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Designing Contracts and Sourcing Channels to Create Shared Value

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Abstract. In complex supply chains, the benefits and costs of technological innovations do not always accrue equitably to all parties; thus, their adoption may critically depend on sourcing relationships and incentives. In a setting with uncertain and endogenous process yield, we study the potential of two features—contract design and sourcing channel—to create mutual benefit in decentralized value chains, where suppliers bear the costs of new technologies while benefits accrue primarily to buyers. Our focus is on agricultural value chains, where parties may transact through a channel that blends farmers' produce ("commodity-based channel") or that allows a one-on-one interaction between farmer and processor ("direct-sourcing channel"). Our study provides insights to companies seeking to incorporate responsible sourcing strategies while also creating economic value—a concept called "creating shared value." We identify that the technology's "cost elasticity" drives whether switching sourcing channel, changing contract structure, or adopting an integrated change is necessary to create shared value. This highlights that value chain innovations need to be properly designed—and sometimes combined—to achieve sustainable implementation. We also find that certain simple contracts with a linear or bonus structure are optimal, while other intuitive contracts could be detrimental. Using a data set of farms in Patagonia, Argentina, we estimate that the proposed mechanism could increase average supply chain profit by 6.9% while realizing positive environmental benefits.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/msom.2017.0627.

Keywords: supply chain management • value chain innovations in developing economies • sustainable sourcing • incentives and contracting • creating shared value

1. Introduction

Millions of farmers in developing economies supply the commodity markets that provide the majority of agricultural raw materials in today's global supply chains. Low incomes and low bargaining power often mean that these farmers make few investments in new management practices and can do little to improve their profits. Yet, in many cases, both the supply chain and the farmer could benefit from improved management practices at the farm level. One example is premature harvesting of produce, which can lead to loss in nutritional and economic value (FAO 2011, APEC 2014). Another example is water-efficiency management by the farmer (e.g., through drip irrigation), which affects water risk in supply chains that are facing depletion of groundwater resources and rising probabilities of droughts (Wilcox 2015, IPCC 2012). A third example is better matching farm practices with raw material end-use. Wheat, for instance, is often grown and traded based on an average quality and variety; yet, synchronizing the breeding and farming of wheat varieties with their different end-uses would benefit all parties in the supply chain (Anupindi and Sivakumar 2007, Barber 2014). Fourth, farm management practices may have a significant impact on process yields downstream, as is the case with palm fruit picking on crude palm oil extraction (Jelsma et al. 2009), parchment coffee drying on coffee milling (McAuley 2013, NCA 2016), and sheep forage use on wool scouring and combing (discussed in this paper).

To encourage farmers to adopt improved management practices, some companies have recently started switching from sourcing on commodity markets—which are based on blending farmers' produce and which lose the identity of individual farmers—to sourcing directly from farmers and developing individual relationships with them (Wal-Mart 2010, BSR 2011, Nestlé 2014, Wang et al. 2014). This change in sourcing practice is often accompanied by a change in procurement pricing, from rates based on regionally set or globally set values to rates that are informed by a farmer's individual costs (Wal-Mart 2010, BSR 2011, Nestlé 2014). Companies claim that such changes bring them closer to their suppliers, enhance their understanding of their suppliers' operating circumstances, and help them realize efficiencies, ultimately generating cost advantages and mutual benefit in the form of "shared value" (Porter and Kramer 2011).

However, creating such shared benefit is not straightforward, even within a single product line. In the Merino wool supply chain, for example, we observed two contrasting cases without a clear understanding of what created the discrepancy. In this supply chain, the greasy wool collected by farmers is sold to a topmaker, who then cleans ("scours") and smooths out ("combs") the greasy wool, and sells the end product in the form of wool tops to a spinner. This conversion process from greasy wool to clean woolen tops has a particular process yield, which is uncertain and is influenced by farmer management practices such as sheep forage use and sheep breeding. In New Zealand, an innovative manufacturer successfully used direct sourcing to incentivize farmers to adopt practices that improved top yields, by offering to share the observed benefits. This created mutual benefit for all parties in the supply chain in the form of cross-party production efficiencies.[1] However, in the Patagonia region of Argentina, a consortium has been grappling with the use of direct sourcing to incentivize the adoption of new management practices at the farmer level. This consortium was led by the international environmental nongovernmental organization (NGO) the Nature Conservancy, the outdoor apparel company Patagonia Inc., and the farmer network Ovis XXI in Argentina, as part of a joint project that spanned 2011–2014. The consortium's attempt was a significant part of a larger effort to combat the regional process of desertification—a severe form of land degradation—that was harmful to the entire supply chain (Mazzonia and Vazquez 2010, Casas 1999). To solve this problem, the consortium championed the use of a new technology known as "management-intensive grazing" (MIG) and subsidized several farms to implement it. Unfortunately, the direct subsidy proved short-lived, as it was not economically sustainable for all parties in the supply chain. The reason for the economic challenge, and for the discrepancy with success stories such as the one in New Zealand, was unclear, making it difficult to resolve the problem.

This prompts several natural research questions. Under what conditions is direct sourcing either sufficient or necessary to incentivize new management practices by the supplier/farmer? What is the structure of the optimal contract? Does a simple, price-only contract suffice? And under what conditions can direct sourcing indeed help create shared value? Lastly, can these insights explain the differences between the two examples in New Zealand and Argentina, as well as provide a resolution for the dilemma faced by the consortium in the latter case?

We use an analytical model and empirical evidence to help formulate answers to these questions. We model a supply chain with one buyer (topmaker) who can source through the commodity market or through a direct sourcing relationship. A key feature of the commodity market is that it is based on blending and thus is always an interaction between multiple suppliers (farmers) and the buyer. In contrast, a direct sourcing relationship allows for one-on-one interactions between a supplier and the buyer. The buyer is the Stackelberg leader, setting contract parameters. The supplier can choose (i) the sourcing channel through which to supply and (ii) whether or not to adopt a new (and more costly) technology. The economic benefit of the technology is modeled in the form of an improved process yield downstream.

We first show that if each farmer in the commodity market is only responsible for a small fraction of the total production, the supply chain will adopt a behavior of "growing to meet minimum specs," which is observed in most commodity markets including wool. This is a phenomenon where individual farmers have little incentive to improve product quality specifications beyond the required minimum, because their (costly) contribution to such value generation is lost in the blending process. As a result, many commodity markets do not properly incentivize new technology adoption by the farmer, even if these technologies would create value for the supply chain.

To induce benefit through technology adoption, it is then necessary to introduce the alternative model of direct sourcing. However, such an innovation in the sourcing channel may not be sufficient. We find that switching the channel to direct sourcing is sufficient to create shared value only when the new technology is relatively cheap, as defined by the cost efficiency relative to process yield improvements. This corresponds to what we observed in New Zealand, where new management practices are relatively cheaper to implement because differences in climatological conditions and historical farming practices have led to healthier farmlands compared to those in Argentina (UNCCD 2012). When the new technology is relatively expensive, simply switching the sourcing channel is insufficient to either incentivize the farmer or create shared value. This corresponds to the case in Patagonia, Argentina, where farmlands are severely degraded. In such cases, direct sourcing contracts with a particular "bonus structure" are necessary to create shared value. Such contracts reward farmers with a per-unit bonus when their process yields are larger than a predetermined threshold. This requirement of an *integrated change* in both sourcing channel and contract structure helps explain the puzzle faced by the consortium. Finally, we examine the potential of this approach for creating shared value in a real-world setting. Using a private data set of farms in Patagonia, Argentina, we estimate that the proposed mechanism would increase supply chain profits by 6.9% on average and realize environmental co-benefits, even though the new production method is 9% more costly.

In summary, we make the following related contributions to the literature:

• First, from a modeling standpoint, we develop a framework that explicitly captures key operating characteristics of value chains in developing economies, such as commodity-based sourcing, the use of simple (linear) payment terms, a fragmented supply base with low bargaining power, and the existence of simple practices/technologies that lead to immediate yield improvements. We endogenize process yield improvements and identify a technical condition that relates contract design to the process yield distribution. This condition is based on the harmonic mean residual life stochastic ordering, which (to the best of our knowledge) has not appeared thus far in operations management (OM) models.

• Second, we find that the required incentives for sustainable technology adoption are driven by (i) a new measure of cost efficiency relative to yield improvements and (ii) market segmentation. Together, these determine whether it is necessary to only change the contract design (from a linear contract to a piecewise-constant contract or a bonus contract), only change the channel design (from commodity sourcing to direct sourcing), or make an integrated change in both channel and contract design. We term our new measure of cost efficiency the "cost elasticity of process yield": it is intuitive, easy to estimate, and appears novel in the supply chain literature.

• Third, by combining our normative analyses with empirical data, we test and study the real-life implications of our theoretical results. We are able to retrieve the specifics of two strategies currently employed in practice—one successful and one challenged—and to provide recommendations and practical rules of thumb to use in the latter case.

The rest of the paper is organized as follows. We provide a review of related literature in Section 2. We present the model formulation and preliminaries in Section 3. We then study the sourcing problem and the contracting problem in Sections 4 and 5. In Section 6, we use an empirical example to infer practical implications of our findings. Our concluding remarks are provided in Section 7. All endnotes are provided after Section 7, and all proofs are in the online technical appendix.

2. Related Literature

The proposed problem is related to several literature streams in supply chain management, microeconomics, and strategy. In the literature on socially responsible operations and value chain innovations in developing economies, the concept of creating shared value (CSV) emerged as an umbrella construct for theories about the mutual dependence between a company's competitiveness and the health of environmental and social communities surrounding it, including its suppliers (Porter and Kramer 2011). However, there is limited understanding about how to operationalize such business models (e.g., London et al. 2010) and how to design contracts that create value to both parties (e.g., Henson et al. 2011, Maertens and Swinnen 2009). This paper contributes to filling this gap. One emerging topic of study is the business model of direct sourcing, which we study here. Wang et al. (2014) provide a review on the topic and conclude that while there is strong support for the welfare and productivity impacts of direct sourcing on farms, there is no consensus on what explains contract participation or nonparticipation. By explaining differences in contract adoption between New Zealand and Argentina, our study contributes to this discussion and helps identify new contract designs when contract participation may initially appear unattractive.

Sodhi and Tang (2014) discuss research opportunities to study operational innovations in supply chains with the poor as suppliers or distributors in developing economies. Sodhi (2015) and Bessiou and Van Wassenhove (2015) identify challenges to studying socially responsible operations. They suggest combining different methodologies to tackle these challenges and link socially responsible operations to targeted, analytical models. Our work closely follows these suggested approaches.

In supply chain management, there is a large literature on supply uncertainty and contracting. Our work is most closely related to papers that model supply uncertainty using random yield, i.e., where variability in the production process results in an uncertain number of items delivered—see, e.g., Ciarallo et al. (1994), Yano and Lee (1995). The focus in this literature is typically on identifying the optimal procurement strategy of a firm in the presence of yield uncertainty, in the form of exogenous supply disruptions (e.g., Wang et al. 2010, Federgruen and Yang 2008, Tomlin 2006). In contrast, our model focuses on yield uncertainty for a downstream buyer and endogenously incorporates decisions made by suppliers that may influence this process yield.

Our focus on incentivizing suppliers to adopt better management practices relates this paper to the large literature on contracting for incentive alignment (see Cachon 2003, Hohn 2010 for recent reviews). Recently, several scholars analyzed such problems in the context of supply disruption risks (e.g., Hwang et al. 2015). While this literature typically assumes a direct sourcing relationship between buyer and supplier, our study incorporates the possibility of commodity sourcing, which is pertinent in the context of the agricultural value chains motivating our work. Using stylized models, Tang et al. (2014) and Li (2013) study various sourcing schemes that the buyer may use to mitigate delivery risk by suppliers, including direct subsidies, inflated order quantities, and supplier diversification. While these studies typically consider contracts with constant marginal price, we find that such schemes may fail to coordinate the supply chain in our setting, and contracts with bonus structures tied to the distribution of the process yields may be required. This is consistent with the literature on managerial compensation, which argues that such nonlinear output-contingent compensation schemes may be optimal in settings with moral hazard (see, for example, Chung et al. 2014, Bernardo et al. 2001, Basu et al. 1985).

The literature on agricultural operations has considered optimal capacity allocation, production, and procurement quantities under uncertain yield and prices (see, e.g., Allen and Schuster 2004, Kazaz and Webster 2011, Huh and Lall 2013). The focus of these studies on *agricultural* yield (also referred to as farm yield) is distinct from our focus on *process* yield downstream in the supply chain. The studies on improving milk quality by Mu et al. (2016) and quality-dependent price schedules by Ayvaz-Cavdaroglu et al. (2016) are most closely related to our setting. Mu et al. (2016) focus on policy interventions to increase the quality of milk in the presence of competition for supply, when farmers can deliberately adulterate quality. In contrast, we focus on buyer interventions to incentivize the adoption of a new, costly technology to create mutual benefit in the presence of different sourcing channels. In contrast to Ayvaz-Cavdaroglu et al. (2016), who focus on farmer risk aversion, investments in quality, and two-part tariff contracting, we study competition among farms of heterogeneous size, and payment schemes tied to observed output, with bonus structures.

A related literature stream in agricultural economics considers factors that influence the adoption and efficient use of new technologies in developing economies (see Foster and Rosenzweig 2010 for a recent review of the topic). This literature has established a strong correlation between propensity for technology adoption and farm-specific characteristics such as farmer schooling and farm size. The causal pathways for these correlations vary from access to credit and insurance markets (e.g., Karlan et al. 2014) to learning models and technology complexity (e.g., Conley and Udry 2010). Our model incorporates features from this literature, including uncertainty in benefits from technology adoption and heterogeneity in farm size. Another feature—heterogeneity in the technology's relative cost—emerges endogenously. Consistent with this literature, we find that large farms are more likely to adopt new technologies under the status quo. Our OM perspective allows deriving prescriptive recommendations for designing incentive contracts for technology adoption when there is uncertainty in benefits and the technology is relatively expensive. We find that such uncertainty may require appropriate bonus-based incentive schemes.

In developmental microeconomics, there is ample literature on the importance of management practices in explaining productivity. The recent empirical focus on specific, measurable management practices has yielded a growing body of literature (Bloom and Van Reenen 2011, Lazear and Oyer 2012) that increasingly supports the association between management practices and higher productivity (Bloom et al. 2013, Lazear 2000) and helps explain differences in management quality between developing and developed countries (De Mel et al. 2008, Bloom et al. 2010). This literature, however, has largely focused on costs and benefits of productivity gains at the locus of production: farms and factories producing for global buyers. Although this focus ostensibly makes sense given that the locus of production is where the technology has to be implemented, in many cases the benefits of the new management practice do not solely lie at the production level but also in the downstream production process. Such an expanded view of costs and benefits in the production network is increasingly recognized as a critical component of making new management practices work, particularly in the context of socially responsible operations (e.g., Locke 2013).

3. Preliminaries and Model Formulation

In the wool supply chain, a farmer typically sells the "greasy wool" collected from his sheep to a topmaker, who then sells clean "wool tops" to a spinner, after "scouring" (cleaning) and "combing" (smoothing out) the greasy wool. This conversion process from greasy wool to clean woolen tops has a particular process yield, known as "top yield" in the industry, which critically depends on the farmer's practices. Under a grazing practice focused on preserving pasture quality and avoiding overgrazing, consistency of greasy wool fiber also improves, leading to increased top yields. Larger top yields translate into larger revenues for farmers, as topmaker payments are directly tied to the top yields. However, such practices also lead to higher costs for the farmer, since they are often "management-intensive" rather than letting sheep graze in one place continually with a subjectively estimated, fixed number of sheep per unit of land, the new practice requires moving the sheep in and out of different pastures depending on the conditions of the grasses (Gunther 2013). The new practice, therefore, requires additional planning of sheep grazing, labor to move the sheep around, and monitoring of grass health. Hence, it has also become known as "management-intensive grazing" or "MIG." (See the online technical appendix for further details about MIG.)

With this motivating example in mind, we consider a stylized supply chain consisting of one buyer (the topmaker) and N suppliers (the farmers), indexed by $i \in \{1, \ldots, N\}$. Farmers have fixed production quantities, denoted by $w_i \geq 0$, correspond to the amount of greasy wool collected from each farm. For simplicity, we normalize these quantities so that $\sum_{i=1}^{N} w_i = 1$ and assume that $w_1 \leq w_2 \leq \cdots \leq w_N$, which makes farmer 1 ($N$) the farmer with least (most) weight in the topmaker's input process. Although production quantities are fixed, farmers can influence the process yield of their produce by changing their management practice. Specifically, each farmer i chooses whether to adopt the new MIG practice or maintain the prevailing practice, and this choice is denoted by a variable m_i taking a value of 1 or 0, respectively. We assume that farmers adopting the same practice achieve homogenous (but variable) response in their yield. We use Y_m to denote the yield associated with management type $m \in \{0, 1\}$, and assume that Y_m is a random variable taking values in $(0, 1)$, with cumulative distribution function F_m, density function f_m, and mean μ_m. Thus, in the wool supply chain, Y_m measures the amount of woolen tops (i.e., output) per unit of greasy wool (i.e., input) achieved under management type m, with randomness in Y_m reflecting inherent yield variability, e.g., due to weather conditions that impact the quality of pasture grass and fiber fineness. Following the quality control literature, Y_m is independent of the quantity produced.

The economic benefit of MIG translates in an improved process yield in manufacturing, experienced by the buyer, i.e., an increase in top yield for the topmaker. To that end, we assume that the yield distributions Y_1 and Y_0 have respective supports $[\underline{y}_1, \bar{y}_1]$ and $[\underline{y}_0, \bar{y}_0]$ satisfying $0 < \underline{y}_0 \leq \underline{y}_1$ and $\bar{y}_0 \leq \bar{y}_1 < 1$, and that MIG leads to a higher mean process yield:

$$\mu_1 > \mu_0, \quad \text{such that } \Delta\mu := \mu_1 - \mu_0 > 0.$$

However, the MIG technology is also more costly to implement for the farmer. A farmer's production cost per unit of produce under management practice $m \in \{0, 1\}$ is given by $c_p(m)$, and—consistent with practice—we assume that

$$c_p(1) > c_p(0), \quad \text{such that } \Delta c_p := c_p(1) - c_p(0) > 0.$$

Every farmer is able to sell his entire produce (greasy wool) to the topmaker, at a per-unit price c_g that is chosen by the topmaker, based on the type of sourcing contract entered (i.e., *commodity-based* or *direct* sourcing), and the process yield achieved by the topmaker. In turn, the topmaker sells all his output (the woolen tops) and is paid a per-unit price c_t by the spinner. The typical material and financial flows are illustrated in Figure 1.

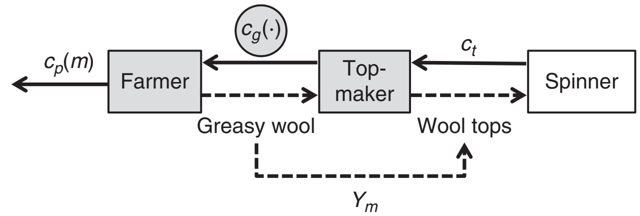


Figure 1. Stylized Illustration of Model Parameters in Interaction Between the Topmaker and a Single Farmer

Notes. The solid lines are financial flows, and the dotted lines are material flows. The grey boxes indicate the decision makers, and the grey circle indicates the optimization variable.

We focus on the interesting case when the adoption of the more expensive MIG practice would improve the expected profit of a centrally coordinated supply chain, i.e.,

$$\mu_0 c_t - c_p(0) < \mu_1 c_t - c_p(1) \quad \text{or equivalently } \Delta c_p < c_t \Delta\mu, \tag{1}$$

since otherwise neither the supply chain nor the farmer would benefit from the practice.

The focal point of our study is the design of contractual arrangements (sourcing channels and payment functions c_g) that would induce farmers to adopt the MIG technology, in an economically sustainable way. We focus on payment functions c_g that are nonnegative and nondecreasing, i.e.,

$$c_g \in \mathcal{V} := \{f : [0, 1] \to [0, \infty), f \text{ nondecreasing}\}, \tag{2}$$

which we refer to as "*valid*," and consider two possible configurations for the sourcing channel. The first is a *commodity-based sourcing model*, which relies on blending the greasy wool of all farmers. The second is a *direct sourcing model*, characterized by an individual interaction between each farmer and the topmaker. We next describe the dynamics of these two different settings in more detail and formalize the topmaker's corresponding problem under each.

3.1. Commodity-Based Sourcing

A key feature of commodity markets is that the farmers' produce is blended before processing. Under this sourcing model, a farmer's greasy wool is thus blended with the greasy wool of other farmers in the region, and the topmaker only observes the average yield of the blend after processing. Accordingly, the topmaker forms an expectation of the average top yield of the blend prior to processing and compensates each farmer with a per-unit price that depends on this "forecasted" average top yield.[2] Thus, all farmers are paid the same per-unit price for their output, assuming their produce meets certain baseline specifications (or "specs") that can be verified using simple tests (see Jelsma et al. 2009 for the description of an analogous process in palm oil extraction).

In our model, with $m_i \in \{0,1\}$ denoting the i-th farmer's MIG adoption decision, the topmaker would achieve an average top yield of $\bar{Y} := \sum_{i=1}^{N} w_i Y_{m_i}$ on the greasy wool blend, and the price c_g paid to each farmer would depend on the expectation of this yield. Therefore, the expected profit achieved by the topmaker and by the i-th farmer would take the following form:

$$\pi_T^b = \mathbb{E}[\bar{Y}]c_t - c_g(\mathbb{E}[\bar{Y}])$$
$$\pi_{F_i}^b = w_i[c_g(\mathbb{E}[\bar{Y}]) - c_p(m_i)], \quad \forall\, i \in \{1,\ldots,N\}.$$

Here, superscript b denotes the model of commodity-based or "blending-based" sourcing, and subscripts F_i and T denote the farmer and topmaker, respectively.

The topmaker always offers the farmers a simple *commodity contract*, which involves per-unit payments that are directly proportional to the anticipated top yield. In particular, such a commodity contract seeks to maximize expected topmaker profit under the assumption that all farmers use the prevailing technology (i.e., $m_i = 0$ for all i), while ensuring that farmers choose to deliver their greasy wool. With a farmer's opportunity cost normalized to zero, the per-unit payment function c_g^{cc} in a commodity contract thus would be given by an optimal solution to the problem:

$$\begin{aligned} \sup_{c_g \in \mathcal{V}} \ & \{\mu_0 c_t - c_g(\mu_0)\} \\ \text{s.t.} \ & c_g(\mu_0) - c_p(0) \geq 0 \\ & c_g(x) = ax, \quad \forall\, x \in [0,1]. \end{aligned} \tag{3}$$

Such simple agreements often constitute the prevailing contracts in commodity markets, where buyers do not explicitly incentivize farmers to adopt new management practices, and only maximize profits while ensuring supplier participation. Thus, the commodity contract becomes a suitable benchmark against which alternative sourcing channels and incentive mechanisms can be compared, and we assume that such a contract is *always* available for the farmers. Note that c_g^{cc} can be summarized in terms of a single number a, which we refer to as the *commodity rate*.

In addition to this benchmark commodity contract, a topmaker seeking to induce MIG adoption by (a subset of) the farmers may also offer an *incentive contract*, characterized by a particular valid per-unit payment function $c_g^{ic} \in \mathcal{V}$.

The overall sequence of events in the interaction between the parties under commodity-based sourcing is depicted in Figure 2. The buyer, acting as a Stackelberg leader, offers all farmers the option of a commodity contract (with payment function c_g^{cc}) and an alternative incentive contract (with payment function c_g^{ic}). The N farmers observe the available contracts and engage in a simultaneous-move game, in which each farmer chooses (i) the contract through which to supply, $\kappa_i \in \{ic, cc\}$, and (ii) whether to adopt the new MIG technology, $m_i \in \{0,1\}$. We assume that a farmer accepts any terms allowing an expected profit greater than or equal to his opportunity cost, which we normalize to zero. Depending on the farmers' choices, the topmaker then proceeds to collect all the greasy wool and pay the farmers based on the expected top yield of the blend. Once the blend is processed, the topmaker then sells the entire output to the spinner at a per-unit price c_t. All information about costs and yield distributions is common knowledge.

Thus, the topmaker's problem under a commodity-based sourcing model entails optimally choosing the payment function c_g^{ic} to use in the incentive contract, taking into account the farmer's responses regarding the technology adoption and contract choice.

3.2. Direct Sourcing

Instead of relying on contracts based on the commodity sourcing model, the topmaker could also innovate in the sourcing channel itself and rely on a direct-sourcing model. A key characteristic of direct sourcing is the individual interaction between the buyer and the farmer. This makes it possible for the topmaker to observe the process yield for a specific farmer's batch of greasy wool, so that the farmer can consequently be paid based on his individual, realized top yield.

Under this setup, the topmaker (T) and the i-th farmer (F_i) making a choice of technology $m_i \in \{0,1\}$ would face the following expected profit functions from their *d*irect interaction:

$$\pi_T^d = w_i[\mathbb{E}[Y_{m_i}]c_t - \mathbb{E}[c_g(Y_{m_i})]] \tag{4a}$$
$$\pi_{F_i}^d = w_i[\mathbb{E}[c_g(Y_{m_i})] - c_p(m_i)]. \tag{4b}$$

It is worth noting that the key distinctive feature here is the topmaker's ability to offer a contract based on the realization of the farmer's individual yield; this is in contrast to commodity-based sourcing, where

Figure 2. Schematic Illustration of Timeline Under Commodity-Based Sourcing.

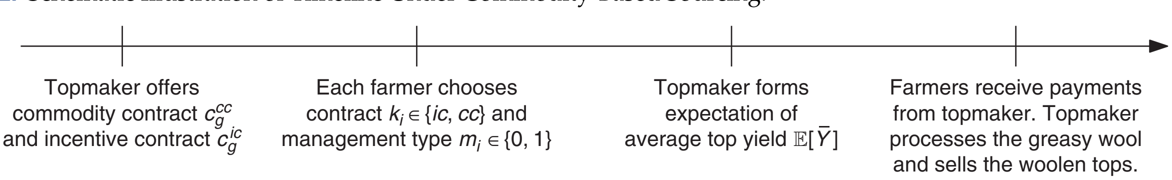
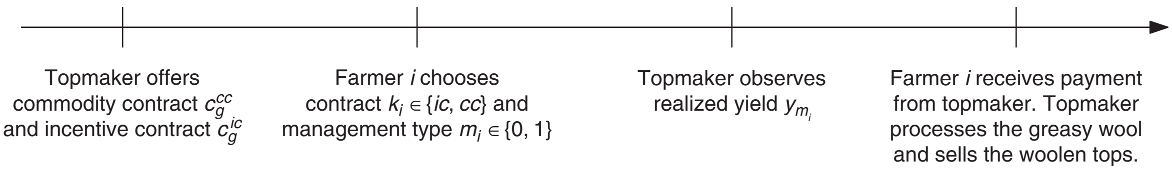


Figure 3. Schematic Illustration of Decision Timeline Under Direct Sourcing



payments were based on the expected average process yield across multiple farmers. In this sense, the contract can be calibrated under direct sourcing, and the topmaker can design the payment function c_g^{ic} in an incentive contract to induce individual farmers to adopt MIG.

Consistent with our earlier assumption under commodity sourcing, we assume that even when offered a direct sourcing incentive contract, farmers have the alternative of the benchmark *commodity contract*. The overall sequence of events, illustrated in Figure 3, parallels the one discussed for commodity-based sourcing, with the sole difference in the way payments for greasy wool are calculated. Table 1 summarizes the contractual agreements considered in this paper. To avoid additional notation, we use c_g^{ic} to denote the incentive contract under both commodity sourcing and direct sourcing, with the intended meaning clear from context.

3.3. Discussion of Modeling Assumptions

Our model incorporates several assumptions intended to either capture practice-based considerations or to maintain the focus on our core research questions, while retaining analytical tractability.

3.3.1. Buyer-driven Supply Chain. We assume the buyer has all the bargaining power. This is consistent with the literature on global value chain governance documenting the prevalence of buyer-driven supply chains in the agricultural sector, where producers are bound to buyer decisions (Rodrigue et al. 2013, Gereffi 2001). That said, our model could be readily extended to include some bargaining power for the farmer, without qualitatively affecting our results (see our discussion in Section 7).

3.3.2. Fixed Quantities. We assume that farmers are unable to influence the per-unit prices c_g and c_t by adjusting their production quantities, but they can influence the per-unit price c_g through the process yield associated with their produce—a variable that has a direct influence on the buyer's profits. Such a price-setting mechanism was communicated to us during interviews with supply chain managers and has been documented as a practice by Jelsma et al. (2009) in the context of palm oil. Furthermore, in agricultural settings consistent with our framework, production quantities involve complex long-term considerations and large upfront investments. For instance, agricultural systems such as livestock, coffee and palm are perennial, so adjusting production quantities requires enlarging the amount of land available (e.g., through land purchase or deforestation) and waiting several years until the planned-for quantities are reached. Since our focus is on examining the adoption of new management practices, we omit explicitly modeling such decisions.

3.3.3. Payment Format. We assume that under commodity-based sourcing, the farmer is paid based on the expected—rather than realized—regional average yield. This reflects real-world practice: when buyers set prices based on the expected yields, it allows farmers to know the price and get compensated immediately upon the delivery of their produce, without waiting for these to be processed. Thus, liquidity-constrained farmers often perceive such early payments as a benefit of supplying through commodity markets (see, e.g., Gupta et al. 2017, Burke 2014, Sun et al. 2013). In contrast, under the direct sourcing model, the farmer is paid a per-unit price that depends on his observed yield. This assumption reflects real-life settings of direct sourcing. For instance, companies in the coffee industry that use direct sourcing pay farmers contingent on coffee quality after tastings or "cuppings" at the buyers' facilities.[3] Our own interviews with manufacturers in New Zealand indicated that their payment to farmers with whom they have a direct sourcing relationship is contingent on top yield. More generally, such contingent payments are also prevalent in certification schemes, where a premium is paid to the farmer only after the realization of demand for certified products (Potts et al. 2014).

3.3.4. Commodity Pricing. We assume that the price paid to the farmer, including in commodity-based sourcing, is only a function of top yield. Clearly, many other factors may affect pricing in commodity markets, including weather shocks in producing regions across the world and other input specs. Our model

Table 1. Overview of Contractual Arrangement Considered

	Commodity sourcing	Direct sourcing
Commodity contract $c_g^{cc}(\cdot)$	$c_g^{cc}(\mathbb{E}[\textit{Yield of Blend}])$	N.A.
Incentive contract $c_g^{ic}(\cdot)$	$c_g^{ic}(\mathbb{E}[\textit{Yield of Blend}])$	$c_g^{ic}(\textit{Farmer Yield})$

Note. The highlighted box is the benchmark contract.

does not purport to capture the complex dynamics of global commodity prices; rather, the commodity contract is intended as a normalized benchmark contract that captures key dynamics of agricultural value chains (blending-based and buyer-driven). Thus, our commodity contract effectively acts as a numeraire, and this approach allows us to relate model results to observations in practice. This is also consistent with the observation that primary processors in agricultural value chains (i.e., topmaker in wool value chains, or mill in palm and coffee value chains) sell in global markets but purchase in local markets. As such, globally set prices of clean wool primarily affect c_t or, in the case of palm value chains, the price of crude palm oil (obtained from milling the fresh fruit bunches of the farmer) and, in the case of coffee value chains, the price of green coffee (obtained from milling parchment coffee from the farmer). In our model, since buyers capture most of the supply chain profit, shocks to global commodity prices are reflected in the buyer's profit margin, rather than price offered to farmers. For our purposes, global commodity prices will, thus, primarily affect whether the commodity contract is feasible and whether condition (1) is satisfied.

3.3.5. Deterministic Demand. To focus on uncertain process yield, we assume that the buyer is able to sell all his output, i.e., he faces deterministic demand. This is a common assumption in models with capacity or yield uncertainty (e.g., Ang et al. 2017, Tang et al. 2014, Babich et al. 2012). Furthermore, for many agricultural products used in processed foods and textiles—such as wool, cotton, and palm oil—there is sufficient demand to absorb all outputs. However, this may come at the cost of a lower price c_t; in our model, such shocks to demand are, thus, captured by c_t.

3.3.6. Other Considerations. Our model also makes several other assumptions, such as lack of MIG adoption under status quo, homogenous production costs, and additional costs/benefits of direct sourcing. We discuss these in Section 7, where we provide robustness checks and outline limitations.

4. Commodity-Based Sourcing

We first analyze optimal contracting under commodity-based sourcing, and we start by discussing the benchmark commodity contract.

4.1. Benchmark Commodity Contract

The benchmark commodity contract is given by the optimal solution to problem (3), i.e., it is characterized by the optimal linear payment function c_g^{cc} that maximizes the expected profits for a topmaker when no farmers adopt the MIG technology. The following result characterizes this simple contract.

Lemma 1. *Payments in the commodity contract are given by*

$$c_g^{cc}(x) = \frac{c_p(0)}{\mu_0} x, \tag{5}$$

where $c_p(0)/\mu_0$ is the nominal commodity rate.

The proof is immediate and is omitted. The nominal commodity rate $c_p(0)/\mu_0$ serves as the prevailing rate against which alternative contracts and sourcing channels can be compared. The linear structure of the commodity contract is in line with linear pricing methods in most commodity markets, including wool and palm oil. Explicitly defining the nominal commodity rate in this setting, which captures key features of buyer-driven and blending-based commodity markets, allows us to relate model results to observations about contracts and sourcing channels in practice (see Section 5.1).

4.2. Incentive Contract in Commodity-based Sourcing

When the topmaker offers the incentive contract, farmers engage in a simultaneous-move game in which they choose the contract through which to supply, and whether to adopt the MIG technology. Thus, the topmaker's problem entails optimally choosing the payment function c_g^{ic} to use in the incentive contract, taking into account the farmers' responses. To facilitate a practical interpretation of the results, we focus our analysis of this game on pure-strategy Nash equilibria. Mathematically, the topmaker's problem can thus be summarized as follows:

$$\sup_{c_g^{ic} \in \mathcal{V}} \sum_{i=1}^{N} w_i \left[c_t \mu_{m_i^*} - c_g^{\kappa_i^*}\left(\sum_{i=1}^{N} w_i \mu_{m_i^*} \right) \right], \tag{6}$$

where

$$(m_i^*, \kappa_i^*) = \underset{\substack{m_i \in \{0,1\} \\ \kappa_i \in \{ic, cc\}}}{\arg\max}\, w_i \left[c_g^{\kappa_i}\left(w_i \mu_{m_i} + \sum_{j \neq i} w_j \mu_{m_j^*} \right) - c_p(m_i) \right], \quad \forall\, i \in \{1, \ldots, N\}. \tag{7}$$

When solving the game, we enforce a unique equilibrium. The reader will observe that if we do not enforce a unique equilibrium for the contract that solves (6)–(7), the problem would turn into a coordination game between the farmers. By analyzing this hypothetical coordination game, one can show that two equilibria would survive, corresponding to *no farmers* or *all farmers* adopting MIG. The contractual payment function ensuring this would take an extremal form (compensating with a per-unit price of $c_p(1)$ only when *all* farmers adopt MIG, and $c_p(0)$ otherwise), inducing all farmers to achieve zero profits in both equilibria and allowing the topmaker to collect all the supply chain profit in the latter (payoff-dominant) equilibrium. While it is theoretically possible for the payoff-dominant equilibrium to be achieved in coordination games (see, e.g., Kim 1996 and references therein), recent experimental research has shown that players generally fail to coordinate in such games (see, e.g., Keser et al. 2012 and Heinemann et al. 2009). Furthermore, in the context of the commodity markets and agricultural value chains motivating our work, it seems ill-suited to assume that a large number of farmers in remote areas would coordinate their actions to adopt MIG. Therefore, we focus our analysis on payment functions that induce a unique equilibrium.

The topmaker's decision problem can then be solved by considering the optimal profit under the farmers' best response. For simplicity of notation, let us define $\mu(S) := \mu_0 + \Delta\mu \sum_{i\in S} w_i$, $\forall S \subseteq \{1,\ldots,N\}$ as the resulting expected average yield at the top-making level when a subset of farmers S adopts the MIG technology and the remaining farmers do not. We also define $[k,N] := \{k,\ldots,N\}$, and the following (potentially empty) sets of farmers:

$$\begin{aligned} S^{cc} &:= \left\{ i \in \{1,\ldots,N\}\colon w_i \geq \frac{\Delta c_p}{\Delta\mu} \frac{\mu_0}{c_p(0)} \right\} \\ &\equiv \{l, l+1, \ldots, N\} \end{aligned} \tag{8}$$

$$\begin{aligned} S^{ic} &:= \left\{ i \in \{1,\ldots,N\}\colon w_i \geq \frac{\Delta c_p}{c_t \Delta\mu} \right\} \\ &\equiv \{k, k+1, \ldots, N\}. \end{aligned} \tag{9}$$

By construction, it can be checked that $S^{cc} \subseteq S^{ic}$. The following result then completely characterizes the unique equilibrium of the game, highlighting the dependency on the relative importance of the farmers, as measured through their weights:

Theorem 1. *In equilibrium,*

(i) *If $w_1 \geq (\Delta c_p/\Delta\mu)(\mu_0/c_p(0))$ (so that $S^{cc} = \{1,\ldots,N\}$), then the topmaker only offers the commodity contract, and all farmers adopt MIG. The i-th farmer makes an expected profit of $[(c_p(0)/\mu_0)\mu_1 - c_p(1)]w_i$, and the topmaker makes an expected profit of $[c_t - c_p(0)/\mu_0]\mu_1$.*

(ii) *If $w_1 < (\Delta c_p/\Delta\mu)(\mu_0/c_p(0))$ and $w_N \geq \Delta c_p/(c_t\Delta\mu)$ (so that $S^{cc} \subset \{1,\ldots,N\}$ and $S^{ic} \neq \varnothing$), then the topmaker offers the following piecewise constant incentive contract:*

$$c_g^{ic}(x) \triangleq \begin{cases} \dfrac{c_p(0)}{\mu_0} \cdot \mu(S^{cc}), & \text{if } x < \mu([l,N]) \\ \dfrac{c_p(0)}{\mu_0} \cdot \mu(S^{cc}) + \Delta c_p, & \\ \quad \text{if } \mu([l,N]) \leq x < \mu([l-1,N]) & \\ \quad \vdots & \\ \dfrac{c_p(0)}{\mu_0} \cdot \mu(S^{cc}) + (l-k)\Delta c_p, & \\ \quad \text{if } \mu([k+1,N]) \leq x < \mu([k,N]) & \\ \dfrac{c_p(0)}{\mu_0} \cdot \mu(S^{cc}) + (l-k+1)\Delta c_p, & \text{otherwise.} \end{cases}$$

All farmers choose to sell through this contract, and farmers in S^{ic} also adopt the MIG technology. The expected profit for the i-th farmer is respectively given by

$$\left\{ \left[\frac{c_p(0)}{\mu_0} \mu(S^{cc}) + (l-k+1)\Delta c_p \right] - c_p(1) \right\} w_i, \quad i \in S^{ic}$$
$$\left\{ \left[\frac{c_p(0)}{\mu_0} \mu(S^{cc}) + (l-k+1)\Delta c_p \right] - c_p(0) \right\} w_i, \quad i \notin S^{ic},$$

and the topmaker's expected profit is given by $c_t\mu([k,N]) - [(c_p(0)/\mu_0)\cdot\mu(S^{cc}) + (l-k+1)\Delta c_p]$.

(iii) *If $w_N < \Delta c_p/(c_t\Delta\mu)$ (so that $S^{cc} = S^{ic} = \varnothing$), then the topmaker only offers the commodity contract, the supply chain does not adopt MIG, and the farmers make zero expected profit, while the topmaker makes an expected profit of $c_t\mu_0 - c_p(0)$.*

For a proof of this result (as well as the succeeding ones), please refer to the paper's online technical appendix. Before discussing the results in Theorem 1, we point out that the threshold values that determine the sets of farmers in (8) and (9) have important interpretations. The latter is the inverse ratio of per-unit increase in supply chain revenue to per-unit increase in supply chain cost, and thus is a measure of the supply chain's profit margin. The threshold value in (8) corresponds to the inverse ratio of relative yield improvements to relative cost increases, which gives it an "elasticity" interpretation. This quantity plays a critical role in the remainder of the paper, and therefore we define it formally as the "cost elasticity of process yield" in analogy to the well-known "price elasticity of supply" in microeconomics.

Definition 1 (Cost Elasticity of Process Yield).

$$\varepsilon \triangleq \frac{c_p(0)}{\mu_0} \frac{\Delta\mu}{\Delta c_p}.$$

When ε is high, the relative increase in process yield for the supply chain is high compared to the relative increase in costs incurred by the farmer. This makes the new technology relatively cheap compared to the benefit it generates. We use this relationship to classify the cost of the new technology into the intuitive categories of "cheap" and "expensive" for the remainder of the paper.

Definition 2 (Relative Cost of New Technology). If $\varepsilon < 1$, we say that the new technology is "expensive," whereas if $\varepsilon \geq 1$ we say that the new technology is "cheap." In the extreme case where $\varepsilon \geq 1/w_1$ we say that the new technology is "very cheap."

Theorem 1 indicates that if MIG is very cheap (i.e., $\varepsilon \geq 1/w_1$), the topmaker does not need to incentivize farmers, since they would automatically adopt MIG through the commodity contract. Equivalently, this condition can be interpreted in terms of farmer weights w_i, requiring that each farmer be responsible for a sufficiently large fraction $1/\varepsilon$ of the total production. Thus, in developing economies where the supply base is typically highly fragmented, the condition is unlikely to hold. For example, using the empirical data set described in Section 6, the smallest farm in the farmer network supplies $w_1 = 1.59\%$ of the blend, whereas $1/\varepsilon = 1.10$, such that condition (i) is not met.

As the technology becomes more expensive (or, equivalently, as some farmers become responsible for an increasingly small fraction of the total production), the topmaker prefers to incentivize only the largest suppliers, who have a significant impact on the process yield of the blend. Interestingly, when these large farms are incentivized, *all* farmers choose to supply through the incentive contract, since this affords a higher per-unit price than the commodity contract. In this regime, smaller farmers—who do not adopt the MIG technology in equilibrium—thus essentially free-ride on the yield improvements generated by the larger farmers. It is worth noting that such an incentive scheme critically depends on having sufficiently large farms (i.e., $w_N \geq \Delta c_p/(c_t\Delta\mu)$). Using the empirical data set described in Section 6, we find that $\Delta c_p/(c_t\Delta\mu) = 0.79$. Thus, a farm would have to contribute at least 79% of the blend for the topmaker to offer the farmer an incentive contract. However, the largest farm in our data set contributes only 16% of the blend on average, so that the condition does not hold. Finally, if there are no sufficiently large farms, i.e., $w_N < \Delta c_p/(c_t\Delta\mu)$, the topmaker never offers an alternative contract that incentivizes the adoption of MIG under commodity sourcing. The supply chain then never adopts MIG, despite the technology being beneficial, by condition (1).

This situation corresponds to the behavior of "growing to meet minimum specs" observed in many commodity markets, including wool.[4] More broadly, these results show that while a farmer could sometimes be better off by adopting a new technology even under a model of commodity sourcing, there are many cases where the benefits to the farmer alone are too small. The supply chain then ends up in a "commodity dilemma," which is the equilibrium outcome unless the business model is innovated by altering traditional sourcing channels. It is also worth noting that this situation is likely to be prevalent in cases where the farmers are not too different in their production quantities, and the number of farmers is very large, so that a given farmer's share of the total production becomes small. This is a typical case in the developing economies, suggesting that MIG adoption in such environments can be particularly challenging through commodity-based sourcing models.

5. Direct Sourcing

We now focus on the case when there are sufficiently many farmers and each is only responsible for a small fraction of the total production (i.e., $w_N < \Delta c_p/(c_t\Delta\mu)$), so that the MIG technology would never be adopted. In this case, the topmaker can engage each farmer through a *direct sourcing* relationship, in which their respective profits are characterized by (4a) and (4b). Therefore, the topmaker would solve the following optimization problem when designing the payment function c_g^{ic} in a direct sourcing contract with any given farmer:

$$\begin{aligned} \max_{c_g\in\mathcal{V}} \quad & \{\mu_1 c_t - \mathbb{E}[c_g(Y_1)]\} \\ \text{s.t.} \quad & \mathbb{E}[c_g(Y_1)] - c_p(1) \geq \mathbb{E}[c_g(Y_0)] - c_p(0) \quad \text{(P1)} \\ & \mathbb{E}[c_g(Y_0)] - c_p(0). \geq 0 \quad \text{(P2)} \end{aligned} \tag{10}$$

The first constraint in this formulation ensures that the farmer (weakly) prefers MIG to no-MIG under calibration; the second constraint ensures that the farmer's expected profit is at least as good as under the commodity contract, irrespective of his choice. Constraint (P1) also justifies the use of Y_1 as the relevant yield for the topmaker's profit from this individual interaction.

Clearly, at a stylized level, the topmaker's problem can be solved by any c_g^{ic} satisfying $\mathbb{E}[c_g^{ic}(Y_0)] = c_p(0)$ and $\mathbb{E}[c_g^{ic}(Y_1)] = c_p(1)$. However, this solution provides little insight into the design of the optimal payment scheme. Therefore, we proceed to develop a more detailed understanding of the optimal scheme and its structure. Our analysis focuses on continuous payment schemes, considering that these are most often used in practice. Within this class, there exist many different schemes with various compositions of a fixed bonus, a per-unit bonus, bonus thresholds, and a fixed earnings intercept (see, for example, Chung et al. (2014) for different compensation schemes used in sales settings). We concentrate the analysis on two-piece linear payments of the following form:

$$c_g^{ic}(x) = \beta_1 x + \beta_2 (x-\theta)^+,$$

where $x^+ \triangleq \max(x, 0)$. Thus, β_1 is the nominal rate paid to the farmer, β_2 is a bonus rate for higher yields, and θ is the bonus threshold. This compensation scheme is a more general representation of the linear payment scheme used in industries with endogenous process yields (see, for example, Jelsma et al. 2009). Because the per-unit price is proportional to the realized yield of the farmer $y_m \in (0,1)$, this pricing practice is sometimes referred to as "ratio pricing" (Boyabatli 2015). In the remainder of our analysis, we make the following assumption about process yields.

Assumption 1 (Technology-Adoption Condition)**.**

$$\mu_0\mathbb{E}[(Y_1-\theta)^+] \geq \mu_1\mathbb{E}[(Y_0-\theta)^+] \quad \forall\, \theta \in (0, \bar{y}_1).$$

Assumption 1 corresponds to requiring that Y_1 is larger than Y_0 in the harmonic mean residual life order. This stochastic ordering has been studied in reliability analysis and actuarial science (Heilmann and Schroter 1991) and is known to be slightly stronger than second order stochastic dominance. For particular classes of distributions, the condition is not very restrictive. For example, for the uniform and exponential distributions, it is equivalent to requiring $\mathbb{E}[Y_1] \geq \mathbb{E}[Y_0]$ (Heilmann and Schroter 1991), which is already satisfied in our basic model. This order also has convenient closure properties, including order preservation under the convolution operation and mixing (Shaked and Shanthikumar 2007). Lastly, we can also confirm that this condition is satisfied in our data set for the case of MIG in Argentina (see Section 6 for details).

Under two-piece linear contracts, the topmaker's problem is then given by

$$\max_{\theta\geq 0,\beta_1,\beta_2} \quad \mathbb{E}[c_t Y_1 - \beta_1 Y_1 - \beta_2 (Y_1-\theta)^+]$$
$$\text{s.t.} \quad \begin{bmatrix} \Delta\mu & \mathbb{E}[(Y_1-\theta)^+] - \mathbb{E}[(Y_0-\theta)^+] \\ \mu_0 & \mathbb{E}[(Y_0-\theta)^+] \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \geq \begin{bmatrix} \Delta c_p \\ c_p(0). \end{bmatrix} \quad \begin{matrix} \text{(P1)} \\ \text{(P2)} \end{matrix} \tag{11}$$

For a fixed θ, the problem of finding the nominal rate $\beta_1(\theta)$ and the bonus rate $\beta_2(\theta)$ reduces to solving a linear program (LP). Note that while we refer to $\beta_2(\theta)$ as a bonus rate, it only acts as a genuine bonus for the farmer when it is positive; otherwise, when $\beta_2(\theta) < 0$, the payment function effectively includes a discount on the per-unit purchase price for high yields. We first solve this LP and subsequently return to the full problem to find the optimal contract by optimizing over θ. Theorem 2 states the finite optimal solution under Assumption 1.

Theorem 2. *Under Assumption 1, the LP in (11) is solved by*

$$\beta_1(\theta) = \frac{c_p(0)\mathbb{E}[(Y_1-\theta)^+] - c_p(1)\mathbb{E}[(Y_0-\theta)^+]}{\mu_0\mathbb{E}[(Y_1-\theta)^+] - \mu_1\mathbb{E}[(Y_0-\theta)^+]}, \quad \textit{and}$$
$$\beta_2(\theta) = \frac{c_p(1)\mu_0 - c_p(0)\mu_1}{\mu_0\mathbb{E}[(Y_1-\theta)^+] - \mu_1\mathbb{E}[(Y_0-\theta)^+]}.$$

Furthermore, $\beta_2(\theta) \geq (>) 0$ *if and only if* $\varepsilon \leq (<) 1$.

Thus, it is always feasible to design an incentive contract under direct sourcing that incentivizes MIG adoption. However, Theorem 2 indicates that the cost elasticity of the new technology (ε) has a critical impact on the structure of the optimal contract. When MIG is expensive ($\varepsilon < 1$), the optimal contract is convex ($\beta_2 > 0$), such that the topmaker has to offer a per-unit bonus for higher yields. In contrast, when MIG is cheap ($\varepsilon \geq 1$), the optimal contract is either concave or linear. Note that the contract offers a larger bonus $\beta_2(\theta)$ and reduces the nominal rate $\beta_1(\theta)$ as the MIG technology becomes more expensive relative to the prevailing one, i.e., as $c_p(1)/c_p(0)$ increases.

To find the overall optimal contract and develop further insight into the dynamics of the optimal contract, we divide the analysis into two cases, depending on whether MIG is cheap or expensive.

5.1. MIG Is Cheap ($\varepsilon \geq 1$)

If MIG is cheap, Theorem 2 indicates that the optimal contract is concave, and the bonus rate is negative. Furthermore, we find that the per-unit price for large yields ($\beta_1^* + \beta_2^*$) when MIG is cheap in the strict sense (i.e., $\varepsilon > 1$) becomes even lower than the nominal commodity rate $c_p(0)/\mu_0$ (see Theorem 3 in the online technical appendix for details). This is a feature that may make the contract more difficult to implement and sustain in practice. However, as formalized in our next result, if the topmaker's main goal were to incentivize the adoption of the new technology, then simply changing the sourcing channel while maintaining the nominal commodity rate would be sufficient when the technology is cheap. In fact, such a simple linear contract would also create "shared value" when MIG is cheap in the strict sense (i.e., $\varepsilon > 1$), meaning that *both* the topmaker and the farmer would be strictly better off by interacting through this contract than by interacting through the existing commodity market.

Theorem 4 (Shared Value Contract)**.** *If $\varepsilon \geq 1$, a contract based on direct sourcing that pays the nominal commodity rate ($c_p(0)/\mu_0$) incentivizes farmers to adopt MIG. Furthermore, if $\varepsilon > 1$, such a contract would create strictly shared value.*

Effectively, this "shared value contract" means that the topmaker pays back the top yield differential to the farmer at a rate that equals the nominal commodity rate. Because of its simple structure, this contract is robust and relatively easy to implement, and calibrating it does not require any additional information about farmer-specific yield distributions. The topmaker only needs to estimate whether the new technology is cheap or not.

This contract is used successfully by an innovative manufacturer who sources directly from farmers in New Zealand.[5] This is plausible and consistent with our model predictions; the equivalent of MIG in New Zealand appears to be relatively "cheap," especially when compared with Argentina. Two main reasons for this difference were conveyed during a personal communication. First, the grasslands in New Zealand are considerably less degraded compared to those in Argentina, implying that $\Delta\mu/\mu_0$ is expected to be larger (this is also consistent with our empirical findings in Argentina alone, where we document a negative relationship between $\Delta\hat{\mu}/\hat{\mu}_0$ and the degree of desertification—see the paper's online technical appendix). Second, management practices in New Zealand are also more sophisticated and efficient than in Argentina, implying that $c_p(0)$ is likely larger and $\Delta c_p/c_p(0)$ smaller. The compounding effect of these two forces is that $\varepsilon = (c_p(0)/\Delta c_p)(\Delta\mu/\mu_0)$ is likely to be higher in New Zealand than in Argentina, making the corresponding MIG "cheap."

5.2. MIG Is Expensive ($\varepsilon < 1$)

We first observe that if MIG is expensive and the topmaker desires to incentivize adoption, it is no longer sufficient to only change the sourcing channel while paying according to the nominal commodity rate, as formalized in our next result.

Corollary 1. *If $\varepsilon < 1$, a contract based on direct sourcing that pays the nominal commodity rate $(c_p(0)/\mu_0)$ cannot incentivize farmers to adopt MIG.*

To incentivize the farmer, it is then necessary to also innovate the contract structure. Our next result characterizes the optimal contract when the process yields can be ordered in the mean residual life order (denoted by $Y_1 \geq_{\text{mrl}} Y_0$). This stochastic ordering is known to be slightly stronger than Assumption 1, but for particular classes of distributions such as the uniform and exponential, the two orderings are equivalent (Heilmann and Schroter 1991). We can also confirm that this condition is satisfied in our data set for the case of MIG in Argentina (see Section 6 for details).

Theorem 5 (Optimal Contract)**.** *When $\varepsilon < 1$, if $Y_1 \geq_{\text{mrl}} Y_0$, then there exists a $\xi > 0$ such that the optimal contract is given by any bonus threshold $\theta^* \in [\xi, \bar{y}_1)$ with corresponding nominal rate $\beta_1(\theta^*)$ and bonus rate $\beta_2(\theta^*)$ given by Theorem 2. The nominal rate and bonus rate satisfy*

$$0 < \beta_1(\theta^*) < \frac{c_p(0)}{\mu_0} < [\beta_1(\theta^*) + \beta_2(\theta^*)],$$

and the threshold $\xi = \underline{y}_0$ if $(c_p(1)\mu_0 - c_p(0)\mu_1)/\Delta c_p \leq \underline{y}_0$, and $\xi > \underline{y}_0$ otherwise. The topmaker captures all the supply chain profit, and adopting direct sourcing increases his per-unit expected profit by $c_t\Delta\mu - \Delta c_p$.

Several comments concerning this result are in order. There is substantial degeneracy in the optimal bonus threshold. This degeneracy can be useful in practice for addressing additional considerations such as profit variability and parameter estimation error. Using Monte Carlo simulations parameterized by the empirical data described in Section 6, we find that increasing the bonus threshold θ monotonically increases profit variability for both the topmaker and the farmer (see Figure 4). Furthermore, when the topmaker has limited data on yield distributions, he may prefer setting contract parameters that are less prone to estimation error. Because $\beta_1(\theta)$ and $\beta_2(\theta)$ depend on the quantiles of the yield distribution (see Theorem 2), setting a lower bonus threshold θ allows using more observations in parameter estimation. Figure 5 indicates the impact of estimation error on the topmaker's expected profit, using Monte Carlo simulations parameterized by the empirical data in Section 6. (The impact on the farmer's expected profit mirrors Figure 5 and is omitted for space considerations.) We find that the topmaker risks eroding his profits when setting θ relatively high. When θ is set relatively low, the estimation error is negligible. In summary, concerns about profit variability and estimation error suggest that it would be recommended to set θ quite low. The lower bound of ξ (always positive when MIG is expensive) thus becomes critical.

When MIG is expensive, the topmaker can always extract all the supply chain profit in optimality. However, the topmaker may wish to ensure shared value, i.e., that *both* the topmaker and the farmer are *strictly* better off. Theorem 6 identifies conditions under which this can be ensured, establishing that it can be difficult to strictly create shared value when the contract is linear.

Theorem 6 (Shared Value Contract)**.** *There always exists a bonus contract $(\theta > 0, \beta_2 > 0)$ that results in shared value. However, a linear contract $(\theta = 0)$ creates shared value if and only if*

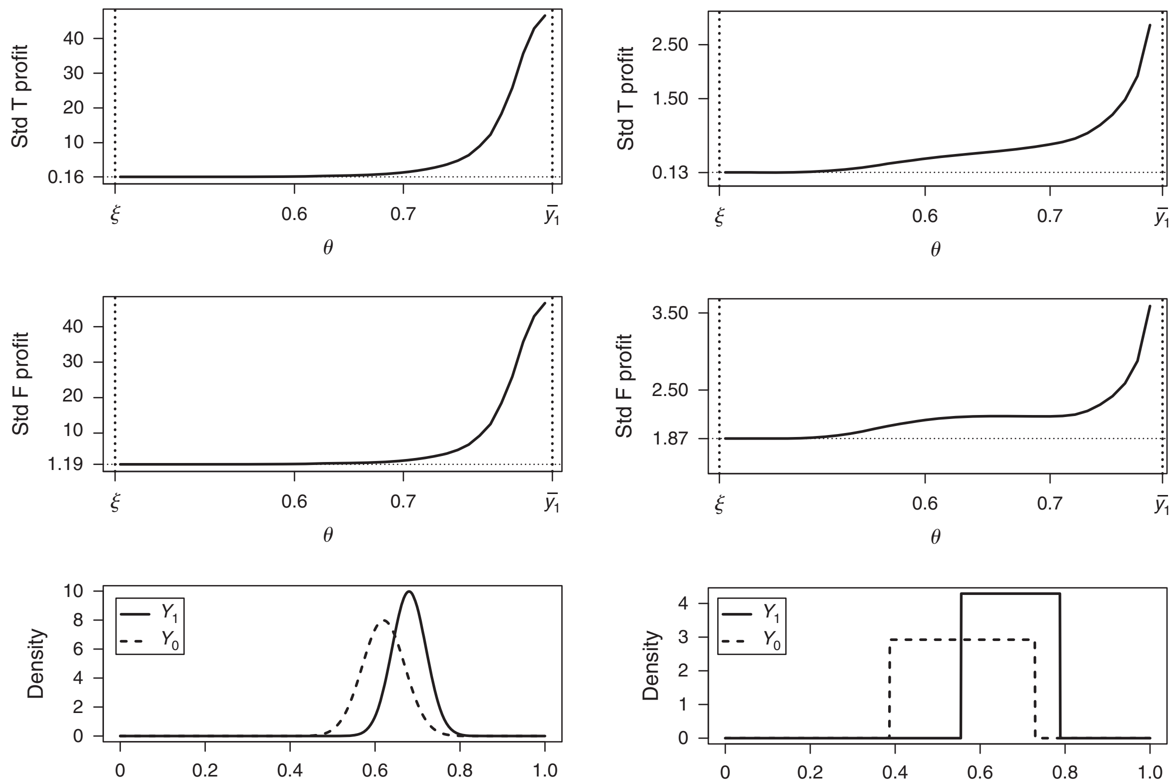
$$\frac{c_t\Delta\mu - \Delta c_p}{c_t\mu_0 - c_p(0)} > \frac{\Delta\mu}{\mu_1}. \tag{12}$$

The left-hand side of (12) is the relative increase in expected supply chain profit from adopting MIG; thus, for a linear contract to create shared value, the relative increase must be large enough. This condition implies that the buyer could be worse off under a linear contract that incorporates a per-unit price premium. Such contracts are common in practice; e.g., some certification schemes have a linear structure that incorporates a nominal per-unit price premium to compensate for cost increases of a new management practice (Potts et al. 2014). This may unnecessarily undermine the economic sustainability of the scheme or would require passing a price premium to the final consumer. Using the empirical data described in Section 6 for the case of MIG in Argentina, we find that (12) was not satisfied during the project. In such cases, only a convex contract that embeds a bonus structure would strictly create shared value. To create such a bonus contract, one could simply increase the value of the nominal rate $\beta_1(\theta)$ or the bonus rate $\beta_2(\theta)$ in the feasible direction.

6. A Puzzle Revisited

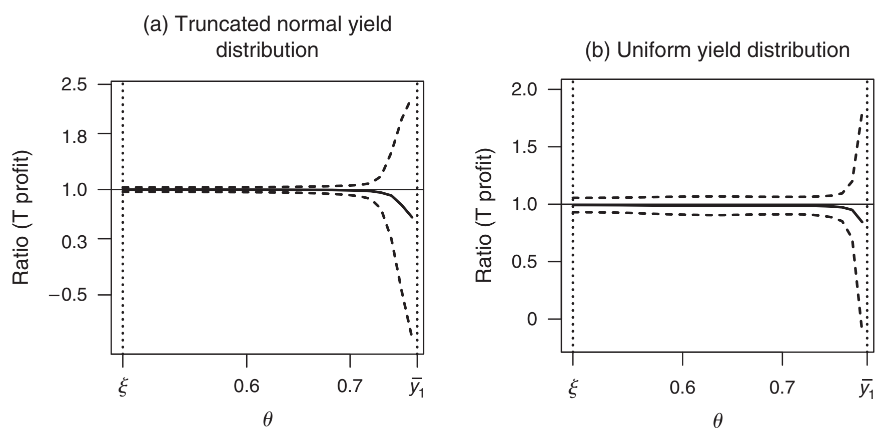
The analyses in Sections 4 and 5 help to explain what may cause the discrepancy in the sufficiency of direct sourcing to incentivize new management practices by

Figure 4. Profit Variability for Various Choices of $\theta^* \in [\xi, \bar{y}_1)$, Under the Optimal Contract



Notes. The standard deviation of the topmaker's (T) profit and of the farmer's (F) profit are displayed in the top row and middle row, respectively. Each row displays this for two distinct distributions that were parameterized using the empirical data described in Section 6 and are shown in the bottom row.

Figure 5. Impact of Estimation Error on Expected Topmaker (T) Profit for $\theta^* \in [\xi, \bar{y}_1)$



Notes. Each panel displays the ratio of $\mathbb{E}[c_g^{100}(Y_1)]$ over $\mathbb{E}[c_g^{1,000}(Y_1)]$, where $c_g^k(Y_1)$ is the contract price when β_1 and β_2 are estimated based on k observations. For each simulation, the distribution with 100 observations is bootstrapped from the distribution with 1,000 observations, considered the "true" yield distribution. This procedure was repeated 10,000 times. The solid line is the average of 10,000 simulations; the dotted line is one standard deviation from the average. Y_1 and Y_0 are drawn from the truncated normal distribution in Figure 4(a) and uniform distribution in Figure 4(b), parameterized by the data set in Section 6.

farmers, for the observed cases of New Zealand and Argentina. These two countries differ in the current state of their farmlands—due to distinct climatological conditions and historical practices—as well as in the current state of farming practices (UNCCD 2012). As a result, in New Zealand the equivalent of MIG is relatively "cheap," and a linear direct sourcing contract with a rate that equals the nominal commodity rate is sufficient to incentivize the adoption of MIG and create shared value. But when MIG is "expensive," as in Argentina, such a simple mechanism is insufficient. Equipped with the insights from our theoretical model, we can revisit the puzzle faced by the consortium.

To apply our analytical results, we perform the following steps. First, we empirically estimate key parameters of the model, i.e., the yield differences ($\Delta\hat{\mu}$) and cost differences ($\Delta\hat{c}_p$) associated with the adoption of MIG. (We use the hat-symbol ˆ to refer to an estimate of a population parameter.) Second, we verify whether key assumptions of the model are satisfied, such as the technology-adoption condition and the mean residual life order. We then combine this information to identify which model results and which insights are applicable. Finally, we use the data to infer the magnitude of the benefits to the supply chain if our proposed strategy were followed.

We draw on two data sets created as part of the consortium's project. The first is a farm-level data set with information about top yields and management types of farmers who participated in the project, which was based on a direct subsidy. The data include yields from farms supplying through a direct sourcing channel, and both farms implementing and not implementing MIG are included. The second is a low-resolution data set with variable costs and mark-ups at each stage of the wool supply chain in the outdoor apparel market, averaged at the industry level. To estimate $\Delta\hat{c}_p$ and $\hat{c}_p(0)$, the Nature Conservancy and Ovis XXI directly tracked farm revenues and additional costs incurred by farmers for MIG during the project's third year (i.e., 2013). In the absence of more granular information on baseline costs, we imputed $\hat{c}_p(0)$ from farm revenues per unit of greasy wool. Consistent with our modeling assumption that the farmer's opportunity cost is normalized to zero, we set the average per-unit cost of greasy wool equal to its average per-unit revenue.[6]

Before presenting our results, it is necessary to point out the limitations of these data sets and to clarify that this empirical section is not intended as a standalone empirical study, but is rather intended to complement and test our theoretical results in practice. First, from the perspective of a rigorous program evaluation, the data set on top yields has important shortcomings. Specifically, the strict method of a controlled experimental design with a control group and a random assignment was not applied at the time of project implementation in 2011. Consequently, the estimate of MIG's impact on top yields may be caused by confounding variables (Imbens and Rubin 2015). We correct for such issues as best as we can, by using a stratified experimental design in which we compare top yields of farms within stratified categories based on ecological regions (see the online technical appendix). As a result of this process, the total number of farms included in the analysis is reduced from 142 to 63. Due to the shortcomings of the experimental design and the small sample size, our quantitative results have to be interpreted with caution; while these are the best estimates currently available in such data poor regions as the world's drylands, they remain rough estimates. Second, the information on costs and margins at each stage of the supply chain has been averaged at the industry level to protect company-specific pricing negotiations.

6.1. Estimation of Key Parameters and Verification of Key Assumptions

Using the farm-level data set described previously on top yields and management types, we estimate that the average yield increase is $\Delta\hat{\mu} = 5.21\%$, with corresponding $\hat{\mu}_0 = 61.81\%$ such that $\hat{\mu}_1 = 67.03\%$. Table 2 provides summary statistics for each year; the online technical appendix provides a more detailed analysis by stratified categories. This estimate is based on a weighted average of top yields, where the relative weight is determined by the number of kilograms (kgs) of greasy wool, to ensure that our estimate is representative of the mean difference observed by the topmaker. Figures 6(a) and 6(b) show the empirical cumulative distribution function (CDF) and probability density function (PDF) of top yields under the two management types. We then used the costs associated with implementing MIG during the project to arrive at an estimate of the cost increase $\Delta\hat{c}_p$, using a weighted average across farms, where the relative weight is determined by the number of kgs of greasy wool. Combining $\Delta\hat{c}_p$ with our estimate of $\hat{c}_p(0)$, we estimate that, on average, the adoption of MIG increases farmer costs by $\Delta\hat{c}_p/(\hat{c}_p(0)) = 9\%$. Putting together our estimates for average yields and production costs, we find that MIG is "expensive":

$$\hat{\varepsilon} := \sum_{h=2011}^{2014} w_h \times \frac{\hat{c}_p(0)}{\hat{\mu}_{0,h}} \frac{\Delta\hat{\mu}_h}{\Delta\hat{c}_p} = 0.91,$$

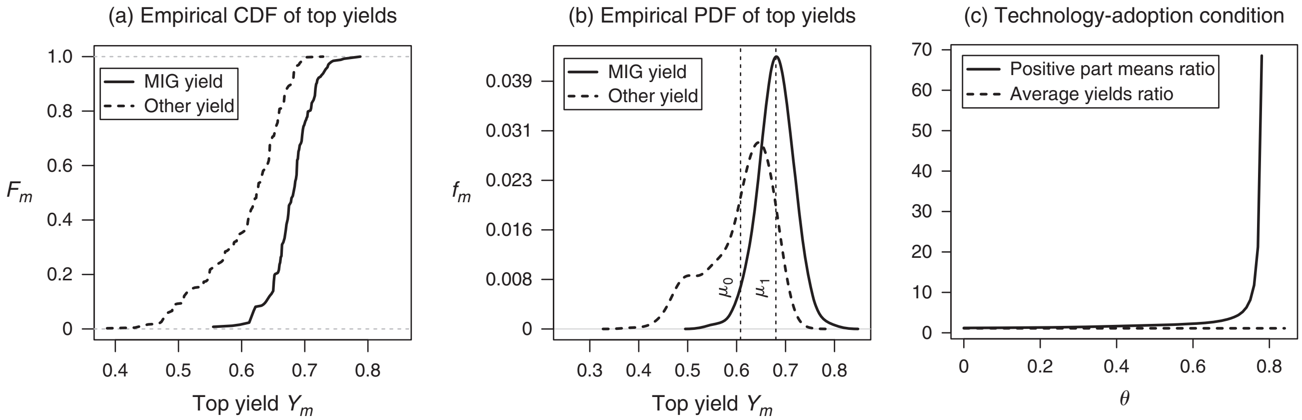
where h refers to the harvest year, and $w_h \in [0,1]$ is the relative weight of greasy wool in kgs in harvest

Table 2. Number of Farms Included in the Analyses, by Year, When Management Type is MIG ($m = 1$) or No-MIG ($m = 0$), and Estimates of Yield Increases $\Delta\hat{\mu}$

	2011		2012		2013		2014		Total	
m	1	0	1	0	1	0	1	0	1	0
# of farms	5	15	5	14	5	12	3	4	18	45
$\Delta\hat{\mu}$ (%)	5.76^{***}		4.50^{**}		4.96^{***}		$5.82^{\dagger}$		5.21^{***}	

Notes. Estimates of $\Delta\hat{\mu}$ are computed based on the weighted average of top yields Y_m, by year, with the relative weight determined by the farmer's share of the total production. For the difference in means, ***, **, and † denote significance at 1%, 5%, and 20% level, for a two-tailed Welch t-test. The significance level was computed at the farm level using clustered standard errors.

Figure 6. Empirical CDF and PDF of Top Yields



Notes. The left and middle panel show the empirical CDF and PDF of top yields under two different management types, using data from 2011–2014. The PDF is estimated using kernel density estimates with a Gaussian smoothing kernel. The right panel shows empirical verification of the technology-adoption condition. The solid line shows the ratio of positive part means $(\mathbb{E}[\widehat{(Y_1-\theta)^+}]/\mathbb{E}[\widehat{(Y_0-\theta)^+}])$ as a function of θ; the dashed line shows $\hat{\mu}_1/\hat{\mu}_0$.

year h. As a result, switching to direct sourcing only is insufficient to incentivize the farmer to adopt MIG (Corollary 1), and offering a simple linear contract that incentivizes the farmer was not economically sustainable for the topmaker (Theorem 6). This may help explain the challenges that the consortium faced. To incentivize farmers and to create shared value, the topmaker needs to offer a direct sourcing contract with a bonus structure. Finally, we argued that the technology-adoption condition (Assumption 1) is a sensible assumption for new technologies to be worthwhile, and therefore we adopted this key assumption in the remainder of our analyses. Using the farm-level data set, we can verify whether this assumption is indeed met. Figure 6(c) plots the ratio of positive part means $(\mathbb{E}[\widehat{(Y_1-\theta)^+}]/\mathbb{E}[\widehat{(Y_0-\theta)^+}])$, and the ratio of average yields $(\hat{\mu}_1/\hat{\mu}_0)$ as a function of the bonus threshold. As the former always exceeds the latter, the technology-adoption condition is indeed satisfied. Furthermore, because the ratio of positive part means is increasing in θ, we also have that $Y_1 \geq_{\text{mrl}} Y_0$ is satisfied (Shaked and Shanthikumar 2007).

6.2. Hypothesized Benefit to the Supply Chain

Since our key assumptions are satisfied, we can use estimates of the model parameters to infer what the benefit of direct sourcing and MIG would be to the supply chain. For this, we also use the data set that contains information about variable costs and markups at each stage of the wool supply chain. We then estimate that, using our proposed mechanism, average supply chain profits would increase by 6.9% even though the new production method is more costly. Specifically,

$$\sum_{h=2011}^{2014} w_h \times \frac{\hat{c}_{t,h}\Delta\hat{\mu}_h - \Delta\hat{c}_p}{\hat{c}_{t,h}\hat{\mu}_{0,h} - \hat{c}_p(0)} = 6.9\%. \tag{13}$$

In the case of Patagonia, Argentina, our proposed mechanism also incentivizes a production method with important environmental benefits, since MIG helps combat regional desertification.

7. Concluding Remarks, Limitations, and Future Research Directions

We study situations where suppliers have an opportunity to create economic (and, possibly, environmental) value by adopting a new technology, but the economic benefit is either too small for the suppliers or accrues primarily to other parties in the value chain. Our principal goal was to provide insights about contract and channel design to companies seeking to innovate their sourcing model, to create economic value while preserving responsible sourcing. We identify that the cost elasticity of the technology's economic benefit (in this case process yields) drives whether the buyer needs to change only its sourcing channel, only its contract structure, or both to incentivize farmers to adopt the new technology and to create shared value. To induce the intended supply chain benefit, it may thus be necessary to adopt an integrated change. We also find that certain simple contracts with either a linear or a "bonus structure" are optimal, while other intuitive contracts could be detrimental. This highlights that value chain innovations need to be properly designed—and sometimes combined—to achieve a sustainable implementation. Table 3 summarizes these findings.

This research was positioned in the context of incentivizing new management practices by farmers in Argentine Patagonia to combat the process of desertification. Although our findings have implications for direct sourcing as a sustainable sourcing strategy in agricultural value chains, we note that direct sourcing

Table 3. Summary of Findings in This Paper

Relative cost of MIG	Suggested channel	Suggested contract	Change in π_T	Change in π_F	Suggested innovation for topmaker
Very cheap ($\varepsilon \geq 1/w_1$)	Commodity	Linear	Increase	Increase	No innovation necessary
Cheap ($\varepsilon \geq 1$)	Direct	Linear	Increase	Increase	Change sourcing channel, maintain contract structure
Expensive ($\varepsilon < 1$)	Direct	Strictly convex	Increase	None/Increase	Change sourcing channel and contract structure

alone may not be sufficient. To ensure sustainable production, companies may also need to invest in capacity-building initiatives, compliance audits, and collaborations with government and other agencies (see, e.g., Locke 2013). There are also limits to what companies can achieve with a for-profit motive alone, particularly when accounting for implementation constraints. Our analyses show that the complexity of the coordinating contract increases as MIG becomes expensive. Developing such an understanding is a first step; e.g., when the technology is "cheap," a small change in procurement contract suffices to induce MIG adoption. Governments, NGOs, or donors could subsidize farmers up to where MIG becomes "cheap" ($\varepsilon \geq 1$) to avoid the need for complex contracts. This would allow resource-constrained agencies to cost effectively facilitate the creation of shared value. Alternatively, to catalyze the implementation of direct sourcing and contract calibration, these agencies could invest in tracking devices and data collection.

In our modeling efforts, we abstracted away from cultural or behavioral aspects of decision making by managers and farmers. However, such variation in contexts highlights the complexity of making innovations work in developing economies. Furthermore, the model assumes that decision makers have visibility of data such as yields and costs. We recognize that in many cases, there is limited data to inform decision making, and we encourage researchers to explore how this impacts our results. As best as we could, we incorporated a modus operandi in our analyses. As a result, we were able to retrieve the specifics of a current strategy used in practice, giving confidence that our results indeed provide insights that can be applied.

7.1. Extensions

Our analyses incorporated three assumptions that may be changed without altering the qualitative insights. First, we assumed that all bargaining power under direct sourcing lies with the topmaker. This assumption could be relaxed in several ways. For instance, we could assume that the i-th farmer has a per-unit opportunity cost $\delta^i \geq 0$, reflective of some bargaining power. By suitably altering the incentives (P2) in the topmaker's problem, it can be seen that this change is equivalent to increasing the farmer's production cost to $c_p(0) + \delta^i$. Our qualitative findings in Section 5 persist under these modified costs, with the sole difference that the i-th farmer now makes a profit $w_i \delta^i$, and the topmaker collects the remainder of the total profit. Interestingly, since the nominal rate $\beta_1(\theta)$ offered under direct sourcing is increasing in $c_p(0)$, this change has nontrivial implications for contract design, as farmers with *lower* opportunity costs are offered *lower* nominal rates. In such cases, the topmaker could use the degeneracy in the optimal contract choice to ensure that all farmers receive the same nominal rate β_1, with potentially different thresholds and bonus rates.

Alternatively, we could consider the direct sourcing contract as a solution to a Nash bargaining game between the topmaker and the farmer. In this case, it can be shown that the equilibrium solution would be to adopt MIG by using any payment function satisfying $\mathbb{E}[c_g(Y_1)] = c_p(1) + (c_t \Delta\mu - \Delta c_p)/2$, which would result in an equal split of profits between the farmer and the topmaker (details are available from the authors upon request). Since examples of such payment functions also include the bonus contracts that we study, our insights again remain robust.

Second, we assumed that all farmers use the prevailing technology when deriving the benchmark commodity contract c_g^{cc}. This is consistent with our focus on the introduction of a new, costly technology not previously adopted by farmers in the commodity market. Our qualitative insights would not change if we assumed instead that a set of farmers T already adopted MIG under the status quo. In fact, the nominal commodity rate would decrease in the latter case compared to our current analysis (becoming $c_p(0)/\mu(T)$), which would imply that even fewer farmers (not in the set T) would adopt the MIG technology through the commodity contract. Interestingly, the set of farmers adopting MIG through an incentive contract based on commodity sourcing would remain the same ($\mathscr{S}^{ic}$), and so would the condition under which the topmaker would find it optimal to offer such a contract ($w_N > \Delta c_p/(c_t \Delta\mu)$). Thus, under a highly fragmented supply, the MIG technology would only be adopted by a subset of farmers under commodity sourcing, motivating the need for direct sourcing.

Finally, we assumed that farmers incurred the same marginal cost for adopting MIG, independent of their production quantities. In practice, larger farms may incur smaller adoption costs, e.g., due to economies of scale. In this case, the set of farmers adopting MIG under the commodity contract would become $\mathcal{S}^{cc} = \{i: w_i \geq (\Delta c_p^i/\Delta\mu)(\mu_0/c_p(0))\}$, where $\Delta c_p^i = c_p^i(1) - c_p(0)$. Thus, the adoption of MIG would depend on each farmer's *individual* cost elasticity of process yield. However, our other qualitative results for commodity-based sourcing remain unaltered: the topmaker would only offer an incentive contract when the market is not too fragmented (i.e., $w_N > \Delta c_p^N/(c_t\Delta\mu)$), and only the largest farmers (with $w_i \geq \Delta c_p^i/(c_t\Delta\mu)$) would adopt MIG through such a contract. Note that the topmaker's preference for incentivizing only the largest farmers becomes even stronger, since this can now be done at lower cost. Interestingly, under direct sourcing, cost heterogeneity may have subtle effects similar to bargaining power: farmers with *higher* adoption costs might be offered *lower* nominal rates β_1, so that degeneracy may once again prove useful (as per our brief discussion in the previous section).

7.2. Future Research Directions

There are multiple avenues for further research that would relax limitations of the current paper. One such direction would be a multiperiod stochastic model capturing long-term costs and gains of sustainability-related concerns. This would also allow explicitly modeling certain long-term decisions made by farmers, with direct economic and environmental implications. Production quantities are one such example, often requiring large upfront investments (e.g., purchasing land) or practices with severe repercussions for the environment (such as deforestation in the case of palm oil crops). Such an extension would also allow capturing liquidity constraints impacting various supply chain parties, or other costs and benefits of direct sourcing, with fixed or variable components.

Additionally, one could extend the model to capture competition among the topmakers, or the interaction among other parties downstream in the supply chain. Lastly, one could also explore different contract designs that could improve upon our commodity incentive contract, eliminating the need to change the sourcing channel. One example of the latter could be a commodity sourcing contract that pays farmers based on the *realized* average yield of the blend, instead of the *expected* average yield. Although preliminary analysis with this model suggests that it may not always dominate our current incentive contract, determining the exact conditions when this holds and characterizing the power of such contracts would be an interesting direction of future research.

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Endnotes

[1] This was conveyed during a personal communication with one of the authors in January 2015. Due to the private nature of the sourcing strategies, the manufacturer preferred to not have their name revealed.

[2] Our model effectively assumes that the topmaker's forecast is consistent with the actual expectation of the average top yield; while this may not hold in a given (single-period) interaction, it is reasonable for it to hold on average, over several repeated, identical interactions.

[3] We obtained this information from a 2013 site visit of Sustainable Harvest, located in Lima, Peru.

[4] This term frequently came up in several interviews by one of the authors between May 2014 and January 2015.

[5] This was conveyed during a personal communication with one of the authors in 2015. Due to the private nature of the sourcing strategies, the manufacturer preferred to not have their name revealed.

[6] Our main results do not change when incorporating a representative profit margin for farmers (profit margin not further disclosed, to protect confidentiality).

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