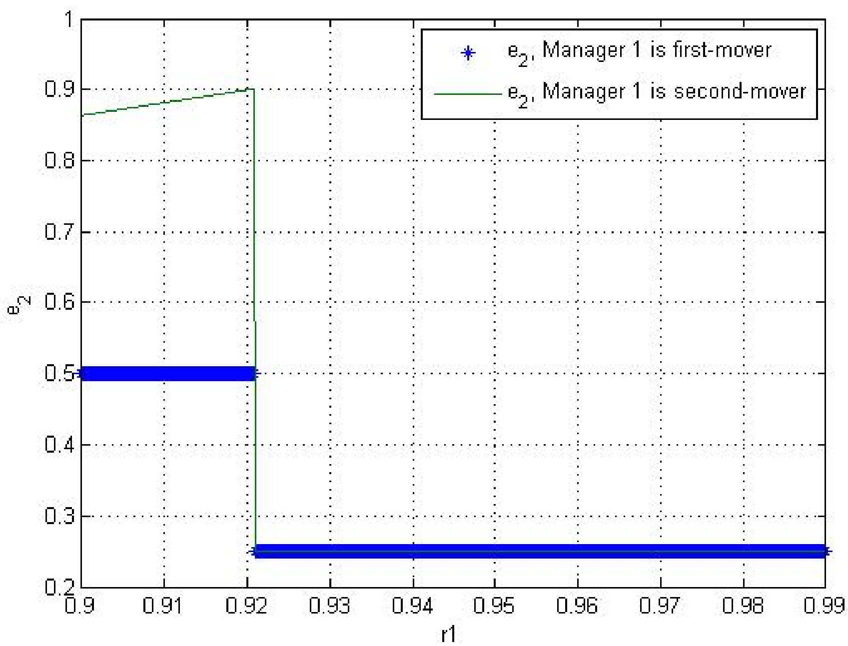

Figure 2.5.2: *Optimal effort levels of manager 2 as a function of subsidy levels* $r_1 \in (r_2, d_1) = (0.90, 0.99)$, $k = 1$, $r_2 = 0.90$, $d_1 = 0.99$, *and* $d_2 = 0.95$. *Note that* $\hat{r}_1 = 0.921$, *the threshold subsidy level above which the probability that the energy efficiency project is implemented increases from* $\frac{1}{4}$ *to* $\frac{1}{2}$.

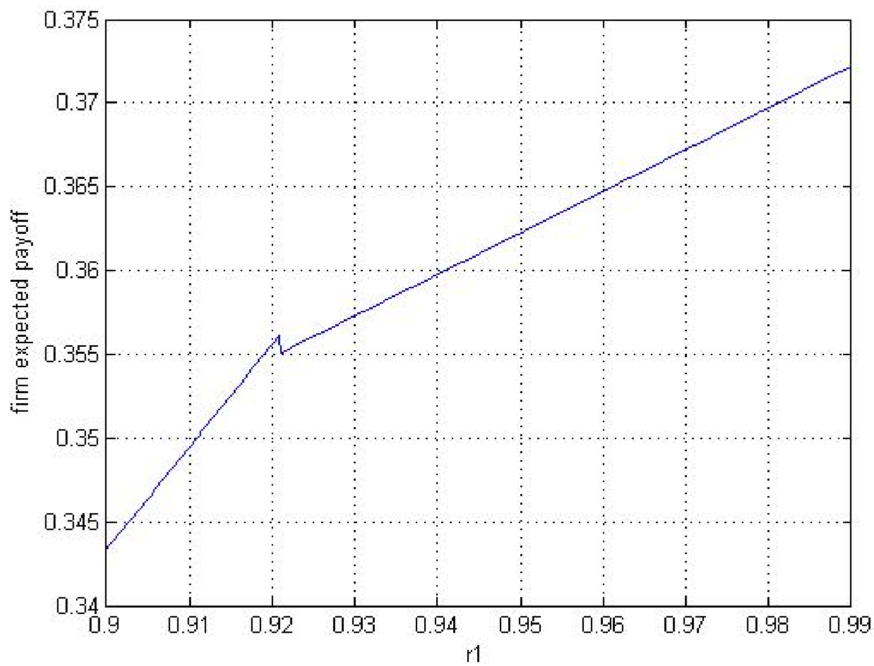

Figure 2.5.3: *Firm's payoffs as a function of subsidy levels* $r_1 \in (r_2, d_1) = (0.90, 0.99)$, $k = 1$, $r_2 = 0.9$, $d_1 = 0.99$, *and* $d_2 = 0.95$. *Note that* $\hat{r}_1 = 0.921$, *the threshold subsidy level above which the probability that the energy efficiency project is implemented increases from* $\frac{1}{4}$ *to* $\frac{1}{2}$.

$k = 1$, $r_2 = 0.9$, $d_1 = 0.99$, and $d_2 = 0.95$. The feasible range of r_1 is then $r_1 \in (r_2, d_1) = (0.90, 0.99)$. From Proposition 4, we can calculate $\hat{r}_1 = 0.921$.

If the subsidy is low (i.e., $r_1 \leq \hat{r}_1$), the subsidy does not change the project selection outcome, thus, subsidy dollars are spent on a project that would have been implemented in a business-as-usual setting. In Figure 2.5.1 (for $r_1 \leq \hat{r}_1$), we see that regardless of whether manager 1 is the first mover or second mover, his effort increases in r_1. This is because his expected payoff increases in r_1. In Figure 2.5.2 (for $r_1 \leq \hat{r}_1$), manager 2's effort increases in r_1 if manager 1 is the second mover because manager 2 needs to pre-empt manager 1 whose payoff is increasing in r_1. Thus, the subsidy increases the expected payoff of the firm (Figure 2.5.3) because both managers' effort levels increase in r_1. Therefore, *low level subsidies have the exact opposite effect of setting an internal environmental goal*: the probability of WHR being implemented does not increase, but the expected payoff of the firm does.

If and only if the subsidy is high enough (i.e., $r_1 > \hat{r}_1$) does the probability of WHR adoption increase. Manager 1, whether he is the first or second mover, increases his effort level because he knows he can change the selection outcome in his favor (Figure 2.5.1). Manager 2 also realizes this and decreases his effort in anticipation of reduced project implementation probability (Figure 2.5.2). Thus, if $r_1 > \hat{r}_1$, the subsidy increases the probability of WHR adoption. However, for $r_1 = \hat{r}_1 + \varepsilon$, the ε portion of the subsidy is above what is required to change the outcome. The expected payoff of the firm decreases at $r_1 = \hat{r}_1$ because at this threshold, manager 1 exerts a lower effort level as a winner than manager 2 does when he wins (Figure 2.5.3 and Corollary 3). For $r_1 > \hat{r}_1$, the expected payoff of the firm increases again because the expected payoff of the WHR project increases in r_1.

2.5.3 Case Study: Combining a Subsidy and an Environmental Goal to Enable WHR Adoption

From the discussion above, it is unclear whether a subsidy alone would increase the adoption of WHR, and the firm will likely incur an opportunity cost by implementing WHR purely to support an environmental goal. However, a combination of these two mechanisms has been shown to be effective. First, the existence of the subsidy highlights the importance of energy efficiency to the firm, potentially paving the way for establishing the environmental goal. Second, the potential cost of achieving the goal becomes more palpable if the firm can leverage the subsidy.

The experience of SCG Cement illustrates the process and impact of adopting WHR. It also illustrates how SCG utilized a combination of a firm-level environmental goal and a subsidy to enable WHR adoption. SCG Cement, one of five core business groups under the diversified Siam Cement Group (SCG, or SCC on the Stock Exchange of Thailand), is the largest cement company in Thailand. In 2006, SCG Cement began investing in electricity-generating WHR projects in its cement-production lines. By 2009, it had installed WHR units in all five of its cement-production facilities in Thailand (11 clinker lines) [127].

The following describes the WHR process implemented on one of the clinker lines in the Kaeng Koi production plant (see Figure 2.5.4). This clinker line produces approximately 1.8 million metric tons of clinker per year. The cement making process is highly energy intensive. The raw input material (such as limestone, shale, and light-brown stone) is ground in the raw mill, heated to 1,000°C in the pre-heater tower and the pre-calciner tower, then heated to 1,450°C in the rotary kiln to form clinker. The clinker is cooled down in the clinker cooler before being ground into cement. Prior to the installation of electricity-generating WHR units, waste heat from the kiln was used to remove moisture from the raw material in the pre-heater and the pre-calciner before it exited the pre-heater and the pre-calciner at 350°C. Part of this residual heat was then used to remove moisture from materials in the raw mill before being vented

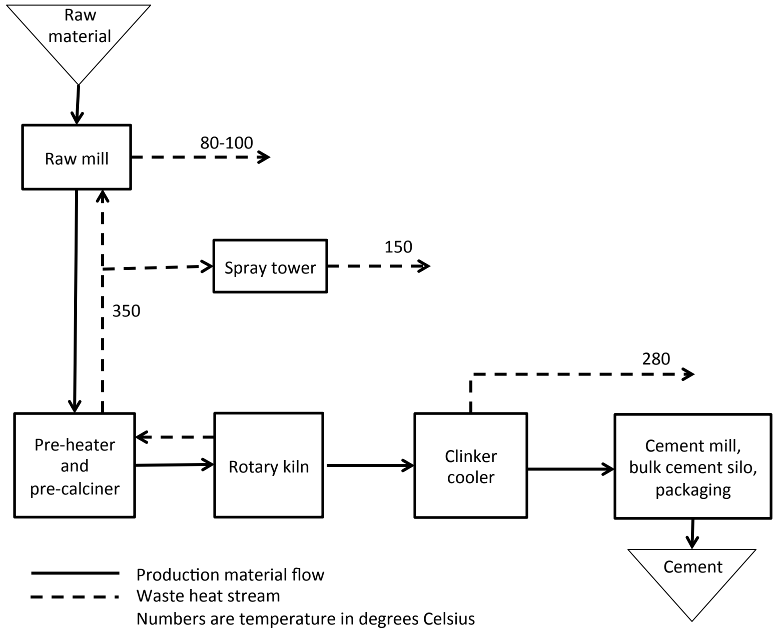

Figure 2.5.4: *Production process at SCG Cement's Kaeng Koi plant before the electricity-generating WHR implementation.*

out at 80-100°C. The remaining waste heat was cooled down to approximately 150°C using water from the spray tower in order to be safely released into the environment. The waste heat from the clinker cooler was vented out at approximately 280°C. The approximate volume of waste heat vented to the atmosphere was 350,000 normal cubic meters (Nm^3)[2] per hour.

The implementation of the WHR unit at the Kaeng Koi plant required installing two pre-heater boilers to take hot gas from the pre-heater and the pre-calciner (350,000 Nm^3 per hour) and an air-quenching cooler boiler to take hot gas from the clinker cooler (189,300 Nm^3 per hour) to generate steam (see Figure 2.5.5). The total amount of steam generated from the three boilers is approximately 51.5 tons per hour (at 7.9 bar and 319-346°C). The steam passes

[2]A normal cubic meter of a gas is the volume of that gas measured under the standard conditions of 0 degrees Celsius, and 1 atmosphere of pressure.

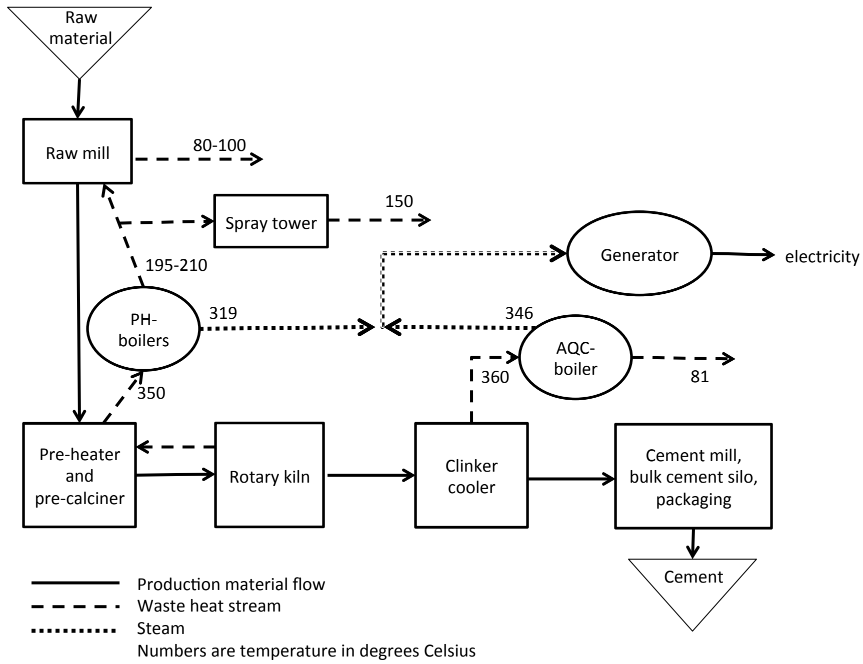

Figure 2.5.5: *Production process at SCG Cement's Kaeng Koi plant after the electricity-generating WHR implementation.*

through a turbine and a generator to create electricity, then passes through a condensing turbine to become water and is fed back to the boilers.

The installation of the WHR unit improved the overall efficiency of the cement-making process from approximately 65% to 85%. The net estimated power generation is 8.3 megawatts,[3] which generates approximately 55.3 gigawatt-hours of electricity per year. At the price of 2.40 Thai baht[4] per kilowatt-hour, this represents revenue of 132.8 million baht per year throughout its 20-year project life. Investments and costs are non-trivial, however, with an initial investment of approximately 547 million baht and annual operating and maintenance cost of 53.9 million baht [128, 134]. Together, the WHR units in 11

[3] The gross power generation is 9.1 megawatts, but the WHR process consumes 0.9 megawatts.

[4] One U.S. dollar is equivalent to approximately 30 Thai baht.

clinker lines at SCG Cement reduced power consumption from the grid by approximately 25% and mitigated CO_2 emissions by over 300,000 metric tons per year [128, 134].

It was the combination of SCG Cement's corporate environmental goal and the projected revenue from a subsidy in the form of Certified Emissions Reduction (CER) credits issued under the Clean Development Mechanism of the Kyoto Protocol that enabled the implementation of the WHR project at SCG Cement [128, 134]. Even with projected sales from CER credits, the increased return on the project was still lower than those for typical capital projects at SCG. However, because WHR supported SCG Group's corporate-wide sustainability objectives, the project was implemented despite its lower than usual return [122]. Thus, the subsidy did not cause SCG Cement to implement WHR, but it allowed the firm to partly monetize the environmental benefit created, thus reducing the opportunity cost.

2.5.4 Partnering with a Technology Provider to Implement Energy Efficiency Projects

A number of technology providers (energy service companies, or ESCOs) help manage capital-intensive energy efficiency projects. In the case of WHR, the host firm can partner with a technology provider who funds the capital investment for the WHR project, installs and operates the equipment, and splits the payoff with the host firm (either from energy cost savings or selling the electricity generated using waste heat). There are many different contractual arrangements between a host manufacturing firm and a technology provider [15, 46, 152, 153].

An example of a technology provider in WHR is Recycled Energy Development (RED) [116]. RED is one of the first, and is among the most well-known, WHR technology providers. RED provides capital investment for the WHR project (typically in the range of $5 to $50 million per project), and designs, installs, and operates WHR equipment for the host firm. Opportunities for WHR are typically identified through collaborative conversations with the host firm. RED then performs a detailed review to investigate the host firm's industry, energy types and use, and energy usage change over time to determine the profitability of the potential investment. RED makes a decision on the most profitable mix of electricity and heat to generate, taking into account tariffs, electricity prices, required investments, and local thermal needs. In a typical case, RED enters into a gains-sharing contract[5] with the host firm, where the gains include savings on energy cost and, if applicable, revenues from selling excess electricity to local utilities [20, 32]. Savings are usually calculated as the "avoided energy cost" by multiplying the power generated during a given billing period by the tariff under which the host firm is otherwise buying power from the utility. Because gains sharing is the most popular form of contract between a host firm and a technology provider [152, 153], we base our model of partnership with a technology provider on RED, which engages in this type of contract, in an approach that is typical to those of its competitors [32, 87].

By partnering with a technology provider, an energy efficiency project like WHR is no longer a capital project for the firm. Instead, the technology provider is responsible for the capital investment and the due diligence of the project, and exerts the effort to obtain information on the feasibility and profitability of the project. The technology provider chooses effort e_T to maximize its payoff, taking into account the host firm's operating characteristics. As before, we restrict the possible range of the technology provider's effort level to be $e_T \in [0, 1]$. If the signal is low, then the waste heat project is not implemented. Let α be the fraction of the project's payoff that the host firm receives, and $1 - \alpha$ be the fraction that the technology provider receives.

The advantage of using a technology provider is twofold. Firstly, a technology provider enjoys an economy of scale for its due diligence effort since it works with many firms and the due diligence performed on one project can be leveraged across $N \geq 1$ similar projects. Secondly, the technology provider's focus on its specific energy efficiency technology allows it to build capabilities through hiring and through experience over multiple projects, particularly if the

[5] Guaranteed savings is another type of contract that is used by ESCOs.

technology provider develops a portfolio of projects in a given industry. With this *learning effect* [32, 111], the cost of effort d_T required to develop technical and organizational solutions decreases with each subsequent project as the technology provider learns more about the manufacturing process and how best to implement the solution: $d_T < d$. The technology provider's expected payoff is:

$$\mathbb{E}(\pi_T(e_T)) = \frac{(1-a)N}{2}\left[\left(\frac{1+e_T}{2}\right)r_1 - \left(\frac{1-e_T}{2}\right)k_1\right] - \frac{d_T e_T^2}{2}. \qquad (2.7)$$

It is easy to show that the unconstrained optimizer of (2.7) is

$$\hat{e}_T = \frac{(1-a)N(r_1+k_1)}{4d_T}. \qquad (2.8)$$

Although the host firm does not need to provide capital, it incurs coordination cost c in order to implement and operate the WHR system. The host firm makes its decision after the signal is revealed and implements WHR if and only if the signal is high and its expected payoff is non-negative. Thus, the host firm's expected payoff if it implements the project is:

$$\mathbb{E}(\Pi|e_T) = a\left[\left(\frac{1+e_T}{2}\right)r_1 - \left(\frac{1-e_T}{2}\right)k_1\right] - c. \qquad (2.9)$$

A challenge associated with partnering with a technology provider is the negotiation of the payoff split a. The following proposition shows how WHR implementation depends on a and N. Specifically, it specifies ranges of a and N that allow the technology provider to choose his effort level to maximize his own expected payoff and also ensure that the host firm's expected payoff is positive.

Proposition 6 *For every $a \in [\frac{c}{r_1}, 1]$, there exists $\hat{N}$ such that for $N \geq \hat{N}$, the technology provider and the host firm receive positive payoff. For $a \in [0, \frac{c}{r_1})$, working with the technology provider is not feasible because the host firm's payoff is never positive. The technology provider's optimal effort level increases in N.*

It is intuitive that the technology provider's optimal effort level increases in N, and that in turn, increases the expected payoff of the firm. Proposition 6 implies that if the payoff split is in the range $\alpha \in [\frac{c}{r_1}, 1]$, as long as there are enough similar projects that the technology provider can leverage its effort across, the technology provider and the host firm can both incur positive payoff (i.e., make positive profit).

Although WHR is no longer a capital project for the firm, its implementation is still non-trivial. Notice from Proposition 6 that if the cost of coordination c is very high, it may not be feasible to implement the project. The operational complexities associated with partnering with a technology provider can contribute to high coordination cost. For example, the technology provider usually operates and maintains a workforce in the host firm's manufacturing facility thus requiring coordination in human resource policies. The technology provider and the host firm may also have different safety systems and planning horizons that must be reconciled for long-term operational planning. These operational complexities require managerial bandwidth and the establishment of clear processes and lines of responsibility, often in situations that cannot be anticipated in advance. Thus, for this type of close operating relationship to work, there must be a high level of trust between the two management teams.

The following proposition shows how the expected payoff to the host firm changes with the fraction of the gains they receive, α. We assume that the number of similar projects, N, is fixed.

Proposition 7 *If $N < \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$, for any $\alpha \in [\frac{c}{r_1}, 1]$, the host firm is indifferent between implementing and not implementing WHR, i.e., its expected payoff is zero. If $N \geq \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$, the host firm's expected payoff first increases in α, then decreases in α.*

If N is small (i.e., $N < \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$), the effort level that would maximize the technology provider's expected payoff is lower than the effort it would take to make the host firm's expected payoff non-negative. The technology provider's optimal effort is low because there are very few similar projects over which to leverage the effort. Thus, the technology provider exerts just enough effort to get the technology provider to implement the project (i.e., non-negative payoff): if a is high, the technology provider dials back the effort, and if a is low, he increases his effort—thus making the host firm's expected payoff constant at the level where the firm is indifferent between implementing and not implementing the WHR project.

If N is large (i.e., $N \geq \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$), the non-monotone effect of a on the host firm's expected payoff arises because of the tension between appropriating the gains, and providing incentive for the technology provider to exert effort. The technology provider's effort can be leveraged over many similar projects, thus he is willing to exert high effort. Therefore, for low to medium values of a, even as a increases, the technology provider still puts in high effort. The host firm's expected payoff increases in a because it gets a bigger piece of the pie *and* benefits from high effort from the technology provider. However, if a gets too big, the technology provider does not capture enough benefit, even with multiple similar projects, and his effort level drops. Even with a bigger share of the pie, the decrease in effort causes the expected payoff to the host firm to decrease. As a gets very high, the technology provider exerts just enough effort to make the firm indifferent between implementing and not implementing the project.

2.6 Discussion

In this section we discuss other barriers to energy efficiency adoption to complement the results in previous sections, explore some limitations and potential extensions, and elaborate on how our results can be applied in other contexts.

2.6.1 Other Barriers to Energy Efficiency Adoption

The above results demonstrate that capital energy efficiency projects are under-adopted even when compared with projects that have comparable economic benefits (NPV profile) and are in the same project category because of the higher due diligence costs exerted by operating managers in the two-stage capital budgeting process. These results complement the fact that capital energy efficiency projects may also face more straightforward barriers to adoption, ones due to less attractive NPV profiles or the project category under which they fall. For completion, we briefly explore these barriers.

A project's economic performance (i.e., project returns) is represented by its net present value (NPV) [19]:

$$NPV = -K + \sum_{t=1}^{T} \frac{v_t}{(1+\delta)^t}, \tag{2.10}$$

where K is the capital investment required, v_t, $t \in \{1, 2, \ldots, T\}$, is the cash flow in period t, and δ is the discount rate. The discount rate reflects the risk of the project category, which is usually evaluated relative to the firm's risk. If the project category is of average risk, the firm's cost of capital of approximately 15% is used for δ. Different categories of projects are evaluated with different discount rates. Low-risk projects in the *cost-reduction* category might be discounted at 10%, whereas projects in the *strategic* category is typically carry higher-than-average risk and would be discounted at rates higher than the company's cost of capital.

Some capital energy efficiency projects may have characteristics that lend themselves to lower NPVs. Firstly, these projects may require high initial investments. For example, the estimated capital investment to implement WHR is $10-15 million for a 4-5 megawatt system, and larger projects can cost more than $50 million [20]. Secondly, for projects that are tightly coupled to the manufacturing process such as WHR, the discount rate δ of the project is higher than the company's cost of capital because the uncertainty of the project includes both the underlying uncertainty of the manufacturer's business, and the uncertainty of the energy market.[6] Thirdly, by the nature of energy efficiency

[6] As a simple illustration, let $X \sim lnN(\mu_x, \sigma_x^2)$ be the output of the plant and $Y \sim lnN(\mu_y, \sigma_y^2)$ be the price of electricity. The output of the WHR project is then $Z = \gamma XY \sim lnN(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2 + 2\sigma_{xy})$, where γ is the kilowatt-hours per unit of output conversion. Unless X and Y

projects, the future revenue stream v_t is bounded by the output of the plant, i.e., the size of existing business. Thus, these projects typically do not provide new market or expansion opportunities.

The low NPV and the project-category consideration by senior management can hinder the adoption of capital energy efficiency projects. Energy efficiency projects are primarily considered to be in one of two possible project categories, cost reduction or strategic. The fact that future cash flow v_t is constrained by existing business makes energy efficiency projects unattractive as strategic projects since they will not create new market opportunities or ways to expand the current business. Moreover, projects in this category should be aligned with the firm's business strategy, but for many manufacturing firms, energy efficiency is not a strategic priority. Placing an energy efficiency project as a cost-reduction project may automatically reduce the likelihood of implementation. Regardless of project specifics, cost-reduction projects in general tend to rank lower in senior managements' priorities [49, 73, 121], and often require a shorter payback period [73, 111] and more stringent justifications for investment [111] than strategic projects. Moreover, compared to other cost-reduction projects, a capital energy efficiency project may be at a disadvantage because of high initial investment K and high discount rate δ, as discussed above.

2.6.2 Limitations and Extensions

Although the set-up of our model allows us to make a fair comparison between an energy efficiency project and other projects with the same economic benefits, this assumption may be restrictive. Future work can explore the idea of relaxing this assumption and allowing the tradeoff between high costs of effort and high economic benefits associated with different projects to guide managers' project proposal decisions. Also, we currently assume that there is no informational asymmetry among different operating managers and between operating managers and senior management. Future work can explore ways in which

are negatively correlated (an unlikely scenario), the variance of the WHR project Z will be higher than the variance of the output of the plant X.

informational asymmetry affects operating managers' effort levels and decisions to propose projects.

Future work can also explore alternative forms of subsidies beyond those considered in our model. We currently consider subsidies that increase the economic benefits (i.e., economic returns) of energy efficiency projects without affecting the operating managers' costs of effort. However, another popular category of subsidies is in the form of energy audit rebate programs offered by local governments. This form of subsidies directly addresses the high costs of effort required to learn about energy efficiency projects by bringing in free expertise on energy efficiency technologies, potentially reducing due diligence costs associated with energy efficiency projects. However, there is a tradeoff between the potential reduction in the due diligence cost due to acquired expertise in energy efficiency and the increase in the due diligence cost due to the operating manager's need to coordinate the audit process and share information about the firm's operations. Whether this form of subsidies can effectively reduce the operating manager's due diligence cost depends on this tradeoff.

2.6.3 Generalizability

The key insight that the high cost of effort due to lack of expertise leads to the under-adoption of energy efficiency projects also applies to contexts beyond the two-stage decision-making structure (i.e., operating manager's project proposal before senior management's decision) in the capital budgeting process. For example, in a small firm in which capital project decisions are fully centralized and made by a few key managers, the high cost of effort associated with a project that is outside the scope of the firm puts that project at a disadvantageous position. However, the two-stage decision-making structure in the capital budgeting process exacerbates the under-adoption of energy efficiency projects due to the local incentives of operating managers and the lack of visibility of these energy efficiency projects to senior management. Because of the limited number of projects each operating manager can propose, each manager has a local incentive to propose a project that will be accepted, leading to systematic under-exploration of energy efficiency projects. Also, because the choices of possible projects available to operating managers are hidden from senior management, the senior management might not be aware that energy efficiency projects are not being pursued by operating managers, and thus cannot properly devise ways to increase the adoption of these projects.

Our model and results are also generalizable beyond the context of energy efficiency. Although our model and results aim to explain the under-adoption of capital energy efficiency projects, the insights from this work can also be applied to explain the under-adoption of other knowledge-based process improvement projects that the operating manager is unfamiliar with. Examples of knowledge-based process improvement projects are investments in process technologies like automation and lean manufacturing [30, 31, 70]. The applicability of our model and results also depends on the scope of the operating manager's decision (e.g., facility-level or division-level) and on how information and expertise is managed and made available to operating managers in the firm.

2.7 Conclusion

To explore the question of whether energy efficiency projects are under-exploited by firms, we studied the firm's capital budgeting process. We found that a critical layer of decision-making at the operating manager level was a key obstacle to implementing energy efficiency projects. Because these projects often lie outside the scope of the core capabilities of the firm, the cost of effort required for performing project due diligence increases, thereby making these projects less desirable for operating managers to propose even when compared with projects of comparable nature and economic benefits. Thus, we find that the energy-efficiency "twenty-dollar bills" might be there, but it is likely that other "twenty-dollar bills" are easier to reach. Given limited chances to reach down, managers, and hence firms, reach for the easier targets.

Using WHR as a grounding example, we studied three mechanisms for increasing implementation of capital energy efficiency projects. We found that the mechanisms that directly overcome the operating manager's reluctance to propose an energy efficiency project are more effective for increasing the implementation of energy efficiency projects. One such mechanism is setting a firm-level environmental goal. Setting such a goal gives priority to the energy efficiency project and increases the probability that the project will be implemented. However, the firm's expected payoff decreases because imposing such a goal introduces an incentive misalignment problem, thus lowering overall managerial effort.

Another way to overcome the manager's reluctance is to provide a subsidy that increases the economic benefit (or returns) of the energy efficiency project. The subsidy mechanism works indirectly through the economic benefit of the project to increase energy efficiency implementation. We found that only when the subsidy is high enough does the project selection outcome shift in favor of the energy efficiency project. However, the firm's payoff always increases under the subsidy mechanism, revealing that subsidy dollars would be allocated to projects that would have been implemented even without the subsidy. Moreover, the threshold level of subsidy differs across firms and across capital planning cycles, making it difficult for the regulator to assess the appropriate subsidy level. These results suggest that a more effective form of subsidies is one that directly overcomes the high due diligence cost on operations managers, such as subsidies related to free energy audits, which provide free expertise in energy audits.

A third mechanism for increasing implementation of capital energy efficiency projects is to partner with a technology provider. The firm partners with another organization that has the necessary technological capabilities, allowing the firm to increase the scope of its own operations. However, this scope comes at the cost of coordination in the face of increased operational complexity. We show that whether the cost of coordination is worthwhile depends on how the two organizations split the gains from their partnership and how much the technology provider benefits from learning effects across multiple similar projects. The firm must tradeoff the payoff from appropriating more of the gains from the project with the benefits of incentivizing the technology provider to exert high effort.

3

Engaging Supply Chains in Climate Change

A growing number of firms are responding to climate change by attempting to mitigate greenhouse gas (GHG) emissions in their operations and supply chains. Reducing the carbon footprint of companies' operations provides an enormous opportunity. The 2,500 largest global corporations account for more than 20% of global GHG emissions, yet emissions resulting from corporate operations are typically exceeded by those associated with their supply chains [27]. There is a growing awareness of the vulnerabilities of supply chains to risks and potential costs associated with the physical and regulatory threats related to global climate change [67, 150**?**]. Suppliers are vulnerable to climate change to the extent that their business activities are likely to be adversely affected by physical changes and regulations related to climate change [76, 124]. On the upside, managing greenhouse gas emissions has also been shown to enhance brand and market value in some circumstances [75, 83]. This combination of managing risks and pursuing opportunities has led many managers to try to better understand supply chain management in conjunction with climate change.

Gathering information from suppliers about their climate change vulnerabilities and GHG emissions enables buyers to benchmark and to identify cost- and risk-reduction opportunities. In addition, information about supplier vulnerabilities to climate change can help companies make better decisions to mitigate risks associated with GHG regulation and with climate change's forecasted physical effects [148]. Information about supply chain GHG emissions is also being used by companies such as PepsiCo to develop carbon-footprint product labels, with the hope of differentiating products and increasing sales.

But such efforts by buyers are thwarted by severe data limitations because few companies report their emissions [148]. A few initiatives have recently emerged to address this data gap. One of the first large-scale requests for supply chain GHG emissions data was by Walmart, in a program launched in 2007 to assess the sustainability of its supply chain. The United States federal government followed suit in 2009, when a new presidential executive order required federal agencies to set reduction targets and track the reduction of GHG emissions, including those associated with their supply chains [110], which led to the launch in 2010 of the Federal Supplier Greenhouse Gas Emissions Inventory Pilot that is expected to run through 2013 [145]. In 2010, the U.S. Securities and Exchange Commission [149] began requiring that the financial annual reports of publicly traded companies include the business, physical, and regulatory risks posed by climate change.

Little is known about the circumstances that might encourage or deter suppliers from sharing with their buyers information about (1) their vulnerability to the physical manifestations of and regulatory responses to climate change, (2) their GHG emission levels, and (3) their GHG reduction strategies. In operations management, information sharing has been used to manage supply chain risks, but most research on information sharing in supply chains has focused on sharing operational parameters such as demand forecasts and inventory levels to mitigate supply chain disruptions [37, 89]. The scant research on the use of shared information to manage other types of risk, such as reputational damage and accidents, has largely focused on management system standards such as ISO 9001 and ISO 14001 [e.g., 41, 93, 107] and on codes of conduct governing workplace conditions [e.g., 98, 140, 163]. Despite the growing interest of managers and policymakers in addressing climate change and an emerging awareness of the potential role of supply chain management, no prior research of which we are aware has examined the conditions under which suppliers and buyers are particularly likely to coordinate efforts to address climate change. We begin to address this opportunity by theorizing circumstances in which suppliers are especially likely to share climate change information with their buyers. We focus on attributes of both the buyers seeking this information and of the suppliers being asked to provide it. We test our hypotheses using proprietary data from the Carbon Disclosure Project's (CDP) Supply Chain Program, a collaboration of multinational corporations that request information about their key suppliers' GHG emissions as well as their vulnerabilities and opportunities associated with climate change. This empirical context provides an unusual opportunity to examine how a variety of suppliers respond to a simultaneous request from various buyers.

We identify several buyer and supplier attributes associated with suppliers' decisions of whether to share climate change information with their buyers and, if so, how much. Specifically, suppliers are more likely to share this information when they face more buyers requesting it and when their buyers convey a commitment to use it in their future procurement decisions. Suppliers operating in more profitable industries or located in countries with GHG emissions regulations are also more likely to share climate change information with buyers. We find that these factors are also associated with suppliers sharing more comprehensive information, sharing key pieces of information, and sharing the requested information with the public.

We find no evidence that the GHG intensity of a supplier's industry directly affects the supplier's propensity to share climate change information, but we do find that GHG intensity moderates the influence of buyer requests on sharing such information. Suppliers in more GHG-intensive industries that do share climate change information are also especially likely to share GHG emissions data, owing perhaps to their greater likelihood of having already conducted a GHG inventory.

3.1 Literature Review

Our examination of the circumstances under which suppliers are particularly likely to share environmental information with their buyers builds on three streams of literature, as described below.

3.1.1 Organizational Adoption of Practices and Standards

Several studies have examined how buyers have sought to cascade their social and environmental values through their supply chains by pressuring suppliers to adopt particular environmental and labor management practices, codes of conduct governing working conditions, and process standards such as the ISO 14001 Environmental Management System standard. These studies found that the diffusion of such practices and standards was promoted by particular organizational, national, and supply chain characteristics. The adoption of environmental practices is more likely among suppliers that are larger, that are more environmentally aware, and that have slack resources and specialized assets [52, 90, 98]. These studies also indicate that adoption is also more likely in countries with more stringent regulations, stronger legal institutions, and regulatory requirements to disclose pollution data. Suppliers are also more willing to adopt practices advocated by buyers that provide technical assistance and training, that engage in joint problem solving, that share best practices, and with whom they have collaborative, cooperative, and longer relationships [98]. Anecdotal evidence suggests that buyers with market power can also more effectively motivate their suppliers to adopt particular management practices [10].

While a good deal is known about factors associated with suppliers adopting environmental and labor practices, it remains unclear whether these factors also apply to suppliers deciding whether to share environmental information with their buyers. The nature of the action requested of suppliers differs substantially: Buyer requests that suppliers share climate change information are based on the notion of encouraging transparency rather than demanding conformity. Whereas the costs to a supplier of adopting prescribed operational practices can often be readily forecasted, sharing climate change information involves not only measurement cost but also great uncertainty as to how the buyer will interpret and use the information. Whether the buyer files the information away or uses it to benchmark and then demand significant GHG emission reductions can impose dramatically different costs on the supplier. The challenge of such unclear benefits and costs enables us to develop novel theory and hypotheses to better understand the factors that motivate suppliers to share such information with their buyers.

3.1.2 Information Sharing in the Supply Chain

Our work also relates to studies of how buyers and suppliers can promote supply chain coordination, improve production-planning decisions, and reduce risk by sharing production parameters such as inventory levels and demand forecasts. Whereas this literature focuses on assessing the value of information sharing, designing information-sharing mechanisms, and developing optimal information-sharing strategies [e.g., 23, 37, 86, 169], several works study the circumstances that promote information sharing between supply chain partners. Greater willingness to share has been associated with firms that are particularly dependent on new products and that engage in more innovation in their organizational processes [170]. Supply chain partners are also more likely to share information the more longstanding their relationship, and the more it is characterized by trust and a shared vision, relationship-specific investments, and an agreement not to share the information with other supply chain partners [89, 95–97]. Other empirical work has focused on buyers sharing information with suppliers [123, 137].

Although this literature highlights the importance of mutual trust and cooperation, very few studies specifically motivate suppliers to share information with buyers. Moreover, the information-sharing literature has focused on operational metrics to the exclusion of increasingly important environmental and social information. Also, whereas sharing operational parameters typically involves information that one party already has available, such as inventory and demand forecasts, sharing climate change information often requires investment in areas quite outside the firm's core competency.

3.1.3 Corporate Environmental Disclosure

The literature on corporate environmental disclosure focuses on information disclosed to regulators, investors, and the public through financial and sustainability reports. Greater disclosure has been found among firms that are larger and more profitable or are more dependent on capital markets and foreign sales [43, 112, 133]. Disclosure propensity differs by industries and by region [43, 112]. Firms also tend to disclose more and higher-quality environmental information when faced with heightened scrutiny by investors [118, 133], regulators [126], and the media [22, 43].

This literature stream examines disclosure to regulators, investors, and the public, but not—to the best of our knowledge—supply chain partners. It is unclear the extent to which this literature's findings apply to suppliers' decisions to share environmental information with their buyers in a business-to-business context (rather than with consumers).

3.2 Theory and Hypotheses

Voluntary information disclosure has long been studied as an information asymmetry problem featuring adverse selection, where the agent possesses private information that is unknown to the principal [e.g., 3]. Although there are many variants of this setting, the fundamental decision by the agent is to maximize its payoff by deciding whether or not to disclose the desired information, given the expected response by the principal [151]. In this context, the supplier's decision to disclose is based on trade-offs between the costs and benefits of disclosure.

In our context, a supplier must weigh the necessary investments against the implications for its competitive position. Disclosing climate change information can require an investment to analyze how climate change and GHG regulations are likely to affect the organization, to identify all of the various sources of GHG emissions, to collect GHG emissions data, and to develop and maintain a GHG reporting system. Firms engaging in these efforts also bear the opportunity cost of the required capital and personnel time. Suppliers weigh these investments against the potential impact on their competitive position, such as whether they will be better positioned to win or retain contracts, whether these tasks can help them develop capabilities that can differentiate them from competitors, and whether responding will help them avoid penalties that might arise from not responding.

Although some of the costs are relatively easy to quantify, the newness of this context and the rapidly changing public and political views regarding climate change render other costs and benefits highly uncertain. For example, because there is no established benchmark for an acceptable level of suppliers' GHG emissions, a supplier might not know whether the information it shares will be viewed by its buyers as acceptable or unacceptable and whether sharing information will bring new business or new and costly requirements. The uncertainty about whatever carbon costs would result from GHG emissions regulations and the uncertainty over changing consumer preferences for less carbon-intensive products and services challenge suppliers to anticipate what—if any—strategic benefits might be achieved by sharing climate change information with their buyers.

We propose a framework that describes the factors that affect a supplier's perceived costs and benefits of sharing information with its buyers. We categorize these factors into two groups: characteristics of the buyer seeking the information and characteristics of the supplier from whom the information is being sought. From the buyers' side, we hypothesize that the breadth and the depth of buyer pressure will affect the suppliers' decisions whether or not to comply with buyers' requests to provide climate change information. From the suppliers' side, we hypothesize that their profitability, their vulnerability to stakeholder scrutiny, and the relative investment required for them to share information all contribute to their decision whether or not to share climate change information with buyers.

3.2.1 Characteristics of Demand for Information Sharing

Suppliers, already occupied with running their businesses, receive many information requests from buyers and other stakeholders [36]. Because gathering information to respond to such requests is costly [54], we theorize that suppliers will prioritize more salient requests and that requests acquire salience when (1) they appear to be part of a growing trend rather than idiosyncratic and (2) suppliers face buyers who appear more committed to using the shared information. In other words, we argue that suppliers will be influenced by the breadth and depth of the pressure they face from buyers.

The Breadth of Buyer Pressure. Upon receiving a buyer's request for a novel type of information, such as climate change vulnerability, suppliers face the challenge of determining whether the request is idiosyncratic or whether it signals a new social movement that represents a broad shift in attitudes and increasingly institutionalized norms [47]. While most research based on social movement theory concentrates on how activist groups use media campaigns, shareholder resolutions, strikes, and boycotts to try to pressure organizations to adopt new norms [47, 118], we assert that social movements can also be driven by organizations leveraging their procurement activities. When suppliers see the request as part of a new trend rather than idiosyncratic, they will anticipate greater benefits from sharing the information, because the cost of fulfilling the request can be seen as a smaller investment to be allocated across the current and future requests. They may also see a refusal to share the information as a risk to their legitimacy and to future orders. More buyers requesting the same information indicates greater breadth of pressure—a greater likelihood that the request is part of a trend and worth a response. We therefore propose:

> *Hypothesis 1 (H1).* Sharing climate change information with buyers is more likely when suppliers face more buyers requesting this information.

The Depth of Buyer Pressure. Research has found that buyers' mandating that their suppliers adopt particular management standards leads to the diffusion of those standards throughout the supply chain [7, 52, 53]. In our context, however, buyer requests for information are not mandates and the penalties—if any—of not responding are very unclear. Buyers requesting climate change information from their suppliers exhibit different levels of commitment to using this information. Our interviews with sustainability officers at some buyers requesting climate change information from their suppliers indicated that they had no current plans to use the information but thought that the data might eventually be useful and that seeking it was virtually costless. In another example, a Fortune 500 manufacturer that was asked to complete the CDP Supply Chain Program questionnaire was unable to find anyone at the requesting buying organization who could explain how the responses would be used [9].

Some companies have expanded their supplier scorecards to include suppliers' willingness to share GHG information, modified their standard request for proposals (RFP) to include climate change information sharing, and added sustainability language to their supplier agreements [9, 11, 154]. For example, climate change management is one of Vodafone's six "pillars" by which supplier performance is measured [154]. In another example, Dell, in requesting its suppliers to respond to the CDP Supply Chain Program questionnaire, stated: "Failure to meet these requirements can impact your [supplier] ranking and potentially diminish your ability to compete for Dell's business" [162], although, even in this case, the cautious phrasing ("can," "potentially") conveys uncertainty about how important the information really is to future procurement decisions.

Suppliers are likely to perceive more intense pressure from those buyers that do plan to use the requested information in their criteria for supplier selection (or retention) and/or as part of procurement contract terms. Indeed, our interviews indicated that buyers often found it difficult to obtain information from suppliers unless the supplier perceived the request to be relationship-critical. Conveying a commitment to use suppliers' climate change information is more likely to lead suppliers to anticipate greater benefits from sharing that information and greater costs of refusing to do so. We therefore propose:

> *Hypothesis 2A (H2A).* Suppliers are more likely to share climate change information with buyers that appear committed to using this information in future procurement decisions.

Alternatively, suppliers might be especially deterred from sharing information with buyers committed to using it. Because "appropriate" levels of climate change management attention and GHG emissions performance have yet to be well established, suppliers risk sharing information that a buyer might judge to be poor when benchmarked against other suppliers. For example, Walmart's senior director of sustainability and strategy acknowledged that the sustainability information Walmart requests from its suppliers, including GHG emissions levels and reduction targets, will "help us recognize who's leading and who's lagging" [55, p. 3]. This reasoning is supported by Verrecchia [151], who stated that a reason for withholding information when disclosure is voluntary is the uncertainty concerning the types of player involved. In our context, the uncertainty concerns both the buyer's type (how the buyer will react to the disclosed information) and the supplier's own type (how the supplier compares to other suppliers). For example, when a supplier requests a price increase due to rising energy costs, few would expect the buyer to consult the energy and climate risk management information that the supplier shared via the CDP Supply Chain Program, but this is what Imperial Tobacco Group does [27]. In addition, sharing data with buyers could lead them to ask suppliers to incur additional costs, as implied by Dell's stated intention to "work with suppliers on emissions reduction strategies once data is collected" [109]. Such concerns would make suppliers less likely to disclose climate change information to buyers that appear especially committed to using it. We therefore propose:

> *Hypothesis 2B (H2B).* Suppliers are less likely to share climate change information with buyers that appear committed to using this information in future procurement decisions.

3.2.2 Characteristics of Information Providers

Beyond buyer's attributes, a supplier's competitive and institutional context will influence its propensity to share climate change information with a buyer. We focus on the profitability of a supplier's industry, the supplier's vulnerability to scrutiny from stakeholders regarding climate change, and the extent to which the investment required for it to share climate change information is reduced through operating in a domain featuring GHG emissions regulations.

Profitability. Firms often provide their highest-quality service to attract and retain the most profitable customers. Airlines offer first-class customers special treatment, some customer call centers prioritize the most profitable customers [84], and some companies deprioritize the quality of service to their least-profitable customers [155]. Theory indicates that bouts of extremely high service quality enhance customer retention [16] and empirical research reveals high returns on investing in the loyalty of high-value customers [117]. Literature on newsvendor stocking quantities also indicates that firms maintain a higher service level for more profitable customers [114]. We argue that, in this regard, agreeing to a buyer's requests for information can be treated as high-quality service. Suppliers in highly profitable industries are more likely to agree to such requests than those in less profitable industries such as commodities, where competition is based on price rather than service. Suppliers in more profitable industries (1) face higher opportunity costs of losing buyers and thus have greater incentives to retain them and (2) are more likely to be able to afford to invest in gathering the requested information, for example, by developing a GHG inventory. We therefore propose:

> *Hypothesis 3 (H3).* Sharing climate change information with buyers is more likely among suppliers operating in more profitable industries.

Vulnerability to Stakeholder Scrutiny. Suppliers in GHG-intensive industries are more likely to face public scrutiny and pressure from nongovernmental organizations (NGOs) regarding climate change [112], and are more likely to be targeted or threatened by GHG regulations. Similarly, they are more likely to be prioritized for scrutiny by buyers and investors seeking to manage their climate change vulnerabilities and to reduce GHG emissions. Those that refuse to share climate change information are likely to be targets of even greater NGO scrutiny [132], which can increase their costs. Research has shown that firms seek to avoid the costs and risks associated with being scrutinized [126] and that sharing environmental information is one way to bolster legitimacy and alleviate scrutiny on environmental matters [108]. We therefore propose:

> *Hypothesis 4 (H4).* Sharing climate change information with buyers is more likely among suppliers operating in GHG-intensive industries.

Investment Required for Information Sharing. Different suppliers would need to make different investments in order to share information with buyers. One important factor is whether regulations already require the company to gather related information. In our context, suppliers in countries where regulations already call for at least some of the requested information or similar information will require less investment to gather and analyze the data necessary to share climate change information with their buyers. For example, suppliers already subject to regulations requiring them to identify and calculate their GHG emissions and to develop a reporting system will require little additional investment to share this information with buyers.

Even suppliers in countries where GHG regulations target companies in other industries but not their own are likely to require lower investments to calculate their GHG emissions than suppliers in unregulated countries will require. GHG emissions regulations create a market of service providers to support the development of GHG inventories in that country, so even suppliers whose GHG emissions are not regulated have superior access to such services. In addition, institutional theory predicts that regulations legitimize certain norms and preferences [125]. In our context, a country's GHG regulations legitimize (1) the management of climate change impacts and (2) being transparent about these efforts, while also lowering the cost of doing so, both of which would tend to delegitimize a supplier's refusal to disclose climate change information. We therefore propose:

> *Hypothesis 5 (H5).* Sharing climate change information with buyers is more likely among suppliers in countries with GHG emissions regulation.

3.3 Data and Measures

3.3.1 Data and Sample

We tested our hypotheses in the context of the Carbon Disclosure Project's Supply Chain Program, which involves a group of multinational corporations (buyers) interested in learning about their key suppliers' vulnerabilities to climate change, strategies to address these vulnerabilities, and GHG emission levels. Participating buyers included financial companies such as National Australia Bank, high-technology firms including Dell and IBM from the United States, consumer product firms such as France's L'Oréal and the United Kingdom's Unilever, and energy service firms such as Italy's Enel. Each buyer provided CDP with a list of the suppliers from whom it sought data. Buyers typically selected a subset of their suppliers that accounted for a significant portion of the buyer's spending [45]. CDP, a UK-based NGO that maintains the world's largest database of corporate climate change information [28], surveyed these suppliers on behalf of the buyers using an online questionnaire. Although the online questionnaire is administered through CDP, buyers also communicate directly with their suppliers to inform them about this request and to encourage them to share the information [29].

Our empirical context offers a unique opportunity to examine how suppliers in different industries around the world respond to an identical set of questions asked simultaneously by a variety of buyers. Each year, all of the suppliers surveyed received an email from CDP on the same date, explaining the online questionnaire and inviting them, on behalf of their particular buyer(s), to complete it. Each supplier, upon accessing the online questionnaire using a custom URL, immediately sees a list of its buyers that are requesting this information. Suppliers could respond privately or publicly. CDP shares private responses only with those buyers that had requested the information. (Suppliers cannot, however, instruct CDP to share their responses with only a subset of their requesting buyers.) Public responses are shared with the requesting buyers and are also posted on CDP's public website (http://www.cdproject.net).

The CDP Supply Chain Program is an extension of CDP's primary program that sends similar questionnaires to predominantly large, publicly traded companies on behalf of their institutional investors. Prior studies have examined the content of information disclosed to CDP [85] and stock market reactions to these disclosures [83]. Other studies found that companies' decisions whether or not to publicly disclose climate change information to the Investor CDP Program were associated with the company's size, environmental performance, media visibility, reliance on foreign sales, the threat of climate change regulation, and having been targeted by environment-related shareholder resolutions [100, 118, 133]. Our research differs from these studies because we examine factors related to supply chain relationships, we exploit institutional variation across firms located in many countries, and the suppliers in our sample are significantly more heterogeneous in size and include both privately held and publicly owned companies, compared to those who receive the Investor CDP questionnaire. CDP provided us with proprietary data from its Supply Chain Program surveys conducted in 2009 and 2010 on condition that we maintain the confidentiality of nonpublic information. Each year, the response deadline was July 31. For the 2009 survey, 44 buyers from 11 countries asked CDP to survey 1,402 of their suppliers in 42 countries. For the 2010 survey, these numbers grew to 57 buyers from 15 countries requesting information from 1,853 suppliers in 45 countries. We linked the CDP data to the Capital IQ and Worldscope databases and to information from the United Nations Framework Convention on Climate Change, the World Economic Forum, Trucost, and the U.S. Department of Agriculture's Economic Research Service. Of the questionnaires sent in 2009 and 2010, totaling 3,255, we were able to link the CDP data to other variables of interest for 3,226 questionnaires (99%) from 2,490 suppliers in 49 countries (the supplier's country is almost always its headquarters country); 1,376 questionnaires for 2009, and 1,850 for 2010. The geographic distribution and industry distribution of these suppliers are reported in Figures 3.3.1 and 3.3.2.

Country	Freq.	Country	Freq.
Argentina	2	Mexico	10
Australia	22	Netherlands	46
Austria	11	New Zealand	1
Belgium	15	Norway	7
Bermuda	1	Philippines	2
Brazil	251	Poland	5
Bulgaria	2	Portugal	21
Canada	44	Romania	19
China	70	Russia	2
Czech Republic	17	Singapore	15
Denmark	20	Slovenia	1
Fiji	1	South Africa	8
Finland	15	South Korea	24
France	102	Spain	352
Germany	108	Sweden	39
Greece	16	Switzerland	32
Hong Kong	17	Taiwan	103
Hungary	1	Thailand	5
India	36	Tunisia	1
Ireland	19	Turkey	9
Israel	8	United Arab Emirates	4
Italy	80	United Kingdom	478
Japan	131	United States	1,047
Lithuania	1	Venezuela	1
Malaysia	4		
		Total (company-years)	3,226

Figure 3.3.1: *Supplier locations.*

Industry	Freq.
Consumer discretionary	253
Consumer staples	213
Energy	59
Financials	98
Healthcare	67
Industrials	753
Information technology	656
Materials	527
Telecommunication services	54
Utilities	42
Unknown	504
Total (company-years)	3,226

Figure 3.3.2: *Supplier industries.*

Our unit of analysis is the supplier-year.

3.3.2 Measures

Dependent Variable. We created a dichotomous variable, *shared climate change information*, coded 1 when a supplier shared climate change information (publicly or privately) by responding to the CDP Supply Chain Program questionnaire in a given year and 0 otherwise. We created this variable based on proprietary data obtained from CDP for survey years 2009 and 2010. Of the 1,376 suppliers that were sent the questionnaire in 2009, 726 (52.8%) shared climate change information. In 2010, 995 of 1,850 surveyed suppliers (53.8%) did so. Although this measure considers even those suppliers that responded to a single question to have shared climate change information, alternative approaches to coding with different comprehensiveness thresholds yielded nearly identical results. In particular, as robustness tests, we employed four alternative approaches to coding this dichotomous variable as 1 based on whether the supplier answered at least two, at least four, at least eight, or at least

12 of 19 core survey questions.

Independent Variables. We captured the degree to which buyer requests were indicative of a social movement rather than being idiosyncratic via *number of buyer requests*—the number of buyers that asked a particular supplier to share climate change information through the CDP questionnaire in a given year. We obtained data for this measure from CDP. To reduce skew, we use the logged value in our models.

To capture the extent to which suppliers perceived their buyers to be more committed to actually using the requested information, we obtained data from CDP Supply Chain Program staff about each buyer's formal mechanism (if any) to incorporate suppliers' responses into future procurement decisions. For example, as mentioned earlier, Dell warns its suppliers that failure to respond can reduce their future business prospects [162]. We created *climate change as a buying criterion* as a dichotomous variable coded 1 for suppliers that faced at least one requesting buyer whose supplier scorecard, RFP process, or other supplier evaluation scheme incorporated responses to the CDP Supply Chain questionnaire and 0 if the supplier had no such buyer. This measure differentiates suppliers facing buyers portraying a commitment to use the requested information from suppliers whose buyers do not portray such a commitment.

Because numerous suppliers in our sample are privately held companies located around the world, we were unable to obtain firm-level profit margin data for most of the suppliers in our sample. We instead measure the profitability of each supplier's industry based on the *median profit margin* of that industry in the supplier's country. We calculated the profit margin (net income divided by sales) of all companies in the Worldscope database, which includes more than 95% of the world's publicly traded companies. Finding large variation across countries in the profit margins of companies within the same industry (four-digit Global Industry Classification Standard [GICS] code), we calculated the *median profit margin* within each industry-country dyad to capture the prevailing profitability of each supplier's industry. We chose median rather than mean to avoid contamination by outliers. We used one-year lagged values in our models, but using the average of one- and two-year lags instead yielded very similar results.

We gauge a supplier's vulnerability to climate change regulations by the GHG-intensity of its industry. Using data obtained from Trucost, we measure *industry's GHG intensity* in metric tons of GHG per million U.S. dollars of revenue in 2009 for each six-digit GICS code. We linked this to our sample based on six-digit GICS codes obtained from Capital IQ. We recoded the 569 cases for which we could not obtain these data from "missing" to "0" (after adding 1). We also included in our models a corresponding dichotomous variable coded 1 for observations for which such recoding had been conducted and 0 otherwise.

To identify whether there were climate change regulations in a supplier's country, we created a dichotomous variable, *Kyoto Annex I country*, coded 1 for suppliers in countries that were listed in the Kyoto Protocol's Annex I and that, by September 2010, had ratified, approved, accepted, or accessed the Protocol, thereby agreeing to promulgate national regulations imposing binding GHG emission limits, and coded 0 otherwise. We coded this variable based on data obtained from the United Nations Framework Convention on Climate Change website [144].

Control Variables. We measured whether a supplier was simultaneously asked to respond to the two other primary questionnaires that CDP administered on behalf of institutional investors and government agencies by creating two dichotomous variables: *received CDP Investor questionnaire* and *received CDP Public Procurement questionnaire*. We obtained data for these measures from CDP. Also, to account for instances in which suppliers in 2010 had also received the CDP Supply Chain Program questionnaire in 2009, we created a dichotomous variable, *received CDP Supply Chain questionnaire in previous year*, coded 1 in such instances and 0 otherwise.

We measure buyer power as each supplier's *largest buyer's revenue* (in U.S. dollars), which we obtained by combining data from CDP and Capital IQ. Because of Capital IQ's limited coverage, we could only obtain this measure for

92% of our sample (2,964 of the 3,226 supplier-year observations) and recoded missing values to 0. We also obtained data for *supplier's revenue* (in U.S. dollars) from Capital IQ, but only for 36% of our sample (1,163 of 3,226 supplier-year observations). We recoded the missing values to 0. In our models, we used one-year lagged values of both variables and logged each of them (after adding 1) to reduce skew. We also included in our models corresponding dichotomous variables coded 1 to denote observations for which recoding-to-zero had been conducted and coded 0 otherwise.

Our model controls for several country-level factors. We measure *country's environmental governance* in each supplier's country based on executives' perceptions of (1) that country's pollution levels, (2) the extent to which environmental challenges negatively impact business operations in that country, and (3) the stringency of that country's environmental regulations and enforcement. We obtained these data from the World Economic Forum's annual Executive Opinion Surveys, in which executives scored each of these dimensions using a seven-point Likert scale ranging from 1 for "extremely weak" to 7 for "extremely strong—the best in the world." Because this set of questions changed slightly during our sample period, we calculated annual country averages (rather than relying on factor-analysis scores) to avoid having our measure be overly dependent on our particular sample [156]. In our models, we use responses lagged one year to capture the circumstances prevailing when the CDP questionnaire was administered.

We measure activist pressure and scrutiny as *environmental NGOs per million population*, which reflects the number of the International Union for Conservation of Nature (IUCN) member organizations (in 2004) per million population (in 2003). IUCN is an international environmental organization whose members include the most significant international environmental NGOs, such as Conservation International, the National Geographic Society, and the Sierra Club. This ratio, which we obtained from Esty et al. [59], has been used for similar purposes by others [e.g., 68]. To reduce skew, we logged this variable after adding 1.

We also obtained data for *country's per capita GDP* in real 2005 U.S. dollars from the U.S. Department of Agriculture's Economic Research Service. We logged this variable to reduce skew and used one-year lagged values.

We control for the potential for management decisions to be influenced by industry norms and trends [102, 118]. We created a set of supplier *industry dummies* based on their two-digit GICS codes, using information from Capital IQ whenever available or else from supplier responses to CDP. The industry dummies also control for potential measurement error issues, such as the possibility that there are unobserved buyer requests that are not managed through CDP and the number of which varies by industry. Our industry dummies had to be fairly coarse to afford ample variation of our hypothesized industry measures (GHG intensity and profit margins) within these categories. We created an *unknown industry* dummy to denote the 506 observations for which we could not obtain industry information from either of our sources. Although industry dummies control for time-invariant industry characteristics, managers might interpret the number of CDP Supply Chain requests they receive in light of industry trends. We therefore also control for the log (after adding 1) of *mean buyer requests* each year within each supplier's industry (two-digit GICS code). We also performed a robustness test using the unlogged version of this variable, which yielded largely similar results.

Figures 3.3.3 and 3.3.4 report summary statistics and correlations for all of these variables. The distribution of industries are reported in Figure 3.3.2.

3.4 Method and Results

3.4.1 Model Specification

We test our hypotheses by estimating the following model:

$$Y_{ijct} = F(\beta_1 \mathbf{X}_{ijct} + \beta_2 \gamma_{it} + \beta_3 \varphi_{ct} + \beta_4 \eta_j + \beta_5 \tau_t + \beta_6 \mu_{jt} + \nu_{ijct}),$$

Variable	Mean	SD	Min	Max
Shared climate change information	0.53	0.50	0	1
Number of questions answered (out of 19)	7.95	7.84	0	19
Number of buyer requests	1.31	0.92	1	10
Number of buyer requests (log)	0.16	0.40	0	2.30
Climate change as a buying criterion	0.41	0.49	0	1
Median profit margin by industry-country (%) §	0.01	0.07	-0.48	0.55
Industry's GHG intensity	240.60	468.99	0	6433.14
Industry's GHG intensity (log)	3.98	2.21	0	8.77
Kyoto Annex I country	0.50	0.50	0	1
Mean buyer requests per industry-year	1.31	0.23	1	1.67
Mean buyer requests per industry-year (log)	0.83	0.10	0.69	0.98
Received CDP Investor questionnaire	0.21	0.41	0	1
Received CDP Public Procurement questionnaire	0.05	0.22	0	1
Received CDP Supply Chain questionnaire in previous year	0.24	0.43	0	1
Largest buyer's revenue (million USD) §	32842.11	26475.76	0	122748.50
Largest buyer's revenue (USD) (log) §	22.03	6.61	0	25.53
Supplier's revenue (million USD) §	5282.88	21684.17	0	458361.00
Supplier's revenue (USD) (log) §	7.88	10.60	0	26.85
Country's environmental governance §	4.84	0.56	0	6.24
County's environmental NGOs per million population	0.49	0.41	0	3.65
County's environmental NGOs per million population (log)	0.37	0.26	0	1.54
Country's per capita GDP (real 2005 USD) §	32538.47	12945.12	850.28	68544.08
Country's per capita GDP (real 2005 USD) (log) §	10.20	0.79	6.75	11.14
Year 2010 dummy	0.57	0.49	0	1

Note: N = 3,226 company-year observations from 2,490 companies in 49 countries. § denotes variables lagged one year.

Figure 3.3.3: *Summary statistics.*

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Shared climate change information	1.00														
(2)	Number of buyer requests (log)	0.27	1.00													
(3)	Climate change as a buying criterion	0.32	0.28	1.00												
(4)	Median profit margin by industry-country §	0.03	-0.01	0.00	1.00											
(5)	Industry's GHG intensity (log)	0.36	0.17	0.18	0.06	1.00										
(6)	Kyoto Annex I country	-0.01	-0.05	-0.03	-0.05	-0.08	1.00									
(7)	Mean buyer requests per industry-year (log)	0.31	0.26	0.27	0.04	0.50	-0.17	1.00								
(8)	Received CDP Investor questionnaire	0.27	0.40	0.17	-0.03	0.21	0.05	0.18	1.00							
(9)	Received CDP Public Procurement questionnaire	0.18	0.25	0.12	0.03	0.04	0.14	-0.01	0.23	1.00						
(10)	Received CDP Supply Chain questionnaire in previous year	0.25	0.26	0.26	-0.04	0.19	-0.06	0.27	0.18	0.14	1.00					
(11)	Largest buyer's revenue (log) §	-0.05	0.15	-0.04	0.00	-0.12	0.15	-0.09	0.03	0.05	-0.09	1.00				
(12)	Supplier's revenue (log) §	0.28	0.37	0.24	-0.03	0.25	-0.05	0.25	0.68	0.18	0.20	-0.02	1.00			
(13)	Country's environmental governance §	0.16	0.14	0.03	-0.13	0.24	0.20	0.14	0.23	0.07	0.07	-0.02	0.21	1.00		
(14)	Country's environmental NGOs per million population (log)	-0.05	-0.03	-0.06	-0.07	-0.08	0.74	-0.17	0.03	0.16	-0.05	0.06	-0.07	0.29	1.00	
(15)	Country's per capita GDP (log) §	0.11	0.10	0.11	-0.19	0.15	0.25	0.05	0.11	0.11	0.06	0.00	0.12	0.63	0.43	1.00
(16)	Year 2010 dummy	-0.01	0.01	0.06	-0.01	-0.02	0.02	0.08	-0.00	0.00	0.48	-0.09	-0.06	-0.17	0.04	-0.11

Notes: N = 3,226 company-year observations from 2,490 companies in 49 countries. § denotes variables lagged one year.

Figure 3.3.4: *Correlations.*

where Y_{ijct} refers to whether supplier *i* in industry *j* located in country *c shared climate change information* in year *t*. The function $F(\cdot)$ refers to the logistic function; $\mathbf{X}_{ijct}$ refers to our hypothesized variables *number of buyer requests*, *climate change as a buying criterion*, *median profit margin*, *industry's GHG intensity*, and *Kyoto Annex I country*; and v_{ijct} is the error term.

The term γ_{it} includes several control variables coded at the supplier-year level. Because repeated requests and information demands from other stakeholders can increase the propensity to share environmental information, we controlled for whether suppliers simultaneously received requests for similar information from CDP on behalf of public procurement agencies (*received CDP Public Procurement questionnaire*) and whether suppliers surveyed in 2010 had also been surveyed in 2009 (*received CDP Supply Chain questionnaire in previous year*). The term γ_{it} also includes a dichotomous variable designating whether the supplier also faced investor pressure to share climate change information, as indicated by its having also *received CDP Investor questionnaire*. Suppliers receiving these additional requests might feel increased pressure to respond and would face lower costs of responding per questionnaire because the questions are largely identical and because responses can be submitted simultaneously through CDP's online system.

Because prior studies have found suppliers to be especially likely to comply with buyers' requests to adopt environmental and labor management practices when the buyers had more market power [10, 163], γ_{it} also includes each supplier's *largest buyer's revenue* (among its requesting buyers). The term γ_{it} also includes *supplier's revenue*, because supplier size can affect environmental disclosure [43, 112, 133] and the adoption of environmental and social practices in supply chains [98, 163].

The term φ_{ct} refers to several institutional variables corresponding to the supplier's country. Because environmental disclosure is more likely among organizations subjected to heightened environmental regulatory scrutiny [126], φ_{ct} includes the supplier *country's environmental governance*. It also includes a measure of activist pressure, *environmental NGOs per million population*, because activist pressure and scrutiny have been shown to affect organizations' disclosure decisions [101]. The term φ_{ct} also includes the supplier *country's per capita GDP* because environmental preferences are sometimes viewed as a luxury good and the environmental interests of stakeholders in the supplier's country might be correlated with economic development.

Because research has shown that firms in different industries exhibit distinct environmental disclosure patterns [43, 112, 118], we include η_j to account for general differences between industries by including the set of suppliers' *industry dummies*. To account for a general increase in awareness of climate change, τ_t refers to a *year 2010* dummy variable to distinguish supplier responses to the 2010 questionnaire from responses to the 2009 questionnaire. Also, because managers might decide whether or not to share climate change information in light of industry trends, we include μ_{jt}, which captures the annual *mean buyer requests* in each supplier's industry.

3.4.2 Results

We use logistic regression to estimate our model that predicts a dichotomous dependent variable, but estimating the model as a linear probability model (using ordinary least squares regression) yields the same inferences. Because our dataset includes some suppliers that were surveyed in both 2009 and 2010, we report robust standard errors clustered by supplier, which accommodates heteroskedasticity as well as the nonindependence of these suppliers' responses over the two-year sample period.

We begin by estimating a baseline model that includes only attributes of the supplier and its institutional environment—which have been the focus of the environmental information disclosure literature so far—and omitting all supply-chain-related variables. We find that being located in a country with GHG emissions regulation ($\beta = 0.50$; $p < 0.01$) and having also received a CDP Investor questionnaire ($\beta = 0.88$; $p < 0.01$) are positive and significant predictors of suppliers sharing climate change information, but find no evidence

	Model:	(1)	(2a)	(2b)	(3a)	(3b)
	Dependent variable:	Shared climate change information			# questions answered	
	Functional form:	Logistic			Negative binomial	
	Sample:	All firms	All firms		All firms	
		Coefficients	Coefficients	AME	Coefficients	AME
H1	Number of buyer requests (log)		0.794**	0.14	0.095*	0.82
			[0.185]		[0.045]	
H2	Climate change as a buying criterion		0.840**	0.15	0.462**	4.00
			[0.103]		[0.049]	
H3	Median profit margin by industry-country §		1.453*	0.25	0.844*	7.31
			[0.698]		[0.362]	
H4	Industry's GHG intensity (log)	0.083	0.034	0.01	0.044	0.38
		[0.060]	[0.062]		[0.035]	
H5	Kyoto Annex I country	0.500**	0.459**	0.08	0.270**	2.34
		[0.144]	[0.146]		[0.069]	
	Mean buyer requests per industry-year (log)		10.815**	1.89	6.520**	56.45
			[2.397]		[1.155]	
	Received CDP Investor questionnaire	0.880**	0.733**	0.13	0.297**	2.57
		[0.184]	[0.191]		[0.075]	
	Received CDP Public Procurement questionnaire		1.455**	0.25	0.267**	2.31
			[0.337]		[0.080]	
	Received CDP Supply Chain questionnaire in previous year		0.683**	0.12	0.532**	4.61
			[0.126]		[0.053]	
	Largest buyer's revenue (log) §		0.064	0.01	-0.031	-0.27
			[0.059]		[0.030]	
	Supplier's revenue (log) §	0.066	0.026	0.00	0.021	0.18
		[0.041]	[0.039]		[0.020]	
	Country's environmental governance §	0.010	0.155	0.03	-0.047	-0.41
		[0.124]	[0.123]		[0.065]	
	Country's environmental NGOs per million population (log)	-0.925**	-0.915**	-0.16	-0.260+	-2.25
		[0.304]	[0.305]		[0.133]	
	Country's per capita GDP (log) §	0.118	-0.023	-0.00	-0.042	-0.36
		[0.081]	[0.086]		[0.049]	
	Observations	3,226	3,226		3,226	
	Companies	2,490	2,490		2,490	
	Countries	49	49		49	
	Log likelihood	-1,803	-1,667		-8,858	
	Mean dependent variable	0.53	0.53		7.95	
	McFadden's adjusted R-squared	0.18	0.24		0.04	

Notes: Brackets contain robust standard errors clustered by supplier. AME, average marginal effect. All models also include dummies for *year 2010*, industry dummy variables, and dummy variables denoting instances in which the following variables were recoded from missing to zero: *industry's GHG intensity* (N = 569), *supplier's revenue* (N = 2,063), and *country's environmental governance* (N = 4). Models 2 and 3 also include dummy variables to denote instances in which *largest buyer's revenue* (N = 262) and *median profit margin* (N = 540) were recoded from missing to zero. ** p<0.01, * p<0.05, + p<0.10. § denotes variables lagged one year.

Figure 3.4.1: *Logistic regression results.*

of a significant influence from being in an industry more vulnerable to climate change. Moreover, the supplier country's number of environmental NGOs per million population ($\beta = -0.93$; $p < 0.01$) is a negative and significant predictor of suppliers sharing climate change information.

Columns (2a) and (2b) of Figure3.4.1 report results of our primary model, with coefficients in Column (2a) and average marginal effects in Column (2b). Examining our control variables, we find that requests by CDP on behalf of other parties and previous buyer requests for climate change information made it more likely that suppliers would share that information with their buyers. Specifically, having simultaneously received a CDP Investor questionnaire ($\beta = 0.73$;

$p < 0.01$) or a CDP Public Procurement questionnaire ($\beta = 1.46$; $p < 0.01$) significantly increased suppliers' probability of sharing climate change information, as did the supplier's having received the CDP Supply Chain questionnaire in both 2009 and 2010 ($\beta = 0.68$; $p < 0.01$). The coefficient on *mean buyer requests per industry-year* is also positive and significant ($\beta = 10.82$; $p < 0.01$), signifying that an increase in the number of requests within an industry between the two years of our study increases the likelihood of a supplier responding to the questionnaire. The negative and significant coefficient on supplier *country's environmental NGOs per million population* ($\beta = -0.92$; $p < 0.01$) suggests that the higher pressure and scrutiny associated with higher NGO density leads to suppliers being less likely to respond to the questionnaire. In contrast, *largest buyer's revenue*, *supplier's revenue*, the supplier *country's environmental governance*, and the supplier *country's per capita GDP* were not significant contributors to the likelihood of a supplier sharing climate change information with its buyers.

Turning to our independent variables, the results yield support for both of our hypothesized demand-side factors. A significant positive coefficient on *number of buyer requests* ($\beta = 0.79$; $p < 0.01$) indicates that the greater the number of buyers requesting climate change information from a supplier, the more likely that supplier is to provide it, which supports *H1*. The average marginal effect indicates that a one-log-unit increase in the number of requesting buyers is associated with a 14.0-percentage-point increase in the probability of sharing climate change information. Estimating the model after substituting the unlogged number of requesting buyers for the logged value also yielded a significant positive coefficient.

The significant positive coefficient on *climate change as a buying criterion* ($\beta = 0.84$; $p < 0.01$) indicates that a buyer's apparent commitment to use its suppliers' climate change information in future procurement decisions increases, rather than decreases, the probability that suppliers will share that information. This supports *H2A* rather than *H2B*. The average marginal effect indicates that having at least one requesting buyer using climate change as a buying criterion boosts the probability of a supplier sharing that information by 15 percentage points, increasing the average predicted probability from 47.0% to 62.2%. This finding is robust to several alternatives to our dichotomous measure, including the proportion of requesting buyers using climate change as a buying criterion, the number of requests from buyers using climate change as a buying criterion, and the largest revenue of a requesting buyer using climate change as a buying criterion.

From the supplier's side, the significant and positive coefficients on *median profit margin* ($\beta = 1.45$; $p < 0.05$) and *Kyoto Annex I country* ($\beta = 0.46$; $p < 0.01$) lend support to *H3* and *H5*. Average marginal effects indicate that (1) a one-standard-deviation increase in median profit margin increases the probability that a supplier shares climate change information by 1.75 percentage points and (2) being located in a country with GHG emissions regulation increases the probability of sharing climate change information by 8 percentage points (increasing the average predicted probability from 49.5% to 57.4%).

The nonsignificant coefficient on *industry's GHG intensity* yields no support for *H4*. Exploring several alternative measures of GHG intensity, such as the log of total GHG emissions associated with each supplier's industry (based on estimates of U.S. industries obtained from the National Center for Manufacturing Sciences' Environmental Roadmapping Initiative) and a dichotomous *environmentally sensitive industries* [38, p. 643], we continued to find no evidence that suppliers in industries more vulnerable to climate change regulation were more likely to share climate change information. Finding no evidence of a direct effect of *industry's GHG intensity*, we explored whether it had an indirect effect. Additional analyses described in Appendix B revealed that buyer requests have a larger impact on the likelihood of sharing climate change information for suppliers in low-GHG-intensity industries than they do for suppliers in high-GHG-intensity industries.

Comparing results of the baseline model (column (1)) to those of the more comprehensive primary model (columns (2a) and (2b)) yields an important insight: A likelihood ratio test indicates that our primary model significantly improves the model fit compared to that of our simpler baseline model ($\chi^2 = 271$; $p < 0.01$). This implies that supply chain factors do significantly improve our understanding of a supplier's decision whether or not to share climate change information with its buyers.

Appendix B reports additional analyses that indicate that the results of our analysis are robust to additional controls, including environmental governance in buyers' countries and the market power of buyers and suppliers relative to each other. Additional analyses in Appendix B also suggest that our results are generalizable to other buyers—including those less committed to disclosing their own climate change information—and to the additional suppliers from whom the buyers did not request climate change information.

3.5 Response Comprehensiveness and Transparency

The analyses in the previous section examine a supplier's decision whether or not to share climate change information, considering such sharing to be a binary activity. In this section, we extend our analysis to explore variation in the comprehensiveness of the information shared—both in terms of the raw amount of information shared and whether key information was shared. We also identify circumstances under which suppliers share information particularly transparently by providing access to the public as well as to their buyers.

3.5.1 Response Comprehensiveness

The comprehensiveness of the information suppliers shared with buyers via the CDP Supply Chain Program differed substantially. Our dichotomous primary dependent variable, *shared climate change information*, does not differentiate between suppliers that answered every question in the questionnaire and those that answered only one. It also does not differentiate between suppliers that provided meaningful answers to core questions and those that provided uninformative responses such as "not applicable."

To better capture different levels of response comprehensiveness, we coded an alternative dependent variable: the *number of questions answered* meaningfully by the supplier. We identified 19 core questions that were asked in both the 2009 and 2010 versions of the CDP questionnaire. These include questions about the supplier's risks and opportunities associated with climate change (six questions), GHG emissions levels (five), reductions in its GHG emissions and energy usage (three), governance of climate change issues (two), and engagement in climate change issues in its own supply chain (three). For each supplier, we counted how many of these 19 questions were answered, excluding responses such as "not applicable" and those that were left blank. Among questionnaires that were at least partially completed, the median response included answers to 16 questions, with a mean of 14.9 questions. Among all questionnaires, including the 1,506 in which none of the questions were answered, the median survey included answers to 9 of the 19 questions, with a mean of 7.95 questions.

We predicted *number of questions answered*, a count dependent variable, with the same set of independent and control variables used in our primary model. We use negative binomial regression because this count variable exhibits overdispersion (with variance 61.5 and mean 7.95). As before, the unit of analysis is the supplier-year. We report standard errors clustered by supplier, so our results are robust to heteroskedasticity and to non-independence among the responses by those suppliers that responded in both 2009 and 2010.

Results from the negative binomial regression are reported in Figure 3.4.1, column (3a), with average marginal effects reported in column (3b). All of the hypothesized variables that our primary model (columns (2a) and (2b)) indicated were significant determinants of sharing climate change information were also significant determinants of response comprehensiveness. For example, average marginal effects indicate that a one-log-point increase in *number of buyer requests* increases the number of questions answered by 0.82. A one-standard-deviation increase in *median profit margin* will increase the number of questions answered by 0.51. The use of *climate change as a buying criterion* and being located in a *Kyoto Annex I country* (changes in values from 0 to 1) are associated with an average of 4.0 and 2.3 additional questions answered, respectively. These results indicate that the factors that significantly increase the likelihood of suppliers sharing climate change information with their buyers at all also predict the comprehensiveness of the information they share.

3.5.2 Sharing Key Metrics

The analyses above have explored the determinants of (1) the supplier's decision to share climate change information with its buyers and (2) the comprehensiveness of the supplier's response, but have not distinguished whether or not the shared information included the metrics of greatest interest to many buyers. Both the CDP reports and our own interviews indicate that many buyers in our sample were motivated by the ultimate objective of reducing their extended carbon footprints [25, 27]. These buyers had requested climate information to learn whether or not their suppliers had begun measuring their GHG emissions and whether they had begun planning to reduce them. For example, approximately one-third of Walmart's supplier sustainability assessment focuses on GHG emissions levels and reduction targets [157]. GHG emissions levels and trends are also among the most common environment, health, and safety metrics reported to senior management and are commonly used by stock analysts to evaluate corporate performance along environmental, social, and governance dimensions [131].

With all this in mind, we extended our analysis to explore whether the determinants we hypothesized to influence suppliers to share climate change information with their buyers also motivated them to share quantitative GHG emissions data and GHG or energy reduction targets in particular. Although the CDP questionnaire requested but did not require suppliers to include these (or any other) elements, suppliers that chose to do so demonstrated that they had invested in calculating their GHG emissions and had given some thought to reduction goals.

We created *shared reduction target* as an ordinal variable, coded 0 when a supplier did not share climate change information in a given year, 1 when it shared climate change information but not a quantitative GHG or energy reduction target, and 2 when the shared information included a quantitative GHG or energy reduction target. Among the 1,721 supplier-year observations with shared climate change information, 696 included a quantitative reduction target and 1,025 did not. Similarly, we created *shared GHG emissions data* as an ordinal variable, coded 0 when a supplier did not share climate change information in a given year, 1 when it shared climate change information but not quantitative GHG emissions data, and 2 when the shared information included quantitative GHG emissions data. Among the 1,721 supplier-year observations with shared climate change information, 1,267 included quantitative GHG emissions data and 454 did not. Our primary approach to coding this variable 2 considered only direct GHG emissions, referred to as "Scope 1" emissions in both the CDP questionnaire and the Greenhouse Gas Protocol [66], a widely used GHG reporting standard.

We predicted *shared reduction target* and *shared GHG emissions data* with the same set of independent and control variables used in our primary model (column (2a) and (2b) of Figure 3.4.1). Because both of these dependent variables are ordered variables, we used ordered logistic regression. The simplest form of ordered logistic regression is appropriate only to data that meet the proportional-odds assumption (that the relationship between any pair of outcome groups is statistically indistinguishable), which can be assessed using the Brant test. Brant tests rejected the proportional-odds assumption for the models predicting *shared reduction target* and *shared GHG emissions data*, which led us to estimate these models instead with generalized ordered logistic regression. To create the most parsimonious model, given our data, we used an iterative process to identify the partial proportional-odds model that best fit the data, relaxing the proportional-odds assumption only for those variables for which the coefficient estimates statistically varied across levels (evaluated at $\alpha = 0.05$) [165]. The iterative process described above yielded roughly 2% of observations with negative predicted probability values, which we resolved, as advised by Williams

[166], by imposing more parallel-line restrictions. Specifically, we impose the parallel-line restriction on all control variables, while continuing to relax it on all hypothesized variables. Results were very similar when we used the iterative process described above and, separately, when we relaxed the parallel-lines assumption for all variables, indicating that results are not sensitive to the particular specification of the parallel-lines assumptions. As before, our unit of analysis is the supplier-year. Because we report standard errors clustered by supplier, our results are robust to heteroskedasticity and to non-independence of the observations from those suppliers that responded in both 2009 and 2010.

Results of the generalized ordered logistic regression model predicting *shared reduction target* are reported in columns (1a)-(1c) of Figure 3.5.1. Column (1a) reports the extent to which the predictor variables shift the dependent variable from not sharing any information (*shared reduction target* equals 0) to sharing information (*shared reduction target* equals 1 or 2). Column (1b) reports the extent to which the predictor variables shift the dependent variable from not sharing a GHG reduction target (*shared reduction target* equals 0 or 1) to doing so (*shared reduction target* equals 2). Column (1c) reports Wald test statistics comparing the coefficients between columns (1a) and (1b) (when applicable). Because the results reported in column (1a) closely match (mechanically) those of our primary model (column (2a) of Figure 3.4.1), we focus here on whether and how our hypothesized variables influence suppliers' sharing of their reduction targets (column (1b)).

The positive and significant coefficients on *number of buyer requests*, *climate change as a buying criterion*, *median profit margin*, and *Kyoto Annex I country* indicate that the breadth of buyer pressure, the buyer's commitment to use shared information for future procurement decisions, the profitability of the supplier's competitive environment, and the GHG emissions regulation in the supplier's country are positively associated with sharing a GHG or energy reduction target. These results comport with those from the primary model, which predicts sharing any climate change information. Being in a *Kyoto Annex I country* has a

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Dependent variable:	Shared reduction target			Shared GHG emissions data		
Coefficients:	Response (with or without reduction target)	Response with reduction target	Wald test statistics	Response (with or without GHG emissions data)	Response with GHG emissions data	Wald test statistics
Number of buyer requests (log)	0.554**	0.638**	0.24	0.795**	0.845**	0.17
	[0.177]	[0.143]		[0.180]	[0.157]	
Climate change as a buying criterion	0.866**	0.508**	9.77**	0.797**	0.641**	4.34*
	[0.103]	[0.112]		[0.100]	[0.098]	
Median profit margin by industry-country §	1.462*	1.289+	0.06	1.139+	0.318	5.86*
	[0.662]	[0.749]		[0.640]	[0.617]	
Industry's GHG intensity (log)	0.047	0.084	0.88	0.042	0.098+	5.33*
	[0.058]	[0.062]		[0.059]	[0.059]	
Kyoto Annex I country	0.481**	0.709**	3.86*	0.395**	0.400**	0.01
	[0.140]	[0.145]		[0.135]	[0.134]	
Mean buyer requests per industry-year (log)	6.716**	6.716**	n/a	9.913**	9.913**	n/a
	[2.066]	[2.066]		[2.235]	[2.235]	
Received CDP Investor questionnaire	0.815**	0.815**	n/a	0.820**	0.820**	n/a
	[0.167]	[0.167]		[0.171]	[0.171]	
Received CDP Public Procurement questionnaire	1.360**	1.360**	n/a	1.278**	1.278**	n/a
	[0.235]	[0.235]		[0.253]	[0.253]	
Received CDP Supply Chain questionnaire in previous year	0.617**	0.617**	n/a	0.737**	0.737**	n/a
	[0.104]	[0.104]		[0.119]	[0.119]	
Largest buyer's revenue (log) §	0.094+	0.094+	n/a	0.047	0.047	n/a
	[0.052]	[0.052]		[0.055]	[0.055]	
Supplier's revenue (log) §	0.137**	0.137**	n/a	0.054	0.054	n/a
	[0.044]	[0.044]		[0.039]	[0.039]	
Country's environmental governance §	0.207+	0.207+	n/a	0.151	0.151	n/a
	[0.107]	[0.107]		[0.112]	[0.112]	
Country's environmental NGOs per million population (log)	-0.931**	-0.931**	n/a	-0.691*	-0.691*	n/a
	[0.278]	[0.278]		[0.275]	[0.275]	
Country's per capita GDP (log) §	-0.118	-0.118	n/a	-0.034	-0.034	n/a
	[0.083]	[0.083]		[0.078]	[0.078]	
Log pseudolikelihood	-2678			-2556		
McFadden's adjusted R^2	0.19			0.19		

Notes: N = 3,226 supplier-year observations from 2,490 distinct suppliers in 49 countries. Brackets contain robust standard errors clustered by supplier. "n/a" indicates the Wald test statistic is not applicable when the parallel-lines assumption is imposed and thus the compared coefficients are identical by construction. All models also include dummies for *year 2010*, industry dummies, and dummy variables to denote instances in which the following variables were recoded from missing to zero: *industry's GHG intensity* (N = 569), *largest buyer's revenue* (N = 262), *supplier's revenue* (N = 2,063), *country's environmental governance* (N = 4), and *median profit margin* (N = 540). Column (1a) reports the extent to which the predictor variables shift the dependent variable from not sharing any information to sharing information (shifting *shared reduction target* from 0 to 1 or 2) whereas column (1b) reports the extent to which the predictor variables shift the dependent variable from not sharing a reduction target to doing so (shifting *shared reduction target* from 0 or 1 to 2). Column (2a) reports the extent to which the predictor variables shift the dependent variable from not sharing any information to sharing information (shifting *shared GHG emissions data* from 0 to 1 or 2) whereas column (2b) reports the extent to which the predictor variables shift the dependent variable from not sharing GHG emissions data to doing so (shifting *shared GHG emissions data* from 0 or 1 to 2).

** p<0.01, * p<0.05, + p<0.10. § denotes variables lagged one year

Figure 3.5.1: *Generalized ordered logistic regression results.*

significantly greater impact on sharing reduction targets than on sharing any climate change information per se (a Wald test comparing this coefficient between columns (1a) and (1b), as shown in column (1c), yields $\chi^2 = 3.86$; $p < 0.05$). Suppliers in countries with GHG emission regulations were more likely to share GHG or energy reduction targets, perhaps because they were more likely to have already invested in developing a GHG emissions inventory and to have begun formulating reduction targets. In contrast, *climate change as a buying criterion* had a significantly greater impact on a supplier's decision to share climate change information than on its decision to share reduction targets (a Wald test comparing this coefficient between columns (1a) and (1b), as shown in column (1c), yields $\chi^2 = 9.77$; $p < 0.01$). This could suggest that buyers are still in the early stages of encouraging their suppliers to reveal the most critical elements for assessing and reducing the supply chain's carbon footprint.

Results for the model predicting *shared GHG emissions data* are reported in columns (2a)-(2c) of Figure 3.5.1. Column (2a) reports the extent to which the predictor variables shift the dependent variable from not sharing any climate change information (*shared GHG emissions data* equals 0) to sharing information (*shared GHG emissions data* equals 1 or 2), whereas column (2b) reports the extent to which the predictor variables shift the dependent variable from not sharing GHG emissions data (*shared GHG emissions data* equals 0 or 1) to doing so (*shared GHG emissions data* equals 2). Column (2c) shows the Wald test statistics. As above, we focus on results associated with column (2b).

The positive significant coefficients on *number of buyer requests, climate change as a buying criterion*, and *Kyoto Annex I country* comport with the results from the primary model (columns (2a) of Figure 3.4.1). Also, as with the results on *shared reduction target, climate change as a buying criterion* has a significantly stronger impact on suppliers' decisions to share climate change information per se than on sharing GHG emissions data (a Wald test comparing columns (2a) to (2b), shown in column (2c), yields $\chi^2 = 4.34$; $p < 0.05$).

Interestingly, being in a more profitable competitive environment has a significantly larger impact on suppliers' propensity to share climate change information per se than on their propensity to share GHG emissions data (a Wald test comparing this coefficient between columns (2a) and (2b), shown in column (2c), yields $\chi^2 = 5.86$; $p < 0.05$). In contrast, the GHG intensity of the supplier's industry is a significantly stronger predictor of sharing GHG emissions data than of sharing climate change information per se (a Wald test comparing this coefficient between columns (2a) and (2b), shown in column (2c), yields $\chi^2 = 5.33$; $p < 0.05$), owing perhaps to the greater likelihood that suppliers in more GHG-intensive industries had already conducted a GHG inventory.

To summarize, the prevalence of buyer requests, the commitment of buyers to use the shared climate change information in their future procurement decisions, and being in a country with GHG emissions regulation increased suppliers' propensity to share GHG emissions data and reduction targets.

3.5.3 Public Disclosure

Suppliers that choose to respond to the CDP Supply Chain Program questionnaire are given the choice of having CDP either share their climate change information only with the requesting buyers or also post the information on its public website. In analyses reported in Appendix B, we find that the same hypothesized variables that have significant positive effects on sharing climate change information in our primary model also have significant positive effects on suppliers sharing this information publicly. Moreover, both indicators of buyer pressure (*number of buyer requests* and *climate change as a buying criterion*) have a significantly greater impact on suppliers' decisions to share climate change information per se than on sharing this information publicly, perhaps due to the fear that publicly disclosed information would leak to competitors. This reveals a potential limitation of supply chain initiatives to generate publicly available data.

3.6 Discussion

Our research connects the operations management information-sharing literature to the environmental information disclosure literature more typically explored in the field of strategy. Prior research had already identified some organization-, industry-, and country-level factors associated with greater environmental information disclosure. We build on this by revealing supply chain factors, including the number of and the commitment of requesting buyers, that appear to bolster an organization's willingness to disclose information. This suggests that researchers using institutional theory to predict organizational conformity to institutional pressures should also consider supply chain influences.

Our work also extends the operations management literature on using information sharing to mitigate supply chain risk. In contrast to that literature's typical focus on mitigating "known-unknown" operational risks [129] about which supply chain members have insights on the distribution of uncertainty, we focus on a supply chain risk of greater uncertainty—climate change. Despite mounting evidence supporting the link between GHG emissions and climate change [61, 76], the extent to which suppliers are vulnerable to climate change is particularly uncertain because the physical impacts of climate change and the business effects of GHG regulation are especially difficult to predict. Our results also provide empirical evidence that suppliers' decisions on whether to share information—and if so, how much—are influenced by regulatory mandates that can reduce the costs of voluntary disclosures.

Our work also contributes insights to the literature on the diffusion of social and environmental practices through supply chains. While institutional (namely, industry and country) factors have been shown to predict the adoption of particular management practices, little research prior to ours has simultaneously examined institutional and organizational factors to predict suppliers' adoption of standards or practices promoted by buyers. While ours is not the very first study to do so, the other studies that have done so have focused on suppliers meeting buyer requests to adopt operational standards [52, 98] rather than to share information.

Our work also advances theory regarding how buyers pressure suppliers to adopt particular standards and practices. Prior studies have predicted suppliers' adoption and compliance behaviors based on transaction cost economics, market power arguments, signaling theory, and institutional theory [10, 52, 53]. By capturing the prevalence of buyer requests, we apply social movement theory to portray how firms seek to cascade practices through their supply chains. Whereas the social movement literature typically examines how activist groups use boycotts, strikes, media campaigns, and shareholder resolutions to try to catalyze changes in organizational behavior [47, 118], we explore a novel social movement tactic and instigator by examining how companies are using procurement preferences to catalyze behavioral changes in their suppliers. We also theoretically distinguish between several forms of buyer pressure: (1) the breadth of buyer pressure, indicative of a social movement, (2) the depth of buyer pressure that represents buyer intentions, and (3) market power. Our findings suggest that considering the breadth and depth of buyer pressure and not merely market power presents a more complete picture of the determinants of suppliers' adoption of practices and standards.

Our research also offers managerial insights, especially as growing awareness of climate change makes collaboration between suppliers and buyers increasingly important. For buyers, our finding that both buyer commitment and the number of buyer requests affect a supplier's likelihood of sharing information suggests that buyers can obtain more information from suppliers not only by investing in activities to convince suppliers of the importance of this information, but also by collaborating with other buyers to send this message collectively.

Understanding how the profitability and GHG-intensity of a supplier's industry influences the supplier's willingness to share climate change information is relevant to buyers and to policymakers. For a buyer, knowing better how to differentiate its efforts to encourage suppliers to respond allows it to allocate its resources more efficiently. Policymakers, increasingly interested in fostering disclosure of GHG emissions, can better gauge where to target disclosure regulations and enforcement efforts. Firms in more profitable industries are particularly likely to publicly disclose climate change information irrespective of GHG regulatory requirements, which suggests that governments can more readily rely on market-driven requests for firm-level supply chain information [e.g., 67, 110]to obtain this information from firms in more profitable industries, but that mandatory information disclosure regulations [e.g., 147] might be needed to compel disclosure by firms in less profitable industries.

There are some limitations to our work. The number of buyer requests could be subject to measurement error if suppliers in our sample receive similar buyer requests to share climate change information through channels other than CDP and if this affects their responsiveness to the frequency of requests they receive from buyers through CDP. It also remains unclear to what extent our results generalize to sharing information in the contexts of emerging social movements other than climate change and to more conventional contexts in which buyers seek supply chain data such as workplace conditions and quality management practices.

Future field research could pursue a deeper analysis of how information disclosure decisions are influenced by the particular staff function and the seniority of the staff members who issue or receive information requests. Moreover, future research could explore the role of third-party verification of the accuracy of information shared among supply chain partners and could investigate temporal dynamics that we were unable to explore in a dataset spanning only two years.

3.7 Conclusion

Suppliers are increasingly being asked to share information about their vulnerability to climate change and their strategies to reduce greenhouse gas emissions. Their responses vary widely. We theorize and empirically identify several factors associated with suppliers being especially willing to share this information with buyers, focusing on attributes of the buyers seeking this information and of the suppliers being asked to provide it. We test our hypotheses using data from the Carbon Disclosure Project's Supply Chain Program, a collaboration of multinational corporations requesting such information from thousands of suppliers in 49 countries.

We find evidence that suppliers are more likely to share this information when requests from buyers are more prevalent, when buyers appear committed to using the information, when suppliers belong to more profitable industries, and when suppliers are located in countries with greenhouse gas regulations. We find evidence that these factors also influence the comprehensiveness of the information suppliers share and their willingness to share the information publicly.

4

The Supply Chain Impact of Environmental Labeling Decisions

Environmental and sustainability concerns are becoming more crucial dimensions in consumers' choices of products and services. Exceptional environmental performance can be a significant source of competitive advantage for products and services, whereas poor performance can lead to potential loss of customers and profitability. Because products' impacts on the environment and climate change cannot be easily observed by consumers, firms endeavor to make the environmental performance of their products more discernible in order to differentiate their products and inform consumers' purchasing decisions. We use the term *environmental labeling* to refer to the means by which a product's environmental performance is made more visible to consumers through labels. Examples of environmental labels are the Carbon Trust's carbon footprint labels, the U.S. Environmental Protection Agency's Energy Star ratings for electrical appliances, and the Forest Stewardship Council (FSC) certified labels for responsibly sourced timber.

Efforts around environmental labeling also extend beyond the scope of individual firms and into the supply chain. Many large retailers, hoping to employ such environmental labels, have begun to measure and control their suppliers' environmental performance. In 2009, Walmart began to develop a *sustainability index* for products bought from its suppliers [159], and has been rolling out criteria to evaluate the sustainability of its suppliers' products since 2011 [167]. However, although its suppliers are being evaluated on these criteria, Walmart has not revealed how it intends to communicate the environmental and sustainability performance of its products to consumers [158]. In another example, Tesco pledged in 2007 to work with the Carbon Trust to put labels on 50,000 of its own-brand products. However, Tesco dropped the initiative in 2012, citing prohibitive time commitment and high costs. It plans to phase out the labels over time and is still considering alternative ways to communicate the carbon impact of its products [99]. Walmart's and Tesco's situations fairly represent the current state of affairs. Despite the increasing importance of such environmental labels and their effect on the supply chain relationship, little is known about how decisions regarding these labels affect supply chain behaviors and what information should be displayed on these labels.

In this paper, we tackle some elements of this far-reaching problem. We focus on two important questions facing a retailer looking to adopt environmental labels for its supply chain: (1) What information about its product's environmental performance should be displayed on the label, and (2) Does the environmental performance of its product depend on the party in the supply chain who decide on such environmental performance? To answer the first question, we focus on two types of environmental labels widely found in practice: information labels (e.g., the Carbon Trust's carbon footprint labels), which communicate the level of environmental performance, and seal of approval labels (e.g., the Green Seal Certification), which assert that the product has good environmental performance according to the labeling organizations' standards. The focus of our paper is the analysis of the game-theoretic models of information labels. We then analyze the scenarios in which a seal of approval label would be preferred over an information label, using the analysis of the information label models as a basis for comparison. To answer the second question, we analyze decisions about the environmental performance of a product made under three models: (1) the Supplier-Choice (SC) model, in which the supplier makes the decision on the environmental performance of the product that it supplies the retailer, (2) the Retailer-Choice (RC) model, in which the retailer chooses the environmental performance of the product for the supplier, and (3) the Benchmark (B) model, in which a vertically integrated firm chooses the environmental performance that maximizes the supply chain profit. We analyze the effect of demand uncertainty on the optimal environmental performance levels from these three models.

We show that when market demand is deterministic, the SC, RC, and B models yield identical optimal levels of environmental performance. We also show that the optimal environmental performance levels under the SC and the RC models that are identical under deterministic demand can differ in the presence of demand uncertainty. In the majority of realistic scenarios, the RC model leads to higher chosen levels of environmental performance than the SC model; thus, the retailer faces reduction in payoff when leaving environmental performance decisions to the supplier. We also expect that seal of approval labels will be more beneficial to the retailer, and thus more prevalent, in the scenarios in which (1) there is high uncertainty in the product demand, (2) the environmental performance is difficult for consumers to interpret, (3) the verification cost to acquire seal of approval labels is low, and (4) the retailer can persuade the supplier to share part of the cost to acquire the seal of approval labels.

The paper is organized as follows. In Section 4.1, we review the relevant literature. In Section 4.2, we give an overview of the game theoretic models of information labels and seal of approval labels that are used as a basis for our analyses. In Section 4.3, we analyze the results of RC, SC, and B information label models to understand the effect of demand variability on optimal levels of environmental performance from these three models and consider incentive alignment schemes. In Section 4.4, we analyze the benefits of seal of approval labels and characterize the scenarios in which they are more likely to be adopted. We discuss limitations and possible extensions in Section 4.5 and conclude in Section 4.6. All proofs are in Appendix C.

4.1 Literature Review

Our work builds upon and contributes to several streams of literature that explore additional product attributes beyond price that are desirable to end customers but are costly to provide. In particular, our work contributes to two streams of literature: (1) the economics literature on vertical differentiation of products and services and, in particular, on economic models of environmental labels, and (3) the operations management literature on price and service competition.

There is a large body of work in economics and industrial organization on vertical differentiation models, in which both price and another aspect beyond price ("quality") affect consumer demand but quality is costly to provide. Examples of these studies include various models of duopolistic price and quality competition as multistage games where qualities and prices are chosen in different stages [39, 91, 103, 104, 160, 161]. There is also a body of work in environmental economics that focuses on game theoretic models of environmental labeling decisions [e.g., 6, 40, 44], and a body of work in sustainable operations management [e.g., 44, 82, 115] which focuses on environmentally related decisions which positively affect demand but are costly to produce. These streams of research differ from ours in several ways. Firstly, both price and "quality" are choices and properties of one firm, which can be a monopolist or, in most cases, a player in a competitive setting with a segmented consumer market. As such, these studies do not touch upon supply chain interactions between the supplier and the retailer. Moreover, with the exception of Raz et al. [115], these studies do not consider stochasticity in consumer demand.

There exists a small number of studies that apply the model of price and quality competition in the vertical differentiation models to the supply chain context. For example, in a model of private labels, Gomez-Arias and Bello-Acebron [64] considered a two-stage game with two suppliers having two exogenous qualities and one common retailer. The suppliers' unit production cost is increasing with quality. In the first stage, the suppliers choose wholesale prices, and in stage 2 the retailer chooses retail prices. Craig [44] extends his model of one-firm environmental labeling decisions to include an upstream supplier. There are two main differences from our work: (1) quality is determined exogenously and thus is not part of the suppliers' or the retailers' decisions, and (2) unlike our models, which focus on *who* chooses the level of quality, these models focus on the competition between the suppliers or the supply chains.

Another stream of literature that models a costly attribute desirable to end consumers is the body of work in operations management on price and service competition. Examples of studies in this area include Bernstein and Federgruen [13, 14], Boyaci and Gallego [18], Cachon and Harker [24], Desiraju and Moorthy [56], Tsay and Agrawal [142] and Allon and Federgruen [5]. Like our study, many of these articles consider the supply chain interaction between a retailer and a supplier with stochastic demand. However, the service levels in these models are the retailer's choice. In our models, environmental performance levels are the supplier's choice. These studies also focus on the horizontal competition between retailers, which is not the current focus of our paper.

Because our models enable the supplier and the retailer to affect demand through price and environmental performance, our work also extends the inventory management literature that focuses on the integration of pricing and inventory [130] to include an additional dimension of environmental performance.

4.2 Models

We use a stylized model to represent the strategic interaction between a retailer and a supplier. The supplier produces goods and supplies them to the retailer, and the retailer purchases the goods at a wholesale price w chosen by the supplier. The primary decision variable is $x \in [0, 1]$, the *environmental performance* associated with the goods, such as reduction in carbon emissions; water, packaging, or energy usage efficiency. We normalize this variable so that $x = 0$ represents the minimum environmental performance and $x = 1$ represents the maximum meaningful environmental performance, which depends on the technology, the firm's budget, the retailer's industry, and the status quo, among others.

The unit production cost $C(x)$ incurred by the supplier is increasing and convex in the goods' environmental performance: $\frac{\partial}{\partial x}C(x) \geq 0$ and $\frac{\partial^2}{\partial x^2}C(x) \geq 0$. We focus on the unit production cost that is quadratic in x: $C(x) = c_0 + \frac{1}{2}c_1x^2$, where c_0 reflects the unit production cost that is independent of the environmental performance and c_1 reflects the supplier's cost efficiency in improving the goods' environmental performance. This model of unit production cost is widely portrayed in the economics and operations literature and fits well with the idea that initial environmental improvements are less costly because they are low-hanging fruit [2, 91, 113, 142].

The retailer is a price-setter, and decides on the (one-period) stocking (ordering) quantity q and the retail price p of the goods. The market demand of the good is $D(p, x, \varepsilon)$, where ε is a stochastic component with mean $\mathbb{E}(\varepsilon) = 0$, variance $Var(\varepsilon) = \sigma^2$, density function $f_\sigma(\cdot)$, and cumulative distribution function $F_\sigma(\cdot)$. The market demand for the goods is increasing in its environmental performance and decreasing in its retail price: $\frac{\partial}{\partial x}D(p, x, \varepsilon) \geq 0$ and $\frac{\partial}{\partial p}D(p, x, \varepsilon) \leq 0$. In particular, we focus on the market demand that is linear in both environmental performance and retail price $D(p, x, \varepsilon) = A - bp + rx + \varepsilon$, where $A, b, r > 0$. This model of demand is used widely in economics and supply chain management to model quality or service [e.g., 142]. The parameter A is the "market base," which reflects the scale of the retailer's market and is the demand when both the retail price and environmental performance are 0. Parameters b and r reflect the responsiveness of the market demand to retail price and environmental performance, respectively.

We assume that unsatisfied demand over the period is filled with an emergency order from an alternative source and that inventory holding or disposal and emergency ordering cost follows $h(t) = h^+ \max\{0, t\} + h^- \max\{0, -t\} = h^+[t]^+ + h^-[-t]^+$, where t is the inventory level after satisfying the demand. Specifically, h^+ is the unit inventory holding or disposal cost if $h^+ \geq 0$ or unit salvage value if $h^+ < 0$, and understocked items are expedited with cost h^- per unit. In other words, $h^+ + w$ is the net unit cost of over-stocking, and $h^- - w$ is the net unit cost of under-stocking. Assume that $h(t)$ is convex in t, and 0 is the minimizer of $wt + h(t)$, which translates into the following assumption on expediting and holding costs:

Assumption 3 *$h^- \geq w \geq \max\{0, -h^+\}$ and $h^- - h^+ \geq 0$.*

We also assume that there is no fixed cost of ordering, and there is no initial inventory level.

To ensure feasibility of the optimization problem over the range of possible environmental performance levels, we make the following assumption so that market demand is non-negative for $x \in [0, 1]$ and that the initial optimal solution when there is no demand uncertainty falls within an appropriate range:

Assumption 4 *$A - bc_0 \geq 0$ and $r \leq bc_1$.*

The supplier's payoff is the product of the margin and the retailer's order quantity:

$$\Pi_S(q, w, x) \quad = \quad (w - C(x))q. \tag{4.1}$$

The retailer's payoff is the expected revenue, minus the cost of ordering the goods from the supplier, and minus the expected cost of mismatched demand, which includes the holding or disposal cost and the cost of expediting from another source:

$$\Pi_R(p, q, w, x) \quad = \quad \mathbb{E}[pD(p, x, \varepsilon)] - wq - \mathbb{E}[h(q - D(p, x, \varepsilon))]. \quad (4.2)$$

As a benchmark, the payoff of the vertically integrated firm that both produces and sells the goods, is the expected revenue, minus the cost of producing the goods, and minus the expected cost of mismatched demand:

$$\Pi_B(p, q, x) \quad = \quad \mathbb{E}[pD(p, x, \varepsilon)] - C(x)q - \mathbb{E}[h(q - D(p, x, \varepsilon))]. \quad (4.3)$$

We focus our analysis on two primary types of environmental labels that are used widely in practice, information labels and seal of approval labels.

4.2.1 Information Labels

An information label's main purpose is to mitigate informational asymmetry pertaining to products and services [136]. An information label communicates to consumers the level of environmental performance of products or services without supplying the interpretation of whether the environmental performance is "good." A primary feature of an information label is that it allows for any amount of environmental performance to be communicated to consumers. Our definition of information labels corresponds to Type-III Labels under ISO categorization [44, 136] and corresponds to Report Cards under EPA categorization [58, 136]. Examples of these types of labels are the various carbon labels (e.g., those issued by the Carbon Trust, the Japan Carbon Footprint Initiative, or Canada's CarbonCounted Initiative) or the EPA's fuel economy label. Tesco, a UK retailer, and Casino, a French food retailer, have worked together with the Carbon Trust and the Bio Intelligence Service Agency, respectively, to develop information labels to use for their stores [136, 167].

A retailer looking to adopt an information label is faced with choosing how much control to exert on the suppliers' environmental performance. On one end of the spectrum, the retailer lets the supplier choose the environmental performance that maximizes the supplier's payoff (SC model). On the other end of the spectrum, the retailer chooses an environmental performance level for the supplier, one that maximizes the retailer's payoff (RC model). Whereas the ability to choose an environmental performance level for the supplier provides the retailer with the "best case" payoff, it might be too costly or impossible for the retailer to accomplish. The retailer is likely to need to invest in significant managerial bandwidth and in learning about measuring and benchmarking environmental performance. Choosing an environmental performance level for the supplier might also be impossible due to the retailer's insufficient buying power and the physical or temporal limitations of producing the product to the retailer's specifications. However, the RC-like model is possible in some cases, such as when the retailer can commission for private label products or when the retailer has very high buying power.

We compare both of these extreme cases to the Benchmark model, that of a vertically integrated firm.

The Supplier-Choice (SC) model. In this model, the decision about the level of a product's environmental performance is left entirely to the supplier. The retailer passes the environmental performance information to consumers through an information label. This model has the following timing:

- *Stage 1:* The supplier chooses a level of environmental performance x
- *Stage 2:* Given x, the supplier chooses wholesale price w to maximize his payoff Π_S.
- *Stage 3:* Observing x and w, the retailer chooses stocking quantity q and retail price p to maximize his payoff Π_R.

The Retailer-Choice (RC) model. In this model, the retailer makes a decision on the environmental performance of the supplier's product in order to maximize the retailer's own payoff. This model has the following timing:

- *Stage 1:* The retailer chooses a level of environmental performance x.
- *Stage 2:* Given x, the supplier chooses wholesale price w to maximize his payoff Π_S.
- *Stage 3:* Observing w, the retailer chooses stocking quantity q and retail price p to maximize his payoff Π_R.

Environmental performance is a primary distinguishing factor between RC and SC models. Without this dimension, SC and RC models reduce to the same model.

BENCHMARK (B) MODEL. We compare the solutions of the RC and SC models with that of a benchmark model. In this model, a vertically integrated firm makes a decision about the environmental performance of the products (or services) that it produces in order to maximize supply chain profit. This model has the following timing:

- *Stage 1:* The vertically integrated firm chooses a level of environmental performance x
- *Stage 2:* Given x, the vertically integrated firm chooses stocking quantity q and retail price p to maximize supply chain payoff Π_B.

4.2.2 Seal of Approval Labels

The main benefit of seal of approval labels is to help consumers interpret the information on environmental performance [136]. Instead of displaying neutral environmental performance information, a seal of approval label asserts that a product's environmental performance exceeds a minimum standard set by the labeling organization. Seal of approval labels correspond to Type-I Labels under ISO categorization [44, 136] and to Single-attribute Certification Labels under EPA categorization [58, 136]. Examples of seal of approval labels are Green Seal certification, Forest Stewardship Council labels, Total Chlorine Free labels, and

Dolphin Safe labels. Many retailers adopt these labels as a way to control environmental qualities of their suppliers and to differentiate their products. For example, Whole Foods Market only carries wild-caught seafood with green and yellow ratings from the Monterey Bay Aquarium and the Blue Ocean Institute [164], and the supermarket chain Safeway has a USDA-certified O-organic product line, in which all products must be composed of at least 95% organically produced ingredients [120].

Seal of approval labels are easier for consumers to understand because the labeling organization has already analyzed the product's environmental performance [44, 136, 168]. Thus, we would expect a higher demand for a product with a seal of approval label than for the same product with an information label. To capture the increase in demand, we include an additional parameter $a \geq 1$ that multiplies with the responsiveness of market demand to x. Thus, the modified market demand is $\tilde{D}(p, x, \varepsilon) = A - bp + arx + \varepsilon$.

However, the cost of obtaining a seal of approval label is strictly higher than the cost of obtaining an information label because the former includes not only all of the same costs associated with information labels (data gathering) but also a payment to the seal provider to verify the label. For example, the fee to obtain an information greenhouse gas label from the Thailand Greenhouse Gas Management Organization is 8,500 Thai baht for two years' usage [138], whereas the fee to obtain a seal of approval greenhouse gas reduction label is 100,000 Thai baht for three years' usage [139]. In our model, we assume the retailer incurs an additional fixed cost of L from adopting a seal of approval label rather than an information label.

Because standards for seal of approval labels are usually developed by third-party organizations, such as industry consortia or independent non-profit organizations, this standard is external to the retailer and the supplier, and limits the choice of minimum standard levels that the retailer can choose. The supplier's product receives a seal of approval only when the environmental performance is above a minimum standard x_m. The retailer does not buy from the supplier if the supplier's product does not receive a seal of approval. The seal of approval label model has the following timing:

- *Stage 1:* The retailer chooses (among possibly several) exogenous minimum standard(s) x_m to adopt. Because of the"all-or-nothing" nature of this type of label, the market demand is limited by $\tilde{D}(p, x_m, \varepsilon)$ for any $x \in (x_m, 1]$ and by $D(p, 0, \varepsilon)$ for any $x \in [0, x_m]$. Thus, the supplier's investment in environmental performance above x_m will not alter the order quantity q by the retailer, while incurring a higher production cost. Thus, Stage 1 translates to an exogenously chosen environmental performance x_m.

- *Stage 2:* Given minimum standard x_m, the supplier chooses wholesale price w to maximize the supplier's payoff Π_S.

- *Stage 3:* The retailer chooses stocking quantity and retail price to maximize the retailer's payoff Π_R, keeping in mind the modified market demand:

$$\max_{p,q} \Pi_R(p, q, w, x) = \max_{p,q} \mathbb{E}[p\tilde{D}(p, x, \varepsilon)] - wq - \mathbb{E}[h(q - \tilde{D}(p, x, \varepsilon))] - L$$

4.2.3 Demand Uncertainty

In the analysis in the next section, we explore how the decision about environmental performance is affected by uncertainty in demand by analyzing the model under deterministic and stochastic market demands. If demand is deterministic, the random component ε is dropped: $D(p, x, \varepsilon) = D(p, x) = A - bp + rx$. Moreover, the retailer's stocking quantity equals demand, $q = D(p, x)$. If demand is stochastic (or there is demand uncertainty), the standard deviation σ of the random demand component ε is positive, thus $D(p, x, \varepsilon) = A - bp + rx + \varepsilon$. Assume that the standard deviation in demand $\sigma > 0$ is small enough such that instances of negative demand are negligible. We are interested in the optimal environmental performance as a function of the standard deviation in demand σ: $x_R^*(\sigma)$, $x_S^*(\sigma)$, and $x_B^*(\sigma)$.

Rewriting the stocking quantity as $q = A - bp + rx + s$, where $A - bp + rx$ is deterministic and s is the safety stock, we show the closed form solution for safety stock as a function of unit purchase or manufacturing cost t, holding or disposal cost h^+, and costs of expediting h^-:

Lemma 2 *Given the unit purchasing or manufacturing cost t, inventory holding or disposal cost h^+ and emergency ordering cost h^-, the retailer's safety stock is $s(t) = F_\sigma^{-1}\left(\frac{h^- - t}{h^+ + h^-}\right)$. The safety stock is decreasing in the unit purchasing or manufacturing cost t.*

For tractability, we focus our analytical results on the special case in which the random component of demand ε is uniformly distributed. The assumption on uniform distribution is as follows:

Assumption 5 *The additive random component ε is distributed uniformly, with mean 0 and variance σ^2. Namely,*

$$f_\sigma(x) = \begin{cases} \frac{1}{2\sigma\sqrt{3}} \text{ if } -\sigma\sqrt{3} \leq x \leq \sigma\sqrt{3} \\ 0 \text{ otherwise} \end{cases}$$

and for $p \in [0, 1]$,

$$F_\sigma^{-1}(p) = \sigma\sqrt{3}(2p - 1).$$

We also provide a discussion on the generalizability of our results, including a numerical simulation using normally distributed ε, which approximates the analytical result derived for uniformly distributed ε.

4.3 Analysis of Information Labels

In this section we present the results of the central analysis of this paper. We analyze the optimal solutions from the three information label models: RC, SC, and B. We first analyze the scenario with no demand uncertainty, then we analyze the effect of demand uncertainty on these optimal solutions. We also consider using contracts as a way to modify optimal environmental performance levels and to gain higher payoff through coordinating the supply chain.

4.3.1 Information Labels Under Deterministic Demand

When demand is deterministic, the RC, SC, and B models yield the same optimal level of environmental performance. Because the retailer's stocking quantity is equal to market demand, the supplier's and retailer's payoffs are aligned such that the optimal level of environmental performance is the same regardless of whether the supplier or the retailer is making this decision. This optimal choice also coincides with that of a vertically integrated firm maximizing the total supply chain payoff. The optimal environmental performance level equates the marginal effect of environmental performance on market demand ($\frac{r}{b}$, the ratio between the responsiveness of market demand to environmental performance and the responsiveness of market demand to price) and the marginal cost of environmental performance $C'(x)$. Let subscripts R, S and B represent solutions of the RC, SC, and B models respectively. Then,

Proposition 8 *If market demand is deterministic, RC, SC and B models yield identical optimal levels of environmental performance ($x_R^* = x_S^* = x_B^* = x^*$), and the optimal condition is defined by*

$$-\frac{\frac{\partial}{\partial x}D(p,x)}{\frac{\partial}{\partial p}D(p,x)} = \frac{r}{b} = C'(x^*). \tag{4.4}$$

Using the above proposition, we derive a closed form solution for optimal environmental performance in our focal case where $C(x) = c_0 + \frac{1}{2}c_1 x^2$. The optimal level of environmental performance is increasing in the responsiveness of demand to environmental performance (r), decreasing in the responsiveness of demand to price (b), and decreasing in the marginal increase in unit production cost associated with environmental performance (c_1).

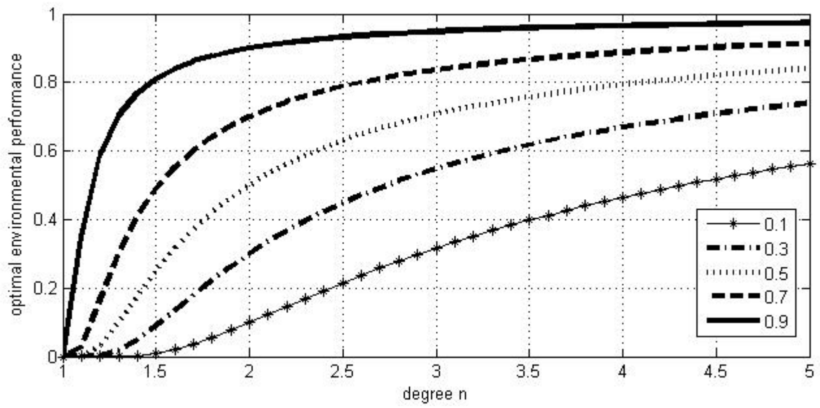

Figure 4.3.1: *Plot of optimal environmental performance levels x^* for different degrees n in unit production cost of the form $C(x) = c_0 + \frac{1}{n}c_1x^n$ and for $\frac{r}{bc_1} = 0.1, 0.3, 0.5, 0.7$ and* 0.9.

Corollary 4 *Suppose demand is deterministic and unit production cost is of the form $C(x) = c_0 + \frac{1}{2}c_1x^2$. The optimal level of environmental performance is $x^* = \frac{r}{bc_1}$.*

Although we focus on the unit production cost that is quadratic in x, Proposition 8 applies to all unit production cost functions that are convex in x. Figure 4.3.1 plots the optimal levels of environmental performance associated with various degrees n of the unit production cost $C_n(x) = c_0 + \frac{1}{n}c_1x^n; n \geq 1$. For a given n, the optimal level of environmental performance is $x_n^* = \frac{r}{bc_1}^{\left(\frac{1}{n-1}\right)}$. Because $x \in [0, 1]$, its contribution to the unit production cost decreases as n increases. Thus, the optimal level of environmental performance increases in degree n.

Although the optimal environmental performance levels of the three models are identical, the differentiated or sequential nature of the RC and SC models causes the retailer and supplier to locally maximize his own payoff. This behavior results in a higher optimal retail price for SC and RC models than for the vertically integrated firm, as shown in Corollary 5, leaving consumers with lower surplus. Moreover, the optimal retail price is increasing in the optimal environmental performance.

Corollary 5 *If demand is deterministic, then the optimal retail price is* $p_B^* = \frac{A+rx^*+bC(x^*)}{2b}$ *for the vertically integrated firm, and* $p_R^* = p_S^* = \frac{3A+3rx^*+bC(x^*)}{4b} > p_B^*$ *for the RC and SC models.*

Corollary 6 characterizes the optimal payoffs when demand is deterministic. Firstly, the misalignment of incentives between the supplier and the retailer in the sequential supply chain of the RC and SC models lowers the total supply chain profit since it is faced with lower consumer demand that results from a higher retail price. The sum of the supplier's and retailer's payoff under the RC and SC models is still smaller than the payoff of the vertically integrated firm. Secondly, the supplier extracts twice the payoff of the retailer.

Corollary 6 *Suppose demand is deterministic. The optimal payoffs of the supplier and the retailer are* $\Pi_S^* = \frac{(A+rx^*-bC(x^*))^2}{8b}$, *and* $\Pi_R^* = \frac{(A+rx^*-bC(x^*))^2}{16b}$ *respectively, yielding the total supply chain payoff* $\Pi_S^* + \Pi_R^* = \frac{3(A+rx^*-bC(x^*))^2}{16b}$. *Moreover,* $\Pi_S^* = 2\Pi_R^*$. *The optimal payoff of the vertically integrated firm is* $\Pi_B^* = \frac{(A+rx^*-bC(x^*))^2}{4b}$.

4.3.2 Information Labels Under Stochastic Demand

If there is demand uncertainty, the complete agreement between SC, RC, and B when demand is deterministic no longer holds. We present analytical results assuming uniformly distributed demand, first by characterizing the optimal levels of environmental performance from each model ($x_B^*(\sigma), x_S^*(\sigma)$ and $x_R^*(\sigma)$) as demand uncertainty σ increases. We then compare these optimal solutions and retail prices. We also make some comments on the generalizabiltiy of our results to other forms of demand distribution.

We show that the behavior of the optimal environmental performance as a function of σ depends on the balance between the unit under-stocking cost, as represented by the expediting cost h^-, and the unit over-stocking cost, as represented by the holding or disposal cost h^+. In the majority of the cases, the retailer chooses a higher level of environmental performance than the supplier.

Only when the retailer is willing to expedite the goods at a cost h^- higher than the retail price does the retailer prefer a lower environmental performance than the supplier.

The central reason for these differences is that the supplier and the retailer bear different sets of costs and benefits. The supplier is fully responsible for the unit production cost, the retailer is fully responsible for the cost of mismatched demand and but also benefits fully from the sales revenue. The supplier bears the cost of unmatched demand indirectly through the stocking quantity and feels the increase in retail price from higher environmental performance indirectly through wholesale price. The retailer bears the unit production cost indirectly through the wholesale price.

Benchmark Model. In the Benchmark model, we find that the behavior of the vertically integrated firm is determined by the relative magnitude of unit over-stocking cost $(h^+ + C(x))$ and unit under-stocking cost $(h^- - C(x))$. Specifically, if it is relatively more costly to over-stock ($h^- - h^+$ is small), the optimal level of environmental performance chosen by the vertically integrated firm is increasing in σ. If it is relatively less costly to over-stock ($h^- - h^+$ is large), the optimal level of environmental performance chosen by the vertically integrated firm is decreasing in σ. More formally,

Proposition 9 *Given Assumption 5 and suppose $C(x) = c_0 + \frac{1}{2}c_1x^2$. Define $K_B \equiv 2c_0 + \frac{r^2}{b^2c_1}$. Then $x_B^*(\sigma)$ is increasing in σ if $h^- - h^+ < K_B$, $x_B^*(\sigma)$ is decreasing in σ if $h^- - h^+ > K_B$, and $x_B^*(\sigma)$ is constant in σ if $h^- - h^+ = K_B$.*

The vertically integrated firm bears the direct cost of mismatched demand and production cost, but also benefits directly from the revenue generated. The optimal level of environmental performance depends on the balance between how x affects the unit production cost and how it affects the cost of mismatched demand through the optimal safety stock level. According to Lemma 2: $s(x) = F_\sigma^{-1}\left(\frac{h^- - C(x)}{h^- + h^+}\right)$, and the safety stock decreases in x. Also, as σ increases, the larger effect x has in decreasing the safety stock. However, the effect of x on unit production cost is constant in σ. When it is relatively costly to under-stock ($h^- - h^+$ is large), the optimal safety stock is positive and the firm has an incentive to try to keep the safety stock high. Thus, as σ increases, the trade-off becomes less favorable towards higher x and $x_B^*(\sigma)$ decreases in σ. In contrast, when it is relatively inexpensive to under-stock ($h^- - h^+$ is small), the optimal safety stock is negative and the firm has the incentive to try to keep the safety stock low. Thus, as σ increases, the trade-off becomes more favorable towards higher x and $x_B^*(\sigma)$ increases in σ.

SUPPLIER-CHOICE MODEL. As in the deterministic demand case, the optimal level of environmental performance in the SC model is increasing in r, and decreasing in b and c_1. More formally,

Proposition 10 *Given Assumption 5 and suppose* $C(x) = c_0 + \frac{1}{2}c_1x^2$, *then* $x_S^*(\sigma) = \frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 8\sqrt{3}\sigma c_1}$. *The optimal environmental performance* $x_S^*(\sigma)$ *is decreasing in* σ.

The notable characteristics of $x_S^*(\sigma)$ are that (1) $x_S^*(\sigma)$ is decreasing in σ and (2) $x_S^*(\sigma)$ is increasing in the sum of unit over-stocking and under-stocking costs $(h^+ + h^-)$. To see (1), consider a fixed σ. For the supplier, a higher level of environmental performance x has the effect of (a) increasing the unit production cost, (b) increasing the supplier's wholesale price, and (c) reducing the retailer's safety stock. The supplier feels the increase in unit production cost directly. However, since the supplier is not responsible for the cost of mismatched demand, only the retailer's stocking quantity affects the supplier's payoff. Similarly, the supplier also does not directly gain the full benefit of the sales revenue and only indirectly experiences it through the wholesale price. Recall that a lower x increases the safety stock, thus the stocking quantity. Moreover, the effect of x on stocking quantity becomes progressively larger as σ increases. On the other hand, the increase in wholesale price from increase in x becomes progressively smaller as σ increases. Thus, the benefits of reduction in x on wholesale price and stocking quantity increases in σ, whereas the contribution of

x on unit production cost is fixed in σ. It follows that the optimal level of environmental performance decreases in σ. To see (2), because $(h^+ + h^-)$ lowers the extent to which the increase in x affects the wholesale price w and safety stock $s(w) = F_\sigma^{-1}\left(\frac{h^- - w}{h^- + h^+}\right)$ (by 2), the optimal level of environmental performance is decreasing in $(h^+ + h^-)$.

Retailer-Choice Model. In the RC model, we also found that the behavior of $x_R^*(\sigma)$ also depends on $h^- - h^+$. More formally,

Proposition 11 *Given Assumption 5 and suppose* $C(x) = c_0 + \frac{1}{2}c_1x^2$. *Then there exist* $\underline{K}_R$ *and* $\overline{K}_R$, *where* $K_B < \underline{K}_R < \overline{K}_R$, *such that* $x_R^*(\sigma)$ *is increasing in* σ *if* $h^- - h^+ \leq \underline{K}_R$, $x_B^*(\sigma)$ *is first increasing, then decreasing in* σ *if* $\underline{K}_R < h^- - h^+ \leq \overline{K}_R$, *and* $x_B^*(\sigma)$ *is decreasing in* σ *if* $h^- - h^+ > \overline{K}_R$.

Like the vertically integrated firm, the retailer is fully responsible for the cost of mismatched demand and benefits fully from the sales revenue. However, the retailer is not fully responsible for the unit production cost, by which it is indirectly affected through the wholesale price. From Lemma 2, the safety stock $s(w) = F_\sigma^{-1}\left(\frac{h^- - w}{h^- + h^+}\right)$ depends on w instead of directly on $C(x)$. This difference generates two implications: (1) The optimal solution for the RC model is increasing in σ on a wider range of $h^- - h^+$ than it does in the B model (i.e., $\underline{K}_R > K_B$). Because $w > C(x)$, the safely stock is lower in the RC model than the B model and thus is negative on a wider range of $h^- - h^+$ than the B model. This leads to $x_R^*(\sigma)$ increasing in σ on a wider range of $h^- - h^+$ than it does in the B model. (2) The optimal solution $x_R^*(\sigma)$ can exhibit non-monotonic behavior when $h^- - h^+$ is intermediate. Whereas x has the same positive effect on $C(x)$ for any σ, the positive effect on w of x decreases in σ since w is increasing in x but decreasing in σ. Thus, the non-monotonic effect can occur because the optimal safety stock can shift signs from negative at low σ (during which $x_R^*(\sigma)$ increases in σ) to positive at high σ (during which $x_R^*(\sigma)$ decreases in σ).

Comparison of Solutions We next compare the optimal environmental performance levels from B, SC, and RC models. We find that this relationship is characterized by the balance between the over-stocking and under-stocking costs, and that the optimal behaviors of the supplier and the retailer fall on opposite sides of the supply chain optimal behavior. In most cases, the retailer prefers a higher environmental performance level than the vertically integrated firm, which in turn chooses a higher environmental performance level than the supplier. However, if it is very costly to under-stock, and the retailer is willing to expedite goods at cost h^- higher than retail price, then the retailer chooses a lower environmental performance level than the vertically integrated firm, which in turn chooses a lower environmental performance level than the supplier. More formally,

Proposition 12 *Given Assumption 5 and suppose* $C(x) = c_0 + \frac{1}{2}c_1 x^2$. *Let* $K' \equiv \frac{2A}{b}$, *and* $K'' \equiv \frac{2A}{b} + \frac{2r^2}{b^2 c1} > K'$. *Then,*

- *If* $h^- - h^+ \leq K'$, $x_R^*(\sigma) > x_B^*(\sigma) > x_S^*(\sigma)$ *for all* $\sigma > 0$.
- *If* $K' < h^- - h^+ \leq K''$, *there exists* $\hat{\sigma} > 0$ *such that* $x_R^*(\sigma) > x_B^*(\sigma) > x_S^*(\sigma)$ *if* $\sigma < \hat{\sigma}$, $x_R^*(\sigma) = x_B^*(\sigma) = x_S^*(\sigma)$ *if* $\sigma = \hat{\sigma}$, *and* $x_R^*(\sigma) < x_B^*(\sigma) < x_S^*(\sigma)$ *if* $\sigma > \hat{\sigma}$
- *If* $h^- - h^+ < K''$, *then* $x_R^*(\sigma) < x_B^*(\sigma) < x_S^*(\sigma)$ *for all* $\sigma > 0$.

Figure 4.3.2 presents the result of a numerical simulation, using $A = 100, b = 2, r = 10, c_0 = 20, c_1 = 20, h^+ = 10$, and $h^- = 50$ and 120. We normalize the market base to a percentage so that $A = 100\%$. Then $r = 10$ means that environmental performance contributes a total of 10 percentage points to demand relative to the market base and $b = 2$ means that a one unit increase in price contributes to a 2 percentage-point drop in demand relative to the market base.

The simulation illustrates two relevant cases of the above proposition. Firstly, under the wide range of realistic scenarios $(h^- - h^+ < K')$,

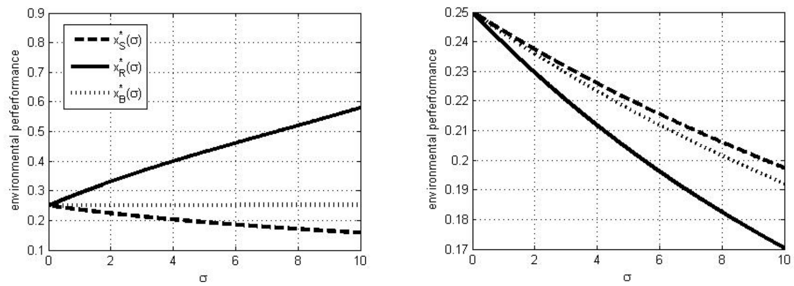

Figure 4.3.2: *Optimal environmental performance levels for the SC, RC, and B models.* $A = 100, b = 2, r = 10, c_0 = 20, c_1 = 20, h^+ = 10, h^- = 50$ *(left) and* 120 *(right).*

$x_R^*(\sigma) > x_B^*(\sigma) > x_S^*(\sigma)$, as illustrated in the left pane of the figure. The retailer generally prefers a higher level of environmental performance because it gets direct benefits from high level of environmental performance while not directly being responsible for the increase in cost. This result implies that the retailer is the crucial party to push the behavior of the supply chain towards a more environmentally friendly result, and might explain the reasons why we observe retailers like Walmart or Tesco pushing green label initiatives rather than seeing the supplier proactively engage in these initiatives.

Secondly, as illustrated in the right pane of Figure 4.3.2, if it is very expensive to under-stock $(h^- - h^+ > K_h)$, $x_R^*(\sigma) < x_B^*(\sigma) < x_S^*(\sigma)$. In this scenario, the retailer wants to maintain very high stock, which translates to low x. Since under-stocking is so costly, the retailer would want to prioritize choosing a low level of x to best facilitate high stocking quantity, leading to a lower level of x than chosen by the supplier, since the supplier is not directly responsible for the cost of mismatched demand. Note that the set of parameters in the right pane implies that $h^-$is greater than the maximal possible retail price, so this scenario is only realistic when the retailer is willing to incur a loss by expediting at a cost higher than the retail price.

There are two immediate insights from the above results. The first insight pertains to the optimal retail prices and stocking quantities from these models. We find that at a given $\sigma > 0$, the following occurs. Firstly, the relationship between optimal retail prices from the RC and SC models, $p_R^*(\sigma)$ and $p_S^*(\sigma)$, are

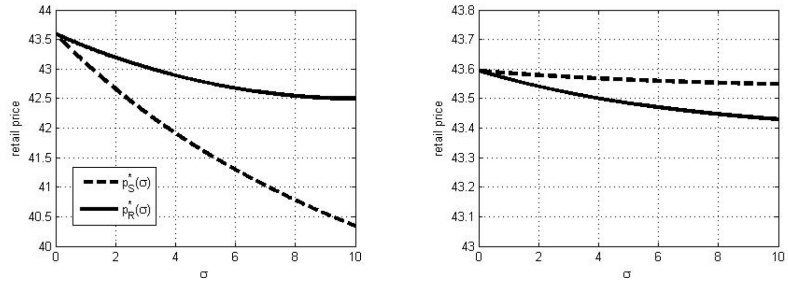

Figure 4.3.3: *Optimal retail prices for SC and RC models.* $A = 100, b = 2, r = 10, c_0 = 20, c_1 = 20, h^+ = 10, h^- = 50$ *(left) and* 120 *(right).*

directly reflected by the relationship between $x_R^*(\sigma)$ and $x_S^*(\sigma)$. This implies that a higher environmental performance level does translate to a higher retail price. Thus, unless the under-stocking cost is very high, the RC model yields a higher retail price than the SC model. Secondly, the optimal stocking quantity under the SC model $q_S^*(\sigma)$ is always higher than that of the RC model $q_R^*(\sigma)$. This is because the supplier directly benefits from high stocking quantity without directly experiencing the cost of mismatched demand for which the retailer needs to be responsible. More formally:

Corollary 7 *Given Assumption 5 and suppose* $C(x) = c_0 + \frac{1}{2}c_1x^2$. *Let* $K' \equiv \frac{2A}{b}$, *and* $K'' \equiv \frac{2A}{b} + \frac{2r^2}{b^2c_1} > K'$. *Then,*

- *If* $h^- - h^+ \leq K'$, $p_R^*(\sigma) > p_S^*(\sigma)$ *for all* $\sigma > 0$.
- *If* $K' < h^- - h^+ \leq K''$, *there exists* $\hat{\sigma} > 0$ *such that* $p_R^*(\sigma) > p_S^*(\sigma)$ *if* $\sigma < \hat{\sigma}$, $p_R^*(\sigma) = p_S^*(\sigma)$ *if* $\sigma = \hat{\sigma}$, *and* $p_R^*(\sigma) < p_S^*(\sigma)$ *if* $\sigma > \hat{\sigma}$
- *If* $h^- - h^+ < K''$, *then* $p_R^*(\sigma) < p_S^*(\sigma)$ *for all* $\sigma > 0$.

Moreover, $q_R^*(\sigma) < q_S^*(\sigma)$ *for all* $\sigma > 0$.

The optimal retail prices and stocking quantities are illustrated by Figures 4.3.3 and 4.3.4, respectively. We can see from Figure 4.3.3 that $p_S^*(\sigma) > p_R^*(\sigma)$ if

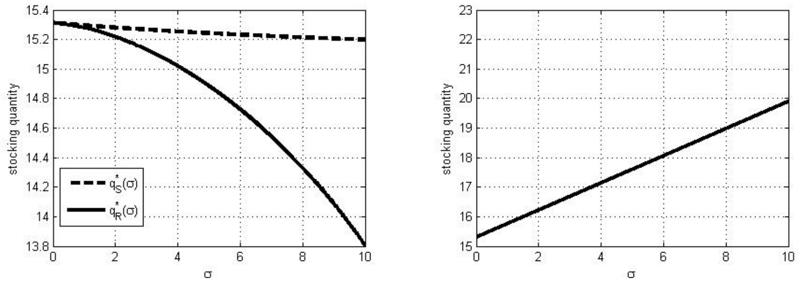

Figure 4.3.4: *Optimal stocking quantities for SC and RC models.* $A = 100, b = 2, r = 10, c_0 = 20, c_1 = 20, h^+ = 10, h^- = 50$ *(left) and* 120 *(right).*

$x^*_S(\sigma) > x^*_R(\sigma)$ and vice versa. Moreover, we can see from Figure 4.3.4 that $q^*_S(\sigma) > q^*_R(\sigma)$. Note also that since it is relatively inexpensive to under-stock when $h^- = 50$ (left pane), the optimal stocking quantity decreases in σ. In contrast, since it is relatively costly to under-stock when $h^- = 120$ (right pane), the optimal stocking quantity increases in σ.

The second insight is the implication on payoffs. Because the preferred environmental levels differ between models under stochastic demand, the retailer incurs a monetary cost in relinquishing the control of the environmental performance level to the supplier. Whereas in the deterministic case, there is no difference in the payoff of the retailer between the RC and SC models, there is now a gap between the payoffs of the retailer when choosing environmental performance levels according to the RC and SC models. More formally:

Corollary 8 $\Pi_r(x^*_R(\sigma), \sigma) - \Pi_r(x^*_S(\sigma), \sigma) > 0$ *for all* $\sigma > 0$.

The retailer's ability to choose the environmental performance level for the supplier may not be feasible due to the retailer's lack of market power. It might not be seriously pursued due to the lack of managerial bandwidth and the organizational cost required for the effort. The above result suggests that, where exerting this control is feasible, the retailer should also take into account the loss of profit from the mismatched choice of environmental performance in addition to considering the managerial bandwidth required and other organizational costs.

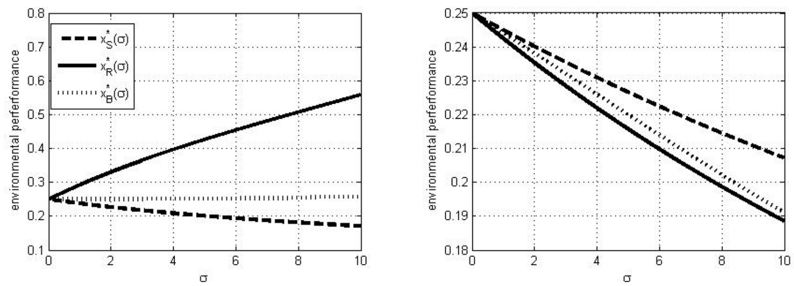

Figure 4.3.5: *Optimal environmental performance levels for SC, RC, and B models.* $A = 100, b = 2, r = 10, c_0 = 20, c_1 = 20, h^+ = 10, h^- = 50$ *(left) and* 120 *(right).*

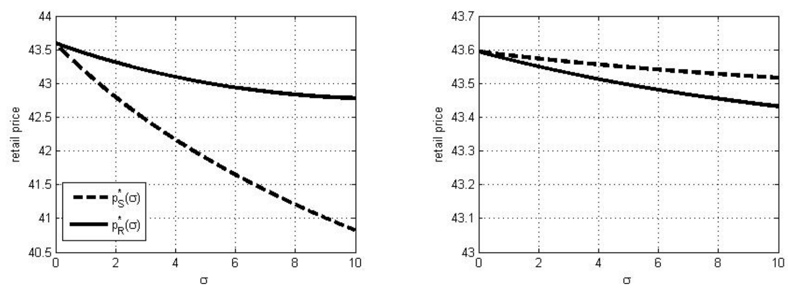

Figure 4.3.6: *Optimal retail prices for SC, RC, and B models.* $A = 100, b = 2, r = 10, c_0 = 20, c_1 = 20, h^+ = 10, h^- = 50$ *(left) and* 120 *(right).*

Generalizability of Results. Although we focus on the analytical results using uniform distribution for tractability, we corroborate our results with those using normal distribution, which covers a wide range of realistic demand distributions. See Figure 4.3.5 for plots of optimal environmental performance levels and Figure 4.3.6 for plots of optimal retail prices. The results on optimal environmental performance levels and optimal retail prices assuming normal distribution largely agrees with those assuming uniform demand distribution.

To summarize, the results from this section illustrate that the optimal levels of environmental performance from the RC, SC, and B models which are the same under deterministic demand differ under stochastic demand. Moreover, the difference in the optimal levels of environmental performance across models is dependent on the levels of the unit over-stocking and under-stocking costs, with the RC model being more sensitive to the difference between the unit under-stocking and over-stocking costs than the SC model. Lastly, in the vast majority of realistic cases, the RC model gives a higher optimal environmental performance level than the SC model, supporting the commonly observed phenomenon that sees effort to promote environmental performance in the supply chain led by retailers rather than suppliers. Because our models incorporate both the element of environmental performance and stocking quantity under the cost of mismatched demand, the two primary dimensions that are driving the difference across models are: (1) the existence of environmental performance dimension x, since all three models are equivalent without the environmental performance dimension, and (2) the retailer and the supplier have different burdens in production and inventory costs.

4.3.3 Incentive Alignment through Contracts

There are two "inefficiencies" in our differentiated supply chain (RC and SC) models relative to that of the vertically integrated firm. The first is inherent in the mismatch between the supplier's and retailer's incentives in the differentiated supply chain that persists even in the deterministic demand case, causing the sum of the retailer's and supplier's profits to be smaller than that of the vertically integrated firm. The second is the inefficiency arising from the choice of environmental performance: under stochastic demand, the optimal choices of environmental performance levels in the RC and SC models are different, and both of them are not the level chosen by the vertically integrated firm maximizing the supply chain payoff. Thus, the retailer incurs a loss in payoff from letting the supplier choose the environmental performance level, and from the fact that it is in a differentiated supply chain. We consider aligning incentives and thus increasing payoffs through contracts.

From the results above, we learn that these inefficiencies are based on a mismatch between the retailer's and the supplier's objective functions: the retailer needs to bear the cost of mismatch demand directly, and the supplier needs to bear the production cost directly although it helps increase sales. The proposition below present a form of contract applied to the SC model that can coordinate the supply chain. We devised a contract based on revenue-sharing contracts that allows the supplier to share the cost of mismatched demand and the retailer to share a portion of his revenue. We find that, with an appropriately chosen wholesale price, this contract eliminates both inefficiencies above.

Proposition 13 *In the SC model, the contract in which the supplier shares portion* $(1-\varphi)$ *of the cost of mismatched demand, the retailer shares portion* $(1-\varphi)$ *of the revenue, and the supplier modifies its wholesale price to* $w_\varphi(x) = \varphi C(x)$ *coordinates the supply chain.*

With the appropriately chosen wholesale price $w_\varphi(x) = \varphi C(x)$, the above contract transforms the retailer's and the supplier's objective function such that the retailer's payoff is fraction φ of the payoff of the vertically integrated firm, and the supplier's payoff is fraction $1-\varphi$ of the payoff of the vertically integrated firm. The retailer will order and price according to the vertically integrated firm, and the supplier's optimal environmental performance level is that of the vertically integrated firm.

Thus, using this form of contracts, the retailer has the opportunity to recoup the loss in payoff that results from allowing the supplier to select the environmental performance level, and to influence the environmental performance in a direction that the retailer prefers without having to exert direct control on the supplier's environmental performance level. Moreover, the payoff of the vertically integrated firm is greater than the sum of the payoffs of the retailer and the supplier in the differentiated supply chain. Therefore, if the retailer can negotiate a large enough split φ which allows adoption of this contact to be incentive compatible for both the retailer and the supplier, the retailer can incentivize the supplier to choose an environmental level that coordinates the supply chain (which in a vast majority of cases is higher than the supplier would have chosen itself) without having to exert direct control on the supplier's choice of environmental performance and also increase its own payoff. However, effective revenue-sharing contracts require both the retailer and the supplier to accurately share sales and cost information, and would likely require an investment in information-sharing tools, monitoring systems, and a high level of trust between the retailer and the supplier.

4.4 Analysis of Seal of Approval Labels

We next consider results for seal of approval label models using the results from the information label models as a basis. Recall the trade-off of the seal of approval label: seal of approval labels generally cost more to adopt (we assume additional cost L to the retailer) and there are fewer choices of external minimum standard x_m to choose from. However, there is a potential demand increase α associated with the consumer's ability to interpret the environmental performance. We found that in both deterministic and stochastic cases, the benefit of seal of approval labels depend on parameters α, L, and x_m as follows:

Proposition 14 *Given $C(x) = c_0 + \frac{1}{2}c_1x^2$. For a fixed σ, the payoff advantage of certification labels increases in α, decreases in L, and is concave in x_m.*

Intuitively, the benefits of seal of approval labels increase the more these labels are able to increase demand beyond that of the information labels. This increase is likely to be greater the more difficult it is for consumers to interpret the product's environmental performance. It is also intuitive that the benefits of seal of approval labels increase as the additional cost to acquire the labels decreases. Since L is a main limiter of the benefit of seal of approval labels, if the retailer can find a way for the supplier to share this additional cost, thus reducing L, the retailer is more likely to prefer seal of approval labels. The non-monotonic benefit of seal of approval labels implies that the benefit of seal of approval labels is greater when x_m is in an intermediate range: if the minimum standard x_m is too low, the retailer does not sufficiently benefit from the increase in revenue due to higher retailer prices and demand. However, if the minimum standard x_m is too high, the increase in unit production cost begins to dominate and decreases the retailer's payoff.

The above proposition can be used to illustrate the trade-off in the debate about proliferation of environmental standards. There is a significant amount of literature and anecdotal evidence that argues that the proliferation of standards or seals of approval confuses consumers and reduces the effectiveness of these standards [44, 51, 57, 92, 168]. On one hand, the more proliferated the standards are (the more values of x_m to choose from), the more likely it is that the retailer will choose a seal of approval label because there is a higher chance that there exists an x_m within the desired intermediate range. On the other hand, the proliferation of standards would likely lead to a smaller α, which discourages the adoption of seal of approval labels by the retailer.

In the special case in which demand is deterministic, we can explicitly characterize the range of x_m, α, and L in which it is more beneficial for the retailer to adopt a seal of approval label than an information label. For a given α, we find that there is a largest additional cost $\underline{L}(\alpha)$ below which it is feasible for a seal of approval label to be preferred. Also, the range of intermediate x_m's under which the seal of approval label is preferred expands in α and contracts in L. More formally,

Corollary 9 *Suppose $C(x) = c_0 + \frac{1}{2}c_1 x^2$ and that demand is deterministic. Then it is feasible for a retailer to prefer a seal of approval label over an information label if*

$$L < \underline{L}(\alpha) = \frac{(A - bc_0 + \frac{\alpha^2 r^2}{2bc_1})^2 - (A - bc_0 + \frac{r^2}{2bc_1})^2}{16b}.$$

For given feasible values of α and L, the retailer prefers a seal of approval label over an information label if $\frac{\alpha r}{2bc_1} - g(\alpha, L) \leq x_m \leq \frac{\alpha r}{2bc_1} + g(\alpha, L)$, where $g(\alpha, L)$ is defined by

$$g(\alpha, L) \equiv \frac{1}{2bc_1}\sqrt{\alpha^2 r^2 + (4bc_1)(A - bc_0) - (4bc_1)\sqrt{(A - bc_0 + \frac{r^2}{4bc_1})^2 + 16bL}},$$

with highest benefit attained at $x_m = \frac{\alpha r}{2bc_1}$. This range expands in α and contracts in L.

When demand is stochastic, the "minimum upper bound" $\underline{L}^*(\sigma)$, below which it is always feasible for the retailer to prefer a seal of approval label over an information label regardless of a, is weakly greater than the minimum upper bound in the deterministic case. In other words, the retailer will tolerate a higher additional cost of seal of approval labels when demand is stochastic compared to when demand is deterministic. This result is driven by the fact that there is a difference between the optimal levels of environmental performance between the SC and RC models under stochastic demand, and a seal of approval label can be used to force the supplier to choose an environmental performance level closer to the one preferred by the retailer.

Corollary 10 *For any $\sigma > 0$, the "minimum upper bound" $\underline{L}^*(\sigma)$, below which it is always feasible for the retailer to prefer a seal of approval label over an information label regardless of a, is weakly greater than the minimum upper bound in the deterministic case. In other words: $\underline{L}^*(\sigma) > \underline{L}^*(0)\ \forall\sigma$.*

The seal of approval label can be an alternative to contracts in encouraging suppliers to behave more responsibly toward the environment. The supplier generally prefers a lower level of environmental performance than the retailer, so imposing a minimum standard through mandating a seal of approval label is a way to directly influence the supplier to invest more in environmental performance. The supplier will agree as long as the supplier's payoff still exceeds its reservation utility. From the above results, we expect that seal of approval labels will be more beneficial to the retailer, and thus more prevalent, in the scenarios or industries in which (1) there is more uncertainty in consumer demand, (2) the environmental performance is more difficult for consumers to interpret, (3) the additional cost of obtaining the label is lower,(4) there is higher availability of external minimum standards x_m to choose from without significantly sacrificing the increase in demand through the perception of exclusivity, and (5) the retailer can persuade the supplier to share part of the additional cost of adopting the label.

4.5 Discussion

Although our model provides a concise framework to compare between different environmental label types and decision-making choices, it has some limitations. Firstly, we currently assume there to be one supplier and one retailer in the supply chain. It will be helpful to see how the results change in a competitive setting in which there are multiple suppliers competing for market share. Secondly, we currently assume there to be no informational asymmetry between the retailer and the supplier. It will be interesting to consider the case of the retailer holding a belief about the supplier's costs rather than knowing the suppliers' costs. Thirdly, we currently take as a given consumers' responses to the level of environmental performance of the product. In particular, we assume that the level of environmental performance contributes positively and linearly to consumer demand, and that there is no uncertainty associated with this contribution. We also use a multiplication factor α to model how a seal of approval label can help increase demand. Although our approach is similar to how other attributes such as service level and service time are modeled, a deeper investigation how consumers actually use environmental performance of products to make purchasing decisions is required. In particular, future work should consider capturing uncertainty in consumers' responses to products' environmental performance. Thirdly, we currently assume that the increase in demand from using a seal of approval label rather than an information label (α) and the additional cost of acquiring a seal of approval label (L) are independent. In practice, these two parameters may be dependent on each other. For example, a seal of approval label associated with a better reputation will likely feature higher increase in demand and higher additional cost to obtain the label. Future work should consider modeling this association.

It would also be interesting to explore how our results generalize under alternative assumptions about inventory models and contractual forms. We currently assume that expedited orders are delivered from a source other than the supplier, thus the expediting cost h^- also partially reflects the difficulty of finding an alternative supplier with a comparable environmental performance to deliver expedited orders. Future work can explore how our current results will change if the retailer considers using the same supplier as a source of expedited orders. Our results focus on simple linear wholesale price contracts, with a brief exploration of a variant of revenue sharing contracts. Future extensions should also explore other forms of contracts, such as buy-back contracts and contracts in which retailers can specify wholesale prices.

We can also explore the impact of different types of designs facing the supply chain. For example, we currently assume that either the environmental performance can be any real number between 0 and 1 in the case of the information label, or "all-or-nothing" in the case of the seal of approval label. Other forms of labels exist, such as ones with discreet "levels" or "grades" or labels that are seal of approval labels but also show environmental performance levels.

Also, we currently consider only one aspect of environmental performance. In reality, "environmental performance" can consist of multiple performance dimensions (such as carbon emissions, water consumption, packing waste, etc.). It is not clear how these dimensions should be chosen and how they should be combined (i.e., whether these dimensions should be combined into a single score using different weights, or whether they should remain separate). It would be interesting to explore how the choice regarding which dimensions to communicate to consumers and how these dimensions are combined will affect consumers' decisions. Lastly, labels can communicate positive and negative qualities. We are currently considering the effect of labeling positive qualities. It might be interesting to consider how our results extend to cases in which labels communicate negative qualities, such as the presence of hazardous materials.

Future work can also explore the contexts in which the insights from our model are applicable and factors that characterize the applicability of our models. The insights from our model could apply more widely to other quality dimensions that, like environmental performance, cannot be observed by consumers even after usage, are technically observable and verifiable by the retailer, and generate some uncertainty from consumers about how to understand or interpret. However, from anecdotal evidence, it is not clear if our models and insights can be generalized beyond the context of traditional retailers like Walmart and Tesco to other product categories like automobiles, in which automobile manufacturers fill the role of suppliers, and automobile dealers fill the role of retailers.

4.6 Conclusion

Environmental performance is becoming more significant as a differentiating feature of a firm's products and services. Many retailers are considering the use of labels to communicate the environmental performance of their offered products more easily to consumers, and have begun to measure and control their suppliers' environmental performance. However, little is known about how decisions regarding these labels affect supply chain behaviors and environmental performance.

In this paper, we use game theoretic models to analyze two important questions facing a retailer contemplating adoption of environmental labels: (1) What type of environmental labels should the retailer choose, and (2) Does the environmental performance of the product depend on the party in the supply chain making this decision? To answer the first question, we focus on two types of widely used environmental labels: information labels (e.g., the Carbon Trust's footprint labels), which communicates the level of environmental performance, and seal of approval labels (e.g., Green Seal Certification), which assert that the product has good environmental performance according to the labeling organization's standard. To answer the second question, we analyze decisions made under three models: (1) the Supplier-Choice model, in which the supplier makes the decision about the environmental performance of the product that it supplies to the retailer, (2) the Retailer-Choice model, in which the retailer chooses the environmental performance of the product for the supplier, and (3) the Benchmark model, in which a vertically integrated supply chain chooses the environmental performance that maximizes the supply chain profit.

We find that when there is no uncertainty in product demand, the retailer, the supplier, and the vertically integrated firm prefer the same optimal level of environmental performance. However, this alignment breaks down in the presence of demand uncertainty. In the majority of realistic scenarios, the retailer prefers a higher environmental performance level than the supplier, thus the retailer faces reduction in payoff when leaving environmental performance decisions to the supplier. We also expect that seal of approval labels will be more prevalent in the scenarios in which (1) there is more uncertainty in product demand, (2) the product's environmental performance is more difficult for consumers to interpret, (3) the additional cost to acquire seal of approval labels is lower, and (4) the retailer can persuade the supplier to share part of the additional cost to acquire the label.

5
Appendix A

This appendix contains the mathematical proofs of the main results shown in Chapter 2.

Proof of Lemma 1. If $b_1 + b_2 \leq B$, the projects do not need to compete against each other for capital dollars, thus both projects will be implemented by senior management if both projects' expected payoff to the firm are positive. It follows that manager i's optimal effort level is independent of e_j and θ_j. From (2.2), since $\mathbb{E}(\pi_i(e_i)|l) = \left[\left(\frac{1-e_i}{2}\right) r_i - \left(\frac{1+e_i}{2}\right) k_i\right] - \frac{d_i e_i^2}{2} < 0$ for all e_i, manager i does not propose project i if $\theta_i = l$. Thus, if $\theta_i = l$, project i is not implemented by senior management and manager i's payoff is $-\frac{d_i e_i^2}{2}$. From (2.1), if $\theta_i = h$, manager i's expected payoff is $\mathbb{E}(\pi_i(e_i)|h) = \left[\left(\frac{1+e_i}{2}\right) r_i - \left(\frac{1-e_i}{2}\right) k_i\right] - \frac{d_i e_i^2}{2}$. Since $\Pr(\theta_i = h) = \Pr(\theta_i = l) = \frac{1}{2}$, the expected payoff of manager i before the signals are realized is $\mathbb{E}(\pi_i(e_i)) \equiv \frac{1}{2}\mathbb{E}(\pi_i(e_i)|h) + \frac{1}{2}(-\frac{d_i e_i^2}{2}) = g_i(e_i)$, which attains a global maximum at $e_i^* = e_{g_i}^* = \frac{r_i + k_i}{4d_i}$. Assumption 2 ensures that the optimal expected payoff of manager i is $\mathbb{E}\pi_i \equiv \mathbb{E}(\pi_i(e_i^*)) > 0$. Because the expected payoff to the manager is positive, manager i will propose the project when $\theta_i = h$ (with probability $\frac{1}{2}$), and since $\mathbb{E}\Pi_i = \mathbb{E}(\Pi_i|h, e_i^*) > \mathbb{E}(\pi_i(e_i^*)) > 0$, senior management will implement the project when proposed.

Suppose $b_i \leq B$ and $b_j > B$ for $i = 1$ or 2, $j \neq i$. Because project j violates the firm's budget constraint, project j will never be implemented by senior management. It is optimal for manager j to exert no effort ($e_j^* = 0$). Also, because only project i can possibly be implemented, manager i's optimal effort level does not depend on e_j or θ_j, and the optimal effort is as derived in the previous paragraph.

Note that these results hold regardless of the order of effort commitment. ■

Proof of Proposition 1. If the timing of effort commitment is random, the probability that each manager is the first mover is $\frac{1}{2}$. We will prove this proposition by showing the probability of project implementation in equilibrium for manager i ($i = 1, 2$) and manager j ($j \neq i$) when manager i moves first. We then argue that because the timing of effort is random, the probability that the first mover i is manager 1 is $\frac{1}{2}$ and the probability that i is manager 2 is also $\frac{1}{2}$. We then take expectation over the realization of the first mover to obtain the probability of each manager's project implementation.

We derive the equilibrium effort levels and probabilities of project implementation corresponding to the case when i is the first mover by backwards induction, using the timing in Section 2.3. We assume that $b_1 + b_2 \geq B$.

In Stage 4, senior management chooses the project to maximize the firm's expected payoff, given the budget constraint. The firm chooses the project with higher expected payoff to the firm, provided the expected payoff to the firm is positive. If the two projects' payoff are identical, senior management randomizes between the two projects with equal probability. Note that if the signal realizations are $\theta_i = \theta_j = h$ and both projects are proposed, the projects' expected payoffs to the firm are $\mathbb{E}\Pi_i = \mathbb{E}(\Pi_i|h, e_i)$ and $\mathbb{E}\Pi_j = \mathbb{E}(\Pi_j|h, e_j)$ according to (2.3). Since the managers and projects are symmetric, the expected payoff to the firm is increasing in effort level: $\mathbb{E}\Pi_i > \mathbb{E}\Pi_j$ if and only if $e_i > e_j$. Thus, if both projects are proposed and if both projects' signals are high, senior management chooses the project whose manager puts a higher effort level.

In Stage 3, the probabilities of the signal outcomes are $\Pr(\theta_i = h, \theta_j = h) = \Pr(\theta_i = h, \theta_j = l) = \Pr(\theta_i = l, \theta_j = h) = \Pr(\theta_i = l, \theta_j = l) = \frac{1}{4}$. Define $\mathbb{E}(\pi_i(e_i, e_j)|\theta_i, \theta_j)$ to be the expected payoff of manager *i* given both managers' effort levels and the realized signals. The expected payoff of manager *i* when $\theta_i = l$, $\mathbb{E}(\pi_i(e_i)|l)$ according to (2.2), is negative for all e_i. Thus, manager *i* never proposes project *i* when $\theta_i = l$. The project is thus not implemented and the expected payoff is $\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = l, \theta_j) = -\frac{de_i^2}{2}$ for all e_i, e_j and θ_j. The expected payoff of manager *i* when $\theta_i = h$ is $\mathbb{E}(\pi_i(e_i)|h)$, according to (2.1). Assume, and we will confirm at the end of the proof that this is true at optimum, that $\mathbb{E}(\pi_i(e_i)|h) \geq 0$, which implies that the project's expected payoff to the firm $\mathbb{E}\Pi_i = \mathbb{E}(\Pi_i|h, e_i) \geq 0$. Because of our assumption, and because it is costless to propose a project, manager *i* always proposes if $\theta_i = h$. Thus, if $\theta_i = h$ and $\theta_j = l$, senior management selects project *i*, and $\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = h, \theta_j = l) = \mathbb{E}(\pi_i(e_i)|h) = \left[\left(\frac{1+e_i}{2}\right) r - \left(\frac{1-e_i}{2}\right) k\right] - \frac{de_i^2}{2}$. If $\theta_i = \theta_j = h$, senior management chooses the project with higher effort level and randomizes if the effort levels are the same:

$$\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = h, \theta_j = h) = \begin{cases} \left[\left(\frac{1+e_i}{2}\right) r - \left(\frac{1-e_i}{2}\right) k\right] - \frac{de_i^2}{2} \text{ if } e_i > e_j \\ -\frac{de_i^2}{2} \text{ if } e_i < e_j \\ \frac{1}{2}\left[\left(\frac{1+e_i}{2}\right) r - \left(\frac{1-e_i}{2}\right) k\right] - \frac{de_i^2}{2} \text{ if } e_i = e_j \end{cases}$$

Thus, in Stages 1 and 2, before the signals are realized, the expected payoff of manager *i* given effort levels e_i and e_j can then be written as

$$\begin{aligned} \mathbb{E}(\pi_i(e_i, e_j)) \equiv \; & \frac{1}{4}\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = h, \theta_j = h) + \frac{1}{4}\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = h, \theta_j = l) + \\ & \frac{1}{4}\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = l, \theta_j = h) + \frac{1}{4}\mathbb{E}(\pi_i(e_i, e_j)|\theta_i = l, \theta_j = l) \end{aligned} \quad (5.1)$$

Recall from (2.5) and (2.6) that $f_i(e_i) = \frac{r_i - k_i}{8} + \left(\frac{r_i + k_i}{8}\right) e_i - \frac{d_i e_i^2}{2}$ and $g_i(e_i) = \frac{r_i - k_i}{4} + \left(\frac{r_i + k_i}{4}\right) e_i - \frac{d_i e_i^2}{2}$ with global maxima at $e^*_{f_i} = \frac{r_i + k_i}{8 d_i}$ and $e^*_{g_i} = \frac{r_i + k_i}{4 d_i}$, respectively. Moreover, e''_{g_i} is the effort level such that $g_i(e''_{g_i}) = f_i(e^*_{f_i})$. Additionally, define $t_i(e_i) \equiv 3\left(\frac{r_i - k_i}{16}\right) + 3\left(\frac{r_i + k_i}{16}\right) e_i - \frac{d_i e_i^2}{2}$. We can equivalently define these values for manager j: $\mathbb{E}(\pi_j(e_j, e_i)|\theta_j, \theta_i)$, $\mathbb{E}(\pi_j(e_j, e_i))$, $f_j(e_j)$, $g_j(e_j)$, and $t_j(e_j)$.

In Stage 2, manager j's best response to manager i's effort level e_i is one of the following:

Case 2a: $e_i \in [0, e^*_g)$**.** Manager j's best response is $\text{BR}_j(e_i) = e^*_g$. To see this, we compare manager j's expected payoff for $e_j(e_i) < e_i$, $e_j(e_i) > e_i$, and $e_j(e_i) = e_i$.

Suppose $e_j(e_i) < e_i$. Project i will be selected by senior management if $\theta_i = \theta_j = h$ in Stage 4, yielding $\mathbb{E}(\pi_j(e_j(e_i), e_i)|\theta_j = h, \theta_i = h) = -\frac{d e_j(e_i)^2}{2}$. The expected payoffs under other signal realizations follow from Stage 3 characterization above. The expected payoff of manager j before the signals are realized as given by (5.1) is

$\mathbb{E}(\pi_j(e_j(e_i), e_i)) = \frac{1}{4}\left[\left(\frac{1+e_j(e_i)}{2}\right) r - \left(\frac{1-e_j(e_i)}{2}\right) k\right] - \frac{d e_j(e_i)^2}{2} = f(e_j(e_i))$.

Suppose $e_j(e_i) > e_i$. Project j will be selected by senior management if $\theta_i = \theta_j = h$ in Stage 4, yielding

$\mathbb{E}(\pi_j(e_j(e_i), e_i)|\theta_j = h, \theta_i = h) = \left[\left(\frac{1+e_j(e_i)}{2}\right) r - \left(\frac{1-e_j(e_i)}{2}\right) k\right] - \frac{d e_j(e_i)^2}{2}$. The expected payoff of manager j before the signals are realized is

$\mathbb{E}(\pi_j(e_j(e_i), e_i)) = \frac{1}{2}\left[\left(\frac{1+e_j(e_i)}{2}\right) r - \left(\frac{1-e_j(e_i)}{2}\right) k\right] - \frac{d e_j(e_i)^2}{2} = g(e_j(e_i))$, which has a global maximum at $e_j(e_i) = e^*_g > e_i$ and yields an expected payoff $g(e^*_g)$.

Suppose $e_j(e_i) = e_i$. If $\theta_i = \theta_j = h$, project j will be selected with probability $\frac{1}{2}$ in Stage 4, because the expected payoff to the firm of the two projects are equal, yielding

$\mathbb{E}(\pi_j(e_j(e_i), e_i)|\theta_j = h, \theta_i = h) = \frac{1}{2}\left[\left(\frac{1+e_j(e_i)}{2}\right) r - \left(\frac{1-e_j(e_i)}{2}\right) k\right] - \frac{d e_j(e_i)^2}{2}$. The expected payoff of manager j before the signals are realized is

$\mathbb{E}(\pi_j(e_j(e_i), e_i)) = \frac{3}{8}\left[\left(\frac{1+e_j(e_i)}{2}\right) r - \left(\frac{1-e_j(e_i)}{2}\right) k\right] - \frac{d e_j(e_i)^2}{2} = t_i(e_j(e_i))$.

We now compare $f(e_j(e_i))$, $g(e_g^*)$, and $t_i(e_j(e_i))$. Since $g(e_g^*)$ is the global maximum of $g(\cdot)$ and $f(e) < t(e) < g(e)\ \forall e \in [0, 1]$, we conclude that $g(e_g^*) > f(e_j(e_i))$ and $g(e_g^*) > t(e_j(e_i))$ for all $e_j(e_i) \in [0, 1]$. Thus, the best response of manager j is $BR_j(e_i) = e_g^*$ if $e_i \in [0, e_g^*)$.

Case 2b: $e_i \in [e_g^*, e_g^{''})$**.** Manager j's best response is $BR_j(e_i) = e_i + \varepsilon$, where $\varepsilon > 0$. To see this, we compare manager j's expected payoff when $e_j(e_i) < e_i$, $e_j(e_i) > e_i$, and $e_j(e_i) = e_i$.

Suppose $e_j(e_i) < e_i$. From the previous case, manager j's expected payoff before the signals are realized is $\mathbb{E}(\pi_j(e_j(e_i), e_i)) = f(e_j(e_i))$, which has a global maximum at e_f^* $(< e_i)$, resulting in expected payoff of $f(e_f^*)$.

Suppose $e_j(e_i) > e_i$. From the previous case, manager j's expected payoff before the signals are realized is $\mathbb{E}(\pi_j(e_j(e_i), e_i)) = g(e_j(e_i))$, which is decreasing in $e_j(e_i)$ for $e_j(e_i) \geq e_g^*$. This results in j's optimal effort level $e_j(e_i) = e_i + \varepsilon$ (where $\varepsilon > 0$), which yields an expected payoff $g(e_i + \varepsilon)$.

Suppose $e_j(e_i) = e_i$. From the previous case, manager j's expected payoff before the signals are realized is $\mathbb{E}(\pi_j(e_j(e_i), e_i)) = t(e_j(e_i)) = t(e_i)$.

We now compare $f(e_f^*)$, $g(e_i + \varepsilon)$, and $t(e_i)$. It is easy to see that for a sufficiently small $\varepsilon > 0$, $g(e_i + \varepsilon) > t(e_i)\ \forall e_i \in [e_g^*, e_g^{''})$. Moreover, $g(e_i + \varepsilon) > f(e_f^*)$ if $e_i \in [e_g^*, e_g^{''})$. Thus, we conclude that $BR_j(e_i) = e_i + \varepsilon$ is manager j's best response if $e_i \in [e_g^*, e_g^{''})$.

Case 2c: $e_i \in [e_g^{''}, 1]$**.** Manager j's best response is $BR_j(e_i) = e_f^*$. To see this, we compare manager j's expected payoff when $e_j(e_i) < e_i$, $e_j(e_i) > e_i$, and $e_j(e_i) = e_i$.

Suppose $e_j(e_i) < e_i$. As in previous cases, manager j's expected payoff before the signals are realized is $\mathbb{E}(\pi_j(e_j(e_i), e_i)) = f(e_j(e_i))$, which has a global maximum at e_f^* $(< e_i)$, resulting in expected payoff of $f(e_f^*)$.

Suppose $e_j(e_i) > e_i$. As in previous cases, manager j's expected payoff before the signals are realized is $\mathbb{E}(\pi_j(e_j(e_i), e_i)) = g(e_j(e_i))$, which is decreasing in $e_j(e_i)$ for $e_j(e_i) > e_i \geq e_g^{''}$.

Suppose $e_j(e_i) = e_i$. As in previous cases, manager j's expected payoff before the signals are realized is $\mathbb{E}(\pi_j(e_j(e_i), e_i)) = t(e_j(e_i)) = t(e_i)$.

We now compare $f(e_f^*)$, $g(e_j(e_i))$, and $t(e_i)$. By our definition of $e_g^{''}$, $g(e_j(e_i)) < f(e_f^*)$ for any $e_j(e_i) > e_i \geq e_g^{''}$. Moreover, it is never optimal to choose $e_j(e_i) = e_i$: for a sufficiently small $\varepsilon > 0$, $g(e_i + \varepsilon) > t(e_i)\ \forall e_i \in [e_g^{''}, 1)$, and when $e_i = 1$, $t(1) < g(1) < g(e_g^{''}) = f(e_f^*)$. Thus, we conclude that $\text{BR}_j(e_i) = e_f^*$ is manager j's best response if $e_i \in [e_g^{''}, 1]$.

In Stage 1, consider manager i's optimal effort level e_i^*, anticipating manager j's best response $\text{BR}_j(e_i)$ in Stage 2. We define the optimal expected payoff of manager i as $\mathbb{E}\pi_i \equiv \mathbb{E}(\pi_i(e_i^*, \text{BR}_j(e_i^*)))$, and equivalently for manager j. We also let $\mathbb{E}\Pi$ denote the firm's optimal expected payoff. There are two possible cases:

Case 1a: $e_i \in [0, e_g^{''})$. Manager i maximizes his profit by setting $e_i^* = e_f^*$, resulting in optimal expected payoff $\mathbb{E}\pi_i = f(e_f^*)$. To see this, we show that manager i's expected payoff before the signals are realized $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i))$ is $f(e_i)$, which is maximized at e_f^*. Recall that $\text{BR}_j(e_i) = e_g^*$ if $e_i \in [0, e_g^*)$ (Case 2a), and $\text{BR}_j(e_i) = e_i + \varepsilon$ if $e_i \in [e_g^*, e_g^{''})$ (Case 2b). Thus, when $e_i \in [0, e_g^{''})$, $\text{BR}_j(e_i) > e_i$. If $\theta_i = \theta_j = h$, senior management will choose project j in Stage 4, and thus the expected payoff of manager i before the signals are realized, as given by (5.1), is $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i)) = \frac{1}{4}\left[\left(\frac{1+e_i}{2}\right) r - \left(\frac{1-e_i}{2}\right) k\right] - \frac{de_i^2}{2} = f(e_i)$.

Case 1b: $e_i \in [e_g^{''}, 1]$. Manager i's maximizes his profit by setting $e_i^* = e_g^{''}$, resulting in optimal expected payoff $\mathbb{E}\pi_i = g(e_g^{''})$. To see this, we show that $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i)) = g(e_i)$, which is maximized at $e_g^{''}$ if $e_i \in [e_g^{''}, 1]$ since $g(e_i)$ is decreasing in e_i for $e_i \geq e_g^*$. Recall that $\text{BR}_j(e_i) = e_f^* < e_i$ if $e_i \in [e_g^{''}, 1]$ (Case 2c). If $\theta_i = \theta_j = h$, senior management will choose project i in Stage 4, and thus the expected payoff of manager i before the signals are realized is $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i)) = \frac{1}{2}\left[\left(\frac{1+e_i}{2}\right) r - \left(\frac{1-e_i}{2}\right) k\right] - \frac{de_i^2}{2} = g(e_i)$.

Manager i's expected payoffs in Case 1a and Case 1b are equivalent because $f(e_f^*) = g(e_g^{''})$. Moreover, by Assumption 2, $f(e_f^*) = g(e_g^{''}) \geq 0$. Thus, there are two equilibria:

In equilibrium 1, manager i's optimal effort level is $e_i^* = e_f^*$, with corresponding optimal effort level by manager j $\text{BR}_j(e_f^*) = e_g^*$. This yields an optimal expected payoff for manager i of $\mathbb{E}\pi_i = f(e_f^*)$ and an optimal expected payoff for manager j of $\mathbb{E}\pi_j = g(e_g^*)$. Project i is chosen by senior management with probability $\frac{1}{4}$ (i.e., when $\theta_i = h, \theta_j = l$), and project j is chosen by senior management with probability $\frac{1}{2}$ (i.e., when $\theta_j = h$). The expected payoff to the firm is $\mathbb{E}\Pi = \frac{1}{4}\mathbb{E}(\Pi_j|h, e_f^*) + \frac{1}{2}\mathbb{E}(\Pi_i|h, e_g^*) = \frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e_f^*}{4} + \frac{e_g^*}{2}\right)$.

In equilibrium 2, manager i's optimal effort level is $e_j^* = e_g^{''}$, with corresponding optimal effort level by manager j $\mathrm{BR}_j(e_g^{''}) = e_f^*$. This yields an optimal expected payoff for manager i of $\mathbb{E}\pi_i = g(e_g^{''})$ and an optimal expected payoff for manager j of $\mathbb{E}\pi_j = f(e_f^*)$. Project i is chosen by senior management with probability $\frac{1}{2}$ (i.e., when $\theta_i = h$) and project j is chosen with probability $\frac{1}{4}$ (i.e., when $\theta_i = l, \theta_j = h$). The expected payoff to the firm is
$\mathbb{E}\Pi = \frac{1}{2}\mathbb{E}(\Pi_i|h, e_g^{''}) + \frac{1}{4}\mathbb{E}(\Pi_j|h, e_f^*) = \frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e_g^{''}}{2} + \frac{e_f^*}{4}\right)$.

Recall our assumption in Stage 3 that $\mathbb{E}(\pi_i(e_i)|h) \geq 0$. Since $\mathbb{E}(\pi_i(e_i)|h) \geq g(e_i) \geq f(e_i)\ \forall e_i \in [0, 1]$, this assumption is satisfied at our optimal solutions since $g(e_g^{''}) = f(e_f^*) \geq 0$ by Assumption 2. The same argument follows for $\mathbb{E}(\pi_j(e_j)|h) \geq 0$ to be satisfied at $\mathrm{BR}_j(e_i^*) = e_g^*$ and $\mathrm{BR}_j(e_i^*) = e_f^*$.

We now comment on the stable equilibrium chosen by the managers in practice. Equilibrium 2 is an unstable equilibrium. If manager i miscalculates slightly on his effort level, manager j may still be able to profitably exert more effort than manager i and present a higher expected payoff project to senior management. In this case, manager i would then prefer to play weak. Thus, equilibrium 1 is the only stable outcome. It follows that when manager i is the first mover, in the stable outcome, manager i's project is implemented with probability $\frac{1}{4}$, manager j's project is implemented with probability $\frac{1}{2}$, and no project is implemented with probability $\frac{1}{4}$.

Lastly, we take expectation over the realization of the first mover to obtain the probability of each manager's project implementation. When the timing of effort commitment is random, the probability that manager i is manager 1 is $\frac{1}{2}$ and the probability that manager i is manager 2 is $\frac{1}{2}$. Thus, manager 1 is the first mover with probability $\frac{1}{2}$ and second mover with probability $\frac{1}{2}$. The probability that manager 1's project is implemented is then $\left(\frac{1}{2}\right)\left(\frac{1}{4}\right)+\left(\frac{1}{2}\right)\left(\frac{1}{2}\right)=\frac{3}{8}$. Analogous reasoning applies for manager 2. Similarly, the probability that no project is implemented is $\left(\frac{1}{2}\right)\left(\frac{1}{4}\right)+\left(\frac{1}{2}\right)\left(\frac{1}{4}\right)=\frac{1}{4}$. The expected payoff to the firm, which is denoted $\mathbb{E}\Pi_s$, is the same regardless which manager commits effort first: $\mathbb{E}\Pi_s=\frac{1}{4}\mathbb{E}(\Pi_j|h,e_f^*)+\frac{1}{2}\mathbb{E}(\Pi_i|h,e_g^*)=\frac{3}{8}\left(r-k\right)+\frac{r+k}{2}\left(\frac{e_f^*}{4}+\frac{e_g^*}{2}\right)$.

This completes the proof. ■

Proof of Corollary 1. This result follows directly from the proof of Proposition 1. ■

Lemma 3 *The value e''_{g_i}, where $g_i(e''_{g_i})=f_i(e^*_{f_i})$, is decreasing in d_i.*

Proof of Lemma 3. Recall expressions for $f_i(\cdot)$ and $g_i(\cdot)$ from (2.5) and (2.6). Solving $g_i(e''_{g_i})=f_i(e^*_{f_i})$ for the feasible root greater than $e^*_{g_i}$ yields $e''_{g_i}=\frac{r_i+k_i}{4d_i}+\sqrt{\frac{3(r_i+k_i)^2}{64d_i^2}+\frac{r_i-k_i}{4d_i}}$. Taking the derivative with respect to d_i gives $\frac{\partial}{\partial d_i}e''_{g_i}=\frac{-(r_i+k_i)^2}{4d_i^2}-\left(\frac{6(r_i+k_i)^2}{128d_i^3}+\frac{r_i-k_i}{8d_i^2}\right)\left(\frac{3(r_i+k_i)^2}{64d_i^2}+\frac{r_i-k_i}{4d_i}\right)^{-\frac{1}{2}}<0$ ■

Lemma 4 *Suppose $d_1>d_2$ and manager 1 is the first mover. The optimal effort levels are $e_1^*=e^*_{f_1}$ and $e_2^*=e^*_{g_2}$, resulting in expected payoffs $\mathbb{E}\pi_1=f_1(e^*_{f_1})$, $\mathbb{E}\pi_2=g_2(e^*_{g_2})$, and $\mathbb{E}\Pi=\frac{3}{8}\left(r-k\right)+\frac{r+k}{2}\left(\frac{e^*_{f_1}}{4}+\frac{e^*_{g_2}}{2}\right)$. Manager 1's project (waste heat recovery) is implemented with probability $\frac{1}{4}$, manager 2's project is implemented with probability $\frac{1}{2}$, and no project is implemented with probability $\frac{1}{4}$.*

Proof of Lemma 4. We prove this lemma by backwards induction, using the timing in Section 2.3. We proceed by the same logic as in the proof of Proposition 1

In Stage 4, senior management chooses the project with higher expected payoff to the firm, provided that the expected payoff to the firm is positive. If the two projects' payoff are tied, senior management randomizes between the two projects with equal probability. Note that if the signal realizations are $\theta_1=\theta_2=h$ and both projects are proposed, the projects' expected payoffs to the firm are $\mathbb{E}\Pi_1=\mathbb{E}(\Pi_1|h,e_1)$ and $\mathbb{E}\Pi_2=\mathbb{E}(\Pi_2|h,e_2)$, according to (2.3). Since the projects' payoffs are symmetric ($r_1 = r_2 = r$ and $k_1 = k_2 = k$) and the projects' expected payoffs to the firm are independent of effort cost d_i, the expected payoff to the firm is increasing in effort level: $\mathbb{E}\Pi_i > \mathbb{E}\Pi_j$ if and only if $e_i > e_j$.

Following the same logic as in the proof of Proposition 1, in Stage 3, manager i ($i = 1, 2$) proposes his project if and only if $\theta_i = h$, and in Stage 2, manager 2's best response $BR_2(e_1)$ given e_1 is as follows:

Case 2c: $e_1 \in [0, e^*_{g_2})$. Manager 2's best response is $BR_2(e_1) = e^*_{g_2}$. See Case 2a from the proof of Proposition 1.

Case 2c: $e_1 \in [e^*_{g_2}, e''_{g_2})$. Manager 2's best response is $BR_2(e_1) = e_1 + \varepsilon$. See Case 2b from the proof of Proposition 1.

Case 2c: $e_1 \in [e''_{g_2}, 1]$. Manager 2's best response is $BR_2(e_1) = e^*_{f_2}$. See Case 2c from the proof of Proposition 1.

In Stage 1, we consider manager 1's effort level taking into account manager 2's best response in Stage 2. There are two possible cases:

Case 1a: $e_1 \in [0, e''_{g_2})$. Manager 1 maximizes his profit by setting $e^*_1 = e^*_{f_1}$, resulting in expected payoff $f_1(e^*_{f_1})$. To see this, we show that manager 1's expected payoff before the signals are realized $\mathbb{E}(\pi_1(e_1, BR_2(e_1))$ is $f_1(e_1)$. If $e_1 \in [0, e''_{g_2})$, $BR_2(e_1) > e_1$, so senior management chooses project 2 when $\theta_1 = \theta_2 = h$. Following Case 1a in the proof of Proposition 1, we obtain $\mathbb{E}(\pi_1(e_1, BR_2(e_1)) = f_1(e_1)$, which is maximized at $e^*_1 = e^*_{f_1}$.

Case 1b: $e_1 \in [e''_{g_2}, 1]$. Manager 1 maximizes his profit by setting $e^*_1 = e''_{g_2}$, resulting in expected payoff $g_1(e''_{g_2})$. To see this, we show that manager 1's expected payoff before the signals are realized $\mathbb{E}(\pi_1(e_1, BR_2(e_1))$ is $g_1(e_1)$. If $e_1 \in [e''_{g_2}, 1]$, $BR_2(e_1) < e_1$, so senior management chooses project 2 when $\theta_1 = \theta_2 = h$. Following Case 1b in the proof of Proposition 1, we obtain $\mathbb{E}(\pi_1(e_1, BR_2(e_1)) = g_1(e_1)$, which is decreasing in e_1 if $e_1 \in [e''_{g_2}, 1]$, and is maximized at $e^*_1 = e''_{g_2}$.

We now compare $f_1(e^*_{f_1})$ and $g_1(e''_{g_2})$, manager 1's expected payoff from the two cases above. From Lemma 3, e''_{g_i} is decreasing in d_i. Given that $r_1 = r_2 = r$;

$k_1 = k_2 = k$ and $d_1 > d_2$, it follows that $e''_{g_1} < e''_{g_2}$. Since $g_1(e_1)$ is decreasing in e_1 for $e_1 \geq e^*_{g_1}$, we conclude that $g_1(e''_{g_2}) < g_1(e''_{g_1}) = f_1(e^*_{f_1})$.

Thus, in equilibrium, manager 1's optimal effort level is $e^*_1 = e^*_{f_1}$ with optimal expected payoff of manager 1 $\mathbb{E}\pi_1 = f_1(e^*_{f_1})$. Since $e^*_{f_1} < e^*_{g_1} < e^*_{g_2}$, the corresponding optimal effort level of manager 2 is $e^*_2 = \text{BR}_2(e^*_{f_1}) = e^*_{g_2}$ which yields optimal expected payoff of manager 2 $\mathbb{E}\pi_2 = g_2(e^*_{g_2})$. By Assumption 2, $f_1(e^*_{f_1}) \geq 0$ and $g_2(e^*_{g_2}) \geq 0$. Project 1 is implemented by senior management with probability $\frac{1}{4}$ (i.e. when $\theta_1 = h$ and $\theta_2 = l$) and project 2 is implemented by senior management with probability $\frac{1}{2}$ (i.e. when $\theta_2 = h$). The expected payoff to the firm is $\mathbb{E}\Pi = \frac{1}{4}\mathbb{E}(\Pi_1|h, e^*_{f_1}) + \frac{1}{2}\mathbb{E}(\Pi_2|h, e^*_{g_2}) = \frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e^*_{f_1}}{4} + \frac{e^*_{g_2}}{2}\right)$.

This completes the proof. ■

Lemma 5 *Suppose $d_1 > d_2$ and manager 1 is the second mover. The optimal effort levels are $e_1 = e^*_{f_1}$ and $e_2 = e''_{g_1} (> e^*_{g_2})$, resulting in expected payoffs $\mathbb{E}\pi_1 = f_1(e^*_{f_1})$, $\mathbb{E}\pi_2 = g_2(e''_{g_1})$, and $\mathbb{E}\Pi = \frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e^*_{f_1}}{4} + \frac{e''_{g_1}}{2}\right)$. Manager 1's project (waste heat recovery) is implemented with probability $\frac{1}{4}$, manager 2's project is implemented with probability $\frac{1}{2}$, and no project is implemented with probability $\frac{1}{4}$.*

Proof of Lemma 5. We prove this lemma by backwards induction, using the timing in Section 2.3. We proceed by the same logic as in the proof of Lemma 4.

In Stage 4, if $\theta_1 = \theta_2 = h$ and both projects are proposed, then $\mathbb{E}\Pi_i > \mathbb{E}\Pi_j$ if and only if $e_i > e_j$ ($i = 1, 2; j \neq i$). In Stage 3, manager i proposes his project if and only if $\theta_i = h$. In Stage 2, manager 1's best response given manager 2's effort, $\text{BR}_1(e_2)$, is as follows:

Case 2a: $e_2 \in [0, e^*_{g_1})$. Manager 1's best response is $\text{BR}_1(e_2) = e^*_{g_1}$. See Case 2a from the proof of Lemma 4.

Case 2b: $e_2 \in [e^*_{g_1}, e''_{g_1})$. Manager 1's best response is $\text{BR}_1(e_2) = e_2 + \varepsilon$. See Case 2b from the proof of Lemma 4.

Case 2c: $e_2 \in [e''_{g_1}, 1]$. Manager 1's best response is $\text{BR}_1(e_2) = e^*_{f_1}$. See Case 2c from the proof of Lemma 4.

In Stage 1, we consider manager 2's effort level taking into account manager 1's best response in Stage 2. There are two possible cases:

Case 1a: $e_2 \in [0, e''_{g_1})$**.** Manager 2 maximizes his profit by setting $e_2^* = e_{f_2}^*$, resulting in expected payoff $f_2(e_{f_2}^*)$. To see this, we show that manager 2's expected payoff before the signals are realized $\mathbb{E}(\pi_2(e_2, \text{BR}_1(e_2))$ is $f_2(e_2)$. Since $\text{BR}_1(e_2) > e_2$ in this range, when $\theta_1 = \theta_2 = h$ senior management chooses project 1. Following Case 1a in the proof of Lemma 4, we obtain $\mathbb{E}(\pi_2(e_2, \text{BR}_1(e_2))$ is $f_2(e_2)$, which is maximized at $e_2^* = e_{f_2}^*$.

Case 1b: $e_2 \in [e''_{g_1}, 1]$**.** Manager 2's maximizes his profit by setting $e_2^* = e''_{g_1}$, resulting in expected payoff $g_2(e''_{g_1})$.

To see this, we first show that $e_2^* = e_{g_2}^*$ if $e''_{g_1} \leq e_{g_2}^*$ and $e_2^* = e''_{g_1}$ if $e''_{g_1} > e_{g_2}^*$. We then show that given Assumption 2, $e''_{g_1} > e_{g_2}^*$ always.

To show the first part, first note that manager 2's expected payoff before the signals are realized $\mathbb{E}(\pi_2(e_2, \text{BR}_1(e_2))$ is $g_2(e_2)$ since $\text{BR}_1(e_2) = e_{f_1}^* < e_2$ if $e_2 \in [e''_{g_1}, 1]$, so senior management chooses project 2 when $\theta_1 = \theta_2 = h$. Now compare e''_{g_1} and $e_{g_2}^*$. If $e''_{g_1} > e_{g_2}^*$, then $e_2^* = e''_{g_1}$ if $e_2 \in [e''_{g_1}, 1]$ since $g_2(e_2)$ is decreasing in e_2 for $e_2 \geq e_{g_2}^*$. If $e''_{g_1} \leq e_{g_2}^*$, then $e_2^* = e_{g_2}^*$ if $e_2 \in [e''_{g_1}, 1]$ because $e_{g_2}^*$ is the global optimal of $g_2(\cdot)$.

To show the second part, recall the expression for e''_{g_1} in the proof of Lemma 3. Then $e''_{g_1} < e_{g_2}^*$ is equivalent to $d_1 < d_2\left(1 + \frac{2(r-k)d_2}{(r+k)^2} + \sqrt{\left(1 + \frac{2(r-k)d_2}{(r+k)^2}\right)^2 - \frac{1}{4}}\right) = \hat{d}_1(d_2, r, k)$. It suffices to show that $\hat{d}_1(d_2, r, k) > k$, which implies $\hat{d}_1(d_2, r, k) > d_1$ by Assumption 2. To see this, notice that for a given d_2, $\hat{d}_1(d_2, r, k)$ is increasing in r (recall that $r < k$), thus by Assumption 2 this expression is smallest when $r = \frac{4}{5}k$. Fix $r = \frac{4}{5}k$, then $d_2 \in (\frac{4}{5}k, k)$. Let $t(d_2, r, k) \equiv \left(1 + \frac{2(r-k)d_2}{(r+k)^2} + \sqrt{\left(1 + \frac{2(r-k)d_2}{(r+k)^2}\right)^2 - \frac{1}{4}}\right)$. It is straightforwad to see that $t(d_2, r, k)$ is decreasing in d_2 for a given r since $r < k$. Substituting the upper and lower bounds of d_2 and $r = \frac{4}{5}k$ gives $t(\frac{4}{5}k, \frac{4}{5}k, k) = 1.6511$, and $t(k, \frac{4}{5}k, k) = 1.5965$. It follows that

$\hat{d}_1(d_2, \frac{4}{5}k, k) > \left(\frac{4}{5}k\right) t(k, \frac{4}{5}k, k) = 1.2772k > k$. Thus, for $r = \frac{4}{5}k$, $\hat{d}_1(d_2, \frac{4}{5}k, k) > k$ for all feasible d_2. It is straightforward to see that $\hat{d}_1(d_2, r, k) > k$ for all feasible r and d_2 as given by Assumption 2.

We now compare manager 2's expected payoff in Case 1a $(f_2(e^*_{f_2}))$ and in Case 1b $(g_2(e''_{g_1}))$. Recall from the proof of Lemma 4 that $e''_{g_1} < e''_{g_2}$. Then because $g_2(e_2)$ is decreasing in e_2 for $e_2 \geq e^*_{g_2}$, we conclude that $g_2(e''_{g_1}) > g_2(e''_{g_2}) = f_2(e^*_{f_2})$. Thus, in equilibrium, manager 2's optimal effort level corresponds to Case 1b: $e^*_2 = e''_{g_1}$ with optimal expected payoff for manager 2 of $\mathbb{E}\pi_2 = g_2(e''_{g_1})$ and $e^*_1 = \text{BR}_1(e''_{g_1}) = e^*_{f_1}$ with optimal expected payoff for manager 1 of $\mathbb{E}\pi_1 = f_1(e^*_{f_1})$. The expected payoff to the firm is

$$\mathbb{E}\Pi = \mathbb{E}\pi_1 + \mathbb{E}\pi_2 + \left(\frac{d_1(e^*_1)^2}{2}\right) + \left(\frac{d_2(e^*_2)^2}{2}\right) = \frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e^*_{f_1}}{4} + \frac{e''_{g_1}}{2}\right).$$

Assumption 2 ensures that $g_2(e''_{g_1}) > 0$ and $f_1(e^*_{f_1}) \geq 0$. Moreover, manager 1's project is implemented with probability $\frac{1}{4}$ (when $\theta_1 = h$ and $\theta_2 = l$), manager 2's project is implemented with probability $\frac{1}{2}$ (when $\theta_2 = h$), and no project is implemented with probability $\frac{1}{4}$.

This completes the proof. ■

Proof of Proposition 2. This result follows directly from Lemmas 4 and 5. Regardless of effort commitment order, manager 1's project (energy efficiency) is implemented with probability $\frac{1}{4}$ and manager 2's project is implemented with probability $\frac{1}{2}$. When managers have symmetric costs of effort, each manager's project is implemented with probability $\frac{3}{8}$ (Proposition 1). Thus, if $d_1 > d_2$, project 1 (energy efficiency) is less likely to be implemented and project 2 is more likely to be implemented. ■

Proof of Proposition 3. If $a_1 > A > a_2$, project 2 will never be implemented by senior management because it violates the emissions reduction constraint. The expected payoff of manager 2 before the signals are realized follows $-\frac{d_2 e_2^2}{2}$, which is maximized at $e^*_2 = 0$, yielding optimal expected payoff of manager 2 $\mathbb{E}\pi_2 = 0$. Because project 2 is never implemented, it follows that manager 1's optimal effort level is independent of e_2 and θ_2. If $\theta_1 = l$, since $\mathbb{E}(\pi_1(e_1)|l) < 0$ for all e_1, manager 1 never proposes project 1. Project i is never implemented and the expected payoff given $\theta_1 = l$ is $-\frac{d_1 e_1^2}{2}$. Now suppose $\theta_1 = h$. If manager 1 proposes project 1 and project 1's expected payoff to the firm is positive ($\mathbb{E}\Pi_1 \geq 0$), project 1 is implemented and the expected payoff of manager 1 given $\theta_1 = h$ is $\left[\left(\frac{1+e_1}{2}\right) r_1 - \left(\frac{1-e_1}{2}\right) k_1\right] - \frac{d_1 e_1^2}{2}$. Since the probability of signal realization is $\Pr(\theta_1 = h) = \Pr(\theta_1 = l) = \frac{1}{2}$, the expected payoff of manager 1 before the signals are realized is $\frac{1}{2}\left(\left[\left(\frac{1+e_1}{2}\right) r_1 - \left(\frac{1-e_1}{2}\right) k_1\right] - \frac{d_1 e_1^2}{2}\right) + \frac{1}{2}\left(-\frac{d_1 e_1^2}{2}\right) = g_1(e_1)$, which attains a global maximum at $e_1^* = e_{g_1}^*$ and yields optimal expected payoff for manager 1 of $\mathbb{E}\pi_1 = g_1(e_{g_1}^*)$. Assumption 2 ensures that $e_1^* \in (0, 1)$ and $\mathbb{E}\pi_1 > 0$. It follows that $\mathbb{E}\Pi_1 \geq 0$, so manager 1 proposes the project when $\theta_1 = h$ with probability $\frac{1}{2}$, and senior management choses project 1 if manager 1 proposes it. The optimal expected payoff to the firm is $\frac{1}{2}\mathbb{E}\Pi_1 = \frac{1}{2}\mathbb{E}(\Pi_1 | h, e_{g_1}^*) = \frac{1}{4}(r-k) + \frac{r+k}{2}\left(\frac{e_{g_1}^*}{2}\right)$. ■

Proof of Corollary 2. If manager 1 moves first, the firm's opportunity cost of setting the environmental goal is the difference between the optimal expected payoffs to the firm in Lemma 4 and Proposition 3: $C_1 \equiv \left[\frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e_{f_1}^*}{4} + \frac{e_{g_2}^*}{2}\right)\right] - \left[\frac{1}{4}(r-k) + \frac{r+k}{2}\left(\frac{e_{g_1}^*}{2}\right)\right] = \frac{1}{8}(r-k) + \frac{r+k}{2}\left(\frac{e_{f_1}^*}{4} + \frac{e_{g_2}^* - e_{g_1}^*}{2}\right)$. If manager 2 moves first, the firm's opportunity cost of setting the environmental goal is the difference between the optimal expected payoffs to the firm in Lemma 5 and Proposition 3: $C_2 \equiv \left[\frac{3}{8}(r-k) + \frac{r+k}{2}\left(\frac{e_{f_1}^*}{4} + \frac{e_{g_1}^{''}}{2}\right)\right] - \left[\frac{1}{4}(r-k) + \frac{r+k}{2}\left(\frac{e_{g_1}^*}{2}\right)\right] = \frac{1}{8}(r-k) + \frac{r+k}{2}\left(\frac{e_{f_1}^*}{4} + \frac{e_{g_1}^{''}}{2} - \frac{e_{g_1}^*}{2}\right)$. Because of Assumption 2, and because $e_{g_2}^* > e_{g_1}^*$ and $e_{g_1}^{''} > e_{g_1}^*$, we obtain C_1 and $C_2 > 0$. Since the probability that each manager moves first is $\frac{1}{2}$, on average, the firm's opportunity cost of setting the environmental initiative is $\frac{1}{2}C_1 + \frac{1}{2}C_2 = \frac{r-k}{8} + \frac{r+k}{8}\left(e_{f_1}^* + e_{g_1}^{''} + e_{g_2}^* - 2e_{g_1}^*\right)$. ■

Proof of Proposition 4. To prove Proposition 4, we proceed by backwards induction using the timing in Section 2.3, following the same reasoning as in the proof of Proposition 1. Note that because of Assumption 2, the feasible range of the subsidy is $r_1 \in (r_2, d_1)$. We then define the critical level of subsidy $\hat{r}_1$ above which the probability that waste heat recovery is implemented increases from $\frac{1}{4}$ to $\frac{1}{2}$ and show that $\hat{r}_1 \in (r_2, d_1)$. Let manager i be the first mover, and let manager j be the second mover.

The reasoning used for Stages 3 and 4 of the game is identical to the reasoning used in the proof of Proposition 1, with one difference. Suppose both signals are high $\theta_i = \theta_j = h$, and thus both projects are proposed. In the proof of Proposition 1, since the payoffs are symmetric $r_1 = r_2 = r$ and $k_1 = k_2 = k$, the project with the higher effort has the higher expected payoff to the firm: $\mathbb{E}\Pi_i > \mathbb{E}\Pi_j$ if and only if $e_i > e_j$. Thus, in this scenario senior management will choose the project with the higher effort level. With the subsidy, the payoffs are not symmetric $(r_1 > r_2)$, and thus the expected payoff to the firm is not determined by the effort level alone. Recall the expected payoff to the firm from project i given $\theta_i = h$: $\mathbb{E}\Pi_i = \mathbb{E}(\Pi_i | h, e_i) = \left(\frac{1+e_i}{2}\right) r_i - \left(\frac{1-e_i}{2}\right) k$. We define $w_j(e_i) \equiv \frac{r_i - r_j}{r_j + k} + \left(\frac{r_i + k}{r_j + k}\right) e_i$ to be manager j's effort level that allows the expected payoff to the firm from project j to equal the expected payoff to the firm from project i, given manager i exerts effort e_i. In other words, $\mathbb{E}(\Pi_i | h, e_i) = \mathbb{E}(\Pi_j | h, w_j(e_i))$. We equilvalently define $w_i(e_j)$. Note that $w_j(w_i(e_j)) = e_j$ and $w_i(w_j(e_i)) = e_i$.

In Stage 2, manager j's best response $\text{BR}_j(e_i)$ given e_i is as follows:

Case 2a: $w_j(e_i) < e^*_{g_j}$**.** Manager j's best response is $\text{BR}_j(e_i) = e^*_{g_j}$. See Case 2a from the proof of Proposition 1. The only difference is that instead of comparing manager j's effort with manager i's effort directly, we compare the equivalent effort level that manager j needs to exert, given e_i, to win if both projects are proposed.

Case 2b: $e^*_{g_j} \leq w_j(e_i) < e''_{g_j}$**.** Manager j's best response is $\text{BR}_j(e_i) = w_j(e_i) + \varepsilon$. See Case 2b from the proof of Proposition 1.

Case 2c: $w_j(e_i) \geq e''_{g_j}$**.** Manager j's best response is $\text{BR}_j(e_i) = e^*_{f_j}$. See Case 2c from the proof of Proposition 1.

In Stage 1, we consider manager i's effort level taking into account manager j's best response in Stage 2. There are two possible cases:

Case 1a: $w_j(e_i) < e''_{g_j}$**.** The expected payoff of manager i before the signals are realized $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i))$ is $f_i(e_i)$. To see this, consider $\text{BR}_j(e_i)$ in Stage 2. If $w_j(e_i) < e''_{g_j}$, then $\text{BR}_j(e_i) > w_j(e_i)$, which implies that the expected payoff to the firm from project j is greater than the expected payoff to the firm from project i if $\theta_j = \theta_j = h$. Thus, senior management chooses project j when $\theta_j = \theta_j = h$. Following Case 1a in the proof of Proposition 1, we obtain $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i)) = f_i(e_i)$.

Case 1b: $w_j(e_i) \geq e''_{g_j}$**.** The expected payoff of manager i before the signals are realized $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i))$ is $g_i(e_i)$. To see this, consider $\text{BR}_j(e_i)$ in Stage 2. If $w_j(e_i) \geq e''_{g_j}$, then $\text{BR}_j(e_i) < w_j(e_i)$, which implies that the expected payoff to the firm from project i is greater than the expected payoff to the firm from project j if $\theta_j = \theta_j = h$. Thus, senior management chooses project i when $\theta_j = \theta_j = h$. Following Case 1b in the proof of Proposition 1, we obtain $\mathbb{E}(\pi_i(e_i, \text{BR}_j(e_i)) = g_i(e_i)$.

We now characterize manager i's optimal effort level. Since, $w_i(w_j(e_i)) = e_i$, conditions $w_j(e_i) < e''_{g_j}$ and $w_j(e_i) \geq e''_{g_j}$ can be written as $e_i < w_i(e''_{g_j})$ and $e_i \geq w_i(e''_{g_j})$, respectively. From Cases 1a and 1b above, manager i's expected payoff is $f_i(e_i)$ if $e_i < w_i(e''_{g_j})$ and $g_i(e_i)$ if $e_i \geq w_i(e''_{g_j})$. By definition of e''_{g_i}, we can characterize the optimal effort level of manager i as follows:

- If $w_i(e''_{g_j}) < e''_{g_i}$, manager i's optimal effort level is the maximizer of $g_i(e_i)$ in this range. Specifically, manager i's optimal effort level is $e^*_i = e^*_{g_i}$ if $w_i(e''_{g_j}) \leq e^*_{g_i}$ and $e^*_i = w_i(e''_{g_j})$ if $e^*_{g_i} < w_i(e''_{g_j}) < e''_{g_i}$. Manager i's project is implemented with probability $\frac{1}{2}$ and manager j's project is implemented with probability $\frac{1}{4}$.

- If $w_i(e''_{g_j}) > e''_{g_i}$, manager i's optimal effort level is the maximizer of $f_i(e_i)$ in this range. Specifically, manager i's optimal effort level is $e^*_i = e^*_{f_i}$. Manager i's project is implemented with probability $\frac{1}{4}$ and manager j's project is implemented with probability $\frac{1}{2}$.

- If $w_i(e''_{g_j}) = e''_{g_i}$, manager i is indifferent between choosing

$$e_i^* = w_i(e_{g_j}^{''}) = e_{g_i}^{''} \text{ and } e_i^* = e_{f_i}^*.$$

By substituting $i = 1, 2$ into the steps above, it is straightforward to show that, regardless of who moves first, the waste heat recovery manager (manager 1) will increase the adoption of his project from $\frac{1}{4}$ to $\frac{1}{2}$ if and only if $w_i(e_{g_j}^{''}) \leq e_{g_i}^{''}$.

We now characterize the critical subsidy level $\hat{r}_1$. Define $\hat{r}_1$ to be r_1 that satisfies $w_i(e_{g_j}^{''}) = e_{g_i}^{''}$. More specifically, $\hat{r}_1$ satisfies

$$r_1 + (r_1 + k)e_{g_1}^{''} \quad = \quad r_2 + (r_2 + k)e_{g_2}^{''} \tag{5.2}$$

By substituting the expressions for $e_{g_i}^{''}$ and $e_{g_j}^{''}$ from Lemma 3, equation (5.2) becomes to

$$r_1 + \frac{(r_1+k)^2}{4d_1} + (r_1+k)\sqrt{\frac{3(r_1+k)^2}{64d_1^2} + \frac{r_1-k}{4d_1}} = r_2 + \frac{(r_2+k)^2}{4d_2} + (r_2+k)\sqrt{\frac{3(r_2+k)^2}{64d_2^2} + \frac{r_2-k}{4d_2}}.$$

First, note that the expression $r + \frac{(r+k)^2}{4d} + (r+k)\sqrt{\frac{3(r+k)^2}{64d^2} + \frac{r-k}{4d}}$ is monotonically increasing in r and monotonically decreasing in d. Since the expression on the left-hand side of (5.2) is increasing in r_1, it follows that manager 1 will increase the adoption of his project from $\frac{1}{4}$ to $\frac{1}{2}$ if and only if $r_1 > \hat{r}_1$.

We now show that $\hat{r}_1 \in (r_2, d_1)$. It is straightforward to show that $\hat{r}_1 > r_2$, since substituting $r_1 = r_2$ makes the expression on the left-hand side smaller than the expression on the right-hand side. To ensure that $\hat{r}_1 < d_1$, since the left-hand side is increasing in r_1, it suffices to show that substituting $r_1 = d_1$ gives

$$d_1 + \frac{(d_1+k)^2}{4d_1} + (d_1+k)\sqrt{\frac{3(d_1+k)^2}{64d_1^2} + \frac{d_1-k}{4d_1}} > r_2 + \frac{(r_2+k)^2}{4d_2} + (r_2+k)\sqrt{\frac{3(r_2+k)^2}{64d_2^2} + \frac{r_2-k}{4d_2}}.$$

Since the right-hand side is decreasing in d_2 and $d_2 > r_2$ (by Assumption 2), it is, in turn, sufficient to show that

$$d_1 + \frac{(d_1+k)^2}{4d_1} + (d_1+k)\sqrt{\frac{3(d_1+k)^2}{64d_1^2} + \frac{d_1-k}{4d_1}} > r_2 + \frac{(r_2+k)^2}{4r_2} + (r_2+k)\sqrt{\frac{3(r_2+k)^2}{64r_2^2} + \frac{r_2-k}{4r_2}}.$$

We can show that this inequality is true by taking the derivative of $x + \frac{(x+k)^2}{4x} + (x+k)\sqrt{\frac{3(x+k)^2}{64x^2} + \frac{x-k}{4x}}$ with respect to x and using Assumption 2 to show that this expression is increasing in x, and by observing that $d_1 > r_2$.

Thus, there exists $\hat{r}_1 \in (r_2, d_1)$ such that for $r_1 > \hat{r}_1$, the probability that the waste heat recovery is implemented increases from $\frac{1}{4}$ to $\frac{1}{2}$. ■

Lemma 6 *If manager 1 is the first mover, the optimal effort levels are as follows. If* $r_1 < \hat{r}_1$, $e_1^* = e_{f_1}^*, e_2^* = e_{g_2}^*$; *if* $r_1 = \hat{r}_1$, *there are two equilibria:* $e_1^* = e_{f_1}^*, e_2^* = e_{g_2}^*$ *and* $e_1^* = w_1(e_{g_2}^{''}) = e_{g_1}^{''}, e_2^* = e_{f_2}^*$; *and if* $r_1 > \hat{r}_1$, $e_1^* = w_1(e_{g_2}^{''})(> e_{g_1}^*), e_2^* = e_{f_2}^*$.

If manager 1 is the second mover, the optimal effort levels are as follows. If $r_1 < \hat{r}_1$, $e_1^* = e_{f_1}^*, e_2^* = w_2(e_{g_1}^{''})(> e_{g_2}^*)$; *if* $r_1 = \hat{r}_1$, *there are two equilibria:* $e_1^* = e_{f_1}^*, e_2^* = w_2(e_{g_1}^{''}) = e_{g_2}^{''}$ *and* $e_1^* = e_{g_1}^*, e_2^* = e_{f_2}^*$; *and if* $r_1 > \hat{r}_1$, $e_1^* = e_{g_1}^*, e_2^* = e_{f_2}^*$.

Proof of Lemma 6. This follows from the proof of Proposition 4. We first derive the optimal effort levels for the case when manager 1 is the first mover, then we derive the optimal effort levels for the case when manager 1 is the second mover.

If manager 1 is the first mover, substituting $i = 1$ into the backwards induction process in the proof of Proposition 4 yields the following:

- Suppose $r_1 < \hat{r}_1$. Then in Stage 1, $w_1(e_{g_2}^{''}) > e_{g_1}^{''}$ and thus $e_1^* = e_{f_1}^*$. In Stage 2, $e_1^* = e_{f_1}^*$ corresponds to Case 2a since it can be shown that $w_2(e_{f_1}^*) < e_{g_2}^*$ by showing that the inequality holds when $r_1 = k, r_2 = \frac{4}{5}k$, and $d_1 = d_2$ (for $d_1 = d_2 \in (\frac{4}{5}k, k)$). Thus $e_2^* = \mathrm{BR}_2(e_{f_1}^*) = e_{g_2}^*$.

- Suppose $r_1 > \hat{r}_1$. Then in Stage 1, $w_1(e_{g_2}^{''}) < e_{g_1}^{''}$ and thus $e_1^* = w_1(e_{g_2}^{''})$ since it can be shown that $e_{g_1}^* < w_1(e_{g_2}^{''})$. To see this, show that this inequality still holds even when using conservative parameters $r_1 = k, r_2 = \frac{4}{5}k$, and $d_1 = d_2$ for $d_1 = d_2 \in (\frac{4}{5}k, k)$. In Stage 2, $e_1^* = w_1(e_{g_2}^{''})$ corresponds to Case 2c, and thus $e_2^* = \mathrm{BR}_2(w_1(e_{g_2}^{''})) = e_{f_2}^*$.

- Suppose $r_1 = \hat{r}_1$. Then in Stage 1, $w_1(e_{g_2}^{''}) = e_{g_1}^{''}$ and manager 1 is indifferent between choosing $e_1^* = w_1(e_{g_2}^{''}) = e_{g_1}^{''}$ and $e_1^* = e_{f_1}^*$. Following the above logic, manager 2's best responses in Stage 2 are $e_2^* = \mathrm{BR}_2(w_1(e_{g_2}^{''})) = e_{f_1}^*$ and $e_2^* = \mathrm{BR}_2(e_{f_1}^*) = e_{g_2}^*$, respectively.

If manager 2 is the first mover, substitute $i = 2$ into the backwards induction process in the proof of Proposition 4 yields the following:

- Suppose $r_1 < \hat{r}_1$. Then in Stage 1, $w_2(e''_{g_1}) < e''_{g_2}$ and thus $e^*_2 = w_2(e''_{g_1})$ since it can be shown that $e^*_{g_2} < w_2(e''_{g_1})$. To see this, show that the inequality still holds with conservative parameters $r_1 = r_2$ for $r_1 = r_2 \in (\frac{4}{5}k, k)$, $d_1 = k$, and $d_2 = \frac{4}{5}k$. In Stage 2, $e^*_2 = w_2(e''_{g_1})$ corresponds to Case 2c, and thus $e^*_1 = \text{BR}_1(w_2(e''_{g_1})) = e^*_{f_1}$.

- Suppose $r_1 > \hat{r}_1$. Then in Stage 1, $w_2(e''_{g_1}) > e''_{g_2}$ and thus $e^*_2 = e^*_{f_2}$. In Stage 2, $e^*_2 = e^*_{f_2}$ corresponds to Case 2a, since it can be shown that $w_1(e^*_{f_2}) < e^*_{g_1}$ by showing that the inequality holds with conservative parameters $r_1 = r_2$ for $r_1 = r_2 \in (\frac{4}{5}k, k)$, $d_1 = k$, and $d_2 = \frac{4}{5}k$. Thus $e^*_1 = \text{BR}_1(e^*_{f_2}) = e^*_{g_1}$.

- Suppose $r_1 = \hat{r}_1$. Then in Stage 1, $w_2(e''_{g_1}) = e''_{g_2}$ and manager 2 is indifferent between choosing $e^*_2 = w_2(e''_{g_1})$ and $e^*_2 = e^*_{f_2}$. Following the above logic, manager 1's best responses in Stage 2 are $e^*_1 = \text{BR}_1(w_2(e''_{g_1})) = e^*_{f_1}$ and $e^*_1 = \text{BR}_1(e^*_{f_2}) = e^*_{g_1}$, respectively.

■

Proof of Proposition 5. We first show that the expected payoff to the firm weakly increases in r_1 for $r_1 < \hat{r}_1$ and $r_1 > \hat{r}_1$. Then we show that at $r_1 = \hat{r}_1$ the expected payoff to the firm is greater than when there is no subsidy, $r_1 = r_2 = r$.

To show that the expected payoff to the firm weakly increases in r_1 for $r_1 < \hat{r}_1$ and $r_1 > \hat{r}_1$, recall the optimal effort levels of both managers from Lemma 6. Suppose $r_1 < \hat{r}_1$, then the expected payoff to the firm is
$\mathbb{E}\Pi_l \equiv \frac{1}{2}\left(\frac{r_2-k}{2} + \left(\frac{r_2+k}{2}\right)\left(\frac{e^*_{g_2}}{2} + \frac{w_2(e''_{g_1})}{2}\right)\right) + \frac{1}{4}\left(\frac{r_1-k}{2} + \left(\frac{r_1+k}{2}\right)e^*_{f_1}\right)$. Since
$w_2(e''_{g_1}) = \frac{r_1-r_2}{r_2+k} + \left(\frac{r_1+k}{r_2+k}\right)\left(\frac{r_1+k}{4d_1} + \sqrt{\frac{3(r_1+k)^2}{64d_1^2} + \frac{r_1-k}{4d_1}}\right)$, simplifying gives
$\mathbb{E}\Pi_l = \frac{r_1-k}{4} + \frac{r_2-k}{8} + \frac{(r_2+k)^2}{32d_2} + \frac{3(r_1+k)^2}{64d_1} + \frac{r_1+k}{8}\sqrt{\frac{3(r_1+k)^2}{64d_1^2} + \frac{r_1-k}{4d_1}}$. It is straightforward to see that $\mathbb{E}\Pi_l$ is increasing in r_1. Similarly, suppose $r_1 > \hat{r}_1$, then the expected payoff to the firm is
$\mathbb{E}\Pi_h \equiv \frac{1}{2}\left(\frac{r_1-k}{2} + \left(\frac{r_1+k}{2}\right)\left(\frac{e^*_{g_1}}{2} + \frac{w_1(e''_{g_2})}{2}\right)\right) + \frac{1}{4}\left(\frac{r_2-k}{2} + \left(\frac{r_2+k}{2}\right)e^*_{f_2}\right)$. Since

$w_1(e''_{g_2}) = \frac{r_2 - r_1}{r_1 + k} + \left(\frac{r_2+k}{r_1+k}\right)\left(\frac{r_2+k}{4d_2} + \sqrt{\frac{3(r_2+k)^2}{64d_2^2} + \frac{r_2-k}{4d_2}}\right)$, simplifying gives $\mathbb{E}\Pi_h = \frac{r_2-k}{4} + \frac{r_1-k}{8} + \frac{(r_1+k)^2}{32d_1} + \frac{3(r_2+k)^2}{64d_2} + \frac{r_2+k}{8}\sqrt{\frac{3(r_2+k)^2}{64d_2^2} + \frac{r_2-k}{4d_2}}$. It is also straightforward to see that $\mathbb{E}\Pi_h$ is increasing in r_1.

Thus, to prove this proposition, it suffices to check that the expected payoff to the firm if $r_1 = \hat{r}_1$ is greater than when there is no subsidy, $r_1 = r_2 = r$. Recall from Lemmas 4 and 5 that the expected payoff to the firm when manager 1 is the first mover is $\frac{3}{8}(r_2 - k) + \frac{r_2+k}{2}\left(\frac{e^*_{f_1}}{4} + \frac{e^*_{g_2}}{2}\right)$, and the expected payoff to the firm when manager 1 is the second mover is $\frac{3}{8}(r_2 - k) + \frac{r_2+k}{2}\left(\frac{e^*_{f_1}}{4} + \frac{e''_{g_1}}{2}\right)$ (where $e''_{g_1} > e^*_{g_2}$). Since the order of the move is arbitrary, the firm's overall expected payoff is $\mathbb{E}\Pi_a \equiv \frac{3}{8}(r_2 - k) + \frac{r_2+k}{2}\left(\frac{e^*_{f_1}}{4} + \frac{e''_{g_1}}{4} + \frac{e^*_{g_2}}{4}\right) =$ $\frac{3}{8}(r_2 - k) + \frac{3(r_2+k)^2}{64d_1} + \frac{(r_2+k)^2}{32d_2} + \frac{r_2+k}{8}\sqrt{\frac{3(r_2+k)^2}{64d_1^2} + \frac{r_2-k}{4d_1}}$. Recall from Lemma 6 the optimal effort levels, then if $r_1 = \hat{r}_1$ there are two equilibria which give expected payoffs to the firm $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1}$ and $\mathbb{E}\Pi_h|_{r_1=\hat{r}_1}$. It is straightforward to see that $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} > \mathbb{E}\Pi_a$ since $\mathbb{E}\Pi_l$ is increasing in r_1. Also, we can show that $\mathbb{E}\Pi_h|_{r_1=\hat{r}_1} > \mathbb{E}\Pi_a$: recall that $\hat{r}_1 > r_2$ and $d_1 > d_2$, thus $\mathbb{E}\Pi_h|_{r_1=\hat{r}_1} = \frac{r_2-k}{4} + \frac{r_1-k}{8} + \frac{(r_1+k)^2}{32d_1} + \frac{3(r_2+k)^2}{64d_2} + \frac{r_2+k}{8}\sqrt{\frac{3(r_2+k)^2}{64d_2^2} + \frac{r_2-k}{4d_2}}|_{r_1=\hat{r}_1} > \mathbb{E}\Pi_a$.
■

Proof of Corollary 3. From the proof of Proposition 5, we see that the firm's (average) expected payoff, denoted $\mathbb{E}\Pi$, is continuous and increasing in r_1 for $r_1 \neq \hat{r}_1$, that $\lim_{r_1 \to \hat{r}_1^-} \mathbb{E}\Pi = \mathbb{E}\Pi_l|_{r_1=\hat{r}_1}$, and that $\lim_{r_1 \to \hat{r}_1^+} \mathbb{E}\Pi = \mathbb{E}\Pi_h|_{r_1=\hat{r}_1}$. Thus, if we can show that $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} - \mathbb{E}\Pi_h|_{r_1=\hat{r}_1} > 0$, choosing $r'_1 = \hat{r}_1 - \varepsilon$ and $r''_1 = \hat{r}_1 + \varepsilon$ for sufficiently small $\varepsilon > 0$ will make the firm's payoff when $r_1 = r'_1$ greater than its payoff when $r_1 = r''_1$.

We next show that $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} - \mathbb{E}\Pi_h|_{r_1=\hat{r}_1} > 0$. From the proof of Proposition 5, $\mathbb{E}\Pi_h|_{r_1=\hat{r}_1} = \frac{r_2-k}{4} + \frac{r_1-k}{8} + \frac{(r_1+k)^2}{32d_1} + \frac{3(r_2+k)^2}{64d_2} + \frac{r_2+k}{8}\sqrt{\frac{3(r_2+k)^2}{64d_2^2} + \frac{r_2-k}{4d_2}}|_{r_1=\hat{r}_1}$ and $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} = \frac{r_1-k}{4} + \frac{r_2-k}{8} + \frac{(r_2+k)^2}{32d_2} + \frac{3(r_1+k)^2}{64d_1} + \frac{r_1+k}{8}\sqrt{\frac{3(r_1+k)^2}{64d_1^2} + \frac{r_1-k}{4d_1}}|_{r_1=\hat{r}_1}$. Substituting equation (5.2) gives $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} - \mathbb{E}\Pi_h|_{r_1=\hat{r}_1} = \frac{(r_2+k)^2}{64d_2} - \frac{(\hat{r}_1+k)^2}{64d_1}$. We argue that $\frac{(r_2+k)^2}{64d_2} > \frac{(\hat{r}_1+k)^2}{64d_1}$. To see this, assume otherwise and rewrite equation

(5.2) as $\hat{r}_1 + \frac{(\hat{r}_1+k)^2}{4d_1} + \sqrt{\frac{(\hat{r}_1+k)^2}{d_1}\left(\frac{3(\hat{r}_1+k)^2}{64d_1} + \frac{\hat{r}_1-k}{4}\right)} =$ $r_2 + \frac{(r_2+k)^2}{4d_2} + \sqrt{\frac{(r_2+k)^2}{d_2}\left(\frac{3(r_2+k)^2}{64d_2} + \frac{r_2-k}{4}\right)}$. Since $\hat{r}_1 > r_2$, $\left(\frac{3(\hat{r}_1+k)^2}{64d_1} + \frac{\hat{r}_1-k}{4}\right) \geq 0$, and $\left(\frac{3(r_2+k)^2}{64d_2} + \frac{r_2-k}{4}\right) \geq 0$, and by assumption $\frac{(\hat{r}_1+k)^2}{d_1} \geq \frac{(r_2+k)^2}{d_2}$, it follows that $\hat{r}_1 + \frac{(\hat{r}_1+k)^2}{4d_1} + \sqrt{\frac{(\hat{r}_1+k)^2}{d_1}\left(\frac{3(\hat{r}_1+k)^2}{64d_1} + \frac{\hat{r}_1-k}{4}\right)} >$ $r_2 + \frac{(r_2+k)^2}{4d_2} + \sqrt{\frac{(r_2+k)^2}{d_2}\left(\frac{3(r_2+k)^2}{64d_2} + \frac{r_2-k}{4}\right)}$, contradiction. Thus, $\frac{(r_2+k)^2}{64d_2} > \frac{(\hat{r}_1+k)^2}{64d_1}$ and $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} - \mathbb{E}\Pi_h|_{r_1=\hat{r}_1} > 0$. This completes the proof.

A comment regarding the interpretation of this result. Note that $\frac{(r_2+k)^2}{64d_2} > \frac{(\hat{r}_1+k)^2}{64d_1}$ implies that $\frac{(r_2+k)}{4d_2} > \frac{(\hat{r}_1+k)}{4d_1}$. This in turn implies that at $r_1 = \hat{r}_1$, $e^*_{g_2} < e^*_{g_1}$. Moreover, from the definition of $\hat{r}_1$ in (5.2), it follows that at $r_1 = \hat{r}_1$, $w_2(e''_{g_1}) = e''_{g_2} > w_1(e''_{g_2}) = e''_{g_1}$. Thus, the main driver of the result $\mathbb{E}\Pi_l|_{r_1=\hat{r}_1} - \mathbb{E}\Pi_h|_{r_1=\hat{r}_1} > 0$ is the fact that manager 1 exerts a lower effort level as a winner than manager 2 does as a winner. ■

Proof of Proposition 6. From (2.7), the expected payoff of the technology provider is $\mathbb{E}(\pi_T(e_T)) = \frac{(1-\alpha)N}{2}\left[\left(\frac{1+e_T}{2}\right)r_1 - \left(\frac{1-e_T}{2}\right)k_1\right] - \frac{d_T e_T^2}{2}$, which is maximized at $\hat{e}_T = \frac{(1-\alpha)N(r_1+k_1)}{4d_T}$. From (2.9), the expected payoff of the host firm is $\mathbb{E}(\Pi|e_T) = \alpha\left[\left(\frac{1+e_T}{2}\right)r_1 - \left(\frac{1-e_T}{2}\right)k_1\right] - c$.

For a feasible solution, the host firm must make positive profit. The firm's expected payoff increases in e_T. Therefore, for a feasible solution, the following must hold: $\mathbb{E}(\Pi|e_T = 1) \geq 0$, which implies $\alpha \geq \frac{c}{r_1}$.

It is straightforward to show that $\mathbb{E}(\pi_T(e_T))$ increases in N. Therefore, there exists $\hat{N}$ such that for $N \geq \hat{N}$, $\mathbb{E}(\pi_T(e_T)) > 0$ for any e_T. Thus, for any $\alpha \in \left[\frac{c}{r_1}, 1\right]$, there exists $e'_T \leq 1$ such that for $e_T \geq e'_T$, $\mathbb{E}(\Pi|e_T) \geq 0$. For every $e_T \geq e'_T$, there exists $\hat{N}$ such that for $N \geq \hat{N}$, $\mathbb{E}(\pi_T(e_T)) > 0$. ■

Proof of Proposition 7. The expected payoff of the technology provider is maximized at $\hat{e}_T = \frac{(1-\alpha)N(r_1+k_1)}{4d_T}$. The expected payoff of the firm must be positive: $\mathbb{E}(\Pi|e_T) = \alpha\left[\left(\frac{1+e_T}{2}\right)r_1 - \left(\frac{1-e_T}{2}\right)k_1\right] - c \geq 0$, which implies $e_T \geq \frac{\frac{2c}{\alpha}+k_1-r_1}{r_1+k_1} \equiv \tilde{e_T}$. Note that both $\hat{e}_T$ and $\tilde{e_T}$ are decreasing in α.

Looking over the feasible range of a, i.e., $a \in [\frac{c}{r_1}, 1]$, $\hat{e}_T\left(a = \frac{c}{r_1}\right) = \frac{\left(1-\frac{c}{r_1}\right)N(r_1+k_1)}{4d_T}$ and decreases to $\hat{e}_T(a = 1) = 0$, and $\tilde{e}_T\left(a = \frac{c}{r_1}\right) = 1$ and decreases to $\tilde{e}_T(a = 1) = \frac{2c+k_1-r_1}{r_1+k_1}$. There are two cases: (1) $\hat{e}_T\left(a = \frac{c}{r_1}\right) < \tilde{e}_T\left(a = \frac{c}{r_1}\right) = 1$, which implies $N < \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$ and (2) $\hat{e}_T\left(a = \frac{c}{r_1}\right) \geq \tilde{e}_T\left(a = \frac{c}{r_1}\right) = 1$, which implies $N \geq \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$.

Consider case (1), $N < \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$. In this case, $\tilde{e}_T > \hat{e}_T$ for the entire range $a \in [\frac{c}{r_1}, 1]$. The technology provider's payoff is maximized at $e_T = \hat{e}_T$, however, it must exert at least $e_T = \tilde{e}_T$ in order for $\mathbb{E}(\Pi|e_T) \geq 0$. Therefore, $e_T^* = \tilde{e}_T$. Thus, $\mathbb{E}(\Pi|e_T^*) = \mathbb{E}(\Pi|\tilde{e}_T) = \frac{a}{2}\left[\left(1 + \left(\frac{\frac{2c}{a}+k_1-r_1}{r_1+k_1}\right)\right) r_1 - \left(1 - \left(\frac{\frac{2c}{a}+k_1-r_1}{r_1+k_1}\right)\right) k_1\right] - c = 0$, independent of a.

Consider case (2), $N \geq \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$. In this case, $\hat{e}_T\left(a = \frac{c}{r_1}\right) \geq \tilde{e}_T\left(a = \frac{c}{r_1}\right) = 1$, but $\hat{e}_T(a = 1) < \tilde{e}_T(a = 1)$. Define $\frac{c}{r_1} \leq a' < a'' < 1$ to be such that $\hat{e}_T(a = a') = 1$ and $\tilde{e}_T(a = a'') = \hat{e}_T(a = a'')$. Then, for $a \in [\frac{c}{r_1}, a')$, $e_T^* = 1$, for $a \in [a', a'')$, $e_T^* = \hat{e}_T$, and for $a \in [a'', 1]$, $e_T^* = \tilde{e}_T$. The payoff to the firm is as follows:

- Suppose $a \in [\frac{c}{r_1}, a')$. Then $e_T^* = 1$, and the payoff to the firm is $\mathbb{E}(\Pi|e_T = 1) = ar_1 - c$, which increases in a.

- Suppose $a \in [a', a'')$. Then $e_T^* = \hat{e}_T$, and the payoff to the firm is $\mathbb{E}(\Pi|e_T = \hat{e}_T) = a\left[\left(\frac{1+\hat{e}_T}{2}\right) r_1 - \left(\frac{1-\hat{e}_T}{2}\right) k_1\right] - c = \frac{a(r_1-k_1)}{2} + \frac{a(1-a)N(r_1+k_1)^2}{8d_T}$. Taking the derivative gives $\frac{\partial}{\partial a}\mathbb{E}(\Pi|e_T = \hat{e}_T) = \frac{r_1-k_1}{2} + \frac{(1-2a)N(r_1+k_1)^2}{8d_T}$ and $\frac{\partial^2}{\partial a^2}\mathbb{E}(\Pi|e_T = \hat{e}_T) = -\frac{N(r_1+k_1)^2}{4d_T} < 0$ which implies that the payoff to firm is strictly concave in a. Moreover, $\frac{\partial}{\partial a}\mathbb{E}(\Pi|e_T = \hat{e}_T)|_{a=1} = \frac{r_1-k_1}{2} - \frac{N(r_1+k_1)^2}{8d_T} < 0$. Therefore, $\mathbb{E}(\Pi|e_T = \hat{e}_T)$ either decreases in a or first increases, then decreases in a for $a \in [\frac{c}{r_1}, 1]$.

- Suppose $a \in [a'', 1]$. Then $e_T^* = \tilde{e_T}$, and the payoff to the firm is $\mathbb{E}(\Pi|e_T = \tilde{e_T}) = a\left[\left(\frac{1+\tilde{e_T}}{2}\right) r_1 - \left(\frac{1-\tilde{e_T}}{2}\right) k_1\right] - c =$ $\frac{a}{2}\left(r_1 - k_1 + (r_1 + k_1)\left(\frac{\frac{2c}{a}+k_1-r_1}{r_1+k_1}\right)\right) - c = 0$, independent of a.

Therefore, for $a \in [\frac{c}{r_1}, a')$, $\mathbb{E}(\Pi|e_T)$ increases in a; for $a \in [a', a'')$, $\mathbb{E}(\Pi|e_T)$ increases then decreases in a or decreases in a; and for $a \in [a'', 1]$, $\mathbb{E}(\Pi|e_T)$ is constant. Thus, if $N \geq \frac{4d_T}{\left(1-\frac{c}{r_1}\right)(r_1+k_1)}$, the host firm's profit first (weakly) increases in a, then (weakly) decreases in a.

This completes the proof. ■

6

Appendix B

This appendix contains supplemental analyses for Chapter 3. Section 6.1 contains the description of various robustness tests. In Section 6.2, we discuss and analyze the generalizability of our results. Section 6.3 contains an additional analysis that examines the relationship between the GHG intensity of the supplier's industry and the buyer pressure. We analyze suppliers' decisions to share climate change information publicly or privately in Section 6.4.

6.1 Additional Robustness Tests

Concerned that obtaining data for suppliers' revenues for only 36% of our sample might bias our results, we also estimated a variant of the primary model by omitting supplier's revenue, which yielded results (not shown) consistent with those of our primary model. Estimates of the hypothesized results were also nearly identical when we controlled for the relative power of the supplier and its largest buyer by including in our models the ratio of the largest buyer's revenue to the supplier's revenue, either in addition to or instead of the two separate components.

Because number of buyer requests does not account for requests from government agencies (which are managed through the CDP Public Procurement program), we also—as robustness tests—estimated our primary model on the subset of suppliers that received only the CDP Supply Chain program questionnaire and not the Public Procurement program questionnaire. Separately, we added the number of government agency buyer requests to our primary measure of (private-sector) number of buyer requests. These two models yielded hypothesized variable coefficients that were nearly identical to those from our primary model.

One might be concerned that suppliers might take more seriously requests from buyers in countries with more stringent environmental governance. To test this, we estimated three additional models, each with an alternative measure of environmental governance in the buyer's country: (1) one-year lagged values of buyer country's environmental governance; (2) stringency of environmental regulations in the buyer's country, and (3) level of enforcement of environmental regulations in the buyer's country, all obtained from the Executive Opinion Surveys of the Global Competitiveness Report of the World Economic Forum. These models yield no evidence that supplier responsiveness was associated with environmental governance in the buyer's country, since the coefficient on buyer country's environmental governance is not significant in any model.

6.2 Generalizability Analysis

The generalizability of our results could be called into question, especially if buyers that self-select into the CDP Supply Chain Program differ substantially from those that do not. CDP staff we interviewed suggested that buyers participating in the CDP Supply Chain Program tended to be especially concerned about and active in climate change and sustainability issues. The analyses described below similarly indicate that the most comprehensive carbon disclosers were significantly more likely to participate as buyers in the CDP Supply Chain Program, but that the comprehensiveness of buyers as disclosers does not significantly affect the magnitudes of our hypothesized relationships. These results yield no evidence that impedes the generalizability of our hypothesized results to buyers less committed to disclosing their own climate change information. Additional analyses described below also yield no indications that prevent our results from generalizing to those suppliers from whom the buyers did not request climate change information.

Generalizability to other buyers. We explore the extent to which participating buyers differed from comparable non-participant buyers by examining the reports CDP produces based on its primary investor project, in which CDP surveys all members of leading public stock exchanges. CDP analyzed the responses in 2009 and 2010 of S&P 500 and FTSE 350 index members and, referring to the most comprehensive disclosers as "carbon disclosure leaders," listed them as members of its "Carbon Disclosure Leadership Index" (CDLI) [26]. We focus here on the S&P 500 and FTSE 350 because 38 of the 68 buyers (56%) in the CDP Supply Chain Program are members of these indices and fewer than five buyers are in any of the other indices covered by the CDP investor survey. A two-group test of proportions revealed that Carbon Disclosure Leadership Index members were significantly more likely to participate as buyers in the CDP Supply Chain Program (17.0% vs. 2.0%; $p < 0.01$). Logistic regression yielded the same insight: Being a carbon disclosure leader increased the predicted probability of participating in the CDP Supply Chain Program from 2.6% to 11.1%. (Specifically, we estimated a logistic regression model predicting a firm's participation as a buyer in the CDP Supply Chain Program based on being a carbon disclosure leader ($\beta = 1.75$; $p < 0.01$), controlling for log of sales and log of employment (both lagged one year) and including fixed effects for industry, country, and year.) We exploit this difference to gain insight on the extent to which buyers' self-selecting into the CDP Supply Chain project might impede the generalizability of our results. We look for heterogeneity in the estimated hypothesized relationships in our subsample, focusing on those suppliers with at least one requesting buyer that is a member of the S&P 500 and FTSE 350. We compare the estimates of our primary model on the subset of suppliers that have at least one requesting buyer that is a CDLI member to the estimates on the subset of suppliers that do not have any requesting buyer that is a CDLI member. The extent to which our results might generalize to non-participant buyers could be called into question if the hypothesized coefficients for these subsets differed, because the population of non-participant buyers consists disproportionately of non-members of CDLI. Estimating the primary model on these two subsamples yielded coefficients on the hypothesized variables that were statistically indistinguishable. Specifically, Wald tests comparing each coefficient across the two models yielded p-values that ranged from 0.22 to 0.62. A joint Wald test simultaneously comparing all hypothesized coefficients across the two samples ($\chi^2 = 3.50$; $p = 0.62$) also indicated no significant difference. These results provide no evidence that undermines the generalizability of our hypothesized results to buyers less committed to disclosing their own climate change information.

Moreover, simply choosing to participate in the CDP Supply Chain program might send a sufficiently strong signal to suppliers that the buyer is very interested in this information. This would imply that our results generalize to all other buyers who might participate. It would also suggest that our results might underestimate the true effect on supplier responsiveness of buyers using scorecards or RFPs to convey their commitment to using this climate change information in future procurement decisions. That is, if merely participating in the CDP Supply Chain already communicates some level of commitment, then the effects of scorecards or RFPs might be attenuated in our context; using these tools outside of the CDP Supply Chain Program would therefore be even more effective in prompting supplier responses.

Generalizability to other suppliers. Buyers' requesting climate change information from a subset of their suppliers might evoke a concern about whether our results accurately generalize to all of their suppliers. Generalizing to other suppliers might not actually be an important concern in practice because, as noted earlier, most buyers in the CDP Supply Chain Program request climate change information from a subset of suppliers accounting for 80-90% of the buyer's total spend on suppliers. Analyzing the relationships pertaining to these suppliers is not only the feasible set due to data availability, but also the relevant set because this prioritization approach is widely acknowledged and endorsed by the Greenhouse Gas Protocol standard governing Scope 3 GHG emissions, which includes the following guidance: "a company may select suppliers based on their contribution to its total spend" [65, p. 78].

For those nonetheless interested in the extent to which our results might generalize to buyers' other suppliers, logical arguments support the notion that our results might either underestimate or overestimate an average effect across all suppliers to our buyers. Our results pertaining to the number of buyer requests and buyers' commitment to use shared information in future procurement decisions might underestimate an average effect across all suppliers if the highest-spend suppliers (those sent the questionnaire) are particularly likely to operate with relative impunity under the assumption that the requesting buyers are particularly vulnerable to them. In this scenario, compared to the suppliers we studied, the buyers' remaining suppliers (those not sent the questionnaire) might be more responsive, perceiving a greater need to comply.

In contrast, our results might overestimate an average effect across all suppliers if the buyers represented a particularly high portion of their selected suppliers' sales. We have no information on the proportion of suppliers' sales flow to these buyers and thus have no indication that the chosen suppliers are particularly dependent on these buyers. In this scenario, the chosen suppliers might be especially vulnerable to these buyers and would be particularly eager to respond in order to retain their business, even more so if they received several requests and if these buyers use climate change in their procurement criteria. The suppliers not sent the questionnaire would accordingly be less responsive, perceiving less of a need to comply with requests from these buyers. To investigate the extent to which responsiveness relationships based primarily on largest-spend suppliers generalize to a buyer's remaining suppliers, or whether they are under- or overestimates, future research could gather data on how buyers select suppliers from whom to request information in order to assess differences in response between suppliers chosen according to different selection criteria.

6.3 The Moderating Influence of Industry GHG Intensity on Buyer Pressure

Our primary model (Figure 3.4.1, column (2a)) having revealed no significant direct effect of supplier *industry's GHG intensity* on the propensity to share climate change information with buyers, we explored the possibility that *industry's GHG intensity* might have an indirect effect via other independent variables. We examined whether our other determinants of sharing climate change information differed between suppliers in higher- versus lower-GHG-intensity industries by estimating our primary model (excluding *industry's GHG intensity*) on two subsamples distinguished by whether the supplier industry's GHG intensity is above or below the 6-digit GICS sample median. The lower-GHG-intensity group primarily included suppliers in the healthcare, financial, telecommunication services, and consumer discretionary industries; the higher-GHG-intensity group primarily included suppliers in the energy, materials, and utilities industries.

The results of estimates on both subsamples (Figure 6.3.1, columns (1a) and (1b)) yield coefficients on the four remaining hypothesized variables of the same sign as in our primary model. Whereas Wald tests (column (1c)) indicated that the coefficients on three of these variables were indistinguishable across the subsamples, the coefficients on *number of buyer requests* statistically differed (Wald $\chi^2 = 6.36$; $p < 0.05$), indicating that buyer requests have a larger impact on the likelihood of sharing climate change information for suppliers in low-GHG-intensity industries than they do for suppliers in high-GHG-intensity industries. Average marginal effects from these models indicate that a one-log-unit increase in the number of requesting buyers is associated with a 24.1-percentage-point increase in the probability of sharing climate change information for suppliers in low-GHG-intensity industries and with a 9.9-percentage-point increase for suppliers in high-GHG-intensity industries. This significant difference was confirmed by estimating (on the entire sample) a separate model that is akin to our primary model (column (2a)) but also interacts the *number of buyer requests* with *industry's GHG intensity*, yielding a significant negative interaction term ($\beta = -0.34$; $p < 0.05$). We speculate that requests for climate change information might be particularly salient for suppliers in low-GHG-intensity industries due to their not being as accustomed to examining their relationship to climate change, causing each additional request to have a greater effect on the likelihood of their sharing climate change information (compared to suppliers in industries that are more GHG-intensive). We also note that coefficients differ on several of the control variables, which future research could explore.

6.4 Public Disclosure of Climate Change Information

Suppliers that choose to respond to the CDP Supply Chain Program questionnaire are given the choice of having CDP either share their climate change information only with the requesting buyers or also post the information on its public website. We extended our analysis to explore whether the determinants we hypothesized would influence suppliers to share climate change information with their buyers would also motivate them to share this information publicly. Viewing this as a continuum of transparency (nontransparent, transparent only to buyers, or transparent to all), we created *response transparency* as an ordered variable coded 0 when the supplier did not share climate change information, 1 when the supplier shared privately by directing CDP to share its

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Functional form:	Logistic			Generalized Ordered Logistic		
Dependent variable:	Shared climate change information			Response transparency		
Sample:	Less intensive industries	More intensive industries		Entire sample		
			Wald test statistics	Response (privately or publicly)	Public response	Wald test statistics
Number of buyer requests (log)	1.778**	0.496*	6.36*	0.804**	0.332*	7.84**
	[0.468]	[0.199]		[0.176]	[0.133]	
Climate change as a buying criterion	0.984**	0.650**	2.29	0.782**	0.377**	14.90**
	[0.176]	[0.134]		[0.098]	[0.108]	
Median profit margin by industry-country §	1.642	1.019	0.20	1.206*	1.206*	n/a
	[1.025]	[0.924]		[0.542]	[0.542]	
Industry's GHG intensity (log)				0.052	0.052	n/a
				[0.054]	[0.054]	
Kyoto Annex I country	0.505+	0.356+	0.21	0.350**	0.350**	n/a
	[0.266]	[0.183]		[0.120]	[0.120]	
Mean buyer requests per industry-year (log)	11.864**	7.865*	0.54	9.086**	9.086**	n/a
	[4.427]	[3.154]		[2.051]	[2.051]	
Received CDP Investor questionnaire	0.806*	0.705**	0.06	0.527**	0.527**	n/a
	[0.338]	[0.247]		[0.150]	[0.150]	
Received CDP Public Procurement questionnaire	1.370**	1.572**	0.08	0.989**	0.989**	n/a
	[0.524]	[0.466]		[0.191]	[0.191]	
Received CDP Supply Chain questionnaire in previous year	1.301**	0.252	13.86**	0.554**	0.554**	n/a
	[0.234]	[0.157]		[0.109]	[0.109]	
Largest buyer's revenue (log) §	-0.164	0.213**	8.49**	0.104*	0.104*	n/a
	[0.104]	[0.077]		[0.053]	[0.053]	
Supplier's revenue (log) §	0.162*	-0.057	4.80*	0.066+	0.066+	n/a
	[0.078]	[0.063]		[0.034]	[0.034]	
Country's environmental governance §	0.102	0.267	0.40	0.164	-0.275*	21.60**
	[0.196]	[0.170]		[0.114]	[0.122]	
Country's environmental NGOs per million population (log)	-0.740	-0.966**	0.11	-0.678**	-0.678**	n/a
	[0.565]	[0.372]		[0.263]	[0.263]	
Country's per capita GDP (log) §	-0.291+	0.117	4.77*	-0.034	-0.034	n/a
	[0.151]	[0.110]		[0.073]	[0.073]	
Observations	1599	1625		3,226		
Companies	1317	1171		2,490		
Countries	40	46		49		
Log likelihood (Log pseudolikelihood for ordered logistic)	-656	-945		-2777		
Mean dependent variable	0.43	0.64				
McFadden's adjusted R-squared	0.37	0.08		0.17		

Notes: Brackets contain robust standard errors clustered by supplier. "Less intensive" ("More intensive") denotes subsample of firms in industries whose GHG intensity is below (above) the sample median. Column (2a) reports the extent to which the predictor variables shift the dependent variable from not sharing any information to sharing information (shifting *response transparency* from 0 to 1 or 2) whereas column (2b) reports the extent to which the predictor variables shift the dependent variable from not sharing publicly to doing so (shifting *response transparency* from 0 or 1 to 2). All models also include dummies for *year 2010*, industry dummies, and dummy variables to denote instances in which the following variables were recoded from missing to zero: *industry's GHG intensity* (N = 569), *largest buyer's revenue* (N = 262), *supplier's revenue* (N = 2,063), *country's environmental governance* (N = 4), and *median profit margin* (N = 540). "n/a" indicates the Wald test statistic is not applicable when the parallel-lines assumption is imposed and thus the compared coefficients are identical by construction.
** p<0.01, * p<0.05, + p<0.10. § denotes variables lagged one year.

Figure 6.3.1: *Supplemental regression results.*

response only with its requesting buyers, and 2 when it shared publicly by directing CDP to share its response with its requesting buyers and to publish the response online. Our 3,226 supplier-year observations include 1,721 instances of suppliers sharing climate change information, privately in 734 instances and publicly in 987 instances.

We predicted *response transparency* with the same set of independent and control variables used in our primary model. As with the earlier models, the Brant test for this model rejected the proportional-odds assumption, which led us to estimate the model with generalized ordered logistic regression using the same iterative process described above that identifies the partial proportional-odds model that best fits the data. As before, our unit of analysis is the supplier-year. Because we report standard errors clustered by firm, our results are robust to heteroskedasticity and to non-independence of the observations from those suppliers that responded in both 2009 and 2010.

The results are presented in columns (2a)-(2c) in Figure 6.3.1. Column (2a) reports the extent to which the predictor variables shift the dependent variable from not sharing any climate change information (*response transparency* equals 0) to sharing this information (*response transparency* equals 1 or 2). Column (2b) reports the extent to which the predictor variables shift the dependent variable from not sharing climate change information publicly (*response transparency* equals 0 or 1) to doing so (*response transparency* equals 2). Column (2c) shows the Wald test statistics comparing the coefficients between columns (2a) and (2b).

The results indicate that the same hypothesized variables that have significant positive effects on sharing climate change information in our primary model (*number of buyer requests, climate change as a buying criterion, median profit margin,* and *Kyoto Annex I country*) also have significant positive effects on suppliers sharing this information publicly. Moreover, both indicators of buyer pressure (*number of buyer requests* and *climate change as a buying criterion*) have a significantly greater impact on suppliers' decision to share climate change information per se (column (2a)) than on sharing this information publicly (column (2b)). (Wald tests comparing each coefficient between column (2a) and (2b), shown in Column 2c, yield $\chi^2 = 7.84$; $p < 0.01$ and $\chi^2 = 14.90$; $p < 0.01$, respectively.) In one of our interviews, a supplier attributed its preference to disclose privately to "competitive issues. We do not want to disclose to our competitors our GHG target and energy usage." Our empirical finding and the anecdotal report of competitiveness concerns reveal a potential limitation in the ability of supply chain climate change initiatives to generate publicly available data.

7
Appendix C

This appendix contains the mathematical proofs of the main results shown in Chapter 4.

Proof of Proposition 8. We first obtain the condition for the optimal environmental performance of the B model. We then compare this condition with those from the RC and SC models. We use backwards induction to solve for the optimal solution in all thee models.

Benchmark model. In Stage 2 the vertically integrated firm chooses p to maximize supply chain payoff:
$\max_p \Pi_B(p,x) = (p - C(x))D(p,x) = (p - C(x))(A - bp + rx)$. Taking the derivative with respect to p gives $\frac{\partial}{\partial p}\Pi_B(p,x) = A + rx + C(x)b - 2bp$ and $\frac{\partial^2}{\partial p^2}\Pi_B(p,x) = -2b < 0$. Since $\Pi_B(p,x)$ is concave in p for a given x, the best

response $p(x)$ is given by the first order condition:

$$p(x) = \frac{A + rx + bC(x)}{2b} \quad (7.1)$$

In Stage 1, substituting the expression for $p(x)$ into $\Pi_B(p, x)$, the optimal environmental performance (x_B^*) is the solution of the following maximization problem:

$$\max_x \Pi_B(x) = \frac{(A + rx - bC(x))^2}{4b} \quad (7.2)$$

Retailer-Choice model. In Stage 3, the retailer chooses p to maximize his payoff p: $\max_p \Pi_R(p, w, x) = (p - w)D(p, x) = (p - w)(A - bp + rx)$. Taking the derivative with respect to p gives $\frac{\partial}{\partial p}\Pi_R(p, w, x) = A + rx + wb - 2bp$ and $\frac{\partial^2}{\partial p^2}\Pi_R(p, w, x) = -2b < 0$. Since this expression is concave in p, the best response $p(w, x)$ is given by the first order condition

$$p(w, x) = \frac{A + rx + wb}{2b}. \quad (7.3)$$

In Stage 2, substituting this expression for $p(w, x)$, the supplier maximizes his payoff by choosing w:
$\max_w \Pi_S(w, x) = (w - C(x))D(p(w, x), x) = (w - C(x))(\frac{A - wb + rx}{2})$. Taking the derivative with respect to w gives $\frac{\partial}{\partial w}\Pi_S(w, x) = -wb + \frac{bC(x) + A + rx}{2}$ and $\frac{\partial^2}{\partial w^2}\Pi_S(w, x) = -b < 0$. Since this expression is concave in w, supplier's best response $w(x)$ is also given by the first order condition

$$w(x) = \frac{A + rx + bC(x)}{2b}. \quad (7.4)$$

In Stage 1, the retailer chooses x to maximize his profit. After substituting the expressions for $w(x)$ and $p(w, x)$ into Π_R, the retailer solves

$$\max_x \Pi_R(x) = \frac{(A + rx - bC(x))^2}{16b}. \quad (7.5)$$

Supplier-Choice model. In Stages 3 and 2, following the same logic as the deterministic RC model, we obtain $p(w.x)$ according to (7.3): $p(w,x) = \frac{A+rx+wb}{2b}$, and $w(x)$ according to (7.4): $w(x) = \frac{A+rx+bC(x)}{2b}$. Substituting $p(w,x)$ and $w(x)$ into Π_S, the supplier solves

$$\max_x \Pi_S(x) = \max_x \frac{(A+rx-bC(x))^2}{8b}. \tag{7.6}$$

Comparing the expressions in (7.2), (7.5), and (7.6), it is straightforward to see that the optimal x under B, RC, and SC models are identical. Note that the feasible optimal x needs to satisfy $x \in [0,1]$, yield non-negative retail price and wholesale prices (which is always true given expressions (7.1), (7.3), and (7.4) above), and yield non-negative consumer demand $D(p(x),x) > 0$. Substituting the appropriate expressions for retail price and wholesale price in (7.1), (7.3), and (7.4), the consumer demand in the B model is $D_B(x) = \frac{A+rx-bC(x)}{2}$, and the consumer demand in the RC and SC models is $D_R(x) = D_S(x) = \frac{A+rx-bC(x)}{4}$.

We next solve for the optimal environmental performance x. In all three models, the maximization problem is equivalent to:

$$\max_x (A+rx-bC(x))^2$$

Because of our assumption that $C(x)$ is convex in x, $(A+rx-bC(x))$ is strictly concave in x, with maximizer defined by the first order condition: $r - bC'(x) = 0$. Moreover, since a feasible x needs to yield positive consumer demand, $A+rx-bC(x)$ is positive and concave over the feasible range of x. It follows that $(A+rx-bC(x))^2$ has the same maximizer as $(A+rx-bC(x))$, and the optimal solution, x^*, is defined by $\frac{r}{b} = C'(x^*)$ ■

Proof of Corollary 4. Substituting $C(x) = c_0 + \frac{1}{2}c_1x^2$ into the expression for optimal environmental performance in Proposition 8, $\frac{r}{b} = C'(x^*)$, gives $\frac{r}{b} = c_1x^*$. Assumption 4 ensures that $x^* \in [0,1]$. ■

Proof of Corollary 5. The optimal retail price from the B model follows directly from (7.1) in the proof of Proposition 8. The optimal retail price of RC and SC models is obtained by substituting the expression for $w(x)$ from (7.4) in the proof of Proposition 8 into the expression for $p(w,x)$ from (7.3) in the proof of Proposition 8. This yields $p(x) = \frac{3A+3rx+bC(x)}{4b}$. The difference between $p_R^*(= p_S^*)$ and p_B^*, $p_R^* - p_B^*$, is $\frac{A+rx^*-bC(x^*)}{4}$ which, according to the non-negative demand condition in the proof of Proposition 8, is positive. ■

Proof of Corollary 6. The optimal payoff of the retailer, the supplier, and the vertically integrated firm follows directly from (7.5), (7.6), and (7.2), respectively, in the proof of Proposition 8. The total supply chain profit is $\Pi_R(x^*) + \Pi_S(x^*) = \frac{(A+rx^*-bC(x^*))^2}{16b} + \frac{(A+rx^*-bC(x^*))^2}{8b} = \frac{3(A+rx^*-bC(x^*))^2}{16b}$ ■

Proof of Lemma 2. We rewrite the ordering quantity in terms of safety stock s, where $q = A - bp + rx + s$. Substituting t for $C(x)$ for the vertically integrated firm and substituting t for w for the retailer, the problem of choosing retail price and stocking quantity (Stage 3 of the RC model or Stage 2 of the B model) becomes:

$$\begin{aligned}
\max_{p,s} \Pi &= \max_{p,s} E\{p(A - bp + rx + \varepsilon)\} - t(A - bp + rx + s) - E\{h(s-\varepsilon)\} \\
&= \max_{p,s}(p-t)(A - bp + rx) + E\{p\varepsilon\} - ts - E\{h^+[s-\varepsilon]^+ + \\
&\quad h^-[\varepsilon - s]^+\}
\end{aligned} \tag{7.7}$$

Where $E\{h^+[s-\varepsilon]^+ + h^-[\varepsilon-s]^+\}$ can be written as:

$$\begin{aligned}
&= h^+\int_{-\infty}^{s}(s-\varepsilon)f_\sigma(\varepsilon)\ d\varepsilon + h^-\int_{s}^{\infty}(\varepsilon - s)f_\sigma(\varepsilon)\ d\varepsilon \\
&= h^+\int_{-\infty}^{s} sf_\sigma(\varepsilon)\ d\varepsilon - h^+\int_{-\infty}^{s}\varepsilon f_\sigma(\varepsilon)\ d\varepsilon + h^-\int_{s}^{\infty}\varepsilon f_\sigma(\varepsilon)\ d\varepsilon - \\
&\quad h^-\int_{s}^{\infty} sf_\sigma(\varepsilon)\ d\varepsilon \\
&= h^+ sF_\sigma(s) - h^+\int_{-\infty}^{s}\varepsilon f_\sigma(\varepsilon)\ d\varepsilon + h^-\int_{s}^{\infty}\varepsilon f_\sigma(\varepsilon)\ d\varepsilon - \\
&\quad h^- s(1 - F_\sigma(s))
\end{aligned} \tag{7.8}$$

By Theorem 9.2.2. in [130], given the wholesale price w and level of sustainability feature x, the optimal selling price for stochastic, additive demand case equals optimal selling price for deterministic demand case. Thus,

$$p(t,x) = \frac{A + rx + tb}{2b} \tag{7.9}$$

Substituting expressions in (7.9) into (7.7), we solve for the optimal safety stock level. Since the first two terms of (7.7) are independent of s, the optimal safety stock level is found by maximizing the following expression and using (7.8):

$$\begin{aligned} \max_s \tilde{\Pi} &= \max_s -ts - E\{h^+[s-\varepsilon]^+ + h^-[\varepsilon - s]^+\} \\ &= \max_s -ts - h^+ sF_\sigma(s) + h^+ \int_{-\infty}^{s} \varepsilon f_\sigma(\varepsilon)\, d\varepsilon - h^- \int_{s}^{\infty} \varepsilon f_\sigma(\varepsilon)\, d\varepsilon + \\ &\quad h^- s(1 - F_\sigma(s)) \end{aligned}$$

Taking derivate and using Leibnitz's Rule,

$$\begin{aligned} \frac{\partial}{\partial s}\tilde{\Pi} &= -t - h^+ F_\sigma(s) + h^-(1 - F_\sigma(s)) \\ \frac{\partial^2}{\partial s^2}\tilde{\Pi} &= -(h^+ + h^-) f_\sigma(s) < 0 \end{aligned}$$

Since this expression is strictly concave in s, the optimal safety stock level is given by the first order condition:

$$F_\sigma(s^*) = \frac{h^- - t}{h^+ + h^-} \tag{7.10}$$

$$s^* = s(t) = F_\sigma^{-1}\left(\frac{h^- - t}{h^+ + h^-}\right) \tag{7.11}$$

■

Lemma 7 *Given the safety stock and retail price defined by Lemma 2, the retailer's* *payoff can be re-written as a function of x and w as*

$$\Pi_R(w,x) = \frac{(A+rx-wb)^2}{4b} + h^+ \int_{-\infty}^{F_\sigma^{-1}\left(\frac{h^- - w}{h^+ + h^-}\right)} \varepsilon f_\sigma(\varepsilon)\ d\varepsilon - h^- \int_{F_\sigma^{-1}\left(\frac{h^- - w}{h^+ + h^-}\right)}^{\infty} \varepsilon f_\sigma(\varepsilon)\ d\varepsilon \quad (7.12)$$

and the vertically integrated firm's payoff can be re-written as a function of x as

$$\Pi_B(x) = \frac{(A+rx-C(x)b)^2}{4b} + h^+ \int_{-\infty}^{F_\sigma^{-1}\left(\frac{h^- - C(x)}{h^+ + h^-}\right)} \varepsilon f_\sigma(\varepsilon)\ d\varepsilon - h^- \int_{F_\sigma^{-1}\left(\frac{h^- - C(x)}{h^+ + h^-}\right)}^{\infty} \varepsilon f_\sigma(\varepsilon)\ d\varepsilon \quad (7.13)$$

Proof of Lemma 7. With $s^* = s(t) = F_\sigma^{-1}\left(\frac{h^- - t}{h^+ + h^-}\right)$, we have $-ts^* - h^+ s^* F_\sigma(s^*) + h^- s^*(1 - F_\sigma(s^*)) = 0$, and together with (7.9) and $E\{p\varepsilon\} = 0$, substituting these expressions into Π gives:

$$\Pi(t,x) = \frac{(A+rx-tb)^2}{4b} + h^+ \int_{-\infty}^{F_\sigma^{-1}\left(\frac{h^- - t}{h^+ + h^-}\right)} \varepsilon f_\sigma(\varepsilon)\ d\varepsilon - h^- \int_{F_\sigma^{-1}\left(\frac{h^- - t}{h^+ + h^-}\right)}^{\infty} \varepsilon f_\sigma(\varepsilon)\ d\varepsilon \quad (7.14)$$

To obtain the retailer's payoff, $\Pi_R(w,x)$, substitute w for t. To obtain the payoff of the vertically integrated firm $\Pi_B(x)$, substitute $C(x)$ for t. ■

Proof of Proposition 9. We use backwards induction to find the optimal solution for the B model. In Stage 2, using the results from the proof of Lemma 2 and substituting $C(x)$ for t, the retail price is defined by the following best response $p(x) = \frac{A+rx+C(x)b}{2b}$. Similarly, the safety stock is $s(x) = F_\sigma^{-1}\left(\frac{h^- - C(x)}{h^+ + h^-}\right)$. In Stage 1, substituting these expressions into the payoff of the vertically integrated firm gives the expression (7.13) in Lemma 7. When demand is uniformly distributed, $F_\sigma^{-1}\left(\frac{h^- - C(x)}{h^+ + h^-}\right) = \sigma\sqrt{3}\left(2\left(\frac{h^- - C(x)}{h^+ + h^-}\right) - 1\right)$ and $f(\cdot) = \frac{1}{2\sqrt{3}\sigma}$. Substitute $C(x) = c_0 + \frac{1}{2}c_1 x^2$. Also, since the vertically integrated firm's payoff is parameterized by σ, rewrite $\Pi_B(x)$ as $\Pi_B(x, \sigma)$. The vertically integrated firm thus solves:

$$\begin{aligned}
\Pi_B(x,\sigma) &= \frac{(A + rx - C(x)b)^2}{4b} - \sqrt{3}\sigma\frac{(h^- - C(x))(h^+ + C(x))}{h^+ + h^-} \\
&= \frac{((A - c_0 b) + rx - \frac{1}{2}c_1 b x^2)^2}{4b} - \\
&\quad \sqrt{3}\sigma\frac{(h^- - c_0 - \frac{1}{2}c_1 x^2)(h^+ + c_0 + \frac{1}{2}c_1 x^2)}{h^+ + h^-} \\
&= \left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{16(h^+ + h^-)}\right)(c_1^2)\right]x^4 - \left(\frac{rc_1}{4}\right)x^3 + \\
&\quad \left[\frac{r^2}{4b} - \frac{(A - bc_0)c_1}{4} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{2(h^+ + h^-)}\right]x^2 + \\
&\quad \left[\frac{(A - bc_0)r}{2b}\right]x + \\
&\quad \left[\frac{(A - bc_0)^2}{4b} - \frac{\sqrt{3}\sigma(h^+ + c_0)(h^- - c_0)}{h^+ + h^-}\right] \qquad (7.15)
\end{aligned}$$

Taking the derivative with respect to x gives:

$$\begin{aligned}
\frac{\partial}{\partial x}\Pi_B(x,\sigma) &= \left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{4(h^+ + h^-)}\right)(c_1^2)\right]x^3 - \left(\frac{3rc_1}{4}\right)x^2 + \\
&\quad \left[\frac{r^2}{2b} - \frac{(A - bc_0)c_1}{2} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{h^+ + h^-}\right]x + \\
&\quad \frac{(A - bc_0)r}{2b} \qquad (7.16)
\end{aligned}$$

And taking the derivative with respect to x and σ give:

$$\frac{\partial}{\partial x \partial \sigma}\Pi_B(x,\sigma) = \frac{\sqrt{3}c_1 x(h^+ - h^- + 2c_0 + c_1 x^2)}{h^+ + h^-} \tag{7.17}$$

Suppose there is a unique maximizer of $\Pi_B(x,\sigma)$ for a given σ, $x_B^*(\sigma)$. By the monotone comparative statics theorem due to Topkis [141][1], if $\frac{\partial}{\partial x \partial \sigma}\Pi_B(x,\sigma) > 0$, then $x_B^*(\sigma)$ is increasing in σ. On the other hand, if $\frac{\partial}{\partial x \partial \sigma}\Pi_B(x,\sigma) < 0$, then $x_B^*(\sigma)$ is decreasing in x.

The payoff $\Pi_B(x,\sigma)$ is a polynomial of degree 4 with positive leading coefficient, which is first decreasing, then increasing, then decreasing, then increasing in x. To guarantee unique maximum $x_B^*(\sigma)$ for each σ, it is sufficient, though not necessary, to restrict $\frac{\partial}{\partial x}\Pi_B(0,\sigma) > 0$ and $\frac{\partial}{\partial x}\Pi_B(1,\sigma) < 0$. It is easy to see that $\frac{\partial}{\partial x}\Pi_B(0,\sigma) = \frac{(A-bc_0)r}{2b} > 0$ (by Assumption 4) for all σ. At $\sigma = 0$, $\frac{\partial}{\partial x}\Pi_B(1,0) = \frac{1}{8b}(A + r - c_0 b - \frac{1}{2}c_1 b)(r - c_1 b) < 0$ (by Assumption 4). Since $\frac{\partial}{\partial x \partial \sigma}\Pi_B(1,\sigma) < 0$ for $h^- - h^+ > 2c_0 + c_1$, it follows that $\frac{\partial}{\partial x}\Pi_B(1,\sigma) < 0$ for all σ if $h^- - h^+ > 2c_0 + c_1$. If $h^- - h^+ < 2c_0 + c_1$, it follows that $\frac{\partial}{\partial x \partial \sigma}\Pi_B(1,\sigma) > 0$ and there is a unique maximum as long as σ is not too large. Specifically, $\sigma < \min\{\overline{\sigma}, \sigma_0\}$, where $\sigma_0 \equiv \frac{(A-bc_0)^2(h^+ + h^-)}{4\sqrt{3}b(h^+ + c_0)(h^- - c_0)}$ is the maximum σ such that $\Pi_B(x,\sigma) > 0$ for all $x \in [0,1]$, and $\overline{\sigma}$ is the maximum σ such that the payoff at $x = 1$ is smaller than the payoff at the local maximum. We have $\overline{\sigma} > \frac{(A + r - bc_0 - \frac{1}{2}bc_1)(bc_1 - r)(h^+ + h^-)}{2\sqrt{3}bc_1(h^+ - h^- + 2c_0 + c_1)} \equiv \tilde{\sigma}$, where $\Pi_B(1,\tilde{\sigma}) = 0$.

Given the above characterization, there is unique $x_B^*(\sigma)$ for each σ. Moreover, $x_B^*(\sigma)$ is increasing in σ if $(h^+ - h^- + 2c_0 + c_1 x_B^*(\sigma)^2) > 0$. Since $h^+ - h^- + 2c_0 + 2c_1 x_B^*(\sigma)^2$ increases in $x_B^*(\sigma)$, if at $\sigma = 0$ it is true that $(h^+ - h^- + 2c_0 + 2c_1 x_B^*(0)^2) > 0$, then $(h^+ - h^- + 2c_0 + c_1 x_B^*(\sigma)^2) > 0$ for all $\sigma > 0$ and $x_B^*(\sigma)$ is increasing in σ for all $\sigma > 0$. Conversely, $x_B^*(\sigma)$ is decreasing in σ if at $\sigma = 0$, $(h^+ - h^- + 2c_0 + 2c_1 x_B^*(0)^2) < 0$. Moreover, $x_B^*(\sigma)$ is constant

[1]Let $X \subset \mathbb{R}$ be compact and T a partially ordered set. Suppose $f : X \times T \to \mathbb{R}$ has increasing differences in (x,t), and is upper semi-continuous in x. Then (i) for all t, $x(t)$ exists and has a greatest and least element $\overline{x}(t)$ and $\underline{x}(t)$; and (ii) if $t' \geq t$, then $x(t') \geq x(t)$ in the sense that $\overline{x}(t') \geq \overline{x}(t)$ and $\underline{x}(t') \geq \underline{x}(t)$.

in σ if $(h^+ - h^- + 2c_0 + 2c_1 x_B^*(0)^2) = 0$. At $\sigma = 0$, the optimal environmental performance is $x^* = x_B^*(0) = \frac{r}{bc_1}$. Thus, it follows that if we let $K_B \equiv 2c_0 + c_1(\frac{r}{bc_1})^2 = 2c_0 + \frac{r^2}{b^2c_1}$, then $x_B^*(\sigma)$ increases in σ if $h^- - h^+ < K_B$, $x_B^*(\sigma)$ decreases in σ if $h^- - h^+ > K_B$, and $x_B^*(\sigma)$ is constant in σ if $h^- - h^+ = K_B$.

■

Proof of Proposition 10. We use backwards induction to solve for the optimal solution. In Stage 3, using the results from Lemma 2, we obtain $p(w,x) = \frac{A+rx+wb}{2b}$ and $s(w) = F_\sigma^{-1}\left(\frac{h^- - w}{h^- + h^+}\right)$. In Stage 2, substituting the expressions from Stage 3 into Π_S, substituting the expression for uniform distribution into $s(w)$, the supplier's maximization problem becomes $\max_w \Pi_S(w,x)$, where

$$\Pi_S(w,x) = (w - C(x))\left(\frac{A+rx}{2} + \sigma\sqrt{3}\left(\frac{h^- - h^+}{h^- + h^+}\right) - \left(\frac{b}{2} + \frac{2\sigma\sqrt{3}}{h^- + h^+}\right)w\right)$$

Taking the derivative with respect to w gives:

$$\begin{aligned}\frac{\partial}{\partial w}\Pi_S(w,x) &= \left(\frac{A+rx}{2} + \frac{(\sigma\sqrt{3})(h^- - h^+)}{h^- + h^+} - \left(\frac{b}{2} + \frac{2\sigma\sqrt{3}}{h^- + h^+}\right)w\right) - \\ &\quad (w - C(x))\left(\frac{b}{2} + \frac{2\sigma\sqrt{3}}{h^- + h^+}\right) \\ \frac{\partial^2}{\partial w^2}\Pi_S(w,x) &= -\left(b + \frac{4\sigma\sqrt{3}}{h^- + h^+}\right) < 0\end{aligned}$$

This expression is concave in w for a fixed x. Thus, for each fixed x, the best response $w(x)$ is given by the first order condition below. Note that $w(x)$ is clearly positive since $h^- - h^+ \geq 0$ and that $w(x)$ increases in x.

$$w(x) = \frac{(A+rx)(h^+ + h^-) + 2\sigma\sqrt{3}(h^- - h^+)}{2(b(h^+ + h^-) + 4\sigma\sqrt{3})} + \frac{C(x)}{2} \qquad (7.18)$$

In Stage 1, substituting this expression back into the supplier's optimization problem, we obtain Π_S in terms of x. Since the payoff is parameterized by σ, rewrite $\Pi_S(x)$ as $\Pi_S(x,\sigma)$. The objective thus becomes: $\max_x \Pi_S(x,\sigma) = \left(\frac{h^-+h^+}{2(b(h^-+h^+)+4\sigma\sqrt{3})}\right)\left(\frac{A}{2}+\frac{\sigma\sqrt{3}(h^- - h^+)}{h^-+h^+}+\frac{rx}{2}-\left(\frac{b}{2}+\frac{2\sigma\sqrt{3}}{h^-+h^+}\right)C(x)\right)^2$

A solution x is feasible if $x \in [0,1]$, $w - C(x) \geq 0$, and $A - bp + rx + s \geq 0$. It can be shown that the latter two conditions are both equivalent to $\left(\frac{A}{2}+\frac{\sigma\sqrt{3}(h^- - h^+)}{h^-+h^+}+\frac{rx}{2}-\left(\frac{b}{2}+\frac{2\sigma\sqrt{3}}{h^-+h^+}\right)C(x)\right) \geq 0$. Next we substitute $C(x) = c_0 + \frac{1}{2}c_1x^2$. Rearranging the terms, the objective function is reduced to:

$$\max_x \Pi_S(x,\sigma) = \left(\frac{h^- + h^+}{2(b(h^- + h^+) + 4\sigma\sqrt{3})}\right)\left(\tilde{A}(\sigma) + \tilde{B}(\sigma) - \tilde{C}(\sigma)x^2\right)^2$$

where

$$\tilde{A}(\sigma) = \frac{A - bc_0}{2} + \frac{\sigma\sqrt{3}(h^- - h^+ - 2c_0)}{h^- + h^+}$$

$$\tilde{B}(\sigma) = \frac{r}{2}$$

$$\tilde{C}(\sigma) = \frac{bc_1}{4} + \left(\frac{\sigma\sqrt{3}c_1}{h^- + h^+}\right)$$

Following the same logic as the proof of Corollary 4, $(\tilde{A}(\sigma) + \tilde{B}(\sigma)x - \tilde{C}(\sigma)x^2)$ is strictly concave in x with maximizer $\frac{B(\tilde{\sigma})}{2C(\tilde{\sigma})} = \frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}$. Also, the maximizer of $\left(\tilde{A}(\sigma) + \tilde{B}(\sigma)x - \tilde{C}(\sigma)x^2\right)^2$ is $\frac{r(h^+ + h^-)}{2bc_1(h^+ + h^-) + 8\sqrt{3}\sigma c_1}$, because $(\tilde{A}(\sigma) + \tilde{B}(\sigma)x - \tilde{C}(\sigma)x^2)$ is positive over the feasible region (since the stocking quantity is restricted to be positive). Thus, the optimal solution is $x_S^*(\sigma) = \frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}$. ∎

Proof of Proposition 11. We use backwards induction to obtain the optimal solution. In Stages 3 and 2, proceed in the exact same manner as in the proof of the SC model (Proposition 10), which we obtain $s(w) = F_\sigma^{-1}\left(\frac{h^- - w}{h^- + h^+}\right)$, $p(w,x) = \frac{A + rx + wb}{2b}$, and $w(x) = \frac{(A+rx)(h^+ + h^-) + 2\sigma\sqrt{3}(h^- - h^+)}{2(b(h^+ + h^-) + 4\sigma\sqrt{3})} + \frac{C(x)}{2}$.

In Stage 1, substituting these expressions into Π_R gives the retailer's payoff in terms of x. Since Π_R is parameterized by σ, we write $\Pi_R(x,\sigma) = \frac{(A+rx-w(x)b)^2}{4b} - \sqrt{3}\sigma\frac{(h^- - w(x))(h^+ + w(x))}{h^+ + h^-}$, or $\Pi_R(x,\sigma) = \frac{(A+rx)^2}{4b} - w(x)\left[\frac{A+rx}{2} + \frac{\sqrt{3}\sigma(h^- - h^+)}{h^- + h^+}\right] + w(x)^2\left(\frac{b}{4} + \frac{\sqrt{3}\sigma}{h^+ + h^-}\right) - \frac{\sqrt{3}\sigma h^+ h^-}{h^+ + h^-}$.
Substituting the expression for $w(x)$, $C(x) = c_0 + \frac{1}{2}c_1x^2$, and rearranging gives:
$\Pi_R(x,\sigma) = \left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{64(h^+ + h^-)}\right)(c_1^2)\right]x^4 - \frac{rc_1}{16}x^3 + \left[\frac{r^2}{16b} + \frac{3\sqrt{3}\sigma r^2}{(4b)(b(h^+ + h^-) + 4\sigma\sqrt{3})} - \frac{(A - bc_0)c_1}{16} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{8(h^+ + h^-)}\right]x^2 + \left[\frac{1}{b(h^+ + h^-) + 4\sqrt{3}\sigma}\left(\frac{Ar(h^+ + h^-)}{8} + \frac{2\sqrt{3}\sigma Ar}{b} + \frac{3\sqrt{3}\sigma r(h^+ - h^-)}{4}\right) - \frac{rc_0}{8}\right]x + \left[\frac{b}{4}\left(\frac{A}{b} - \tilde{w}\right)^2 - \frac{\sqrt{3}\sigma}{h^+ + h^-}\left(h^- - \tilde{w}\right)\left(h^+ + \tilde{w}\right)\right]$, where $\tilde{w} = \frac{A(h^+ + h^-) + 2\sqrt{3}\sigma(h^- - h^+)}{2b(h^+ + h^-) + 8\sqrt{3}\sigma} + \frac{c_0}{2}$. Taking the derivative with respect to x yields:
$\frac{\partial}{\partial x}\Pi_R(x,\sigma) = \left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{16(h^+ + h^-)}\right)(c_1^2)\right]x^3 - \frac{3rc_1}{16}x^2 + \left[\frac{r^2}{8b} + \frac{3\sqrt{3}\sigma r^2}{(2b)(b(h^+ + h^-) + 4\sigma\sqrt{3})} - \frac{(A - bc_0)c_1}{8} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{4(h^+ + h^-)}\right]x + \frac{1}{b(h^+ + h^-) + 4\sqrt{3}\sigma}\left(\frac{Ar(h^+ + h^-)}{8} + \frac{2\sqrt{3}\sigma Ar}{b} + \frac{3\sqrt{3}\sigma r(h^+ - h^-)}{4}\right) - \frac{rc_0}{8}$,
And taking the derivative with respect to x and σ yields: $\frac{\partial}{\partial x\partial\sigma}\Pi_R(x,\sigma) = \frac{\sqrt{3}xc_1}{4(h^+ + h^-)}(h^+ - h^- + 2c_0 + c_1x^2) + \frac{3\sqrt{3}r(h^+ + h^-)(2A + 2rx + b(h^+ - h^-))}{4(b(h^+ + h^-) + 4\sqrt{3}\sigma)^2}$.

Suppose there is a unique maximizer of $\Pi_R(x,\sigma)$ for a given σ, $x_R^*(\sigma)$. By the monotone comparative statics theorem due to Topkis [141][2], if $\frac{\partial}{\partial x\partial\sigma}\Pi_R(x,\sigma) > 0$, then $x_R^*(\sigma)$ is increasing in σ. On the other hand, if $\frac{\partial}{\partial x\partial\sigma}\Pi_R(x,\sigma) < 0$, then $x_R^*(\sigma)$ is decreasing in x.

The payoff $\Pi_R(x,\sigma)$ is a polynomial of degree 4 with positive leading coefficient, which is first decreasing, then increasing, then decreasing, then increasing in x. To guarantee unique maximum $x_R^*(\sigma)$ for each σ, it is sufficient, though not necessary, to restrict $\frac{\partial}{\partial x}\Pi_R(0,\sigma) > 0$ and $\frac{\partial}{\partial x}\Pi_R(1,\sigma) < 0$. Using the same logic as in the proof of Proposition 9, this can be done by choosing σ not

[2]Let $X \subset \mathbb{R}$ be compact and T a partially ordered set. Suppose $f : X \times T \to \mathbb{R}$ has increasing differences in (x,t), and is upper semi-continuous in x. Then (i) for all t, $x(t)$ exists and has a greatest and least element $\overline{x}(t)$ and $\underline{x}(t)$; and (ii) if $t' \geq t$, then $x(t') \geq x(t)$ in the sense that $\overline{x}(t') \geq \overline{x}(t)$ and $\underline{x}(t') \geq \underline{x}(t)$.

too large.

Define $\tilde{x}_1 \equiv \sqrt{\frac{h^- - h^+ - 2c_0}{c_1}}$ (the first term of $\frac{\partial}{\partial x \partial \sigma}\Pi_R(x,\sigma)$ is positive for $x > \tilde{x}_1$) and $\tilde{x}_2 \equiv \frac{b(h^- - h^+) - 2A}{2r}$ (the second term of $\frac{\partial}{\partial x \partial \sigma}\Pi_R(x,\sigma)$ is positive for $x > \tilde{x}_2$). We first see that if $x_0^* > \tilde{x}_1$ and $x_0^* > \tilde{x}_2$ then $\frac{\partial}{\partial x \partial \sigma}\Pi_R(x,\sigma) > 0$ for all σ (since both terms are positive at x_0^* when $\sigma = 0$, and are positive for all $x^*(\sigma) > x_0^*$). Since $x_0^* > \tilde{x}_1$ can be written as $h^- - h^+ < 2c_0 + \frac{r^2}{b^2 c_1}$ and $x_0^* > \tilde{x}_2$ can be written as $h^- - h^+ < \frac{2A}{b} + \frac{2r^2}{b^2 c_1}$, the sufficient condition for $\frac{\partial}{\partial x \partial \sigma}\Pi_R(x,\sigma) > 0$, or for $x_R^*(\sigma)$ to be increasing in σ, is $h^- - h^+ < 2c_0 + \frac{r^2}{b^2 c_1}$. Similarly, the sufficient condition for $\frac{\partial}{\partial x \partial \sigma}\Pi_R(x,\sigma) < 0$, or for $x_R^*(\sigma)$ to be decreasing in σ, is $x_0^* < \tilde{x}_1$ and $x_0^* < \tilde{x}_2$, which translates to $h^- - h^+ > \frac{2A}{b} + \frac{2r^2}{b^2 c_1}$.
■

Proof of Proposition 12. Suppose the optimal solutions of the B, SC, and RC models are obtained according to the proofs of Propositions 9, 10, and 11 respectively. We compare the optimal solutions between the models by comparing the slopes of the payoff.

We first compare the solutions between B and SC models. Note that these solutions are obtained based on the restriction that there is a unique maximizer at which the derivative of the payoff with respect to x is zero. Consider the optimal solution of the benchmark model. The optimal solution $x_B^*(\sigma)$ needs to satisfy $\frac{\partial}{\partial x}\Pi_B(x_B^*(\sigma),\sigma) = 0$. Any $x < x_B^*(\sigma)$ will yield positive slope $\frac{\partial}{\partial x}\Pi_B(x,\sigma) > 0$, and any $x > x_B^*(\sigma)$ will yield negative slope $\frac{\partial}{\partial x}\Pi_B(x_B^*(\sigma),\sigma) < 0$. Thus, we can use the sign of the slope $\frac{\partial}{\partial x}\Pi_B(x_S^*(\sigma),\sigma)$ to compare $x_S^*(\sigma)$ and $x_B^*(\sigma)$. Substituting $x_S^*(\sigma) = \frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}$ into the expression for $\frac{\partial}{\partial x}\Pi_B(x,\sigma)$ in (7.16) yields the following: $\frac{\partial}{\partial x}\Pi_B(x_S^*(\sigma),\sigma) =$
$\left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{4(h^+ + h^-)}\right)(c_1^2)\right]\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right)^3 - \left(\frac{3rc_1}{4}\right)\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right)^2 +$
$\left[\frac{r^2}{2b} - \frac{(A - bc_0)c_1}{2} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{h^+ + h^-}\right]\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right) + \frac{(A - bc_0)r}{2b}$. Simplifying further yields the following expression:
$\frac{\partial}{\partial x}\Pi_B(x_S^*(\sigma),\sigma) = \left(\frac{2\sqrt{3}\sigma r(h^+ + h^-)}{bc_1(b(h^+ + h^-) + 4\sqrt{3}\sigma)}\right)\left(\frac{r^2}{b(h^+ + h^-) + 4\sqrt{3}\sigma} + \frac{c_1(2A - b(h^- - h^+))}{2(h^+ + h^-)}\right)$.

If $h^- - h^+ < \frac{2A}{b}$, then $\frac{\partial}{\partial x}\Pi_B(x_S^*(\sigma), \sigma) > 0$ for all σ, which implies that $x_B^*(\sigma) > x_S^*(\sigma)$ for all σ. If $h^- - h^+ > \frac{2A}{b} + \frac{2r^2}{bc_1}$, then the expression $\frac{r^2}{b(h^+ + h^-) + 4\sqrt{3}\sigma} + \frac{c_1(2A - b(h^- - h^+))}{2(h^+ + h^-)}$ is negative for all σ (since it is negative when $\sigma = 0$), which implies $x_B^*(\sigma) < x_S^*(\sigma)$ for all σ. Suppose $\frac{2A}{b} < h^- - h^+ < \frac{2A}{b} + \frac{2r^2}{bc_1}$, then define $\hat{\sigma} \equiv \frac{(h^+ + h^-)\left[(c_1 b)(2A - b(h^- - h^+)) + 2r^2\right]}{(4\sqrt{3}c_1)(b(h^- - h^+) - 2A)} > 0$ such that $\frac{r^2}{b(h^+ + h^-) + 4\sqrt{3}\hat{\sigma}} + \frac{c_1(2A - b(h^- - h^+))}{2(h^+ + h^-)} = 0$. Then, $x_B^*(\sigma) > x_S^*(\sigma)$ for $\sigma < \hat{\sigma}$, $x_B^*(\sigma) = x_S^*(\sigma)$ for $\sigma = \hat{\sigma}$, and $x_B^*(\sigma) < x_S^*(\sigma)$ for $\sigma > \hat{\sigma}$.

We next compare the optimal solutions of the RC and SC models. As above, we use the sign of the slope $\frac{\partial}{\partial x}\Pi_R(x_S^*(\sigma), \sigma)$ to compare $x_S^*(\sigma)$ and $x_R^*(\sigma)$. Substituting $x_S^*(\sigma) = \frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}$ into the expression for $\frac{\partial}{\partial x}\Pi_R(x, \sigma)$ from Proposition 11 yields the following:
$\frac{\partial}{\partial x}\Pi_R(x_S^*(\sigma), \sigma) = \left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{16(h^+ + h^-)}\right)(c_1^2)\right]\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right)^3 - \frac{3rc_1}{16}\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right)^2 + \left[\frac{r^2}{8b} + \frac{3\sqrt{3}\sigma r^2}{(2b)(b(h^+ + h^-) + 4\sigma\sqrt{3})}\right]\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right) + \left[-\frac{(A - bc_0)c_1}{8} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{4(h^+ + h^-)}\right]\left(\frac{r(h^+ + h^-)}{bc_1(h^+ + h^-) + 4\sqrt{3}\sigma c_1}\right) + \frac{1}{b(h^+ + h^-) + 4\sqrt{3}\sigma}\left(\frac{Ar(h^+ + h^-)}{8} + \frac{2\sqrt{3}\sigma Ar}{b} + \frac{3\sqrt{3}\sigma r(h^+ - h^-)}{4}\right) - \frac{rc_0}{8}$, which reduces to:
$\frac{\partial}{\partial x}\Pi_R(x_S^*(\sigma), \sigma) = \left(\frac{2\sqrt{3}\sigma r(h^+ + h^-)}{bc_1(b(h^+ + h^-) + 4\sqrt{3}\sigma)}\right)\left(\frac{r^2}{b(h^+ + h^-) + 4\sqrt{3}\sigma} + \frac{c_1(2A - b(h^- - h^+))}{2(h^+ + h^-)}\right)$.
This is the same condition as the one above. Thus, if $h^- - h^+ < \frac{2A}{b}$, $x_R^*(\sigma) > x_S^*(\sigma)$ for all σ. If $h^- - h^+ > \frac{2A}{b} + \frac{2r^2}{bc_1}$, $x_R^*(\sigma) < x_S^*(\sigma)$ for all σ. If $\frac{2A}{b} < h^- - h^+ < \frac{2A}{b} + \frac{2r^2}{bc_1}$, then, $x_R^*(\sigma) > x_S^*(\sigma)$ for $\sigma < \hat{\sigma}$, $x_R^*(\sigma) = x_S^*(\sigma)$ for $\sigma = \hat{\sigma}$, and $x_R^*(\sigma) < x_S^*(\sigma)$ for $\sigma > \hat{\sigma}$.

Next, we compare the solutions of the B and the RC models. For each σ, it follows that $\frac{\partial}{\partial x}\Pi_B(x_B^*(\sigma), \sigma) = 0$. Since $\frac{\partial}{\partial x}\Pi_R(x, \sigma) = \frac{1}{4}\frac{\partial}{\partial x}\Pi_B(x, \sigma) + \frac{3\sqrt{3}\sigma r(2A + (h^+ - h^-)b + 2rx)}{4b(b(h^+ + h^-) + 4\sqrt{3}\sigma)}$. Substituting $x = x_B^*(\sigma)$ into $\frac{\partial}{\partial x}\Pi_R(x, \sigma)$ gives

$$\frac{\partial}{\partial x}\Pi_R(x_B^*(\sigma), \sigma) = \frac{3\sqrt{3}\sigma r(2A + (h^+ - h^-)b + 2rx_B^*(\sigma))}{4b(b(h^+ + h^-) + 4\sqrt{3}\sigma)} \qquad (7.19)$$

Using the same logic as above comparisons, it follows that $x_R^*(\sigma) > x_B^*(\sigma)$ if $\frac{\partial}{\partial x}\Pi_R(x_B^*(\sigma), \sigma) > 0$ and $x_R^*(\sigma) < x_B^*(\sigma)$ if $\frac{\partial}{\partial x}\Pi_R(x_B^*(\sigma), \sigma) < 0$. If

$h^- - h^+ < \frac{2A}{b}$, then (7.19) is positive for all $x_B^*(\sigma) \geq 0$, so $x_R^*(\sigma) > x_B^*(\sigma)$ for all σ. If $h^- - h^+ > \frac{2A}{b} + \frac{2r^2}{bc_1}$, then (7.19) is negative for all $\sigma \geq 0$ since it is negative at $x_B^*(0) = x^* = \frac{r}{bc_1}$ and $x_B^*(\sigma)$ is decreasing in σ within this range (by Assumption 4). Thus, if $h^- - h^+ > \frac{2A}{b} + \frac{2r^2}{bc_1}$ then $x_R^*(\sigma) < x_B^*(\sigma)$ for all σ. Suppose $\frac{2A}{b} < h^- - h^+ < \frac{2A}{b} + \frac{2r^2}{bc_1}$, then $(2A + (h^+ - h^-)b + 2rx_B^*(\sigma))$ is decreasing σ since $x_B^*(\sigma)$ is decreasing in σ within this range. Substitute $\sigma = \hat{\sigma}$, then we can see that $(2A + (h^+ - h^-)b + 2rx_S^*(\hat{\sigma})) = 0$ and it follows that $x_B^*(\hat{\sigma}) = x_S^*(\hat{\sigma})$. Thus, if $\frac{2A}{b} < h^- - h^+ < \frac{2A}{b} + \frac{2r^2}{bc_1}$, then $x_R^*(\sigma) > x_B^*(\sigma)$ for $\sigma < \hat{\sigma}$, $x_R^*(\sigma) = x_B^*(\sigma) = x_S^*(\sigma)$ for $\sigma = \hat{\sigma}$, and $x_R^*(\sigma) < x_B^*(\sigma)$ for $\sigma > \hat{\sigma}$.

Let $K' \equiv \frac{2A}{b}$, and $K'' \equiv \frac{2A}{b} + \frac{2r^2}{b^2c1}$. Then, from the results above, it is straightforward to see that if $h^- - h^+ \leq K'$, $x_R^*(\sigma) > x_B^*(\sigma) > x_S^*(\sigma)$ for $\sigma > 0$. If $K' < h^- - h^+ \leq K''$, then there is $\hat{\sigma} \equiv \frac{(h^+ + h^-)((c_1 b)(2A - b(h^- - h^+)) + 2r^2)}{(4\sqrt{3}c_1)(b(h^- - h^+) - 2A)}$ such that $x_R^*(\sigma) > x_B^*(\sigma) > x_S^*(\sigma)$ for $\sigma < \hat{\sigma}$, $x_R^*(\sigma) = x_B^*(\sigma) = x_S^*(\sigma)$ for $\sigma = \hat{\sigma}$, and $x_R^*(\sigma) < x_B^*(\sigma) < x_S^*(\sigma)$ for $\sigma > \hat{\sigma}$. Lastly, when $h^- - h^+ > K''$, then $x_R^*(\sigma) < x_B^*(\sigma) < x_S^*(\sigma)$ for all σ.

∎

Proof of Corollary 7. From Propositions 10 and 11, for both RC and SC models, $w(x) = \frac{(A+rx)(h^+ + h^-) + 2\sigma\sqrt{3}(h^- - h^+)}{2(b(h^+ + h^-) + 4\sigma\sqrt{3})} + \frac{C(x)}{2}$ and the relationship between w and p is $p(w, x) = \frac{A + rx + wb}{2b}$. Thus for both RC and SC models:

$$p(x) = \frac{A + rx}{2b} + \frac{(A + rx)(h^+ + h^-) + 2\sqrt{3}\sigma(h^- - h^+)}{4(b(h^+ + h^-) + 4\sqrt{3}\sigma)} + \frac{C(x)}{4}. \quad (7.20)$$

The retail price $p(x)$ is increasing in x. Thus, the relationship between the retail prices of the RC and SC models is the same as the relationship between the optimal environmental performances between the RC and SC models.

From the proofs of Propositions 10 and 11, the stocking quantity is of the form:

$$q(x) = \left(\frac{A + rx}{4} + \frac{\sigma\sqrt{3}(h^- - h^+)}{2(h^+ + h^-)} - \left(\frac{b}{2} + \frac{2\sigma\sqrt{3}}{h^- + h^+} \right) \frac{C(x)}{2} \right) \quad (7.21)$$

for both RC and SC models. From the proof of Proposition 10, $x_S^*(\sigma)$ maximizes $q(x) \geq 0$ for each σ. Since $q(x)$ is strictly concave, any $x_R^*(\sigma) \neq x_S^*(\sigma)$ will give lower stocking quantity.

■

Proof of Corollary 8. From Proposition 12, $x_R^*(\sigma) \neq x_S^*(\sigma)$ for $\sigma > 0$. Since $\Pi_R(x, \sigma)$ has a unique maximizer $x_R^*(\sigma)$, it follows that any different $x_S^*(\sigma) \neq x_R^*(\sigma)$ would result in smaller payoff for the retailer.

■

Proof of Proposition 13. Consider the following contract applied to the SC model:

1. Supplier shares portion $(1 - \varphi)$ of the cost of mismatched demand $\mathbb{E}[h(q - D(p, x, \varepsilon)]$
2. Retailer shares portion $(1 - \varphi)$ of the revenue $pD(p, x, \varepsilon)$
3. Supplier modifies its wholesale price to $w_\varphi(x)$

In Stage 3, the retailer solves:

$$\begin{aligned} \max_{p,q} \quad & pD(p, x, \varepsilon) - w_\varphi(x)q - \varphi\mathbb{E}[h(q - D(p, x, \varepsilon))] - (1 - \varphi)pD(p, x, \varepsilon) \\ = \quad & \varphi \left(pD(p, x, \varepsilon) - \mathbb{E}[h(q - D(p, x, \varepsilon))] \right) - w_\varphi(x)q \qquad (7.22) \end{aligned}$$

In Stage 2, the supplier's objective function is:

$$\begin{aligned} \Pi_S \quad = \quad & (w_\varphi(x) - C(x))q - (1 - \varphi)\mathbb{E}[h(q - D(p, x, \varepsilon))] + \\ & (1 - \varphi)pD(p, x, \varepsilon) \qquad (7.23) \end{aligned}$$

Choose $w_\varphi(x) = \varphi C(x)$. Then the retailer's optimization problem becomes:

$$\max_{p,q} \quad \varphi \left[pD(p,x,\varepsilon) - \mathbb{E}[h(q - D(p,x,\varepsilon))] - C(x)q\right], \tag{7.24}$$

and the supplier's optimization problem becomes:

$$\begin{aligned} \max_{x} \quad & (1-\varphi)\left[p(x)D(p(x),x,\varepsilon) - \mathbb{E}[h(q - D(p,x,\varepsilon))]\right] - \\ & (1-\varphi)C(x)q(x). \end{aligned} \tag{7.25}$$

Both the retailer and the supplier maximize a fraction of the objective function of the vertically integrated firm (B model). Thus, the retailer will order and price according to the vertically integrated firm, and the supplier's optimal environmental performance level is that of the vertically integrated firm. ■

Proof of Proposition 14. The retailer would choose a seal of approval label over an information label if $\tilde{\Pi}_R(x_m) - \Pi_R(x_S^*(\sigma)) > L$, in the case where the retailer leaves environmental performance decision to the supplier, or if $\tilde{\Pi}_R(x_m) - \Pi_R(x_R^*(\sigma)) > L$ in the case where the retailer chooses the environmental performance decision for the supplier. Let's use $x^*(\sigma)$ to substitute for both $x_S^*(\sigma)$ and $x_R^*(\sigma)$. Then the benefit from seal of approval label $\tilde{\Pi}_R(x_m) - \Pi_R(x^*(\sigma)) - L \equiv \Delta$ is given by

$$\begin{aligned} \Delta = & \left[\left(\frac{b(h^+ + h^-) + 4\sqrt{3}\sigma}{64(h^+ + h^-)}\right)(c_1^2)\right]\left(x_m^4 - (x^*(\sigma))^4\right) - \frac{rc_1}{16}\left(ax_m^3 - (x^*(\sigma))^3\right) + \\ & \left[-\frac{(A - bc_0)c_1}{16} + \frac{\sqrt{3}\sigma c_1(h^+ - h^- + 2c_0)}{8(h^+ + h^-)}\right]\left(x_m^2 - (x^*(\sigma))^2\right) + \\ & \left[\frac{1}{b(h^+ + h^-) + 4\sqrt{3}\sigma}\left(\frac{Ar(h^+ + h^-)}{8} + \frac{2\sqrt{3}\sigma Ar}{b} + \frac{3\sqrt{3}\sigma r(h^+ - h^-)}{4}\right)\right](ax_m - x^*(\sigma)) - \\ & \left(\frac{rc_0}{8}\right)(ax_m - x^*(\sigma)) + \left[\frac{r^2}{16b} + \frac{3\sqrt{3}\sigma r^2}{(4b)(b(h^+ + h^-) + 4\sigma\sqrt{3})}\right]\left(a^2x_m^2 - (x^*(\sigma))^2\right) - L \end{aligned}$$

It is straightforward to see that $\frac{\partial}{\partial L}\Delta < 0$. Taking the derivative with respect to a gives $\frac{\partial}{\partial a}\Delta > 0$. As for behavior with respect to x_m, Δ is a polynomial in x_m of degree 4. In order for us to be able to find an optimal solution, we restrict ourselves to σ's that are not too large, so that Δ is concave in x_m.

■

Proof of Corollary 9. Suppose demand is deterministic. Fix a. Then the maximal benefit obtained from the seal of approval label is attained when x_m maximizes $\tilde{\Pi}_R(x_m) = \frac{(A+arx_m-bC(x_m))^2}{16b}$. Using the same derivation as in Proposition 8, $x_m^* = \frac{ar}{bc_1}$. Thus, the maximum benefit attained from a seal of approval label (given that we have some freedom to change x_m) is $\tilde{\Pi}_R(x_m^*) - \Pi_R(x^*) - L = \frac{(A-bc_0+\frac{a^2r^2}{2bc_1})^2-(A-bc_0+\frac{r^2}{2bc_1})^2}{16b} - L$. Define $\underline{L}(a)$ to be the maximal additional cost such that $\tilde{\Pi}_R(x_m^*) - \Pi_R(x^*) - \underline{L}(a) = 0$. Then, $\underline{L}(a) = \frac{(A-bc_0+\frac{a^2r^2}{2bc_1})^2-(A-bc_0+\frac{r^2}{2bc_1})^2}{16b}$.

Fix a and L. The retailer prefers a seal of approval label when $\tilde{\Pi}_R^* - \Pi_R^* - L > 0$. Using the expression from Corollary 6 and substituting $C(x_m) = c_0 + \frac{1}{2}c_1x_m^2$, this expression translates to $\frac{(A-bc_0+arx_m-\frac{1}{2}bc_1x_m^2)^2}{16b} - \frac{(A-bc_0+\frac{r^2}{4bc_1})^2}{16b} - L > 0$. This reduces to $(A - bc_0 + arx_m - \frac{1}{2}bc_1x_m^2) > \sqrt{(A - bc_0 + \frac{r^2}{4bc_1})^2 + 16bL}$ since $(A + arx_m - bC(x_m)) > 0$ for all feasible x_m. Rearranging the terms give a quadratic equation in x_m

$$0 > \left(\frac{1}{2}bc_1\right)x_m^2 - (ar)x_m + \left[\sqrt{(A - bc_0 + \frac{r^2}{4bc_1})^2 + 16bL} - (A - bc_0)\right]. \qquad (7.26)$$

The optimal value is $x_m^* = \frac{-(-ar)}{2\left(\frac{1}{2}bc_1\right)} = \frac{ar}{bc_1}$. Let $g(a, L) \equiv \sqrt{\frac{a^2r^2}{b^2c_1^2} - \frac{2}{bc_1}\left[\sqrt{(A - bc_0 + \frac{r^2}{4bc_1})^2 + 16bL} - (A - bc_0)\right]}$. By obtaining the roots of the quadratic equation in (7.26), it follows that seal of approval labels are preferred by the retailer when $x_m \in (\underline{x}_m, \overline{x}_m)$, where $\underline{x}_m = x_m^* - g(a, L)$ and $\overline{x}_m = x_m^* + g(a, L)$. Since $g(a, L)$ is increasing in a and decreasing in L, the range $\overline{x}_m - \underline{x}_m$ is expands in a and contracts L. ■

Proof of Corollary 10. Recall from Corollary 9 that when demand is deterministic $\underline{L}(a) = \tilde{\Pi}_R(ax^*) - \Pi_R(x^*)$. Fix $\sigma \geq 0$. Define $\underline{L}(a, \sigma)$ in a similar way based on the proof of Proposition 14: $\underline{L}(\alpha,\sigma) = \tilde{\Pi}_R(\tilde{x}_R^*(\sigma)) - \Pi_R(x^*(\sigma))$, where $\tilde{x}_R^*(\sigma)$ is the maximizer of $\tilde{\Pi}_R$, $x^*(\sigma) = x_S^*(\sigma)$ if the retailer leaves the environmental performance decision to the supplier, and $x^*(\sigma) = x_R^*(\sigma)$ if the retailer chooses the environmental performance for the supplier. From Proposition 14, $\tilde{\Pi}_R(\tilde{x}_R^*(\sigma))$ increases in α for a given σ, and is smallest when $\alpha = 1$. Define $\underline{L}^*(\sigma) \equiv \underline{L}(1,\sigma)$. Then, for a fixed σ, $\underline{L}^*(\sigma)$ is the "minimum upper bound", below which it is always feasible for the retailer to prefer seal of approval label over information label regardless of α. In the deterministic demand case, $\underline{L}^*(0) = 0$, since at $\alpha = 1$, $\tilde{\Pi}_R(\alpha x^*) = \Pi_R(x^*)$. In the stochastic demand case, $\underline{L}^*(0) = 0$ when $x^*(\sigma) = x_R^*(\sigma)$ but $\underline{L}^*(0) > 0$ when $x^*(\sigma) = x_S^*(\sigma)$ due to Corollary 8. Thus, $\underline{L}^*(\sigma) \geq \underline{L}^*(0)\ \forall\sigma$.

■

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Colophon

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