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# Dynamic incentives for sustainable contract farming

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**Abstract**
The rise of contract farming has transformed millions of farmers' lives. We study a new class of contract farming problems, where the farmer holds superior information and can invest effort to improve productivity over time. Despite their prevalence, the literature offers little guidance on how to manage such farmers with dynamic incentives. We build a game-theoretic model that captures the dynamic incentives of learning and gaming, with hidden action and information. We characterize the optimal contract: it internalizes both the vertical and intertemporal externalities, with performance pay and deferred payment; the performance pay is to motivate the farmer to invest and improve the relationship-specific productivity; the deferred payment is to ensure that the farmer is willing to share information and behave honestly over time. Even with random yield, the optimal contract can still have a simple implementation of a yield-adjusted revenue-sharing policy. Using real data, we show that the learning effect is significant. We then quantify when and how contract farming can improve smallholder farmers' productivity and income, creating shared value. We find when buyers have a long-term perspective and can internalize the benefit of farmer improvement, they will pay higher prices to ensure farmers' long-term viability. Our results inform the policy debate on contract farming: traditional procompetitive policies (based on spot transactions) can be counterproductive for modern agrifood value chains, hurting both buyers and farmers.

**KEYWORDS**
agricultural supply chains, adverse selection, learning, moral hazard, revenue sharing, sustainability

## 1 | INTRODUCTION

"*You are what you eat*." In developed countries, more and more consumers take food as a matter of identity and morality (Akerlof & Kranton, 2000; Brekke et al., 2003).[1] They value expanding attributes of food *quality*: beyond *search and experience attributes* (e.g., taste, appearance, and convenience), they are increasingly willing to pay for *credence attributes*, such as safety, localvore, organic, pesticide-free, humanely raised, fairly traded, and environment friendly (Mu et al., 2016). Yet in traditional spot markets, consumers cannot reliably recognize and reward these credence attributes, even after consumption. To credibly ensure product quality (especially credence attributes), agrifood industries have transformed dramatically with increasing consolidation and contract farming (de Zegher et al., 2019).

*Contract farming* is an institutional arrangement wherein a buyer delegates the production of an agricultural commodity to a producer, a farmer, or farmers' cooperative (Otsuka et al., 2016). It dominates modern agriculture and expands rapidly in developing countries. The arrangement comes in all shapes and colors; two main types are production and marketing contracts (Bellemare & Lim, 2018).[2] These arrangements allow buyers to ensure reliable supply of farm products, with requisite volume and quality, to operate capital-intense processing, packing, or retailing facilities at efficient capacity (Barrett et al., 2020). They also help farmers gain access to high-value markets, upgrade quality and technology, relax financial constraints, and reduce production and price risks.

To ensure sustainable growth, buying firms take various initiatives to build long-term relationships. For example, Tesco establishes the Tesco Sustainable Farming Group and offers its farmers a 3–5-year rolling commitment with guaranteed procurement volume and price (Tesco, 2015); Starbucks develops C.A.F.E. (Coffee and Farmer Equity) program to

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build long-term partnerships with its farmers (Starbucks, 2020); other initiatives for long-term partnerships include Walmart's Direct Farm program (London & Fay, 2017) and Cargill's multiyear cocoa purchasing program (Cargill, 2015). In such long-term relationships, farmers not only hold superior knowledge of local conditions but also can learn to improve production capability over time. How should buying firms design contracts?

This class of contracting problems is challenging for two reasons. The first is information asymmetry. In contract farming, farmers enjoy an information advantage over buyers, due to their knowledge of local conditions (Federgruen et al., 2019). Although they can share the information truthfully to improve channel efficiency, they can also manipulate it for higher payment—*information rent*. For example, farmers may renege on delivery (Huh et al., 2012), engage in side-selling (Swinnen & Vandeplas, 2010), leak the proprietary technology (Sexton, 2013), and produce adulterated products (Mu et al., 2016). These gaming behaviors are prevalent and costly, calling for new contractual responses.

The second challenge is learning. Contract farming often involves long-term relationships, during which farmer productivity evolves over time.[3] For example, a farmer can learn from experience, invest short-term effort to improve cost efficiency, thereby strengthening his information and capability advantages. The learning effect has been well-documented in agriculture; see, for example, Conley and Udry (2010), Fuglie et al. (2019), Geylani and Stefanou (2011), Geylani and Stefanou (2013), Luh and Stefanou (1993), Luh (1995), and Shee and Stefanou (2016). A main finding is that learning breeds *intertemporal externalities*: current production and investment affect the farmer's future capability and payoffs, and potential future gain affects his actions taken now. In response, the buyer must consider how current policies affect the farmer's future incentives for production and information sharing.

The agricultural operations literature provides little guidance on how to design such contracts (Clay, 2018). So far, it has mainly focused on *simplistic farmers* (agents): they are myopic with no learning ability. These behavioral assumptions are suitable for static settings (e.g., single growing season), with one-shot interaction and a single piece of fixed private information. But they are inadequate for the class of contract farming problems, where dynamic incentives of learning and gaming are salient. To fill the void, we investigate how dynamic incentives affect contract design. We address three questions: (i) What is the optimal contract with dynamic incentives? (ii) How do the dynamic incentives change the existing insights? (iii) What are the managerial and policy implications?

We make four contributions to the agricultural supply chain literature. The first is modeling. We formulate a new class of contract farming problems with dynamic learning and gaming. In our model, the farmer (agent, he) holds superior knowledge about his evolving capability, as driven by past production experience, current capability, and random shocks. At the outset, the buyer (principal, she) offers a long-term contract that governs the relationship for multiple periods. In each period, the farmer observes new supply information and learns from production experience; from the farmer's choice, the buyer can also infer the farmer's private information and revise the production plan. Both parties are strategic, forward-looking, and profit maximizing. We formalize the intertemporal externalities as the marginal impact of current capability and production on future capability. Using this framework, we are able to quantify the performance pay as the sum of the weighted payoffs from gaming opportunities, where the weight is the risk-adjusted carryover effect. As such, our model helps define and quantify the *performance pay* in a precise way: it is the option value of all gaming opportunities during the relationship.

Our second contribution is to characterize the optimal contract. We find it differs substantially from the existing ones in structure and performance. It resolves a dynamic trade-off between exploiting farmer learning, deterring farmer gaming, and optimizing channel surplus. (i) To exploit learning, the buyer may deploy either upward or downward distortions in production, to improve productivity and control rent. (ii) To deter gaming, the buyer should institute deferred payment: she should withhold expected future rent in the current period and release it later contingent on realized cost efficiency. This mechanism ensures that the farmer has a stake in future channel efficiency, thereby committing him to improve efficiency and behaving honestly over time. (iii) To optimize channel surplus, the buyer should internalize both vertical and intertemporal externalities, while allowing the farmer to make dynamic adjustments over time. Dynamic adjustments help the buyer to tailor production to the prevailing farmer's capability, thereby adapting to changing conditions.

Our third contribution is to provide practical guidance. Using real data, we first show that the learning effect is significant. We then quantify *how contract farming can improve farmer productivity and income, despite their weak bargaining power*. Our central argument is that a short-term policy suffers both incentive and information deficiencies. Without a long-term perspective, it orders too little, discourages farmer effort investment, and fails to internalize the intertemporal externalities of carryover and learning effects. As such, it traps the supply chain in a low-efficiency equilibrium, wasting farmers' learning potential. Because it is renewed every period, the short-term policy allows the farmer to retain real information advantage over time; this deficiency prolongs production distortion, thereby perpetuating efficiency loss. By contrast, our long-term policy can mitigate both deficiencies, improve productivity, and create shared value in a wide range of situations. Using a calibrated numerical study, we show the improvement is substantial when the learning effect is strong and the carryover effect is large. In these situations, the long-term policy should prevail. Our results inform agricultural policy debate: in modern agricultural markets, traditional procompetitive policies—such as restrictions on contract provisions and minimum requirement of spot purchases—*can* be counterproductive, hurting both buyers and farmers.

Our fourth contribution is to develop a simple implementation for a general random yield model. The problem is technically challenging because random yield imposes an additional moral hazard problem. Despite the challenge, we find the buyer can still implement the optimal contract, in the form of *yield-adjusted revenue sharing*. Importantly, the conventional revenue-sharing contract will not work because its incentives are overpowered; to provide the right incentives, we must account for the yield factor and adjust the revenue term by a linear factor. Our finding is reassuring: one would expect efficiency loss because random yield weakens managerial control and simple implementation limits contractual choices. Yet our result shows the yield-adjusted revenue-sharing contract can overcome both problems. When the contract is properly calibrated, the farmer finds it impossible to gain from manipulation: he will share the information truthfully, equate his marginal production cost to his expected marginal benefit, and thereby maximize his continuation payoff.

## 1.1 | Related literature and contributions

Our work studies a new class of contract farming problems. It connects learning curves with incentive design. Contract farming is the backbone of modern agrifood value chains, in key sectors such as fruit, vegetable, and livestock production (Otsuka et al., 2016). In the United States, contract farming has expanded rapidly since the Green Revolution (Sexton & Xia, 2018). In 1969, only 5% of farms engaged in contract farming, covering 11% of the value of production; by 2013, 35% of the production value of all commodities was transacted via contracts (MacDonald, 2015). Today, contract farming dominates U.S. livestock and most produce industries. It is also expanding rapidly in developing countries (Otsuka et al., 2016).

The contract farming literature is enormous. A main finding is contract farming can improve farmer productivity and income by reducing transaction costs and overcoming market failures, in labor, purchased input, technology, credit, insurance, and product. For comprehensive reviews, see, for example, Bellemare and Lim (2018), Otsuka et al. (2016), Wu (2014), and Bijman et al. (2020). However, as Bellemare and Bloem (2018) and Barrett et al. (2020) pointed out, these studies are heavily empirical, descriptive, and context specific; they often struggle with credible causal identification. As such, they offer little theoretical guidance on how firms should best structure contracts nor as to what policymakers should do about contract farming. In particular, because buyers hold dominant market power, it is unclear *when and how farmers can benefit from contract farming* (Michelson, 2016). Our model addresses this question analytically. We show symbiotic relationships can arise from contract farming when (i) buyers have a long-term perspective and (ii) they can internalize the gain from farmer learning. In these relationships, to ensure stable supply of volume and quality, buyers are willing to pay higher prices—performance pay—to maintain the long-run viability of their farmers. As such, contract farming can create shared value, the mutual dependence between buyers and farmers.

Our central argument is an efficiency rationale based on learning. Learning embodies the adage of "practice makes perfect": the more time one performs a task, the less time he needs for the subsequent iteration. The empirical literature has shown that learning is fundamental to farm productivity; see, for example, Barrett et al. (2020), Conley and Udry (2010), Fuglie et al. (2019), Luh and Stefanou (1993), and Luh (1995).[4] Despite its importance, the analytical literature has yet to study how learning affects contract farming.[5] In this paper, we model learning-by-doing as a "*by-product*" of production experience, a standard approach in the theoretical literature on learning; see, for example, Arrow (1962), Cabral and Riordan (1997), Fudenberg and Tirole (1983), Hiller and Shapiro (1986), Jin et al. (2004), C. Li and Wan (2016), Shum et al. (2016), and S. Yang and Shumway (2020).

Our work builds on the dynamic principal–agent framework; the solution relies on the standard first-order approach; see, for example, Baron and Besanko (1984), Battaglini (2005), Courty and Hao (2000), Kakade et al. (2013), Pavan et al. (2014), and Battaglini and Lamba (2019). This framework has broad applications; see, for example, auctions (Board, 2007; Eső & Szentes, 2007), compensation design (Chen, Gao, et al., 2021; Gao, 2022; Garrett & Pavan, 2015), taxation (Kapička, 2013; Stantcheva, 2017), product line design (Xiong & Chen, 2013), and dynamic pricing (Akan et al., 2015; Oh & Özer, 2013). For a recent review, see Bergemann and Välimäki (2019) and references therein.[6]

Our work is also related to the experimentation literature that studies dynamic contracts with learning; see, for example, Hörner and Samuelson (2013), Halac et al. (2016, 2017), Guo (2016), and Khalil et al. (2020). Our work differs in two substantial ways. First, the experimentation literature studies *statistical learning*: the agent takes sequential actions to observe signals and update his belief of the underlying state. By contrast, we study *learning-by-doing*: the agent improves its capability as a by-product of production experience. Second, the experimentation literature typically assumes binary types (for otherwise high-dimensional beliefs defy tractability). By contrast, our work assumes continuous types and derives closed-form solutions.

The contract farming literature on payment design is scant. Four recent studies are the most relevant.[7] (i) de Zegher et al. (2019) study how to motivate farmers to adopt new technologies/practices through contract farming; they find that the joint change in channel and contract structures can be necessary and that simple contracts with bonus structure can be optimal. (ii) Federgruen et al. (2019) study a joint farmer selection and contract design problem under information asymmetry; among other results, they find simple menus can suffice when the farmer heterogeneity is low. (iii) Ayvaz-Cavdaroğlu et al. (2021) study how to incentivize farmers for quality investment; they find quality-based payment with a two-part tariff structure can coordinate the channel.

(iv) J. Chen and Chen (2021) study the welfare impact of buyers' effort investment; they find farmers' income disparity can either widen or narrow, depending on the type of participating farmers.

These studies focus on one-shot transactions, with a static perspective. We complement them by studying dynamic incentives, the core of many contract farming problems. We provide an analytical lens with a *dynamic and strategic perspective*. We show once dynamic incentives are considered, the structure and performance of the optimal contract can change substantially from the existing ones. Our model helps explain when and why contract farming can improve farmer productivity and income and create shared value, despite dominant buyer power and information asymmetry. To our knowledge, this is the first analytical treatment on how dynamic incentives affect contract farming when symbiotic relationships can arise naturally over time.

## 2 MODEL FORMULATION

Consider an agrifood supply chain that produces and sells a perishable product. It has one farmer (he) and one buyer (she). To ensure food quality and stable supply, the buyer seeks a long-term relationship: she offers a long-term contract $\pi \equiv (p_t, q_t)_{t\le T}$ that governs the relationship for $T$ periods. In each period $t \le T$, the buyer pays the farmer $p_t$ for producing quantity $q_t \in \mathcal{Q} \subset \mathbb{R}_+$. The farmer has production capability $\theta_t \in \Theta \equiv [\underline{\theta}, \bar{\theta}] \subset [0,1]$, which he can improve in two ways: (i) by learning from experience $q_t$, he can improve capability to $\theta_{t+1} = Z(\theta_t, q_t, \omega_{t+1})$, where $\omega_{t+1} \sim G$ is the random shock; (ii) by investing unobservable effort $e_t \in \mathcal{E} \subset [0,1]$, he suffers disutility $\frac{\phi}{2}e_t^2$, but he can reduce the unit cost and produce output $q_t$ at total production cost $\tilde{\psi}(\theta_t, e_t, q_t) \equiv c_0(1-\theta_t-e_t)q_t + \frac{c_1}{2}q_t^2$, where $c_0$ and $c_1$ are cost coefficients. Hence, the higher the capability $\theta_t$, the higher the effort investment $e_t$, the lower the total and marginal cost.[8]

Our problem is a dynamic game with adverse selection and moral hazard. For expositional ease, we mainly focus on the two-period setup. The game plays out as follows. (i) In period 1, upon privately observing initial capability $\theta_1$, the farmer decides whether to accept the contract $\pi$. If he rejects, the game ends. If he accepts, then he privately exerts effort $e_1$, produces output $q_1$ at cost $\tilde{\psi}(\theta_1, e_1, q_1)$, and receives payment $p_1$; the buyer receives sales revenue $v(q_1)$. (ii) In period 2, the farmer learns from experience $q_1$ and improves capability to $\theta_2 = Z(\theta_1, q_1, \omega_2)$; upon privately observing shock $\omega_2$, the farmer infers $\theta_2$, invests effort $e_2$, and produces $q_2$ at cost $\tilde{\psi}(\theta_2, e_2, q_2)$ for payment $p_2$; the buyer receives revenue $v(q_2)$ and the relationship ends. Importantly, the relationship suffers hidden action and information problems. Both effort $e_t$ and capability $\theta_t$ are the farmer's private information. Neither is observable to the buyer: she only knows the prior distribution $F_1$ of $\theta_1$ and the transition probability $F(\cdot|\theta_1, q_1)$ for $\theta_2$. All other parameters are common knowledge. We call the farmer with capability history $\theta^t \equiv (\theta_1, \theta_2, \dots, \theta_t)$, *farmer-$\theta^t$*. Table 1 defines all the notation.

**TABLE 1** Notation.

| Symbol | Definition |
|---|---|
| $\equiv$ | equal by definition |
| $\pi$ | contract |
| $c_0$ | type-dependent production cost |
| $c_1$ | type-independent production cost |
| $\alpha$ | carryover coefficient |
| $\beta$ | learning coefficient |
| $\xi$ | relative learning rate |
| $\phi$ | the effort cost coefficient |
| $\omega_2$ | random shock, with distribution $G$ and density $g$ |
| $\delta$ | discount factor, $\delta \in (0,1)$ |
| $e_t$ | farmer's effort in period $t$, $e_t \in \mathcal{E}$ |
| $\theta_t$ | farmer's supply state in period $t$, $\theta_t \in \Theta \equiv [\underline{\theta}, \bar{\theta}]$ |
| $\theta^t$ | farmer's supply state history up to period $t$, $\theta^t \equiv (\theta_1, \dots, \theta_t) \in \Theta^t \equiv \times_{\tau=1}^t \Theta$ |
| $q_t$ | production at period $t$, $q_t \in \mathcal{Q}$ |
| $p_t$ | total payment for the farmer in period $t$ |
| $h$ | the inverse hazard rate function of the initial supply capability |
| $Z$ | the capability dynamic function |
| $V_t$ | the buyer's profit from period $t$ onward |
| $U_t$ | the farmer's profit from period $t$ onward |
| $F$ | the transition kernel of the supply capability |
| $F_1$ | the distribution of the initial supply capability |
| $\tilde{\psi}$ | farmer's production cost |
| $\psi$ | farmer's cost function in period $t$ under optimal effort |
| $f_\theta$ | derivatives of function $f$ w.r.t. the first argument, $f_\theta(\theta_t, q_t) \equiv \partial_{\theta_t} f(\theta_t, q_t)$ |
| $f_q$ | derivatives of function $f$ w.r.t. the second argument, $f_q(\theta_t, q_t) \equiv \partial_{\theta_t} f(\theta_t, q_t)$ |
| $f_{\theta q}$ | cross derivatives of function $f$ w.r.t the two arguments, $f_{\theta q}(\theta_t, q_t) \equiv \partial_{\theta_t q_t} f(\theta_t, q_t)$ |
| $\mathsf{E}_t^\pi$ | expectation taken with respect to the information available at time $t$ under $\pi$ (if given) |

We use *capability* $\theta_t$ as an overarching term to model the farmer's private information about his relation-specific productivity. The empirical literature shows that the farmer's capability $\theta_t$ can evolve over time; see, for example, Conley and Udry (2010), Luh and Stefanou (1993), Luh (1995), and Fuglie et al. (2019). Following the literature, we specify the capability evolution by

$$\theta_{t+1} = Z(\theta_t, q_t, \omega_{t+1}) = \alpha\theta_t + \beta q_t + \xi\theta_t q_t + \omega_{t+1}, \quad (1)$$

where $\alpha$ is the carryover coefficient, $\beta$ is the learning coefficient, $\xi$ is the relative learning rate, and $\omega_{t+1} \sim G$ is the random shock. We assume carryover rate $Z_{\theta_t} = \alpha + \xi q_t \ge 0$, and learning rate $Z_{q_t} = \beta + \xi\theta_t \ge 0$. The assumption captures

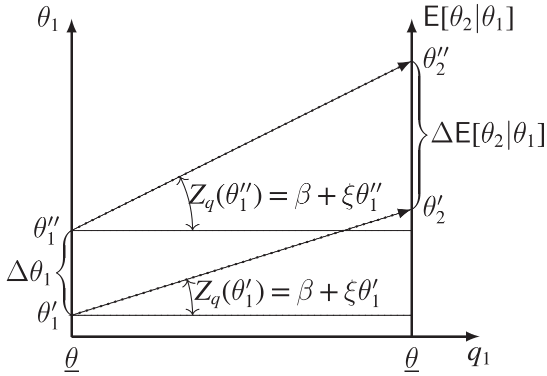


**FIGURE 1** Capability expansion: $\xi > 0$.

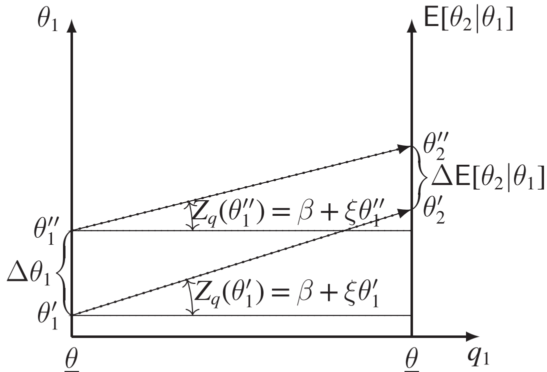


**FIGURE 2** Capability contraction: $\xi < 0$.

the essence of empirical learning curves: the higher the current capability, the higher the current production, the higher the future capability, stochastically. In this model, effort $e_t$ is the short-term labor input for reducing current production cost, but it does not affect future capability $\theta_{t+1}$ directly. To validate this learning model, we conduct an empirical analysis with real data; see Supporting Information Appendix B for details.

The relative learning rate $\xi$ is critical: It allows *nonlinear learning*, with type-dependent learning rate $Z_{q_t} = \beta + \xi\theta_t$; when $\xi = 0$, we recover the standard linear learning curves (Fudenberg & Tirole, 1983). Importantly, learning empowers farmer-$\theta_1$ with *endogenous information asymmetry*. He derives his bargaining power from his capability lead (gap) $\Delta\theta_1$ over low types (Figure 1). By manipulating $q_1$, the farmer can leverage learning to control future capability gap $\Delta\mathsf{E}[\theta_2|\theta_1]$. (See Figure 2 for an illustration.)

By the revelation principle, we can find the optimal contract within the class of direct truthtelling mechanisms (Myerson, 1986). In this framework, farmer-$\theta^t$ *self-selects* a payment-output option $(\hat{p}_t, \hat{q}_t)$ from the contract (menu) $\pi$ by *reporting* $\theta^t$, and the contract $\pi = (p_t, q_t)_{t \le T}$ can be modeled as a sequence of function pairs $p_t, q_t$: $\Theta^t \to \mathbb{R}_+$. We first consider the farmer's problem. Given contract $\pi$, farmer-$\theta_1$ chooses his best response to optimize his expected payoff over two periods:

$$U_1(\theta_1) = \max_{(\hat{p}_t,\hat{q}_t)_{t=1}^2 \in \pi} \left\{ \max_{\hat{e}_1 \in \mathcal{E}} \left[ \hat{p}_1 - \tilde{\psi}(\theta_1, \hat{e}_1, \hat{q}_1) - \frac{\phi}{2}\hat{e}_1^2 \right] + \delta \int_\Theta F(d\theta_2|\theta_1, \hat{q}_1) \cdot \max_{\hat{e}_2 \in \mathcal{E}} \left[ \hat{p}_2 - \tilde{\psi}(\theta_2, \hat{e}_2, \hat{q}_2) - \frac{\phi}{2}\hat{e}_2^2 \right] \right\}.$$

This entails dynamic optimization: each period farmer-$\theta^t$ reports $\hat{\theta}_t$ to maximize his continuation payoff

$$\tilde{U}_2(\hat{\theta}_2; \hat{\theta}_1, \theta_2) = \max_{\hat{e}_2 \in \mathcal{E}} \left[ p_2(\hat{\theta}^2) - \tilde{\psi}(\theta_2, \hat{e}_2, q_2(\hat{\theta}^2)) - \frac{\phi}{2}\hat{e}_2^2 \right],$$

$$\tilde{U}_1(\hat{\theta}_1; \theta_1) = \max_{\hat{e}_1 \in \mathcal{E}} \left[ p_1(\hat{\theta}_1) - \tilde{\psi}(\theta_1, \hat{e}_1, q_1(\hat{\theta}_1)) - \frac{\phi}{2}\hat{e}_1^2 \right] + \delta \int_\Theta F(d\theta_2|\theta_1, q_1(\hat{\theta}_1)) \cdot U_2(\hat{\theta}_1, \theta_2),$$

where $U_2(\hat{\theta}_1, \theta_2) \equiv \tilde{U}_2(\theta_2; \hat{\theta}_1, \theta_2)$ is his period-2 payoff, given his period-1 report $\hat{\theta}_1$ and period-2 *truthful* report $\hat{\theta}_2 = \theta_2$. The optimal contract must respect sequential incentive compatibility and individual rationality. Specifically, the farmer seeks to maximize his continuation payoff, so truthtelling must be his best response in all periods $t \le T$:

$$\theta_t \in \operatorname{argmax}_{\hat{\theta}_t \in \Theta} \tilde{U}_t(\hat{\theta}_t; \theta^{t-1}, \theta_t), \quad \forall \theta^t \in \Theta^t. \qquad (IC_t)$$

He accepts the deal only if it is more profitable than his outside option $\underline{U}$ over $T$ periods:

$$U_1(\theta_1) \ge \underline{U}, \quad \forall \theta_1 \in \Theta. \qquad (IR)$$

Anticipating the farmer's best response, the buyer must factor it into payment design:

$$\max \tilde{V}_1(\pi) = \mathsf{E}\big\{ [\nu(q_1(\theta_1)) - p_1(\theta_1)] + \delta \mathsf{E}\big[\nu(q_2(\theta^2)) - p_2(\theta^2)|\theta_1, q_1(\theta_1)\big] \big\}$$
$$\text{s.t. } (IR), (IC_1), (IC_2). \qquad (\mathcal{P})$$

Our model captures the essence of contract farming problems, in which learning and gaming are common (Barrett et al., 2020). We focus on marketing contracts. The key assumptions are consistent with the practice and literature. *We assume both parties are forward-looking*. This captures a defining feature of modern agrifood value chains: they are capital-intensive, requiring substantial sunk investments, for example, in farming, processing, packing, and selling specific products.[9] The sunk investments lock farmers and buyers into long-term relationships, whose success hinges on a stable supply of the farm product, with requisite quality and volume, so that the buyer can operate its facilities at efficient capacity. As a result, both parties are forward-looking, with a long-run perspective (Sexton & Xia, 2018).[10]

*We assume the buyer is the principal with full commitment power*. This reflects the reality that downstream processors and supermarkets often hold dominant bargaining power in agrifood chains (Sexton, 2013).[11] For such a buyer, contracting with commitment is beneficial, for example, when sunk investments are significant when the possibility of renegotiation invites opportunistic behavior (from the farmer), when the renegotiation costs outweigh the benefit, or when renegotiation undermines the buyer's reputation and jeopardizes his relationships with other farmers (Clay, 2018). In particular, without commitment, the buyer will suffer from the infamous "*ratchet effect*": the farmer will hold back on revealing information that could be used against her in later stages of the relation (Roberts & Milgrom, 1992). Moreover, the contractual commitment can be enforced by court,[12] or new technologies such as smart contracts (Keskin et al., 2021). For these reasons, almost all contracting papers in the operations literature assume full commitment; see, for example, Y.-J. Chen (2011), Xiong and Chen (2013, 2014, 2016), and Lobel and Xiao (2017).

*We assume the buyer is willing to engage all qualified farmers*, who have capabilities in $\Theta = [\underline{\theta}, \bar{\theta}]$. In our model, $\underline{\theta}$ and $\bar{\theta}$ are the minimal and maximal capabilities the buyer is willing to pay for; their precise values are context-dependent. These farmers are willing to participate in contract farming, because the buyer ensures their long-run viability, by paying them a premium $U_1(\theta_1)$ above their outside option $\underline{U}$ (e.g., producing for traditional markets): $U_1(\theta_1) \geq \underline{U}, \forall \theta_1 \in \Theta$. We stress $\underline{U}$ is the farmer's *cumulative return* from his outside option over $T$ periods—a payment higher than that in static models. As we shall show, the buyer is willing to sustain the long-run viability of participating farmers, a prediction consistent with empirical findings (Crespi et al., 2012). To ease exposition, we normalize $\underline{U}$ to zero and interpret $U_1(\theta_1)$ as the extra payment beyond $\underline{U}$.[13]

*We focus on learning-by-doing*. In agriculture, there are two main drivers for productivity growth (S. Yang & Shumway, 2020): (i) learning by doing, as a by-product of the experience (Arrow, 1962); (ii) direct investment (R&D), for technological change and knowledge acquisition (Argote, 2012). Depending on the context, either one can arise. In this paper, we mainly focus on smallholder farmers in the developing world, who lack the financial ability to invest in capital-intense facilities and technologies (Clark & Wu, 2016; Oya, 2012). In this context, learning-by-doing is the main driver (Fuglie et al., 2019); effort $e_t$ represents labor input, without direct effect on future productivity. In Supporting Information Appendix A, we use real data to show that the learning effect is significant. In Supporting Information Appendix B, we consider an alternative, direct-investment model, wherein the farmer has the financial ability to make capital-intense investment $e_t$ that improves productivity *directly*, $\theta_{t+1} = Z(\theta_t, e_t, \omega_{t+1})$. This case arises in the *developed* world, for example, in the U.S. boiler and beef industries (MacDonald, 2015). Due to the complexity, however, we are able to characterize the solution only partially.

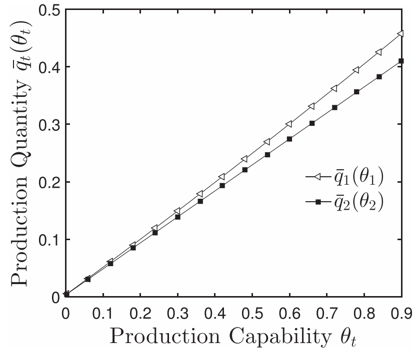


**FIGURE 3** Monotone production: $\xi = 0.15$, $\phi = 5$ , $\alpha = 0.85$, $\beta = 0.13$, $c_0 = 0.99$, $\delta = 0.979$, $\nu(q) = q - q^2$.

## 3 | PRELIMINARY RESULTS: TWO BENCHMARKS

We first develop two benchmarks—the classical first- and second-best solutions. Both are standard in the literature; we list them for further reference.

### 3.1 | Full-information benchmark

In the full-information regime $\bar{\mathcal{P}}$, the buyer has *perfect* visibility and control. She solves

$$\bar{V}_1 = \max_{\pi \in IR} \mathsf{E}_0^{\pi}[\nu(q_1(\theta_1)) - p_1(\theta_1) + \delta \mathsf{E}_1^{\pi}[\nu(q_2(\theta_2)) - p_2(\theta_2)]], \qquad (\bar{\mathcal{P}})$$

where the expectation $\mathsf{E}_t^{\pi}$ is taken with respect to the information available at time $t$ under contract $\pi$. To ensure $(IR)$, beyond outside option $\underline{U}$, the buyer only needs to pay $\psi(\theta_t, q_t) \equiv \min_{e_t \in \mathcal{E}}[\tilde{\psi}(\theta_t, e_t, q_t) + \frac{\phi}{2} e_t^2]$, that is, the minimal cost farmer-$\theta^t$ incurs in period $t$. Let $s(\theta_t, q_t) \equiv \nu(q_t) - \psi(\theta_t, q_t)$ be the (flow) *channel surplus*.

**Proposition 1.** *In regime $\bar{\mathcal{P}}$, the optimal contract $\bar{\pi}$ pays farmer-$\theta^t$ production cost $\bar{p}_t(\theta_t) = \psi(\theta_t, \bar{q}_t(\theta_t))$ only, requests effort investment $\bar{e}_t(\theta_t) = \frac{c_0}{\phi} \bar{q}_t(\theta_t)$, and schedules production $\bar{q}_t(\theta_t)$ by*

$$s_q(\theta_2, \bar{q}_2(\theta_2)) = 0,$$
$$s_q(\theta_1, \bar{q}_1(\theta_1)) = -\delta \mathsf{E}[s_\theta(\theta_2, \bar{q}_2(\theta_2)) \cdot (\beta + \xi\theta_1) | \theta_1, \bar{q}_1(\theta_1)]. \qquad (\overline{FOC})$$

This is the dynamic first-best solution $\bar{\pi}$ (see Figures 3 and 4). We have two main results. First, learning has an

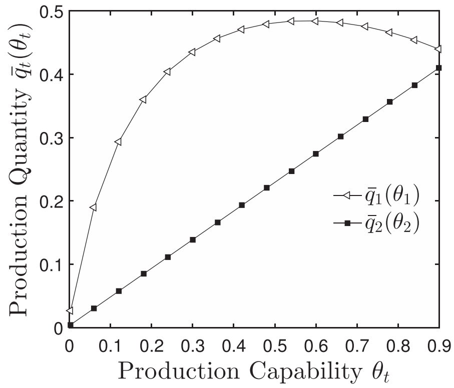


**FIGURE 4** Non-monotone production: $\xi = -1.98$, $\phi = 5$, $\alpha = 2.05$, $\beta = 1.86$, $c_0 = 0.99$, $\delta = 0.979$, $\nu(q) = q - q^2$.

efficiency effect. Formally, let $Z_q(\theta_1) \equiv \beta + \xi\theta_1$ be the *learning rate* (*effect*). Then the *learning gain* is $\mathsf{E}_1[s_\theta \cdot Z_q(\theta_1)] \equiv \partial_{\bar{q}_1}\mathsf{E}[s(\theta_2, \bar{q}_2(\theta_2)) \mid \theta_1, \bar{q}_1(\theta_1)] \geq 0$, $\forall\theta_1$. Intuitively, richer experience $q_1$ improves future capability $\theta_2$, which helps reduce future production cost and improve future surplus. Hence, the learning effect $Z_q$ enhances channel surplus. To internalize the learning gain, the buyer must take a long-term perspective with upward adjustment; in Figures 3 and 4, the adjustment is the gap between $\bar{q}_1$ and $\bar{q}_2 = q^f$, where $q^f$ is the *static first-best* solving $s_q(\theta, q) = 0$.[14]

Second, the initial production $\bar{q}_1(\theta_1)$ can be non-monotone (Figure 4). This is driven by two effects of infinitesimal change $dq_1$ in $q_1$: immediate cost overrun and future learning gain. To internalize both effects, the buyer must resolve the intertemporal trade-off between them. The key is the relative learning rate $\xi = \partial_{\theta_1}Z_q(\theta_1)$: for the same production $q_1$, a higher type farmer gains more from learning if $\xi > 0$, but he gains less if $\xi < 0$. As capability $\theta_1$ increases, the cost efficiency always improves ($\psi_\theta \leq 0$), but the learning gain may decrease ($\xi < 0$). The relative strength of the two forces determines the monotonicity of $\bar{q}_1(\theta_1)$.[15] Formally, let $\underline{q} \equiv \min Q$, and $\Theta^d \equiv \{\theta \in \Theta \,|\, \theta \geq -\frac{1}{\xi}(\frac{N}{\delta\alpha c_0} + \frac{q\xi N}{\alpha c_0} + \beta)\}$.

**Proposition 2.** *In regime $\bar{\mathcal{P}}$, if $\xi \geq 0$, the optimal production $\bar{q}_1(\theta_1)$ always increases in farmer capability; if $\xi < 0$; however, it decreases on $\Theta^d$.*

## 3.2 | Classical second-best solution

In the classical second-best world ($\mathcal{P}^c$), the transaction is one-shot ($T = 1$), the farmer has private information $\theta \in \Theta$, and both parties are myopic without learning ability. The problem becomes

$$V^c = \max_\pi \left\{\mathsf{E}^\pi[\nu(q(\theta)) - p(\theta)] \colon (IR), (IC)\right\}, \qquad (\mathcal{P}^c)$$

where ($IR$): $U^c(\theta) \equiv \tilde{U}(\theta; \theta) \geq \underline{u}$ is the participation constraint (with one-shot outside option $\underline{u}$ normalized to 0), and ($IC$): $U^c(\theta) = \max_{\hat{\theta}} \tilde{U}(\hat{\theta}; \theta)$ is the truthtelling constraint. Let $h(\theta) \equiv \frac{1-F_1(\theta)}{f_1(\theta)}$ be the inverse hazard rate of type $\theta$. Then $S(\theta, q) \equiv \nu(q) - \psi(\theta, q) \; + \; h(\theta) \cdot \psi_\theta(\theta, q)$ is the *virtual surplus*, adjusted for information friction.[16]

**Proposition 3.**

(*a*) *In regime ($\mathcal{P}^c$), the optimal contract $\pi^c = \{p^c(\theta), q^c(\theta)\}_{\theta\in\Theta}$ rewards farmer-$\theta$ with performance pay $U^c(\theta) = \int_{\underline{\theta}}^{\theta} -\psi_\theta(\tilde{\theta}, q^c(\tilde{\theta}))\, d\tilde{\theta}$. It stipulates production and payment by*

$$s_q(\theta, q^c(\theta)) = -h(\theta)\psi_{\theta q}(\theta, q^c(\theta)),$$
$$p^c(\theta) = \psi(\theta, q^c(\theta)) + U^c(\theta). \qquad (2)$$

(*b*) *In regime ($\mathcal{P}^c$) under contract $\pi^c$, farmer-$\theta$ invests effort $e^c(\theta) = \frac{c_0}{\phi}q^c(\theta)$. Relative to the first-best $\pi^f$, both production and effort investment are reduced: $q^c(\theta) \leq q^f(\theta)$, $e^c(\theta) \leq e^f(\theta)$, $\forall\theta$.*

This is the classical second-best solution $\pi^c$. It has three predictions: (i) *The buyer should reward honesty with performance pay* $U^c(\theta)$, beyond the farmer's one-shot outside option $\underline{u}$. Intuitively, farmer-$\theta$ enjoys a strategic advantage of lower cost over type $(\theta - d\tilde{\theta})$; to keep him honest, the buyer must pay the *option value* $U^c(\theta)$ of gaming.[17] (ii) *The buyer should restrict production to deter gaming*. This is because the performance pay increases in production. To reduce $U^c(\theta)$, the buyer can restrict production for lower type farmers ($\tilde{\theta} < \theta$), making it less tempting for farmer-$\theta$ to underreport.[18] (iii) *The channel cannot achieve the first-best coordination*. Except for top performer-$\bar{\theta}$, the production $q^c(\theta)$ is below the first-best $q^f(\theta)$, $\forall\theta < \bar{\theta}$. Importantly, both performance pay and production restriction deter gaming but reduce channel surplus. Hence, the surplus loss is the *shadow price* paid for ensuring the farmer's honesty—a friction of information asymmetry.

The classical second-best $\pi^c$ is an upper bound for static settings (Tirole, 1988). Using nonlinear pricing, it can internalize the *vertical externality of double marginalization*, a well-known inefficiency of spot markets and linear pricing (Chen, Gui, et al., 2021). However, contract farming often seeks long-term relationships with dynamic incentives. $\pi^c$ is inadequate for this class of problems, because of its myopic perspective. To make credible predictions, we must model dynamic incentives from a long-term perspective.

## 4 | OPTIMAL CONTRACT FOR DYNAMIC REGIME

The original problem ($\mathcal{P}$) entails repeated interactions with dynamic learning and gaming. It enhances the farmer's strategic advantage in two ways. First, it increases his information advantage: besides initial capability $\theta_1$, he can also *learn* new information $\omega_2$ arising during production; both pieces of information are valuable to the buyer but costly to extract. Second, regime $(\mathcal{P})$ provides a new latitude for *dynamic gaming*: by manipulating production $q_1$, farmer-$\theta_1$ can control future capability $\theta_2 = Z(\theta_1, q_1, \omega_2)$ for a higher payment.

To tackle the problem, the buyer must estimate how the capabilities are intertemporally linked—how the initial change $d\theta_1$ affects the learning outcome $\theta_2$ of production $q_1$. The notion is akin to the expected *marginal effect* of initial $\theta_1$ on outcome $\theta_2$, holding constant the production and the random shocks producing history $\theta^2 = (\theta_1, \theta_2)$. We formalize the notion of *carryover effect* (*rate*) by $Z_\theta(q_1) \equiv \alpha + \xi q_1$. Next, we define per-period *virtual surpluses*, adjusted for information friction, by $S_1(\theta_1, q_1) \equiv \nu(q_1) - \psi(\theta_1, q_1) + h(\theta_1)\psi_\theta(\theta_1, q_1)$, and $S_2(\theta^2, q^2) \equiv \nu(q_2) - \psi(\theta_2, q_2) + h(\theta_1)\psi_\theta(\theta_2, q_2) \cdot Z_\theta(q_1)$. We can then simplify the problem $(\mathcal{P})$ to optimizing the net present value of virtual surpluses:

$$V_1 = \max_{\pi \in IR} \mathsf{E}^\pi \left[S_1(\theta_1, q_1(\theta_1)) + \delta S_2(\theta^2, q^2(\theta^2))\right]. \quad (\mathcal{P}^r)$$

**Proposition 4.**

(*a*) *In regime* $(\mathcal{P})$*, the optimal contract* $\pi^*$ *stipulates quantity and payment by*

$$\partial_{q_1}\left[S_1\left(\theta_1, q_1^*(\theta_1)\right) + \delta \mathsf{E}_1 S_2(\theta^2, q^{2*}(\theta^2))\right] = 0,$$

$$\partial_{q_2} S_2(\theta^2, q^{2*}(\theta^2)) = 0,$$

$$p_1^*(\theta_1) = \psi(\theta_1, q_1^*(\theta_1)) + U_1(\theta_1) - \delta \mathsf{E}_1 U_2(\theta^2),$$

$$p_2^*(\theta^2) = \psi(\theta_2, q_2^*(\theta^2)) + U_2(\theta^2).$$

(*b*) *In regime* $(\mathcal{P})$ *under* $\pi^*$*, farmer-*$\theta^t$ *invests effort* $e_t^*(\theta^t) = \frac{c_0}{\phi} q_t^*(\theta^t)$*, and earns performance pay*

$$U_1(\theta_1) = -\int_{\underline{\theta}}^{\theta_1} \mathsf{E}\left[\psi_\theta(\tilde{\theta}_1, q_1^*(\tilde{\theta}_1)) + \delta\psi_\theta\left(\tilde{\theta}_2, q_2^*(\tilde{\theta}^2)\right) \cdot Z_\theta\left(q_1^*(\tilde{\theta}_1)\right) \middle| \tilde{\theta}_1, q_1^*(\tilde{\theta}_1)\right] d\tilde{\theta}_1, \quad U_2(\theta^2) = -\int_{\underline{\theta}}^{\theta_2} \psi_\theta(\tilde{\theta}_2, q_2^*(\tilde{\theta}^2)) d\tilde{\theta}_2.$$

The proposition characterizes the optimal contract, with three key features: performance pay $U_1$, deferred payment $\delta \mathsf{E}_1 U_2(\theta^2)$, and production distortion. Next, we explain the driving forces and managerial implications of these features. To ease exposition, we suppress the functions' arguments when no confusion arises; for example, we write $p_t^*$ for $p_t^*(\theta^2)$.

First, we explain the performance pay $U_1$. It hinges on the carryover effect $Z_\theta(q_1^*) = \alpha + \xi q_1^*$, which measures the farmer's *intertemporal advantage*. Intuitively, the pay $U_1$ is driven by the farmer's strategic advantage. Because of the serial correlation in $(\theta_1, \theta_2)$ that advantage also spills over time: a high type farmer enjoys the cost advantage not only today but also tomorrow. Along each path $\theta^2$, the initial condition $\theta_1$ has the carryover effect $Z_\theta$. This intertemporal linkage confers *additional* cost advantage $-\psi_\theta(\theta_2, q_2^*)$, resulting in new cost saving of $-\psi_\theta(\theta_2, q_2^*) \cdot Z_\theta \cdot d\theta_1$, the wedge driven by initial $\theta_1$ in period 2. Conceptually, the performance pay $U_1(\theta_1)$ is the sum of carryover-adjusted cost savings that farmer-$\theta_1$ can gain from gaming over two periods. Technically, the buyer must take future saving (wedge) into account, averaging them across type and over time. Relative to farmer-$(\theta_1 - d\theta_1)$, she must reward farmer-$\theta_1$ an extra performance pay of $-\mathsf{E}[\psi_\theta(\theta_1, q_1^*) + \delta\psi_\theta(\theta_2, q_2^*) \cdot Z_\theta | \theta_1, q_1^*]\, d\theta_1$. There are $[\underline{\theta}, \theta_1)$ such gaming opportunities, so the buyer must reward farmer-$\theta_1$ with the total performance pay[19]:

$$U_1(\theta_1) = -\int_{\underline{\theta}}^{\theta_1} \mathsf{E}\left[\psi_\theta(\tilde{\theta}_1, q_1^*(\tilde{\theta}_1)) + \delta\psi_\theta\left(\tilde{\theta}_2, q_2^*(\tilde{\theta}^2)\right) \cdot Z_\theta\left(q_1^*(\tilde{\theta}_1)\right) \middle| \tilde{\theta}_1, q_1^*(\tilde{\theta}_1)\right] d\tilde{\theta}_1. \quad (3)$$

This result helps explain *when and why smallholder farmers can benefit from contract farming, despite weak bargaining power*. Managerially, the performance pay $U_1$ is a form of *efficiency wage* (*premium*)—the pay differential that ensures each farmer is willing to produce to the best of his capability.[20] It is important, especially in developing countries with weak institutions (Swinnen & Vandeplas, 2012). For example, under a resource-providing scheme, the buyer provides the farmer-$\theta_1$ with inputs on credit. Yet without strong contract enforcement, the farmer can use the inputs but sell his output to another buyer without paying back the credit. To prevent this, the buyer can offer attractive contract terms, for example, extra performance pay $U_1(\theta_1)$ beyond the farmer's (best) outside option $\underline{U}$. Because $\underline{U}$ is his *cumulative return* over $T$ periods, it also exceeds the one-shot return $\underline{u}$ (in $\mathcal{P}^c$) from spot markets:

$$U_1(\theta) + \underline{U} \geq \underline{U} = \sum_{t=0}^{T} \delta^t \underline{u} = \frac{(1 - \delta^{T+1})}{1 - \delta} \underline{u} \geq \underline{u}.$$

Hence, poor farmers can benefit from participating in contract farming, despite weak bargaining power.

Next, we explain the deferred payment $\delta \mathsf{E}_1 U_2(\theta^2)$. It is an instrument for screening future private information $\theta_2$ for free. The idea is to leverage the farmer's uncertainty: in period 1, the farmer is uncertain about his future capability $\theta_2$. Hence, the buyer can withhold the expected rent

$\delta \mathsf{E}_1 U_2(\theta^2)$ from current payment $p_1^*$ and pay back later contingent on the realized outcome $\theta_2$. This mechanism allows the buyer to offset the rent she has to pay for ($IC_2$), thereby screening the private information $\theta_2$ at no cost. Conceptually, the deferred payment implements the classical idea of *residual claimant* (Laffont & Martimort, 2001, p. 58): by making the agent the residual claimant, the principal can extract postcontract information at no cost. Similar findings have been reported in different settings; see, for example, Eső and Szentes (2007) for auction and Cachon and Feldman (2017) for advance selling. We complement their work by exploiting the idea to extract *endogenous* supply information. Moreover, the literature often sees the deferred (delayed) payment as inefficiency, a defect to correct (de Zegher et al., 2018). We show it need not be pathological: the deferred payment can arise as the buyer's best response to farmers' information advantage of observing $\theta_2$.

Finally, we explain the production distortion in $q_1^*$. It entails two types of trade-offs. (i) The inter-type trade-off follows the classical rationale of adverse selection: increasing production for $\theta_1$ by $dq_1$ improves current surplus by $s_q\, dq_1$, but it also increases current performance pay for $\theta_1' > \theta_1$ by $-h(\theta_1)\psi_{\theta q}(\theta_1, q_1)\, dq_1$. (ii) The intertemporal trade-off is new: the infinitesimal change $dq_1$ affects future virtual surplus via $\partial_{q_1} \mathsf{E} S_2 \cdot dq_1$, producing both learning and carryover effects; the learning effect $Z_q$ shifts the distribution of $\theta_2$, resulting in $\mathsf{E}[\partial_{\theta_2} S_2 \cdot Z_q] \cdot dq_1 = \mathsf{E}[s_\theta \cdot Z_q] \cdot dq_1$; the carryover effect $Z_\theta$ determines the size of future rent, resulting in $\mathsf{E}[\partial_{q_1} S_2]\, dq_1 = \mathsf{E}[h\psi_\theta \cdot \partial_q Z_\theta] \cdot dq_1 = \mathsf{E}[h\psi_\theta \cdot \xi] \cdot dq_1$. (iii) As Proposition 4 predicts, the optimal production $q_1^*$ must balance all these effects, resulting in

$$
\begin{aligned}
\underbrace{s_q(\theta_1, q_1)}_{\text{marginal surplus}} \quad = \quad & \underbrace{-h(\theta_1)\cdot \psi_{\theta q}(\theta_1, q_1)}_{\text{downward distortion for private info. } \theta_1} \\
& - \underbrace{\delta \mathsf{E}\left[ s_\theta\left(\theta_2, q_2^*(\theta^2)\right) \cdot (\beta + \xi\theta_1) \,\middle|\, \theta_1, q_1 \right]}_{\text{upward distortion for learning effect } Z_q} \\
& - \underbrace{\delta \mathsf{E}\left[ h(\theta_1) \cdot \psi_\theta(\theta_2, q_2^*(\theta^2)) \cdot \xi \,\middle|\, \theta_1, q_1 \right]}_{\text{distortion for carryover effect } Z_\theta}.
\end{aligned}
\tag{$FOC_1^*$}
$$

Equation ($FOC_1^*$) reveals how $\pi^*$ reconciles three competing incentives—to exploit learning, to deter gaming, and to elicit information. Relative to the first-best $q^f$ without learning, $\pi^*$ *employs three distortions in* $q_1^*$. (i) The downward distortion from $h\psi_{\theta q} \leq 0$ is unproductive, driven by the precontract information $\theta_1$, for the purpose of rent control. (ii) The upward distortion from $\delta \mathsf{E}_1[s_\theta \cdot Z_q] \geq 0$ is productive, driven by the marginal gain from learning, for the purpose of capability development. (iii) The distortion from $\delta \mathsf{E}_1[h\psi_\theta \cdot \xi]$ is unproductive, driven by the carryover

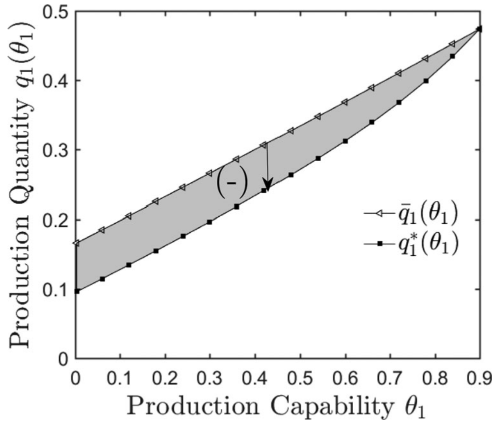


**FIGURE 5** Downward distortion: $\xi = 0.1$, $\alpha = 0.85$, $\beta = 0.134$, $\phi = 5$, $c_0 = 0.99$, $\delta = 0.979$, $\nu(q) = 1.5(q - q^2)$.

effect $Z_\theta$ of $\theta_1$, for the purpose of ensuring period-2 payoff wedge ($IC_2$); the direction of this distortion depends on the *relative learning rate* $\xi$: it is downward if $\xi > 0$, and upward otherwise. (iv) The relative strength of the three forces determines the net distortion in $q_1$: *either upward or downward distortion is possible, and they can exist at the same time*. The key determinant is again $\xi$: when $\xi \geq 0$, the distortion is always downward ($q_1^*(\theta_1) \leq \bar{q}_1(\theta_1), \forall\theta_1$); when $\xi < 0$, however, the distortion *can* go upward—even exceed the dynamic first-best $\bar{q}_1$—despite information asymmetry. As such, the exploitation of learning must weigh its strategic effect on increasing the performance pay—the agency effect.

## 5 | HOW DO DYNAMIC INCENTIVES CHANGE THE CONVENTIONAL INSIGHTS?

Dynamic incentives are central to contract farming. As we have shown, they can change contract structure in a fundamental way. As a result, the conventional insights based on static settings may no longer work (see Section 3). In what follows, we examine managerial implications of dynamic incentives in contract farming.

We find farmer learning plays a dual role in contract farming. (i) The first is the well-known *efficiency role*: by developing capability and reducing production cost, learning can improve efficiency. The key contractual response is to make upward adjustment early in the relationship so that costs will fall with cumulative production (Section 3.1). (ii) The second is the *agency role*: by changing farmer's future capability distribution $F(\cdot|\theta_1, q_1)$ and capability gap $\Delta \mathsf{E}[\theta_2|\theta_1]$, learning can either alleviate or exacerbate information friction. The contractual response depends on *relative learning rate* $\xi$: when learning expands the capability gap ($\xi > 0$), the buyer should discourage learning and distort production downward (e.g., in Figure 5, $q_1^*(\theta_1) \leq \bar{q}_1(\theta_1)$, $\forall\theta_1$); when learning compresses the capability gap ($\xi < 0$); however, she

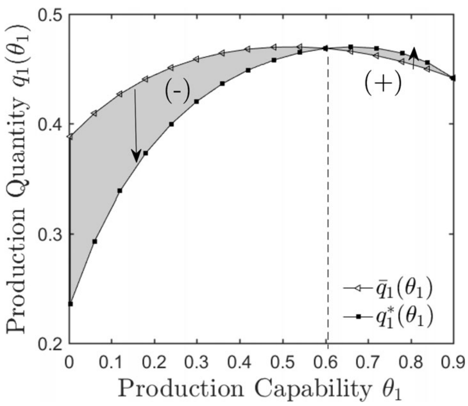


**FIGURE 6** Up- and downward distortion: $\xi = -2.18$, $\alpha = 2.05$, $\beta = 2.06$, $\phi = 3$, $c_0 = 0.99$, $\delta = 0.979$, $\nu(q) = 1.5(q - q^2)$.

may encourage learning for certain types and distort their production $q_1^*$ upward (e.g., in Figure 6, $q_1^*(\theta_1) > \bar{q}_1(\theta_1)$, $\forall \theta_1 \in (0.6, 0.9)$). In both cases, to control rent, the buyer should exploit learning, *strategically*.

The agency role of learning can overturn conventional insights. One such insight is downward distortion for rent control. This insight hinges on the relation that raising output increases the value of private information and hence inflates rent payment. The relation holds naturally in static settings, with one-shot interaction and fixed private information. We show this insight may fail in dynamic settings: learning may entail *u*pward distortion for rent control—*even above the first-best level*. Formally, let $\Theta^u \equiv \{\theta \in \Theta \,|\, \theta - h(\theta) \geq -\frac{1}{\xi}(\frac{N}{\delta\alpha c_0} + \frac{q\xi N}{\alpha c_0} + \beta)\}$.

**Proposition 5.** *In regime ($\mathcal{P}$), when $\xi < 0$, the buyer should distort production upward for farmers in $\Theta^u$: $q_1^*(\theta_1) \geq \bar{q}_1(\theta_1)$, $\forall \theta_1 \in \Theta^u$.*

This result contrasts sharply with the conventional recommendation: downward distortion for rent control. Learning changes the recommendation. In regime ($\mathcal{P}$), the buyer has the extra channel of learning—$\delta \mathsf{E}_1[h\psi_\theta \cdot \xi]$ in ($FOC_1^*$)—to control rent. When $\xi < 0$, learning compresses the future capability gap $\Delta \mathsf{E}[\theta_2|\theta_1]$ among farmers (see Figure 2). When the capability compression is substantial, the buyer can order overproduction to *homogenize* farmers' future capability, thereby reducing the information rent. For example, in Figure 6, the overproduction for farmers in $\Theta^u = (0.6, 0.9)$ is to reduce their future capability gap with lower types. Although the upward distortion hurts channel surplus, the buyer is still willing to take such a costly action, because it can cut the rent she would otherwise pay. Hence, the upward distortion here is driven by rent control, serving the strategic purpose of reducing the capability gap, even at the expense of channel surplus. As such, it also differs fundamentally from the upward adjustment—driven by the learning gain $\delta \mathsf{E}_1[s_\theta \cdot Z_q(\theta_1)]$—in $\overline{FOC}_1$.

## 6 | THE PERIL OF IGNORING DYNAMIC INCENTIVES

The theoretical literature on contract farming predominantly focuses on static settings with one-shot interaction (Barrett et al., 2020). Under asymmetric information, the optimal solution is the classical second-best $\pi^c$, with a main prediction that *the first-best is unattainable* (Wu, 2014). Taking a static perspective, this prediction ignores *two-sided learning* in the relationship. It is true that knowing $\theta_1$ gives the farmer an information advantage initially. So information rent (performance pay) is imperative for truthtelling, and production distortion is necessary for rent control. Both measures reduce efficiency. Hence the first-best is unattainable in the one-shot, static world ($\mathcal{P}^c$).

Yet a typical contract farming relationship involves multiple interactions, through which both parties can learn about each other. Given this reality, one may conjecture, the buyer-side learning should weaken the farmer's advantage, soften his temptation to misbehave, and dampen the distortion in the long run. When the relationship is sufficiently long, the buyer should be able to coordinate the channel, achieving the first-best. Therefore, the classical second-best $\pi^c$ should be suboptimal in the long run; perpetual distortion should be an exception ($\alpha = 1$), not the rule.

We now formalize this conjecture. Consider dynamic regime $\mathcal{P}_\infty$, with asymmetric information, infinite horizon $T = \infty$, capability evolution $\theta_{t+1} = \alpha\theta_t + \beta q_t + \omega_{t+1}$, revenue function $\nu(q) = nq - \frac{m}{2}q^2$, and optimal contract $\pi^*$. Let $\bar{\mathcal{P}}_\infty$ be the full-information counterpart of $\mathcal{P}_\infty$ with optimal contract $\bar{\pi}$. We find:

**Proposition 6.**

(*a*) *In regime $\mathcal{P}_\infty$, the optimal production $q_t^*(\theta^t) = m_t^*\theta_t + n_t^*(\theta_1)$ converges to the first-best $\bar{q}_t(\theta_t) = \bar{m}_t\theta_t + \bar{n}_t$ in the long run:*

$$\lim_{t\to\infty} \bar{m}_t = \lim_{t\to\infty} m_t^* = m^*, \quad \lim_{t\to\infty} \bar{n}_t = \lim_{t\to\infty} n_t^* = n^*.$$

(*b*) *In regime $\mathcal{P}_\infty$ under $\pi^*$, if $\alpha + \beta m^* < 1$, the capability converges to the first-best in the long run*[21]*:*

$$\lim_{t\to\infty} \mathsf{E}^{\pi^*}[\theta_t] = \lim_{t\to\infty} \mathsf{E}^{\bar{\pi}}[\theta_t] = \frac{\beta n^*}{1 - (\alpha + \beta m^*)}.$$

The proposition characterizes the long-run trend of $\pi^*$. It has three implications. (i) *When selecting a farmer, the buyer should favor the incumbent*. Intuitively, the buyer-side learning reduces information asymmetry and distortion; for the same capability level, the incumbent farmer demands less rent, produces more, and hence is more preferable. (ii) *When the farmer can learn over time, the buyer should not pay rent or distort production indefinitely*. Instead, the buyer should distort production and pay rent only initially; she should phase out both measures and adopt the first-best eventually. The rationale is simple: both measures are meant to neutralize the farmer's information advantage at the time of contracting; they are most effective in the early stage of the relationship when the performance is most responsive to initial information $\theta_1$. (iii) *Ignoring dynamic incentives can mislead contract design*. In essence, learning-by-doing means increasing return over time. To internalize such intertemporal externality, the buyer must take a long-term perspective: the short-term concern of information asymmetry—the key driver of the classical second-best $\pi^c$—should not dictate her long-term relationship with the farmer.[22]

Our result helps explain *when and why contract farming can improve farmer productivity and income*. The existing literature offers several explanations (Otsuka et al., 2016). For example, contract farming can help farmers gain access to high-value markets, upgrade quality and technology, relax financial constraints, and reduce production and price risks. However, these explanations are largely descriptive not analytical. We provide a new analytical explanation. The central argument is that short-term arrangements suffer both *incentive and information deficiencies*: they discourage farmer investment, ignore learning potential, and perpetuate production distortion. These drawbacks conspire to undermine channel efficiency in the long run. Unlike short-term arrangements, contract farming seeks long-term relationships with repeated interactions, which can mitigate both deficiencies, thereby improving productivity and income.

We now elaborate with $\pi^*$ and $\pi^c$, the representative solutions for the long- and short-term arrangements. First, the short-term contract $\pi^c$ suffers incentive deficiency. It focuses on the immediate gain, ignoring the intertemporal externality of current production on future farmer improvement (see Section 3.2). Such a *myopic perspective* sets a low expectation of productivity and fails to incentivize farmer learning and effort investment. The short-term contract $\pi^c$ also suffers information deficiency. $\pi^c$ is renewed every period *after* the farmer has obtained new private information. The new information is precontract, allowing the farmer to extract rent payment in every period; in response, the buyer must distort production and payment in every period. Without long-term commitment, the second-best policy $\pi^c$ will perpetuate distortion and inefficiency.

By contrast, the long-term contract $\pi^*$ can mitigate both deficiencies. First, it offers sufficient incentives for learning and effort investment. Taking a *long-term perspective*, it sets an aggressive production schedule and investment requirement. Using the upward adjustment, it internalizes all future gains from learning (see Section 4). Second, the long-term contract $\pi^*$ improves information efficiency. Except for the initial information $\theta_1$, it can eliminate all information advantages the farmer would obtain (under $\pi^c$). At the outset, it specifies all foreseeable contingencies during the relationship, *before* the farmer can learn any new information beyond $\theta_1$. This preemptive arrangement denies the farmer any new edge from learning information arising later, thereby limiting his advantage to $\theta_1$ only. After the initial period, the farmer can still learn private information, but the buyer can use a deferred payment to extract it, without further distorting payment and production. Indeed, the distortion is entirely driven by $\theta_1$, and it vanishes over time (Proposition 6). In this sense, the long-term contract $\pi^*$ is information efficient for all but the initial period.

## 7 | A CALIBRATED NUMERICAL STUDY

We now quantify *when* and *how much* the long-term contract $\pi^*$ can improve over the short-term one $\pi^c$. We use a dataset from the International Coffee Organization to calibrate the baseline case. It covers coffee production from 2014 to 2019. We aggregate years 2014–2015 as period one and years 2016–2017 as period 2. We use years 2018–2019 to test the calibration performance. The dataset contains the retail price, the price paid to the farmers, and the total production quantity from different regions. To estimate the learning effect, we assume

$$\theta_2 = \alpha\theta_1 + \beta\left(\sum_{y=2014}^{2015} q_y\right) + \xi\theta_1\left(\sum_{y=2014}^{2015} q_y\right) + \mu_\theta + \omega_2,$$

where $q_y$ is the production quantity in year $y$ and $\mu_\theta$ is the trend term (constant) in farmer capability. We assume that $\theta_1 \sim \mathcal{N}(\mu_1, \sigma^2)$ and $\omega_2 \sim \mathcal{N}(0, \sigma^2)$ and that the demand in each period follows normal distribution $\mathcal{N}(\mu_{d_t}, \sigma^2_{d_t})$.

We use the *moment matching* estimation method. To simplify the estimation, we focus on estimating parameters $\chi = (\alpha, \beta, \xi, \mu_1, \sigma)$ and calibrate other parameters exogenously. Given the spot price, the farmer decides his production quantity to maximize his profit myopically. Let $q_{n,t}$ and $Q_{n,t}$ be the production quantity of farmers in country $n$ in period $t$ based on the data and the model given parameter, respectively. Moreover, the production quantity $q_{n,t}$ represents the total production quantities within period $t$. To obtain the estimation, we minimize the loss function

$$L(\chi) \equiv \sum_{t=1}^{2}\sum_{k=1}^{2}\left(\frac{moment^{model}_{t,k}(\chi) - moment^{data}_{t,k}}{moment^{data}_{t,k}}\right)^2,$$

with $\bar{Q}_t = \frac{1}{N}\sum_{n=1}^{N} Q_{n,t}$, $\bar{q}_t = \frac{1}{N}\sum_{n=1}^{N} q_{n,t}$ and

$$moment^{model}_{t,1}(\chi) \equiv \frac{\sum_{n=1}^{N} Q_{n,t}}{N}, \quad moment^{data}_{t,1} \equiv \frac{\sum_{n=1}^{N} q_{n,t}}{N},$$

$$moment^{model}_{t,2}(\chi) \equiv \frac{\sum_{n=1}^{N}(Q_{n,t} - \bar{Q}_t)^2}{N},$$

$$moment^{data}_{t,2} \equiv \frac{\sum_{n=1}^{N}(q_{n,t} - \bar{q}_t)^2}{N}.$$

Table 2 reports the estimation results: it provides a *representative* farmer and buyer for our computation. To measure

**TABLE 2** Parameters estimation.

| Model parameter | Value | Source |
|---|---|---|
| Retail price per lb: $r$ | \$4.50 | Assumption |
| Mean of demand (B): $(\mu_{d_1}, \mu_{d_2})$ | (2.728, 3.169) | Assumption |
| SD of demand (B): $(\sigma_{d_1}, \sigma_{d_2})$ | (1.111, 1.234) | Assumption |
| Discount factor: $\delta$ | 0.979 | Assumption |
| Cost parameter: $c_0$ | 26.797 | Estimation |
| Cost parameter: $c_1$ | 8.312 | Estimation |
| Investment cost: $\phi$ | 130.652 | Estimation |
| Carryover rate: $\alpha$ | 0.647 | Estimation |
| Learning rate: $\beta$ | 0.053 | Estimation |
| Interaction rate: $\xi$ | 0.016 | Estimation |
| Mean of $\theta_1$: $\mu_1$ | 0.265 | Estimation |
| SD of shocks: $\sigma$ | 0.234 | Estimation |
| Trend term: $\mu_\theta$ | −0.007 | Estimation |

*Note*: (i) Retail price comes from the data; we use the average price during the 2014–2019 in United States. (ii) The mean and standard deviation (SD) of demands are calibrated exogenously. (iii) For the discount factor $\delta$, we set it manually and keep it close to the literature (Shi et al., 2019).

the improvement of long-term contract $\pi^*$ over short-term $\pi^c$, we use percentage changes in rent payment $\mathsf{E}U$, buyer profit $V$, and channel surplus $S$; for example, $\Delta U\% = \frac{U^*-U^c}{U^c} \times 100\%$. We report the results of policy comparison in Table 3. We find: (i) The long-term contract $\pi^*$ can increase channel surplus ($\Delta S\% > 0$) because it leverages learning and minimizes distortion. (ii) It can improve buyer profit ($\Delta V\% > 0$), because it eliminates the two deficiencies of the short-term contract. The improvement can be substantial, especially when learning is salient and persistent. To the extent these situations prevail, the buyer should favor the long-term contract (i.e., contract farming). Our results are consistent with the rapid structural changes in agricultural markets around the world: while spot markets become niche means of exchange, contractual arrangements, and vertical integration completely dominate modern agrifood value chains (Barrett et al., 2020).

Our results inform agricultural policy debates on contract farming. For example, U.S. policymakers are increasingly concerned about the dominant market power of downstream buyers over upstream farmers (Sexton & Xia, 2018). A key question is whether the government should restrict the *buyer power* and encourage spot transactions to promote competition.[23] The traditional models based on static settings would predict that, without government intervention, the buyers would abuse market power and exploit farmers for higher profits (Oya, 2012). Our view is more sanguine: in modern agrifood supply chains, when buyers (a) have a long-term perspective and (b) can internalize the benefit from farmer learning, they are unlikely to abuse market power because their long-term interest in maintaining viable farmers dominates their short-run benefit from exploiting them.

Our optimistic view is consistent with the empirical literature, which finds little evidence of buyer power. For example, the U.S. Government Accountability Office reported in 2009[24]: The empirical economic literature has not established that concentration in the processing segment of the beef, pork, or dairy sectors or the retail sector overall has adversely affected commodity or food prices. Most of the studies that we reviewed either found no evidence of market power or found efficiency effects that were larger than the market power effects of concentration. A policy implication of our model is that, in modern agricultural markets, it can be counterproductive to promote competition blindly, for example, by restricting agricultural contracts and forcing buyers to engage in spot transactions (as in the proposals for the U.S. 2012 Farm Bill; see Saitone & Sexton, 2012).

## 8 | THE RANDOM-YIELD MODEL WITH SIMPLE IMPLEMENTATION

Our baseline model ($\mathcal{P}$) focuses on deterministic production. In agriculture, random yield is also common (Kazaz & Webster, 2011). In this case, one may ask: Is the contract $\pi^*$ for ($\mathcal{P}$) still optimal? Does it have a simple implementation?

To address these questions, we consider a random *y*ield regime ($\mathcal{P}^y$) with linear learning. Let $y_t \sim H$ be period-$t$ yield factor beyond the farmer's control (e.g., extreme weather conditions, seed quality variation). At the outset, the buyer offers a long-term contract $\pi = (\pi_t)_{t=1}^2$. In each period $t$, the farmer observes his capacity $\theta_t$, selects production quota $q_t$, invests effort $e_t$, and produces output $\eta_t \equiv y_t q_t$; the buyer pays $p_t(\theta^t, \eta_t)$ and receives sales revenue $\nu(\eta_t)$. Importantly, besides capacity $\theta_t$ and effort $e_t$, yield $y_t$ is also unobservable to the buyer: she only knows the prior distributions $F_1$ and $H$. As such, the buyer can only contract on the observable output $\eta_t$. Formally,

$$\begin{aligned}\max \tilde{V}_1(\pi) = \mathsf{E}\big\{&\big[\nu(y_1 q_1(\theta_1)) - p_1(\theta_1, y_1 q_1(\theta_1))\big] \\ &+ \delta \mathsf{E}\big[\nu\left(y_2 q_2(\theta^2)\right) \\ &- p_2\left(\theta^2, y_2 q_2(\theta^2)\right) | \theta_1, q_1(\theta_1))\big]\big\} \qquad (\mathcal{P}^y)\end{aligned}$$

$$\text{s.t.} \quad \theta_t \in \operatorname{argmax}_{\hat{\theta}_t \in \Theta} \tilde{U}_t(\hat{\theta}_t; \theta^{t-1}, \theta_t), \quad \forall \theta^t \in \Theta^t, \ (IC_t)$$

$$U_1(\theta_1) \geq \underline{U}, \quad \forall \theta_1 \in \Theta. \qquad (IR)$$

where $U_t(\theta^t) \equiv \tilde{U}_t(\theta_t; \theta^{t-1}, \theta_t)$, $\tilde{U}_2(\hat{\theta}_2; \hat{\theta}_1, \theta_2) = \max_{\hat{e}_2} \mathsf{E}[p_2(\hat{\theta}^2, \eta_2) - \tilde{\psi}(\theta_2, \hat{e}_2, q_2(\hat{\theta}^2)) - \frac{\phi}{2}\hat{e}_2^2]$, $\tilde{U}_1(\hat{\theta}_1;\ \theta_1) = \max_{\hat{e}_1} \mathsf{E}[p_1(\hat{\theta}_1,\ \eta_1) - \tilde{\psi}(\theta_1,\ \hat{e}_1,\ q_1(\hat{\theta}_1)) - \frac{\phi}{2}\hat{e}_1^2] + \delta\mathsf{E}[U_2(\hat{\theta}_1,\ \theta_2)|\theta_1, q_1(\hat{\theta}_1)]$, and $q_t(\hat{\theta}^t)$ is the production quota the farmer chooses.

At first glance, problem ($\mathcal{P}^y$) may seem intractable because the unobservable yield $y_t$ poses new challenges. First, the buyer wants to compensate true effort, not luck. But random yield makes output $\eta_t$ a noise measure: depending on luck $y_t$, the same farmer with the same effort can produce a drastically different output $\eta_t = y_t \cdot q_t$. Second, besides the adverse

**TABLE 3** Performance comparison.

| parameter | Improvement % | | | Optimal policy $\pi^*$ | | | Classic policy $\pi^c$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\Delta$E$U$% | $\Delta V$% | $\Delta S$% | E$U$ | $V$ | $S$ | E$U$ | $V$ | $S$ |
| $\alpha = 0.2$ | 4.20 | 12.01 | 10.14 | 44.29 | 151.80 | 196.09 | 42.50 | 135.53 | 178.03 |
| 0.4 | 4.77 | 7.51 | 6.80 | 51.75 | 152.90 | 204.65 | 49.39 | 142.23 | 191.62 |
| 0.6 | 2.32 | 5.10 | 4.32 | 58.36 | 154.57 | 212.94 | 57.04 | 147.08 | 204.12 |
| 0.8 | −0.73 | 4.25 | 2.75 | 64.74 | 156.82 | 221.56 | 65.21 | 150.43 | 215.64 |
| 0.9 | −5.14 | 3.34 | 0.65 | 67.18 | 157.61 | 224.79 | 70.82 | 152.52 | 223.34 |
| 1 | −5.11 | 3.06 | 0.42 | 69.56 | 157.80 | 227.36 | 73.31 | 153.10 | 226.41 |
| $\beta = 0.1$ | −4.49 | 8.51 | 4.54 | 63.64 | 164.68 | 228.32 | 66.63 | 151.77 | 218.40 |
| 0.2 | −13.59 | 15.37 | 5.47 | 70.71 | 181.78 | 252.49 | 81.83 | 157.56 | 239.39 |
| 0.3 | −17.25 | 20.41 | 6.80 | 75.33 | 193.53 | 268.86 | 91.03 | 160.73 | 251.75 |
| 0.4 | −22.29 | 23.14 | 5.99 | 76.74 | 200.67 | 277.41 | 98.76 | 162.97 | 261.73 |
| 0.5 | −27.48 | 24.65 | 4.48 | 75.16 | 204.66 | 279.82 | 103.63 | 164.19 | 267.82 |
| 0.6 | −33.23 | 25.10 | 2.10 | 71.70 | 206.39 | 278.09 | 107.39 | 164.98 | 272.36 |
| $\xi = 0.00$ | 4.24 | 4.98 | 4.77 | 59.42 | 154.31 | 213.74 | 57.01 | 146.99 | 204.00 |
| 0.02 | 2.15 | 4.99 | 4.18 | 60.33 | 155.25 | 215.58 | 59.05 | 147.87 | 206.93 |
| 0.04 | −0.35 | 5.04 | 3.47 | 60.80 | 156.22 | 217.02 | 61.02 | 148.72 | 209.74 |
| 0.06 | −1.04 | 5.45 | 3.53 | 61.97 | 157.35 | 219.31 | 62.62 | 149.22 | 211.84 |
| 0.08 | −2.95 | 5.71 | 3.10 | 62.77 | 158.33 | 221.10 | 64.68 | 149.78 | 214.46 |
| 0.1 | −4.43 | 5.65 | 2.55 | 63.76 | 159.09 | 222.85 | 66.72 | 150.58 | 217.30 |

selection problem (from hidden information $\theta_t$), the buyer must also solve the moral hazard problem arising from hidden action $q_t$—the farmer carries out production $q_t$ to maximize his own profit $U_t$, not the buyer's. Third, for practicality, the buyer must implement the contract in a simple format, with commonly used instruments.

Despite the new challenges, we are able to characterize the optimal contract with a simple implementation. Let $y \equiv \mathsf{E} y_t$, $k \equiv \frac{c_0}{y f_0(\underline{\theta})}$, $\tilde{\nu}(q_t) \equiv \mathsf{E}\nu(y_t q_t)$, $S_1(\theta_1, q_1) \equiv \tilde{\nu}(q_1) - \psi(\theta_1, q_1) + h(\theta_1)\psi_\theta(\theta_1, q_1)$, and $S_2(\theta^2, q^2) \equiv \tilde{\nu}(q_2) - \psi(\theta_2, q_2) + h(\theta_1)\psi_\theta(\theta_2, q_2) \cdot Z_\theta(q_1)$. We find:

**Proposition 7.**

(*a*) *In regime* ($\mathcal{P}^y$)*, the optimal contract* $\pi^*$ *induces the farmer to select production quota* $q_t^*(\theta^t)$ *and invest effort* $e_t^*(\theta^t) = \frac{c_0}{\phi} q_t^*(\theta^t)$*, for the expected performance pay* $U_t(\theta^t)$*, where*

$$\partial_{q_1}\left[S_1\left(\theta_1, q_1^*(\theta_1)\right) + \delta \mathsf{E}_1 S_2(\theta^2, q^{2*}(\theta^2))\right] = 0,$$

$$\partial_{q_2} S_2(\theta^2, q^{2*}(\theta^2)) = 0,$$

$$U_1(\theta_1) = -\int_{\underline{\theta}}^{\theta_1} \mathsf{E}\left[\psi_\theta(\tilde{\theta}_1, q_1^*(\tilde{\theta}_1)) + \delta\psi_\theta(\tilde{\theta}_2, q_2^*(\tilde{\theta}^2)) \cdot Z_\theta\left(q_1^*(\tilde{\theta}_1)\right) | \tilde{\theta}_1, q_1^*(\tilde{\theta}_1)\right] d\tilde{\theta}_1,$$

$$U_2(\theta^2) = -\int_{\underline{\theta}}^{\theta_2} \psi_\theta(\tilde{\theta}_2, q_2^*(\tilde{\theta}^2))\, d\tilde{\theta}_2.$$

(*b*) *In regime* ($\mathcal{P}^y$)*, the optimal contract* $\pi^*$ *can be implemented by a yield-adjusted revenue-sharing contract*

$$p_t(\theta^t, \eta_t) = A_t^*(\theta^t)[\nu(\eta_t) - k\eta_t] + B_t^*(\theta^t),$$

*where* $A_t^*(\theta^t)$ *is the share of the modified revenue for the buyer and* $B_t^*(\theta^t)$ *is the fixed payment.*[25]

The optimal contract $\pi^*$ works as follows. First, it uses dynamic quota adjustment to tailor production and extract new information. The dynamic adjustment is necessary because the farmer is better informed of his local condition and evolving capability $\theta_t$. To produce efficiently, the buyer should allow the farmer to adjust the quota over time, within the system of prespecified terms. Under optimal contract $\pi^*$, farmer-$\theta^t$ will select the quota $q_t^*(\theta^t)$ that matches his capability $\theta_t$; for his quota choice, the buyer can then infer the farmer's new information $\theta_t$ and plan production accordingly.

Second, the optimal contract $\pi^*$ uses the share $A_t^*$ and fixed payment $B_t^*$ to control moral hazard and adverse selection: given the quota choice $q_t^*$, the buyer should set the fixed payment $B_t^*$ so that the farmer would not lie even if he could; she should set the share $A_t^*$ so that the farmer is motivated to exert the requisite effort for reaching the quota $q_t^*$ in expectation. Crucially, all three instruments should be set jointly, so that the higher the quota, the higher the share, and the higher the payment. This monotonicity is necessary for keeping the incentives alive when the high-type farmer reaches the low-type quota. When the instruments are properly calibrated, the farmer finds it impossible to gain from manipulation: he will share the information truthfully, equate his marginal production cost to his expected marginal benefit, and thereby maximize his continuation payoff.

Proposition 7 is reassuring: despite the noisy measurement and the moral hazard problem, the buyer can still implement the optimal contract with a simple contract. Relative to the deterministic case ($\mathcal{P}$), one would expect efficiency loss because random yield weakens managerial control and simple implementation limits contractual choices. Yet our result shows the yield-adjusted revenue-sharing contract $\pi^*$ can overcome both problems. To see why, we rewrite the payment as

$$p_t(\theta^t, \eta_t) = p_t^*(\theta^t) + A_t^*(\theta^t) \times \underbrace{\left[(\nu(\eta_t) - k\eta_t) - \mathsf{E}\left[\nu(y_t \cdot q_t^*(\theta^t)) - ky_t \cdot q_t^*(\theta^t)\right]\right]}_{= 0 \text{ in expectation}}.$$

For the same quota $q_t^*(\theta^t)$, although the buyer has to use differential pay $p_t(\theta^t, \eta_t)$ based on realized output $\eta_t = y_t q_t^*(\theta^t)$, she can filter out random yield and ensure the same payment $\mathsf{E}p_t(\theta^t, \eta_t) = p_t^*(\theta^t)$ *in expectation*. Technically, this requires the share $A_t^*(\theta^t)$ to increase in $\theta_t$. Unfortunately, the conventional revenue-sharing contract will not work, because its incentives are overpowered (Cachon & Lariviere, 2005). To overcome this technical challenge, we adjust the revenue by a linear factor $k = \frac{c_0}{yf_0(\underline{\theta})}$. The resulting contract $\pi^*$ then achieves the requisite monotonicity.

## 9 | CONCLUSION

Contract farming is the backbone of modern agrifood value chains. It often entails long-term relationships, allowing farmers to learn and game the system over time. How should buyers design the contract? Existing models treat farmers in a simplistic fashion, ignoring dynamic incentives of learning and gaming—the heart of contract farming. We study this new class of payment design problems. We find that, once the dynamic incentives are considered, the optimal contract differs substantially from the existing ones in structure and performance: it uses performance pay and deferred payment, to resolve several dynamic trade-offs over time; even for the random yield case, it has a simple implementation of yield-adjusted revenue-sharing policy.

A key question is when and why contract farming can benefit smallholder farmers, creating shared value. (i) Our results show that, when buyers have a long-term perspective and can internalize the benefit from farmer improvement, they will pay higher prices to ensure farmers' long-run viability. The resulting long-term policy can remedy both incentive and information deficiencies of short-term policies: taking a long-term perspective, it provides sufficient incentives to internalize the intertemporal externalities of learning and carryover effects; to mitigate information friction, it leverages deferred payment to elicit new information and eliminate production distortion eventually. (ii) Using real-world data, we demonstrate that the learning effect is significant. We show that performance improvement can be substantial when the learning and carryover effects are salient. In these situations, the short-term policies would trap the agrifood value chain in a low-efficiency equilibrium, while the optimal long-run policy can sustain win-win outcomes. (iii) A policy implication is that traditional procompetitive policies (based on spot transactions) can be counterproductive for modern agrifood industries, hurting both buyers and farmers. By highlighting the critical role of the dynamic incentives, this study deepens our understanding of contract farming theory and practice.

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## ENDNOTES

[1] As Bennett's law predicts, income growth drives this trend (Bennett, 1941). In addition, the Internet and social media have also shaped consumers' tastes for quality, identity, and morality. The impact of this trend is well articulated by the Europe's Common Agricultural Policy: "The EU's common agricultural policy is designed to support farming that ensures food safety (in a context of climate change) and promotes sustainable and balanced development across all Europe's rural areas, including those where production conditions are difficult. *Such farming must thus fulfill multiple functions: meeting citizens' concerns about food* (*availability, price, variety, quality and safety*)*, safeguarding the environment and allowing farmers to make a living. At the same time, rural communities and landscapes must be preserved as a valuable part of Europe's heritage.*" (See https://ec.europa.eu/commission/presscorner.)

[2] Under *production contracts*, farmers provide land, labor, and equipment, while buyers control main production decisions, by providing key inputs on credit and technical assistance, in return for the delivery of an agreed quantity and quality of product, usually at a predetermined price. Under *marketing contracts*, farmers largely control the production decisions, and the contract terms specify the quantity and quality of delivered commodity at a future date, either at a predetermined price or a pricing formula (Otsuka et al., 2016).

[3] For example, in molecular farming and biomass electricity, the lack of alternative markets for the novel crops combined with high investments faced by the processor, often locks growers into long-term contractual agreements, with durations of 10–20 years (Choinière, 2002; Parsons, 2008). In the banana industry, Del Monte has a 20-year contract with Panama banana producers in the province of Chiriqui (Monte, 2017).

[4] For an overview of the learning curve literature, see Argote and Epple (1990); Syverson (2011); Yelle (1979). For empirical studies in other sectors, see, for example, airframes (Wright, 1936), automobile assembly (Baloff, 1966), chemical processing (Lieberman, 1984), construction (De Jong, 1957), machine tools (Hirsch, 1952), petroleum refining (Hirschmann, 1964), pharmaceuticals (Pisano, 1996), and semiconductors (Hatch & Mowery, 1998).

[5] Most learning models focus on manufacturing; see, for example, Bavafa and Jónasson (2021), Fine and Porteus (1989), Gao et al. (2022), G. Li and Rajagopalan (1998), T. Li et al. (2015), and Mazzola and McCardle (1997). Besides the learning curve, cost reduction can also come from deliberate investment (Fine & Porteus, 1989; G. Li & Rajagopalan, 1998). For recent studies, see Bernstein and Kök (2009) for gradual investment in process improvement, and Kim and Netessine (2013) for collaborative investment in product development.

[6] There is also extensive literature on supply chain contracting and operations (Cachon, 2003). The main themes include, e.g., demand uncertainty (Gao et al., 2012; Gao, Thomas, et al., 2014; Gao et al., 2020; Hwang et al., 2010; Kuzu et al., 2019; Xu et al., 2007; Yan & Zhao, 2011; H. Zhang et al., 2010), channel coordination (Cakanyıldırım et al., 2012; Gao, 2015a; Gao & Mishra, 2019; Gao et al., 2021; Z. Li & Gao, 2008), supply risk (Akcay & Gao, 2020; Chen & Lee, 2017; Gao, Li, et al., 2014; Gao, 2015b; Gao et al., 2017; Luo et al., 2016; Z. Yang et al., 2009), collaborative investment (Kim & Netessine, 2013), assembly procurement (Fang et al., 2014; B. Hu & Qi, 2018), service requirement (F. Zhang, 2010), contract simplicity (Bolandifar et al., 2017), and contract rigidity (Corbett et al., 2004; Chen et al., 2017). This literature mainly relies on the static principal–agent framework, which cannot capture sequential learning and progressive information revelation—the heart of our problem.

[7] The agricultural supply chain literature is extensive. The main themes include, for example, food security, quality, and safety (Ata et al., 2019; Alizamir et al., 2019; Levi, Singhvi, et al., 2020; Mu et al., 2016, 2019); inclusive value chain (An et al., 2015; Y.-J. Chen et al., 2013; Dawande et al., 2013; M. Hu et al., 2019; Liao et al., 2019; Lim et al., 2019; Levi, Rajan, et al., 2020); eco-friendly agriculture (Akkaya et al., 2021; Boyabatlı et al., 2019; de Zegher et al., 2018, 2019; Dong et al., 2021; Huh & Lall, 2013); procurement (Boyabatlı et al., 2011; Devalkar et al., 2011; Ferreira et al., 2017), and risk management (Allen & Schuster, 2004; Bansal & Nagarajan, 2017; Boyabatlı et al., 2017; Y.-J. Chen & Tang, 2015; Federgruen et al., 2019; Jones et al., 2001; Maatman et al., 2002; Kazaz & Webster, 2011; Kouvelis et al., 2021; Swaminathan & Zhang, 2020; Y. Zhang & Swaminathan, 2020). For comprehensive reviews, see Dong (2021) and Roth and Zheng (2021).

[8] To rule out unrealistic cases, we assume $(1 - \theta_t - e_t) > 0$ almost surely.

[9] As Sexton (2013) pointed out, *modern agricultural markets* differ substantially from traditional spot/cash markets: they entail a capital-intensive food-marketing infrastructure, produce differentiated finished products, require specific amounts of farm products with precise characteristics to operate plants efficiently (meaning buyer demand in the short run is highly inelastic). In modern agricultural markets, vertical coordination, contract production, and *lock-in* between farmers and downstream buyers are *inevitable*. In traditional spot markets, however, both buyers and farmers can adopt a myopic horizon, pursuing short-run interest.

[10] Besides sunk investments, *reputation* is another mechanism that induces the forward-looking and long-term perspective. For example, Swinnen and Vandeplas (2010) find that in monopsonistic markets, contract farmers are less likely to renege, even when other selling opportunities are available, because of the long-term, negative reputation effects.

[11] For example, the U.S. Department of Justice found that, in the poultry industry, "the lack of competition in a given geographic region has led to integrators with all the power, this leaves the grower with little to no choice." Indeed, it is always the buyer who exercises control over the farmer, for example, in terms of varieties produced, inputs used, production schedules, and handling practices (Sexton, 2013).

[12] In the United States, multiyear contracting is protected by the law; see, for example, Subpart 17.1. Special Contracting Methods: Multi-Year Contracting, https://www.acquisition.gov/far/part-17#FAR_Subpart_17_1.

[13] *Direct sourcing* and *commodity sourcing* in de Zegher et al. (2019) are contract farming and outside option in our model.

[14] The resulting contract $\bar{\pi}$ implements the *internalization principle*, but it is extremely harsh: the buyer can extract the entire channel surplus, leaving the farmer with zero payoff ($U_1(\theta_1) = \underline{U}, \forall \theta_1$). The *internalization principle* states that a contract achieves the first-best, if and only if it makes the agent (farmer) internalize all the social benefits and costs of his actions; see, for example, Tirole (1988).

[15] In Figure 3, a higher type farmer should produce increasingly more, because he is more cost efficient ($\psi_\theta < 0$) and gains more from learning ($\xi > 0$). In Figure 4, however, the learning gain decreases in $\theta_1$ ($\xi < 0$); as a result, the middle farmer with $\theta_1 = 0.5$ should produce more than higher types $\theta_1' > 0.5$, because his learning gain dominates his cost inefficiency; hence the non-monotone schedule.

[16] Recall $\psi_\theta(\tilde{\theta}, q^c(\tilde{\theta}))$ is the value of the partial derivative $\frac{\partial}{\partial \theta}\psi(\theta, q)$, evaluated at the point $(\theta, q) = (\tilde{\theta}, q^c(\tilde{\theta}))$; that is,

$$\psi_\theta(\tilde{\theta}, q^c(\tilde{\theta})) \equiv \frac{\partial}{\partial \theta}\psi(\theta, q)\big|_{(\theta,q)=(\tilde{\theta},q^c(\tilde{\theta}))}.$$

[17] The higher the capability, the higher the performance pay ($\partial_\theta U^c(\theta) \geq 0$).

[18] The optimal production must balance its effects on revenue, production cost, and performance pay, resulting in the first-order condition ($FOC^c$) for $q^c(\theta)$: $s_q(\theta, q) = -h(\theta)\psi_{\theta q}(\theta, q)$.

[19] Because we normalize the outside option $\underline{U} = U_1(\underline{\theta})$ to zero, farmer-$\theta_1$'s absolute payoff is $U_1(\theta_1) + \underline{U}$.

[20] The notion of *efficiency wage* dates back to Marshall (1890): an employer pays different wages to the workers of different abilities, such that she would be indifferent between high- and low-ability workers. For contract farming, see Swinnen and Vandeplas (2012); for another application, see Henry Ford's the five-dollar day introduced in 1914 (Raff & Summers, 1987); for labor markets in general, see Stiglitz (1976).

[21] A sufficient condition is $m \geq \frac{2\beta c_0}{1-\alpha} - N$.

[22] This result is consistent with reality. For example, U.S. food processing and retailing industries are highly concentrated. The traditional models would predict the abuse of buyer market power. Yet the empirical literature finds little evidence of buyer power (Crespi et al., 2012). This implies buyers' long-term interest in viable farmers trumps their short-run benefit of exercising market power.

[23] By *buyer power*, we mean a buyer's ability to obtain terms better than a supplier's normal trade terms, for example, the ability to extract price concession from a supplier (Z. Chen, 2003).

[24] The report GAO-09-746R is available at http://www.gao.gov/new.items/d09746r.pdf.

[25] Specifically,

$$A_1^*(\theta_1) = \frac{\psi_q(\theta_1, q_1^*(\theta_1)) - \delta\partial_{q_1}\mathsf{E}_1[U_2(\theta^2)]}{\tilde{\nu}_q(q_1^*(\theta_1)) - ky},$$

$$B_1^*(\theta_1) = U_1(\theta_1) + \psi(\theta_1, q_1^*(\theta_1)) - \delta\mathsf{E}_1\left[U_2(\theta^2)\right] - \tilde{\nu}(q_1^*(\theta_1))A_1^*(\theta_1),$$

$$A_2^*(\theta^2) = \frac{\psi_q(\theta_2, q_2^*(\theta^2))}{\tilde{\nu}_q(q_2^*(\theta^2)) - ky},$$

$$B_2^*(\theta^2) = U_2(\theta^2) + \psi(\theta_2, q_2^*(\theta^2)) - \left[\tilde{\nu}\left(q_2^*(\theta^2)\right) - kyq_2^*(\theta^2)\right]A_2^*(\theta^2).$$

## REFERENCES

Akan, M., Ata, B., & Dana, J. D., Jr. (2015). Revenue management by sequential screening. *Journal of Economic Theory*, *159*, 728–774.

Akcay, Y., & Gao, L. (2020). *Sourcing for continuous supplier improvement* (UCR Working Paper).

Akerlof, G. A., & Kranton, R. E. (2000). Economics and identity. *The Quarterly Journal of Economics*, *115*(3), 715–753.

Akkaya, D., Bimpikis, K., & Lee, H. (2021). Government interventions to promote agricultural innovation. *Manufacturing & Service Operations Management*, *23*(2), 437–452.

Alizamir, S., Iravani, F., & Mamani, H. (2019). An analysis of price vs. revenue protection: Government subsidies in the agriculture industry. *Management Science*, *65*(1), 32–49.

Allen, S. J., & Schuster, E. W. (2004). Controlling the risk for an agricultural harvest. *Manufacturing & Service Operations Management*, *6*(3), 225–236.

An, J., Cho, S.-H., & Tang, C. S. (2015). Aggregating smallholder farmers in emerging economies. *Production and Operations Management*, *24*(9), 1414–1429.

Argote, L. (2012). *Organizational learning: Creating, retaining and transferring knowledge*. Springer Science & Business Media.

Argote, L., & Epple, D. (1990). Learning curves in manufacturing. *Science*, *247*(4945), 920–924.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173.

Ata, B., Lee, D., & Sönmez, E. (2019). Dynamic volunteer staffing in multicrop gleaning operations. *Operations Research*, *67*(2), 295–314.

Ayvaz-Cavdaroğlu, N., Kazaz, B., & Webster, S. (2021). Incentivizing farmers to invest in quality through quality-based payment. *Production and Operations Management*.

Baloff, N. (1966). Startups in machine-intensive production systems. *Journal of Industrial Engineering*, *17*(1), 25.

Bansal, S., & Nagarajan, M. (2017). Product portfolio management with production flexibility in agribusiness. *Operations Research*, *65*(4), 914–930.

Baron, D. P., & Besanko, D. (1984). Regulation, asymmetric information, and auditing. *The RAND Journal of Economics*, *15*, 447–470.

Barrett, C. B., Reardon, T., Swinnen, J., & Zilberman, D. (2020). Agri-food value chain revolutions in low-and middle-income countries. *Journal of Economic Literature*, *58*, 1–67.

Battaglini, M. (2005). Long-term contracting with Markovian consumers. *American Economic Review*, *95*, 637–658.

Battaglini, M., & Lamba, R. (2019). Optimal dynamic contracting: The first-order approach and beyond. *Theoretical Economics*, *14*(4), 1435–1482.

Bavafa, H., & Jónasson, J. O. (2021). The variance learning curve. *Management Science*, *67*(5), 3104–3116.

Bellemare, M. F., & Bloem, J. R. (2018). Does contract farming improve welfare? A review. *World Development*, *112*, 259–271.

Bellemare, M. F., & Lim, S. (2018). In all shapes and colors: Varieties of contract farming. *Applied Economic Perspectives and Policy*, *40*(3), 379–401.

Bennett, M. K. (1941). International contrasts in food consumption. *Geographical Review*, *31*(3), 365–376.

Bergemann, D., & Välimäki, J. (2019). Dynamic mechanism design: An introduction. *Journal of Economic Literature*, *57*(2), 235–74.

Bernstein, F., & Kök, A. (2009). Dynamic cost reduction through process improvement in assembly networks. *Management Science*, *55*(4), 552–567.

Bijman, J., Mugwagwa, I., & Trienekens, J. (2020). Typology of contract farming arrangements: A transaction cost perspective. *Agrekon*, *59*(2), 169–187.

Board, S. (2007). Selling options. *Journal of Economic Theory*, *136*(1), 324–340.

Bolandifar, E., Feng, T., & Zhang, F. (2017). Simple contracts to assure supply under noncontractible capacity and asymmetric cost information. *Manufacturing & Service Operations Management*, *20*(2), 217–231.

Boyabatlı, O., Kleindorfer, P. R., & Koontz, S. R. (2011). Integrating long-term and short-term contracting in beef supply chains. *Management Science*, *57*(10), 1771–1787.

Boyabatlı, O., Nasiry, J., & Zhou, Y. (2019). Crop planning in sustainable agriculture: Dynamic farmland allocation in the presence of crop rotation benefits. *Management Science*, *65*(5), 2060–2076.

Boyabatlı, O., Nguyen, J., & Wang, T. (2017). Capacity management in agricultural commodity processing and application in the palm industry. *Manufacturing & Service Operations Management*, *19*(4), 551–567.

Brekke, K. A., Kverndokk, S., & Nyborg, K. (2003). An economic model of moral motivation. *Journal of Public Economics*, *87*(9-10), 1967–1983.

Cabral, L. M., & Riordan, M. H. (1997). The learning curve, predation, antitrust, and welfare. *The Journal of Industrial Economics*, *45*(2), 155–169.

Cachon, G. P. (2003). Supply chain coordination with contracts. *Handbooks in Operations Research and Management Science*, *11*, 227–339.

Cachon, G. P., & Feldman, P. (2017). Is advance selling desirable with competition? *Marketing Science*, *36*(2), 214–231.

Cachon, G. P., & Lariviere, M. A. (2005). Supply chain coordination with revenue-sharing contracts: Strengths and limitations. *Management science*, *51*(1), 30–44.

Cakanyıldırım, M., Feng, Q., Gan, X., & Sethi, S. P. (2012). Contracting and coordination under asymmetric production cost information. *Production and Operations Management*, *21*(2), 345–360.

Cargill (2015). Improving livelihoods for cocoa farmers and their communities. https://www.cargill.com/doc/1432076281572/ccp-full-report.pdf

Chen, F., Gao, L., & Zhang, W. (2021). *Optimal payment for dynamic treatment regimes* (UCR Working Paper).

Chen, J., & Chen, Y.-J. (2021). The impact of contract farming on agricultural product supply in developing economies. *Production and Operations Management*, *30*, 2395–2419.

Chen, J., Hu, Q., & Song, J.-S. J. (2017). *Contract types and supplier incentives for quality improvement* (SSRN 2608772). https://doi.org/10.2139/ssrn.2608772

Chen, L., & Lee, H. L. (2017). Sourcing under supplier responsibility risk: The effects of certification, audit, and contingency payment. *Management Science*, *63*(9), 2795–2812.

Chen, Y.-J. (2011). Optimal selling scheme for heterogeneous consumers with uncertain valuations. *Mathematics of Operations Research*, *36*(4), 695–720.

Chen, Y.-J., Gui, Z., von Thadden, E.-L., & Zhao, X. (2021). *Optimal retail contracts with return policies* (SSRN 2826319). https://doi.org/10.2139/ssrn.2826319

Chen, Y.-J., J George, S., & Zuo-Jun Max, S. (2013). Training, production, and channel separation in ITC's e-Choupal network. *Production and Operations Management*, *22*(2), 348–364.

Chen, Y.-J., & Tang, C. S. (2015). The economic value of market information for farmers in developing economies. *Production and Operations Management*, *24*(9), 1441–1452.

Chen, Z. (2003). Dominant retailers and the countervailing-power hypothesis. *RAND Journal of Economics*, *34*, 612–625.

Choinière, C. J. (2002). *Contract structure, learning-by-doing and the viability of new agricultural industries*. University of Michigan (Technical report).

Clark, H., & Wu, H. (2016). The sustainable development goals: 17 goals to transform our world. In *Furthering the of the United Nations* (pp. 36–54). United Nations.

Clay, J. (2018). How long-term contracts can help drive more sustainable agriculture. https://medium.com/the-markets-institute/long-term-contracts-c0ccc09dbbc9

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, *100*(1), 35–69.

Corbett, C. J., Zhou, D., & Tang, C. S. (2004). Designing supply contracts: Contract type and information asymmetry. *Management Science*, *50*(4), 550–559.

Courty, P., & Hao, L. (2000). Sequential screening. *The Review of Economic Studies*, *67*(4), 697–717.

Crespi, J. M., Saitone, T. L., & Sexton, R. J. (2012). Competition in US farm product markets: Do long-run incentives trump short-run market power? *Applied Economic Perspectives and Policy*, *34*(4), 669–695.

Dawande, M., Gavirneni, S., Mehrotra, M., & Mookerjee, V. (2013). Efficient distribution of water between head-reach and tail-end farms in developing countries. *Manufacturing & Service Operations Management*, *15*(2), 221–238.

De Jong, J. (1957). The effects of increasing skill on cycle time and its consequences for time standards. *Ergonomics*, *1*(1), 51–60.

de Zegher, J. F., Iancu, D. A., & Lee, H. L. (2019). Designing contracts and sourcing channels to create shared value. *Manufacturing & Service Operations Management*, *21*(2), 271–289.

de Zegher, J. F., Iancu, D. A., & Plambeck, E. L. (2018). Sustaining smallholders and rainforests by eliminating payment delay in a commodity supply chain—It takes a village. *Management Science* (Stanford Working Paper).

Devalkar, S. K., Anupindi, R., & Sinha, A. (2011). Integrated optimization of procurement, processing, and trade of commodities. *Operations Research*, *59*(6), 1369–1381.

Dong, L. (2021). Toward resilient agriculture value chains: Challenges and opportunities. *Production and Operations Management*, *30*(3), 666–675.

Dong, L., Rashkova, I., & Shi, D. (2022). Food safety audits in developing economies: Decentralization vs. centralization. *Manufacturing & Service Operations Management*, *24*(6), 2863–2881.

Eső, P., & Szentes, B. (2007). Optimal information disclosure in auctions and the handicap auction. *The Review of Economic Studies*, *74*(3), 705–731.
Fang, X., Ru, J., & Wang, Y. (2014). Optimal procurement design of an assembly supply chain with information asymmetry. *Production and Operations Management*, *23*, 2075–2088.
Federgruen, A., Lall, U., & Şimşek, A. S. (2019). Supply chain analysis of contract farming. *Manufacturing & Service Operations Management*, *21*(2), 361–378.
Ferreira, K., Goh, J., & Valavi, E. (2017). *Intermediation in the supply of agricultural products in developing economies* (Harvard Business School Research Paper Series). Harvard Business School.
Fine, C. H., & Porteus, E. L. (1989). Dynamic process improvement. *Operations Research*, *37*(4), 580–591.
Fudenberg, D., & Tirole, J. (1983). Learning-by-doing and market performance. *The Bell Journal of Economics*, *14*, 522–530.
Fuglie, K., Gautam, M., Goyal, A., & Maloney, W. F. (2019). *Harvesting prosperity: Technology and productivity growth in agriculture*. World Bank.
Gao, L. (2015a). Collaborative forecasting, inventory hedging and contract coordination in dynamic supply risk management. *European Journal of Operational Research*, *245*(1), 133–145.
Gao, L. (2015b). Long-term contracting: The role of private information in dynamic supply risk management. *Production and Operations Management*, *24*(10), 1570–1579.
Gao, L. (2022). Optimal incentives for salespeople with learning potential. *Management Science*. Advanced online publication. https://doi.org/10.1287/mnsc.2022.4509
Gao, L., Guo, L., & Orsdemir, A. (2021). Dual-channel distribution: The case for cost information asymmetry. *Production and Operations Management*, *30*(2), 494–521.
Gao, L., Li, Z., & Shou, B. (2014). Information acquisition and voluntary disclosure in an export-processing system. *Production and Operations Management*, *23*(5), 802–816.
Gao, L., & Mishra, B. K. (2019). The role of market evolution in channel contracting. *Management Science*, *65*(5), 2432–2441.
Gao, L., Nikoofal, M., & Zhang, W. (2022). *The strategic role of supplier learning* (UCR Working Paper).
Gao, L., Shi, J., Gorman, M. F., & Luo, T. (2020). Business analytics for intermodal capacity management. *Manufacturing & Service Operations Management*, *22*(2), 310–329.
Gao, L., Thomas, D. J., & Freimer, M. B. (2014). Optimal inventory control with retail pre-packs. *Production and Operations Management*, *23*(10), 1761–1778.
Gao, L., Xu, S. H., & Ball, M. O. (2012). Managing an available-to-promise assembly system with dynamic short-term pseudo-order forecast. *Management Science*, *58*(4), 770–790.
Gao, L., Yang, N., Zhang, R., & Luo, T. (2017). Dynamic supply risk management with signal-based forecast, multi-sourcing, and discretionary selling. *Production and Operations Management*, *26*(7), 1399–1415.
Garrett, D. F., & Pavan, A. (2015). Dynamic managerial compensation: A variational approach. *Journal of Economic Theory*, *159*, 775–818.
Geylani, P. C., & Stefanou, S. E. (2011). Productivity growth patterns in US dairy products manufacturing plants. *Applied Economics*, *43*(24), 3415–3432.
Geylani, P. C., & Stefanou, S. E. (2013). Linking investment spikes and productivity growth. *Empirical Economics*, *45*(1), 157–178.
Guo, Y. (2016). Dynamic delegation of experimentation. *American Economic Review*, *106*(8), 1969–2008.
Halac, M., Kartik, N., & Liu, Q. (2016). Optimal contracts for experimentation. *Review of Economic Studies*, *83*(3), rdw013.
Halac, M., Kartik, N., & Liu, Q. (2017). Contests for experimentation. *Journal of Political Economy*, *125*(5), 1523–1569.
Hatch, N. W., & Mowery, D. C. (1998). Process innovation and learning by doing in semiconductor manufacturing. *Management Science*, *44*(11, Part-1), 1461–1477.
Hiller, R. S., & Shapiro, J. F. (1986). Optimal capacity expansion planning when there are learning effects. *Management Science*, *32*(9), 1153–1163.
Hirsch, W. (1952). Progress functions of machine tool manufacturing. *Econometrica*, *20*(1), 81–82.
Hirschmann, W. B. (1964). Profit from the learning-curve. *Harvard Business Review*, *42*(1), 125–139.
Hörner, J., & Samuelson, L. (2013). Incentives for experimenting agents. *The RAND Journal of Economics*, *44*(4), 632–663.
Hu, B., & Qi, A. (2018). Optimal procurement mechanisms for assembly. *Manufacturing & Service Operations Management*, *20*(4), 655–666.
Hu, M., Liu, Y., & Wang, W. (2019). Socially beneficial rationality: The value of strategic farmers, social entrepreneurs, and for-profit firms in crop planting decisions. *Management Science*, *65*(8), 3654–3672.
Huh, W. T., Athanassoglou, S., & Lall, U. (2012). Contract farming with possible reneging in a developing country: Can it work? *IIMB Management Review*, *24*(4), 187–202.
Huh, W. T., & Lall, U. (2013). Optimal crop choice, irrigation allocation, and the impact of contract farming. *Production and Operations Management*, *22*(5), 1126–1143.
Hwang, J., Gao, L., & Jang, W. (2010). Joint demand and capacity management in a restaurant system. *European Journal of Operational Research*, *207*(1), 465–472.
Jin, J. Y., Perote-Pena, J., & Troege, M. (2004). Learning by doing, spillovers and shakeouts. *Journal of Evolutionary Economics*, *14*(1), 85–98.
Jones, P. C., Lowe, T. J., Traub, R. D., & Kegler, G. (2001). Matching supply and demand: The value of a second chance in producing hybrid seed corn. *Manufacturing & Service Operations Management*, *3*(2), 122–137.
Kakade, S. M., Lobel, I., & Nazerzadeh, H. (2013). Optimal dynamic mechanism design and the virtual-pivot mechanism. *Operations Research*, *61*(4), 837–854.
Kapička, M. (2013). Efficient allocations in dynamic private information economies with persistent shocks: A first-order approach. *The Review of Economic Studies*, *80*(3), 1027–1054.
Kazaz, B., & Webster, S. (2011). The impact of yield-dependent trading costs on pricing and production planning under supply uncertainty. *Manufacturing & Service Operations Management*, *13*(3), 404–417.
Keskin, N. B., Li, C., & Song, J.-S. J. (2021). *The blockchain newsvendor: Value of freshness transparency and smart contracts* (SSRN 3915358). https://doi.org/10.2139/ssrn.3915358
Khalil, F., Lawarree, J., & Rodivilov, A. (2020). Learning from failures: Optimal contracts for experimentation and production. *Journal of Economic Theory*, *190*, 105107.
Kim, S.-H., & Netessine, S. (2013). Collaborative cost reduction and component procurement under information asymmetry. *Management Science*, *59*(1), 189–206.
Kouvelis, P., Liu, Y., Qiu, Y., & Turcic, D. (2021). *Managing operations of a hog farm facing volatile markets: Inventory and selling strategies* (SSRN 3912801). https://doi.org/10.2139/ssrn.3912801
Kuzu, K., Gao, L., & Xu, S. H. (2019). To wait or not to wait: The theory and practice of ticket queues. *Manufacturing & Service Operations Management*, *21*(4), 853–874.
Laffont, J., & Martimort, D. (2001). *The theory of incentives: the principal-agent model*. Princeton University Press.
Levi, R., Rajan, M., Singhvi, S., & Zheng, Y. (2020). The impact of unifying agricultural wholesale markets on prices and farmers's profitability. *Proceedings of the National Academy of Sciences*, *117*(5), 2366–2371.
Levi, R., Singhvi, S., & Zheng, Y. (2020). Economically motivated adulteration in farming supply chains. *Management Science*, *66*(1), 209–226.
Li, C., & Wan, Z. (2016). Supplier competition and cost improvement. *Management Science*, *63*(8), 2460–2477.
Li, G., & Rajagopalan, S. (1998). Process improvement, quality, and learning effects. *Management Science*, *44*(11, Part-1), 1517–1532.
Li, T., Sethi, S. P., & He, X. (2015). Dynamic pricing, production, and channel coordination with stochastic learning. *Production and Operations Management*, *24*(6), 857–882.
Li, Z., & Gao, L. (2008). The effects of sharing upstream information on product rollover. *Production and Operations Management*, *17*(5), 522–531.

Liao, C.-N., Chen, Y.-J., & Tang, C. S. (2019). Information provision policies for improving farmer welfare in developing countries: Heterogeneous farmers and market selection. *Manufacturing & Service Operations Management*, *21*(2), 254–270.

Lieberman, M. B. (1984). The learning curve and pricing in the chemical processing industries. *The RAND Journal of Economics*, *15*(2), 213–228.

Lim, M. K., Mak, H.-Y., & Park, S. J. (2019). Money well spent? Operations, mainstreaming, and fairness of fair trade. *Production and Operations Management*, *28*(12), 3023–3041.

Lobel, I., & Xiao, W. (2017). Optimal long-term supply contracts with asymmetric demand information. *Operations Research*, *65*(5), 1275–1284.

London, T., & Fay, C. (2017). *Walmart and small producers from the developing world: Linking demand with supply*. WDI Publishing.

Luh, Y.-H. (1995). Are farmers learning by doing? Experience in Taiwan. *Review of Agricultural Economics*, *17*, 213–227.

Luh, Y.-H., & Stefanou, S. E. (1993). Learning-by-doing and the sources of productivity growth: A dynamic model with application to US agriculture. *Journal of Productivity Analysis*, *4*(4), 353–370.

Luo, T., Gao, L., & Akçay, Y. (2016). Revenue management for intermodal transportation: the role of dynamic forecasting. *Production and Operations Management*, *25*(10), 1658–1672.

Maatman, A., Schweigman, C., Ruijs, A., & van Der Vlerk, M. H. (2002). Modeling farmers' response to uncertain rainfall in Burkina Faso: A stochastic programming approach. *Operations Research*, *50*(3), 399–414.

MacDonald, J. M. (2015). Trends in agricultural contracts. *Choices*, *30*(3), 1–6.

Marshall, A. (1890). *Principles of economics*. MacMillan.

Mazzola, J. B., & McCardle, K. F. (1997). The stochastic learning curve: Optimal production in the presence of learning-curve uncertainty. *Operations research*, *45*(3), 440–450.

Michelson, H. (2016). Small farmers, big retailers: Are new sourcing strategies a path to inclusion. *The Chicago Council on Global Affairs*, *1*(1), 1–15.

Monte, D. (2017). Del Monte, Panama sign contract on banana production. https://www.thepacker.com/news/industry/del-monte-panama-sign-contract-banana-production

Mu, L., Dawande, M., Geng, X., & Mookerjee, V. (2016). Milking the quality test: Improving the milk supply chain under competing collection intermediaries. *Management Science*, *62*(5), 1259–1277.

Mu, L., Hu, B., Reddy, A., & Gavirneni, S. (2019). Negotiating G2G contracts for India's pulses importing. *Srinagesh, Negotiating G2G Contracts for India's Pulses Importing (December 18, 2019)*.

Myerson, R. B. (1986). Multistage games with communication. *Econometrica*, *54*, 323–358.

Oh, S., & Özer, Ö. (2013). Mechanism design for capacity planning under dynamic evolutions of asymmetric demand forecasts. *Management Science*, *59*(4), 987–1007.

Otsuka, K., Nakano, Y., & Takahashi, K. (2016). Contract farming in developed and developing countries. *Annual Review of Resource Economics*, *8*, 353–376.

Oya, C. (2012). Contract farming in sub-Saharan Africa: A survey of approaches, debates and issues. *Journal of Agrarian Change*, *12*(1), 1–33.

Parsons, J. E. (2008). The value of long-term contracts for new investments in generation. In *Unveiling the future of energy frontiers, 28th USAEE/IAEE North American Conference, 2008*. International Association for Energy Economics. https://www.mit.edu/~jparsons/Presentations/Contract%20Value%20w%20Berger.pdf

Pavan, A., Segal, I., & Toikka, J. (2014). Dynamic mechanism design: A Myersonian approach. *Econometrica*, *82*(2), 601–653.

Pisano, G. P. (1996). Learning-before-doing in the development of new process technology. *Research Policy*, *25*(7), 1097–1119.

Raff, D. M., & Summers, L. H. (1987). Did Henry Ford pay efficiency wages? *Journal of Labor Economics*, *5*(4, Part 2), S57–S86.

Roberts, J., & Milgrom, P. (1992). *Economics, organization and management*. Prentice-Hall.

Roth, A., & Zheng, Y. (2021). A tale of two food chains: The duality of practices on well-being. *Production and Operations Management*, *30*(3), 783–801.

Saitone, T. L., & Sexton, R. J. (2012). Market structure and competition in the US food industries: Implications for the 2012 Farm Bill. *American Boondoggle: Fixing the Farm Bill*. American Enterprise Institute. https://www.aei.org/wp-content/uploads/2012/04/-market-structure-and-competition-in-the-us-food-industries_102234192168.pdf

Sexton, R. J. (2013). Market power, misconceptions, and modern agricultural markets. *American Journal of Agricultural Economics*, *95*(2), 209–219.

Sexton, R. J., & Xia, T. (2018). Increasing concentration in the agricultural supply chain: Implications for market power and sector performance. *Annual Review of Resource Economics*, *10*, 229–251.

Shee, A., & Stefanou, S. E. (2016). Bounded learning-by-doing and sources of firm level productivity growth in Colombian food manufacturing industry. *Journal of Productivity Analysis*, *46*(2), 185–197.

Shi, J., Zhao, Y., Kiwanuka, R. B. K., & Chang, J. (2019). Optimal selling policies for farmer cooperatives. *Production and Operations Management*, *28*(12), 3060–3080.

Shum, S., Tong, S., & Xiao, T. (2016). On the impact of uncertain cost reduction when selling to strategic customers. *Management Science*, *63*(3), 843–860.

Stantcheva, S. (2017). Optimal taxation and human capital policies over the life cycle. *Journal of Political Economy*, *125*(6), 1931–1990.

Starbucks (2020). *C.A.F.E. practices: Starbucks approach to ethically sourcing coffee*. https://stories.starbucks.com/press/2020/cafe-practices-starbucks-approach-to-ethically-sourcing-coffee

Stiglitz, J. E. (1976). The efficiency wage hypothesis, surplus labour, and the distribution of income in LDCs. *Oxford Economic Papers*, *28*(2), 185–207.

Swaminathan, J. M., & Zhang, Y. (2020). Improving crop yields through better planting schedules. *Responsible Business Operations: Challenges and Opportunities*, *10*, 35.

Swinnen, J., & Vandeplas, A. (2012). Rich consumers and poor producers: quality and rent distribution in global value chains. *Journal of Globalization and Development*, *2*(2).

Swinnen, J. F., & Vandeplas, A. (2010). Market power and rents in global supply chains. *Agricultural Economics*, *41*, 109–120.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature*, *49*(2), 326–365.

Tesco (2015). *How Tesco works with suppliers*. https://www.thegrocer.co.uk/promotional-features/how-tesco-works-with-suppliers/596398.article

Tirole, J. (1988). *The theory of industrial organization*. MIT Press.

Wright, T. P. (1936). Factors affecting the cost of airplanes. *Journal of the Aeronautical Sciences*, *3*(4), 122–128.

Wu, S. Y. (2014). Adapting contract theory to fit contract farming. *American Journal of Agricultural Economics*, *96*(5), 1241–1256.

Xiong, H., & Chen, Y.-J. (2013). Product line design with seller-induced learning. *Management Science*, *60*(3), 784–795.

Xiong, H., & Chen, Y.-J. (2014). Product line design with seller-induced learning. *Management Science*, *60*(3), 784–795.

Xiong, H., & Chen, Y.-J. (2016). Nonlinear pricing with consumer satiation. *Naval Research Logistics*, *63*(5), 386–400.

Xu, S., Gao, L., & Ou, J. (2007). Service performance analysis and improvement for a ticket queue with balking customers. *Management Science*, *53*(6), 971–990.

Yan, X., & Zhao, H. (2011). Decentralized inventory sharing with asymmetric information. *Operations Research*, *59*(6), 1528–1538.

Yang, S., & Shumway, C. R. (2020). Knowledge accumulation in US agriculture: Research and learning by doing. *Journal of Productivity Analysis*, *54*(2), 87–105.

Yang, Z., Aydın, G., Babich, V., & Beil, D. (2009). Supply disruptions, asymmetric information, and a backup production option. *Management Science*, *55*(2), 192–209.

Yelle, L. E. (1979). The learning curve: Historical review and comprehensive survey. *Decision Sciences*, *10*(2), 302–328.

Zhang, F. (2010). Procurement mechanism design in a two-echelon inventory system with price-sensitive demand. *Manufacturing & Service Operations Management*, *12*(4), 608–626.

Zhang, H., Nagarajan, M., & Sošić, G. (2010). Dynamic supplier contracts under asymmetric inventory information. *Operations Research*, *58*(5), 1380–1397.
Zhang, Y., & Swaminathan, J. M. (2020). Improved crop productivity through optimized planting schedules. *Manufacturing & Service Operations Management*, *22*(6), 1165–1180.

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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