Journal of Agricultural and Resource Economics 47(1):77–96 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.307460

Technology and Managerial Gaps in Contract Farming: The Case of Specialty Crop Production

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We use a stochastic frontier approach corrected for self-selection to separate technology and managerial gaps between the treatment and control groups of smallholders in baby corn production in India. We also assess the impact of contract farming on output prices, profitability, and resource usage. We find that technical efficiency is consistently higher among contract farmers than among independent farmers and that significant technology and managerial gaps exist between contracted and independent growers. Ultimately, contract farming intervention benefits the livelihood of smallholders, increases efficiency, and reduces environmental degradation without compromising yield.

Key words: baby corn, India, metafrontier, output prices, selection bias, stochastic production frontier, technical efficiency

Introduction

The Green Revolution—which introduced high-yielding varieties of rice and wheat to the developing world—increased food production and food security in India, leading to higher incomes for farm families and rural households (Hazell, 2009). Farm families in the northwestern states, including Punjab and Haryana, enjoyed significant prosperity in income and farmland holdings as a result. The Green Revolution also introduced modern agricultural technologies, including new irrigation technologies and heavy doses of chemical fertilizer (Binswanger, Khandker, and Rosenzweig, 1993; Saifi and Drake, 2008). In India, farmers in major grain-producing states, including Punjab and Haryana, adopted rice–wheat crop rotation. Because both grains require large amounts of water and fertilizer, this crop rotation method led to the overexploitation of groundwater and heavy use of chemical fertilizers, which lowered the water table and increased soil salinity (Singh and Sidhu, 2004; Ladha, Pathak, and Gupta, 2007). Removal of nutrients has adversely impacted both rice and wheat yield in Punjab (Government of Punjab, 2012).

As a result, farmers in Punjab and Haryana are adopting maize as an alternative crop for income and livelihood security (Bhatt et al., 2016; Gulati, Roy, and Hussain, 2017). An interesting recent development is that of growing maize for vegetable purposes (Bhatt et al., 2016). Adding value to traditional maize, niche crops of "specialty corn" have recently been popularized and cultivated by large numbers of farmers (Parihar et al., 2011). Urbanization, rising incomes, and greater interest

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We are grateful to two anonymous referees and the managing editor for useful comments and edits on an earlier version of the paper. The views expressed here are those of the authors and do not necessarily reflect the views of the donor or the authors' institution. The usual disclaimer applies.

Review coordinated by Dragan Miljkovic.

in convenience foods are increasing consumer demands for certain kinds of specialty corn (Yadav and Supriya, 2014), including baby corn. Many common sweet corn and field corn cultivars can be used to grow baby corn.[1] Baby corn is rich in proteins, vitamins, and iron and is one of the richest sources of phosphorus. It is a good source of fibrous protein and is easy to digest. Increased demand, premium prices, and the global spread of baby corn make it an attractive option for Indian farmers. In particular, baby corn farming can have a significant role in ensuring livelihood security and augmenting the income of farmers in peri-urban areas. Because it can be grown in any season, baby corn cultivation has increased employment opportunities for farmers and their family members.

This study focuses on the adoption of baby corn and its potential for improving the income and livelihood of smallholders in India, especially in regions (e.g., Punjab and Haryana) facing declining agricultural productivity and environmental degradation. Baby corn provides income from direct sales within 2 months of sowing (Chaudhary et al., 2016). Additionally, green fodder, a by-product of baby corn, can be consumed by cattle, which makes it an attractive product for India's dairy industry (Mahajan et al., 2007). In another study, Sharma and Banik (2013) found that intercropping of baby corn and legumes can improve soil health and reduce the use of weedicide.[2] Finally, sustainable production of minor crops, like baby corn, is vital for human health, nutritional food supplies, and food security as well as for national economies (Lamichhane et al., 2015).

Baby corn is becoming popular in domestic and foreign markets and has processing and export potential. Joshi et al. (2005) concluded that changing food preferences would cause demand for quality protein maize like baby corn to increase rapidly. Producers and consumers would benefit from the development of institutional arrangements such as contract farming (CF) to strengthen production-marketing-processing linkages. The Government of India has also been introducing policy reforms to promote private-sector agribusiness growth through CF. CF plays a crucial role in farming practices, quality, and competitiveness, not least because farmers benefit from risk assurances in price, marketing, and other production factors when selling their products, which improves income stability (Baumann, 2000). Additionally, in the context of sustainable agriculture, many smallholders, researchers, and policy makers in India are interested in self-sustaining, low-input, energy-efficient agricultural systems.[3]

The goal of this study is to estimate the impact of CF on technology, technical efficiency (TE), and farm performance indicators among baby corn farmers. We aim to determine technology, TE, and managerial gaps and other farm performance variables between contract and independent baby corn farmers controlling for biases from observables and unobservables. Specifically, the study uses unmatched and matched samples to estimate conventional and sample-selection correction stochastic production frontiers (SPF) models. We then use the estimates from the sample-selection corrected SPF models to conduct a metafrontier analysis on TE, technology and managerial gaps between adopters and nonadopters. Finally, we evaluate the effects of CF on farm performance variables, namely profits, marketing costs, prices, and input used. The study uses a farm-level survey of smallholders in two Indian states, Punjab and Haryana, which have been at the forefront of the Green Revolution but now face significant productivity, crop choice, and soil and environmental problems.

A plethora of studies have investigated the issue of productivity and technical efficiency in developing countries (e.g., Sharif and Dar, 1996; Rahman, Schmitz, and Wronka, 1999; Wadud and White, 2000; Coelli, Rahman, and Thirtle, 2002). Similarly, a couple of studies (Bravo-Ureta, Greene, and Solís, 2012; Villano et al., 2015) have investigated the impact of program participation

[1] Baby corn is a short-duration crop of 50–70 days during the Kharif growing season (July to October). Two crops of baby corn can be cultivated in a year after wheat, adding to the income of smallholders and providing a better substitute for rice in the rice–wheat cropping system, thus maintaining good soil health.

[2] Intercropping is a way to increase diversity in an agricultural ecosystem. Intercropping not only enhances productivity but also provides security against the potential risks of monoculture (Lithourgidis et al., 2011).

[3] According to Flora (1992), sustainable agriculture encompasses a set of dynamic practices and technologies that provide stable agricultural income but cause minimal damage to the environment (e.g., contamination of water, water table and soil salinity issues).

on technical efficiency using the sample-selection correction stochastic frontier approach proposed by Greene (2010). However, only Mishra et al. (2018b) has corrected for selection bias to investigate the impact of contract farming on the technical efficiency of Nepalese farmers. To best of our knowledge, no study has investigated the effects of CF on technology and managerial gaps.

This study contributes to the literature on several fronts. First, the study estimates the impact of CF on productivity by correcting for self-selection into CF by smallholders. Second, the study separates the effects of technology and managerial gaps on the productivity of baby corn producers in India. Third, the study evaluates the impact of CF on farm performance measures such as prices received, profitability, and marketing and fertilizer expenses. Fertilizer usage is directly linked to groundwater contamination and soil degradation. If private market interventions, like CF, can increase or maintain yields and simultaneously decrease fertilizer usage, it bodes well for farmers and policy makers and provides environmental benefits for society.[4] We use the framework proposed by Villano et al. (2015) to estimate technology and managerial gaps. Specifically, we use the metatechnology ratio and metafrontier approach to compare technology and managerial gaps between contracted and independent farmers.

Background

High-yielding crops, irrigation water, and the use of chemical fertilizers have significantly increased India's output of rice and wheat and have made India a food-secure nation (Singh and Sidhu, 2004). The increased production has resulted in higher incomes for Indian farmers who specialize in rice and wheat crops, especially in Punjab and Haryana—the epicenter of the Green Revolution. Conventionally, rice and wheat crops are water-, capital- and energy-intensive and have adversely affected natural resources as a result. Recent data reveal that yield growth has declined by about 2.7% per year and yield stagnation, a declining underground water table, soil degradation and atmospheric pollution have made rice–wheat cropping systems unsustainable (Bhatt et al., 2016).[5]

Maize—specifically, baby corn—has economic benefits. For instance, Dass et al. (2008) found that farmers in India earned about Rs. 50,000–60,000[6] per year (about $658–$790 per year) through the cultivation of two to three crops of baby corn. A baby corn crop also afforded farmers about 100 quintals/acre per crop of nutritious fodder (Dass et al., 2008). Additionally, the authors note that green fodder, a by-product of baby corn, has the potential to enhance milk production by 15%–20%. In the peri-urban region, particularly around highly populated cities, baby corn has emerged as a good source of income for farmers within two months of sowing, along with good-quality green fodder (Chaudhary et al., 2016). Finally, increased demand for baby corn, changing food habits and improved economic status (Kumar et al., 2012) give baby corn producers the potential to earn higher profits. Even though baby corn production in India is likely to have multiple economic and environmental benefits, including reduced use of water and chemical fertilizer, relative to water-intensive rice crops, the literature falls short in quantifying the reduction in either irrigation or fertilizer costs. This study intends to fill this gap.

With looming budget deficits, loss of agricultural productivity, and increased food security goals, the Government of India's National Agriculture Policy has encouraged private-sector investments through contract farming (CF).[7] CF can help accelerate technology transfer, secure capital inflow, and ensure markets for crop production, especially for high-value horticultural crops like baby

[4] Aldy, Hrubovcak, and Vasavada (1998) and Ruttan (2002) point out that market failure constrains the development of more sustainable practices. Society underinvests in more sustainable agricultural practices.

[5] Declining diversity in crops, resulting from an overuse of natural resources and ecology, is a reason for the deceleration in agricultural growth (Singh and Sidhu, 2004).

[6] The exchange rate at the time of survey was 1 U.S. dollar = 66 Indian rupees (Rs.).

[7] Contract farming is a system for producing and supplying agricultural/horticultural produce under forward contracts between producers/suppliers and buyers. Different variants have different names, such as the centralized model (a company–farmer arrangement) and out-grower schemes (a government/public sector/joint venture). CF varies depending on the nature and type of contracting agency, the technology used, the nature of the crop/produce and the local and national context.

corn. CF may also reduce cultivation costs, as it can provide access to better inputs and more efficient production methods. CF benefits smallholders by reducing production and marketing risks (Allen and Lueck, 1995) by providing inputs, access to credit, and technical assistance. Through CF, contractors or corporations can overcome land size constraints and achieve reliability and consistency in production (Eaton and Shepherd, 2001). CF is common in developed countries, principally driven by concerns about food safety and quality (Otsuka, Nakano, and Takahashi, 2016).

The role and impact of CF in developing countries have prompted extensive debate (see Masakure and Henson, 2005; Simmons, Winters, and Patrick, 2005; Oya, 2012; Prowse, 2012). Most of the empirical literature on the topic investigates two primary aspects of CF: (i) drivers of CF participation and (ii) the impact of CF on farms and households. The literature on how CF affects economic well-being (e.g., income, profits, yields) in many developing countries presents a mixed picture, with both successes and failures (see Glover, 1984; Goldsmith, 1985; Glover and Kusterer, 1990; Little and Watts, 1994; Morvaridi, 1995; Porter and Phillips-Howard, 1997; Baumann, 2000; Key and Runsten, 1999; Opondo, 2000; Simmons, Winters, and Patrick, 2005). Researchers have studied the impact of CF on income and employment (see Glover, 1984; Goldsmith, 1985; Glover and Kusterer, 1990; Key and Runsten, 1999) and found that CF helps improve farmers' income and generate employment for poor rural workers (Singh, 2002; Warning and Key, 2002; Birthal, Joshi, and Gulati, 2005; Simmons, Winters, and Patrick, 2005; Tripathi, Singh, and Singh, 2005; Ramaswami, Birthal, and Joshi, 2006; Leung, Sethboonsarng, and Stefan, 2008; Miyata, Minot, and Hu, 2009; Xu and Wang, 2009; Kalamkar, 2012; Wainaina, Okello, and Nzuma, 2012; Michelson, 2013).

Evidence of the impact of CF in India is also mixed. A set of Indian studies has found that contract producers earned almost three times the profits of independent producers owing to higher yields and assured output prices (see Dileep, Grover, and Rai, 2002; Birthal, Joshi, and Gulati, 2005; Dev and Rao, 2005; Tripathi, Singh, and Singh, 2005; Kumar, 2006; Ramaswami, Birthal, and Joshi, 2006; Kumar and Kumar K., 2008; Nagaraj et al., 2008; Kalamkar, 2012). Contrary to popular belief, studies have found that CF in labor-intensive and that perishable crops generated more employment. These studies include examinations of gherkin cultivation in India (Dev and Rao, 2005; Kumar and Kumar K., 2008; Nagaraj et al., 2008), tomato cultivation in Punjab (Dileep, Grover, and Rai, 2002; Singh, 2002) and milk production in Punjab and Rajasthan (Birthal, Joshi, and Gulati, 2005; Birthal et al., 2008).

Despite these findings, researchers have found that CF can have a negative impact on the environment, farmer welfare, and the power structure between contractors and farmers (see Little and Watts, 1994; Morvaridi, 1995; Key and Runsten, 1999; Opondo, 2000; Singh, 2002). For instance, Little and Watts (1994) disputed the positive welfare impacts of CF on the income of beneficiaries; Singh (2002) highlighted the exploitative nature of CF—namely, the monopsonistic power of CF companies. Similarly, Key and Runsten (1999) argued that rural inequalities in income are a negative outcome of CF.

In assessing the impact of CF on productivity, a recent study by Mishra et al. (2018a) found that CF among Nepalese farmers increased the TE by 7% among rice seed farmers and by 8% among ginger farmers. The authors used self-selection-corrected SPF to estimate the empirical model. However, the study did not address the issue of technology and managerial gaps between contracted and independent farmers. The present study departs from the above literature by quantifying the impact of CF on productivity, technology, and managerial gaps and farm performance (profits and costs savings) and fertilizer usage—those having a negative impact on the environment (water and salinity).

Conceptual Framework

In this study, we use the three-step framework introduced by Villano et al. (2015). The first step uses matching methods to form comparable treatment and control groups based on observables. Recall that the current study uses a cross-sectional and nonexperimental data. The second step estimates standard stochastic frontier models using the pooled sample as well as the control and treatment subsamples. To correct for sample-selection bias arising from unobservable characteristics such as managerial ability, the study estimates the stochastic frontier model with correction for sample-selection bias for both control and treatment groups (Greene, 2010). The final step uses the stochastic frontier results to estimate a metafrontier to compare the technology and technical efficiency (TE) gaps for treatment and control groups (O'Donnell, Rao, and Battese, 2008). The steps are described below.

In the first step, we use Stata to implement propensity score matching (PSM) to generate treatment and control groups to control for bias from observables. We use a probit model to estimate the probability that a farmer chooses to participate in CF to grow baby corn. Then, a matching algorithm uses the probit model scores to construct treatment and control groups. The matching aims to construct treatment and control groups with statistically similar means. Provided that there are no biases from unobservables, the PSM can estimate the effect of CF on technology gaps, technical efficiency, and farm performance variables (i.e., output prices, profits, and input usage).

In the second step, we use Nlogit to estimate stochastic production frontiers (SPFs) and TE scores. Initially, we use estimate standard stochastic frontier models given by

$$y_i = \beta' \boldsymbol{x}_i + v_i - u_i, \tag{1}$$

where $\boldsymbol{x}_i$ is a vector of inputs, v_i is a normally distributed error representing the stochastic frontier, and u_i is a technical inefficiency component following a half-normal distribution (Aigner, Lovell, and Schmidt, 1977). The estimations with the matched and unmatched samples are used to test whether the production functions follow Cobb–Douglas or translog technology specifications and whether the contract and independent farmers use different technologies. Then, we estimate the Greene (2010) stochastic frontier model with correction for sample selection. This method corrects for biases stemming from unobservable characteristics. Greene's sample-selection SPF model consists of a blend of conventional SPF (Aigner, Lovell, and Schmidt, 1977) and Heckman's (1976) sample-selection model. The sample-selection correction SPF model is described by the following equations:

$$\begin{aligned}
&\text{Sample selection: } d_i^k = 1[\alpha^{k'} \boldsymbol{z}_i + w_i^k > 0], w_i^k \sim N[0,1] \\
&\text{SPF: } y_i^k = \beta^{k' \boldsymbol{x}_i^k} + \varepsilon_i^k \sim N\left[0, \sigma_{k,\varepsilon}^2\right] \\
&\left(y_i^k, \boldsymbol{x}_i^k\right) \text{ observed only when } d_i^k = 1 \\
&\text{Error structure: } \varepsilon_i^k = v_i^k - u_i^k \\
&u_i^k = \left|\sigma_{k,u} U_i^k\right| = \sigma_{k,u}\left|U_i^k\right|, \text{ where } U_i^k \sim N[0,1] \\
&v_i^k = \sigma_{k,v} V_i^k, \text{ where } V_i^k \sim N[0,1] \\
&\left(w_i^k, v_i^k\right) \sim N_2\left[(0,1), \left(1, \rho\sigma_{k,v}, \sigma_{k,v}^2\right)\right]
\end{aligned} \tag{2}$$

The sample-selection equation is the probit model that farmer i participates in CF or independent, where $k = 0$ and $k = 1$ represent independent farmers and contract farmers, respectively. $\boldsymbol{z}_i$ is a vector of observable characteristics. The SPF consists of deterministic and stochastic ingredients represented by $\beta^{k'} \boldsymbol{x}_i^k$ and ε_i^k, respectively, where $\boldsymbol{x}_i^k$ is a vector of observable inputs. The error term, ε_i^k, consists of two parts, the stochastic component of the frontier, v_i^k, and the parameter capturing inefficiencies, u_i^k. TE scores are defined as

$$TE_i^k = \mathrm{e}^{-u_i^k} \tag{3}$$

and obtained using the method proposed by Jondrow et al. (1982). The absence or presence of selectivity bias is captured by the parameter ρ, as it scales the covariance between the errors of the stochastic frontier and the selection equation. In particular, failing to reject the null hypothesis that $\rho = 0$ suggests the absence of selection bias due to unobservables. Conversely, rejecting that $\rho = 0$ is evidence of selectivity bias.

Finally, in the third step, we use Matlab to construct a metafrontier enveloping the production frontiers of the control and treatment groups to compare technology and managerial gaps of contracted and independent baby corn growers. Following O'Donnell, Rao, and Battese (2008), we estimate the metafrontier by solving the following problem:

$$\min_{\beta^*} \beta^{*'} \bar{\boldsymbol{x}}, \tag{4}$$

such that $\beta^{*'} \boldsymbol{x}_i^k \geq \beta^{k'} \boldsymbol{x}_i^k$ for all k and i, where $\bar{\boldsymbol{x}}$ is the arithmetic average of the $\boldsymbol{x}_i^k$ vectors. With the solution to the problem, the output can be written as

$$y_i = e^{-U_i^k} \times \frac{e^{x_i' \beta^k}}{e^{x_i' \beta^*}} \times e^{x_i' \beta^* + V_i^k}. \tag{5}$$

The authors define the second component of the righthand side of the expression as the metatechnology ratio (MTR):

$$\text{MTR}_i^k = \frac{e^{x_i' \beta^k}}{e^{x_i' \beta^*}}. \tag{6}$$

In this study, we use the MTR to measure technology gaps, with higher MTRs representing more productive technologies. Thereafter, we use the predictors of TE_i^k and MTR_i^k to estimate the TE score with respect to the metafrontier, defined as the TE–metafrontier:

$$\widehat{\text{TE}}_i = \widehat{\text{TE}}_i^k \widehat{\text{MTR}}_i^k. \tag{7}$$

In this study, we measure technology and managerial gaps using the differences in MTR and TE–metafrontier between contracted and independent baby corn producers, respectively.

Empirical Framework

Table 1 reports the variables used to implement the PSM, consisting of household and farm characteristics. Following the probit specifications of Villano et al. (2015) and Bravo-Ureta, Greene, and Solís (2012), we select the demographic characteristics of age, schooling, and farming experience of the household head. Additionally, the study includes an indicator variable equal to 1 if the household head is risk loving, and 0 otherwise.[8] We also include dummy variables representing smallholders' affiliation to co-operatives, access to credit from co-operatives, and extension visits to the farm from agricultural organizations. The variable of own land (in acres) serves as a measure of the wealth of the household. The indicator variable equal to 1 if the smallholder household owns one or more diesel engines, and 0 otherwise, serves as a proxy for the farm's capital stock. Table 2 provides descriptive statistics of the variables used in the empirical model. On average, independent corn growers are more experienced in farming and are less likely to own diesel engines compared to smallholders with contracts.

[8] Following Charness, Gneezy, and Imas (2013), we construct a measure of risk preferences. We present six gambles in increasing order of risk to the respondents. The first option is a sure pay-off of Rs. 30, while the sixth and riskiest gamble pays Rs. 80 if a coin toss results in heads and Rs. 0 if the outcome is tails. If a respondent chooses the fifth or sixth riskiest gambles, we classify them as risk loving. For more details, see Mishra et al. (2018a).

Table 1. Description of Variables Used in the Propensity Score Matching and Stochastic Production Frontier (SPF) Models

Variable	Notation	Definition
Probit		
Age	Z_1	Years of age of household head (HH)
Schooling	Z_2	Years of education by the household head
Experience	Z_3	Years of experience by the household head
Risk loving	Z_4	=1 if household head is risk lover, 0 otherwise
Extension visits	Z_5	=1 if household was visited by extension workers of agricultural organizations, 0 otherwise
Cooperative affiliation	Z_6	=1 if a member of the HH is affiliated with a co-operative, 0 otherwise
Cooperative credit access	Z_7	=1 if HH has access to credit from a co-operative, 0 otherwise
Own land	Z_9	Land owned (acres)
Distance to Thana	Z_{10}	Distance to Thana or police station (km)
Distance to village leader	Z_{11}	Distance to house of village leader (km)
Diesel engine	Z_{12}	=1 if household owns one or more diesel engines, 0 otherwise.
SPF model		
Output	Y	Total baby corn production (KG)—Dependent variable
Area	X_1	Total baby corn area planted in acres
Labor	X_2	Total labor used in baby corn production (worker-days)
Seed	X_3	Seed used (kg)
Fertilizer	X_4	Total kilograms of urea, DAP, and other chemical fertilizer (kg)
Cow dung	D_1	=1 if applied cow dung or green manure, 0 otherwise
Contract farming	CF	=1 if engaged in contract farming, 0 otherwise

The PSM approach uses matching criteria to construct treatment and control groups. Column 1 of Table 3 shows the estimates of the probit model. Results reveal that age has a positive impact on the likelihood of participation in CF. In contrast, schooling, experience, being risk loving, and owning diesel engines have a negative and significant impact on the probability of participation CF. Table 3 also shows the selection equations of the matched and unmatched samples. The models have similarities, as we observe that the signs of the coefficients are equal for both estimations, but there are two key differences between them. First, the matched sample model displays fewer statistically significant coefficients, as only the age, schooling, and experience coefficients remain statistically significant. And second, the hypothesis that all coefficients are simultaneously 0 is rejected by the unmatched model but not the matched estimation. These two differences are consistent with the reduction in the variability of the sample characteristics induced by the PSM.

Figure 1 plots the densities of the propensity scores of contracted and independent baby corn producers. We employ the nearest-neighbor matching with a caliper of $0.25\sigma_p$[9] pairing a maximum of five independent farmers per contract farmer over the common support. Matching with a larger number of neighbors decreases the variance, as more precise matches are constructed, but increases the bias, as the differences between propensity scores potentially increase (Caliendo and Kopeinig, 2008). To mitigate the bias, we use a caliper with a size based on Cochran and Rubin's (1973) simulation results.

The matched sample consists of 120 farms, with 59 adopters and 61 nonadopters. We excluded 17 farmers from the unmatched sample to form the matched sample. We compare the means of variables of treatment and control groups to evaluate whether the matching satisfies the balancing property of the covariates (Bravo-Ureta, Greene, and Solís, 2012; Villano et al., 2015). Table 4

[9] σ_p is defined as $\sqrt{(\sigma_0^2 + \sigma_1^2)/2}$, where σ_0 and σ_1 are the standard deviations of the estimated propensity scores for the control and treatment groups, respectively.

Table 2. Descriptive Statistics of Unmatched Sample

	Pooled		Adopters		Nonadopters		Difference in Means
	Mean	SD	Mean	SD	Mean	SD	Mean
Probit							
Age	49.8	11.9	50.3	12.3	49.4	11.6	0.98
Schooling	9.8	3.4	9.3	3.4	10.2	3.4	−0.91
Experience	21.2	12.3	19.1	10.7	22.9	13.2	−3.74*
Risk loving	0.2	0.4	0.1	0.3	0.2	0.4	−0.10
Extension visits	0.6	0.7	0.5	0.7	0.6	0.7	−0.12
Cooperative affiliation	0.2	0.4	0.2	0.4	0.1	0.4	0.09
Cooperative credit	0.7	0.5	0.8	0.4	0.6	0.5	0.11
Own land (acres)	3.5	3.8	3.0	2.5	3.8	4.6	−0.80
Dist. to Thana (km)	0.2	0.9	0.3	1.1	0.2	0.8	0.11
Dist. to village leader (km)	0.4	0.2	0.4	0.2	0.4	0.2	−0.01
Diesel engine	0.1	0.3	0.1	0.3	0.2	0.4	−0.13**
SFA							
Output	8,849.8	6,929.4	7,797.9	6,831.4	9,669.5	6,938.4	−1,871.56
Area	8.6	6.6	7.4	6.4	9.5	6.7	−2.08*
Labor	246.5	226.9	195.2	163.1	286.5	260.3	−91.25**
Seed	85.4	66.8	75.6	65.4	93.1	67.2	−17.49
Fertilizer	2,002.1	1,636.4	1,681.5	1,553.6	2,251.9	1,665.4	−570.39**
Cow dung	0.2	0.4	0.2	0.4	0.2	0.4	0.01
No. of obs.	137		60		77		137

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

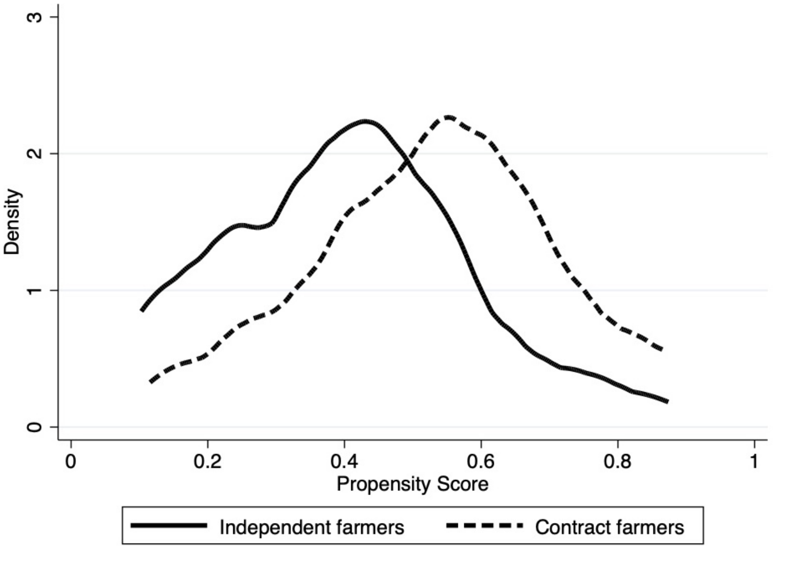

Figure 1. Densities of Propensity Scores

Table 3. Parameter Estimates of the Propensity Score Matching (PSM) and Stochastic Frontier Analysis (SFA) Probit-Selection Equations

	Unmatched Sample (PSM and SFA) 1		Matched Sample (SFA) 2	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Contract farming				
Age	0.03**	0.01	0.02*	0.01
Schooling	−0.07*	0.04	−0.06*	0.04
Experience	−0.04***	0.01	−0.04**	0.01
Risk loving	−0.57*	0.32	−0.47	0.33
Extension visits	−0.07	0.18	−0.11	0.19
Cooperative affiliation	0.43	0.32	0.39	0.33
Cooperative credit access	0.37	0.27	0.29	0.28
Own land (acres)	−0.04	0.03	−0.03	0.04
Distance to Thana (km)	0.13	0.12	0.11	0.12
Distance to village leader (km)	0.29	0.66	0.34	0.66
Diesel engine	−0.66*	0.40	−0.27	0.48
Constant	−0.29	0.72	−0.07	0.74
No. of obs.	137		120	
Log likelihood	−80.87		−76.01	
χ^2	26.06		14.30	
p-value	0.01		0.22	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

reports that the means of the observable household and farm characteristics are not statistically different from 0, providing evidence that the balancing property is satisfied. We use the data from the matched and unmatched samples to select the specification of the selection and SPF equations. The equation describing the decision to engage in CF in baby corn is specified as

$$d_i^k = \alpha_0 + \sum_{j=1}^{11} \alpha_i^k z_{j,i} + w_i^k. \tag{8}$$

Using the likelihood ratio test, we evaluate whether the specification of the stochastic frontier model is Cobb–Douglas or translog. The null hypothesis of the test states that the production technology follows a Cobb–Douglas specification, a function nested by the translog model. Table 5 shows that the null hypothesis for both the unmatched and matched samples is rejected. In other words, in our study, the production frontiers of baby corn producers in India are represented by a translog function. The production frontiers are estimated using the following specification:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j \ln X_{ij} + \sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} \ln X_{ij} \ln X_{ik} + D_1 + CF + v_i - u_i, \tag{9}$$

where the dependent variable is the logarithm of baby corn production (in kilograms), while covariates consist of baby corn planted area, total labor, seeds used, fertilizer, a dummy variable equal to 1 if the farmer used cow dung and 0 otherwise, and an indicator variable equal to 1 if the farmer participates in CF and 0 otherwise. The bottom row of Table 5 shows the results of the likelihood ratio test with the null hypothesis that the functional forms do not vary between contract and independent baby corn growers. The likelihood ratio test indicates that independent and contract baby corn growers use different technologies in both the matched and unmatched samples, supporting the estimation of separate models when conducting the metafrontier analysis in this study.

Table 4. Descriptive Statistics of Matched Sample

	Pooled		Adopters		Nonadopters		Difference in Means
	Mean	SD	Mean	SD	Mean	SD	Mean
Probit							
Age	49.9	12.0	50.1	12.2	49.7	11.8	0.38
Schooling	9.9	3.4	9.5	3.2	10.2	3.6	−0.72
Experience	21.1	12.3	19.3	10.7	22.8	13.5	−3.43
Risk loving	0.2	0.4	0.1	0.3	0.2	0.4	−0.09
Extension visits	0.6	0.7	0.5	0.7	0.6	0.7	−0.10
Cooperative affiliation	0.2	0.4	0.2	0.4	0.1	0.4	0.07
Cooperative credit	0.7	0.5	0.7	0.4	0.7	0.5	0.06
Own land (acres)	3.0	3.4	2.9	2.3	3.2	4.2	−0.33
Dist. to Thana (km)	0.2	1.0	0.3	1.1	0.2	0.9	0.12
Dist. to village leader (km)	0.4	0.2	0.4	0.2	0.4	0.2	0.00
Diesel engine	0.1	0.3	0.1	0.3	0.1	0.3	−0.03
SFA							
Output	8,261.5	6,190.4	7,811.4	6,889.2	8,696.7	5,452.7	−885.28
Area	8.0	5.9	7.5	6.4	8.6	5.3	−1.14
Labor	222.1	183.9	196.0	164.4	247.3	199.0	−51.27
Seed	79.5	59.8	75.7	66.0	83.3	53.4	−7.62
Fertilizer	1,856.0	1,465.0	1,686.3	1,566.5	2,020.2	1,352.2	−333.98
Cow dung	0.2	0.4	0.2	0.4	0.2	0.4	−0.01
No. of obs.	120		59		61		120

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Table 5. Likelihood Ratio Tests for Functional Form for Production Function and between Matched and Unmatched Sample

	Unmatched Sample		Matched Sample	
Null Hypothesis	χ^2	*p*-Value	χ^2	*p*-Value
Functional form is Cobb–Douglas	30.226	0.001	19.230	0.037
Functional form does not vary across groups	26.330	0.069	26.761	0.062

Data

We analyze data from a primary survey of smallholder households producing baby corn, where some farmers engage in contract farming. The survey was conducted during March and April 2016 in the state of Haryana, India. Baby corn growers were chosen randomly from the Aterna village in the Sonipat district of Haryana. All contract farmers had formal contracts (marketing contracts) with the agribusiness firm Aterna Baby Corn Production and Marketing Cooperative Society Limited (ABCPMCSL).[10] The marketing contract allowed contracted baby corn farmers to sell their produce to the contracting firms at spot prices. Contracts were renewed every year.

The agribusiness firm ABCPMCSL does not provide any services, farm inputs, or credit to the contracting farmers, but farmers receive training-cum-consultation related to baby corn cultivation practices from the firm. The farmers must supply peeled baby corn to the firm to facilitate quality assessment by the firm before accepting produce. The firm accepts good-quality produce as per

[10] The ABCPMCSL, an agribusiness co-operative registered in 2009, is based in the Aterna village of Sonipat district in Haryana.

contract specification and rejects poor-quality produce. The farmers deliver the produce to the premises of the processing unit. They can bring any quantity of harvested produce daily. The contract farmers are assured of a minimum price of Rs. 50/kg for their produce. This price was based on the spot price of baby corn in the Azadpur Fruit and Vegetable Market in Delhi,[11] not far from the village. ABCPMCSL, the contracting firm, exports fresh baby corn to the United Kingdom and sells processed baby corn to hotels, restaurants, and corporations such as Del Monte, Holyland Group, and Birla Foods in India.

Results and Discussion

Stochastic Production Function Estimates

The results of the conventional SPFs for the unmatched and matched samples are presented in Tables 6 and 7, respectively.[12] Following standard practice in the literature, we normalize the input variables by their geometric mean to interpret the first-order coefficients as partial elasticities at the mean (see Bravo-Ureta, Greene, and Solís, 2012; Villano et al., 2015). Input elasticities are all positive but differ in magnitude. In all cases, farm size and seeds contribute most to the production of baby corn, followed by fertilizer. The coefficients of farm size (area in acres) have the largest partial elasticities in most models, suggesting that farms may use some nonland inputs in proportion to land availability. Interestingly, in the case of unmatched sample, all partial elasticities for adopters of CF, both in conventional and sample-selection SPF, are unitary ($=1.00$), revealing constant returns to scale. However, for independent farmers in both cases, the sum of partial elasticities is less than 1, indicating decreasing returns to scale. Our findings are consistent with those reported by Kalirajan (1991), Chavas, Petrie, and Roth (2005), González and Lopez (2007), Solís, Bravo-Ureta, and Quiroga (2009), and Bravo-Ureta, Greene, and Solís (2012) but in contrast to those reported by Mishra, Rezitis, and Tsionas (2019), who found that Nepalese farmers engaged in CF had decreasing returns to scale. The inefficiency components, λ, are statistically different from 0 in the models, indicating that inefficiency is associated with output loss for both contract and independent farmers.

Tables 6 and 7 report the results of the sample-selection correction models. The models are estimated for contract and independent farmers using matched and unmatched samples. We test the null hypothesis that the selectivity bias parameter, ρ, is equal to 0. Both the unmatched and matched models for adopters reject the null hypothesis, suggesting the presence of sample-selection bias in both samples. Our finding is consistent with several other empirical works that have found evidence of selection bias related to program participation or technology adoption (Rahman, Schmitz, and Wronka, 1999; Bravo-Ureta, Greene, and Solís, 2012; Villano et al., 2015; Mishra et al., 2018b). Additionally, the magnitude of the estimated coefficients is smaller in the selectivity-corrected SPF model than in the conventional SPF model. Tables 6 and 7 show that the inefficiency parameter, σ_u, is statistically significant in all models, suggesting that inefficiency is a driver in output loss for baby corn growers in India. The presence of selectivity bias suggests using the results from the sample-selection SPF models rather than the conventional models to carry out the metafrontier analysis.

Technical and Other Efficiency Estimates

Table 8 shows the descriptive statistics of the MTRs (equation 6) and TE–metafrontier (equation 7) stemming from the minimization problem in equation (4). For comparison purposes, we show the results for the metafrontier analysis with both the conventional and sample-selection models. As

[11] Azadpur Fruit and Vegetable Market in Delhi is Asia's largest wholesale market for fruits and vegetables. It is operated by the Agricultural Produce Marketing Committee, Azadpur, Delhi.

[12] The matched sample models are estimated using unweighted SPF estimators, as simulations with linear regressions suggest that incorporating the PSM weights may increase the bias of the estimates (Freedman and Berk, 2008).

Table 6. Maximum Likelihood Estimates of the Conventional and Sample-Selection Stochastic Production Frontier (SPF) Models Using the Unmatched Sample

			Conventional SPF		Sample-Selection SPF	
Variable	**Symbol**	**Pooled**	**Adopter**	**Nonadopter**	**Adopter**	**Nonadopter**
Constant	β_o	8.931***	8.944***	8.910***	9.010***	8.891***
Area	β_1	0.543***	0.538	0.401**	0.417	0.403*
Labor	β_2	0.042	0.138	0.021	0.132	0.021
Seeds	β_3	0.271*	0.252	0.389**	0.403	0.400*
Fertilizer	β_4	0.122**	0.078	0.145*	0.053	0.133
Area^2	β_{11}	−2.218**	−11.132***	−1.369	−11.498	−1.503
Labor^2	β_{22}	−0.049	0.025	−0.070	0.039	−0.056
Seeds^2	β_{33}	1.434***	−8.295	1.588**	−9.685	1.684
Fertilizer^2	β_{44}	0.030	−0.018	−0.023	−0.024	0.024
Area×Labor	β_{12}	0.308**	1.890	0.259*	2.060	0.251
Area×Seeds	β_{13}	0.563	9.348***	0.222	10.333	0.311
Area×Fertilizer	β_{14}	1.251**	−0.810	0.975	−1.621	1.063
Labor×Seeds	β_{23}	−0.412**	−1.822	−0.331*	−2.117	−0.356
Labor**Fertilizer*	β_{24}	0.052	−0.222	0.098	−0.143	0.127
Seeds×Fertilizer	β_{34}	−1.359*	1.275	−1.251	2.016	−1.432
Cowdung	D_1	0.059**	0.070*	0.036	0.049	0.036
Contract farming	*CF*	−0.006				
λ	λ	2.202***	1.571***	2.140***		
σ^2	σ^2	0.165***	0.141***	0.145***		
σ_u	σ_u				0.123**	0.131***
σ_v	σ_v				0.091**	0.064**
ρ	ρ				−0.806***	0.413
Log likelihood		107	69.22	50.94	10.18	30.76
No. of obs.		137	60	77	60	77

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

expected from the detection of selection bias, we find that correcting for selection bias has noticeable consequences for the estimates. The signs and magnitudes of the effects of CF on MTR and TE–metafrontier change after correcting for selection bias. Therefore, we focus our attention on the last panel of Table 8. After correcting for sample-selection bias, the TE of contracted baby corn growers is significantly higher (93%) than that of independent growers (90%). Findings indicate that TE without correcting for sample-selection bias overestimates inefficiency for contract farmers. Table 8 shows that CF has a positive and statistically significant effect on technology gaps and managerial gaps, as shown by the last three rows of Table 8. Specifically, findings reveal that CF in baby corn increases the MTR by 5% and the TE–metafrontier by 7%. In other words, both the technology and managerial gaps favor contract farmers in baby corn over independent baby corn farmers.

The effect of CF on the TE–metafrontier is larger than the effect on the MTR because contract farmers are technically more efficient relative to their own-group frontier than independent farmers. This is plausible because one of the cornerstones of CF is technology transfer and technical assistance. In our case, findings show that the technical support provided by the agribusiness firms—contractors—to contract farmers translates to more efficient agricultural production practices. These findings underscore the importance of vertical coordination activities, such as CF, in increasing technical efficiency, productivity, and transfer of knowledge to smallholders in developing countries.

Table 7. Maximum Likelihood Estimates of the Conventional and Sample-Selection Stochastic Production Frontier (SPF) Models Using the Matched Sample

			Conventional SPF		Sample-Selection SPF	
Variable	**Symbol**	**Pooled**	**Adopter**	**Nonadopter**	**Adopter**	**Nonadopter**
Constant	β_o	8.939***	8.949***	8.920***	9.021***	8.902***
Area	β_1	0.505***	0.556	0.420**	0.430	0.440
Labor	β_2	0.055	0.117	0.005	0.080	0.010
Seeds	β_3	0.315*	0.267	0.297	0.456	0.280
Fertilizer	β_4	0.097	0.067	0.223**	0.034	0.214*
Area^2	β_{11}	−2.597*	−11.196***	−1.288	−11.509	−1.482
Labor^2	β_{22}	−0.094	0.008	−0.102	−0.013	−0.086
Seeds^2	β_{33}	1.544***	−8.582	1.115	−10.707	1.094
Fertilizer^2	β_{44}	−0.003	−0.020	−0.201	−0.028	−0.201
Area×Labor	β_{12}	0.516**	1.697	0.269*	1.672	0.271
Area×Seeds	β_{13}	0.346	9.601***	0.289	10.947*	0.392
Area×Fertilizer	β_{14}	1.485**	−0.803	1.021	−1.863	1.132
Labor×Seeds	β_{23}	−0.305	−1.694	−0.314*	−1.803	−0.344
Labor×Fertilizer	β_{24}	−0.169	−0.164	0.145	−0.064	0.156
Seeds×Fertilizer	β_{34}	−1.301	1.207	−1.133	2.179	−1.232
Cowdung	D_1	0.073***	0.069	0.042	0.046	0.047
Contract farming	CF	−0.019				
λ	λ	2.132***	1.659***	2.530***		
σ^2	σ^2	0.160***	0.144***	0.147***		
σ_u	σ_u				0.117*	0.142***
σ_v	σ_v				0.105**	0.055*
ρ	ρ				−0.893***	0.560
Log likelihood		92.90	49.70	56.58	13.10	19.05
No. of obs.		120	59	61	59	61

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Other Farm Performance Outcomes

Table 9 presents the impact of CF on outcome variables of interest—including the price of output, profits, and fertilizer and marketing costs—after controlling for observables. The comparison of means between the treatment and control groups of the matched sample finds that CF has no impact on yield. However, results show that CF increases the use of seeds and decreases expenditures on fertilizer and marketing costs. In the case of seeds—a technology imparted by the contracting firms—estimates in Table 9 show that contracted baby corn producers use 3% more seeds per acre than their counterpart. Our finding is consistent with studies in the literature (Little and Watts, 1994; Porter and Phillips-Howard, 1997; Singh, 2002; Casaburi, Kremer, and Mullainathan, 2016; Mishra et al., 2018b,a) arguing that CF increases income and input usage. Results show that CF smallholders producing baby corn spend less on fertilizer. This effect is driven by the fact that contract farmers tend to apply less fertilizer per acre (220 kg/acre) compared to independent baby corn producers (236 kg/acre).[13] Reducing chemical fertilizer use may deaccelerate environmental degradation without compromising yield (Singh, 2002; Ladha, Pathak, and Gupta, 2007).[14]

An interesting finding is the significant effect of CF on marketing expenditures. Findings in Table 9 show that CF decreases marketing expenditures (per acre) of smallholders engaged in baby

[13] Since we are using cross-sectional data, one can assume that both types of farmers are facing same prices of fertilizer.
[14] The average baby corn yield is about 1,041 kg/acre and 1,050 kg/acre for contracted and independent baby corn growers, respectively. The difference is statistically insignificant.

Table 8. Effects of Contract Farming on Technical Efficiency (TE), Technology and Managerial Gaps among Baby Corn Producers in India

	Adopters		Nonadopters		Difference in Means
	Mean	SD	Mean	SD	Mean
Unmatched sample					
Conventional stochastic production frontiers (SPF)					
TE	0.91	0.05	0.90	0.06	0.01
Metatechnology ratio (MTR)	0.93	0.07	0.94	0.04	−0.02*
TE–metafrontier	0.84	0.08	0.85	0.06	−0.01
Sample-selection SPF					
TE	0.92	0.04	0.90	0.05	0.01*
MTR	0.94	0.07	0.89	0.05	0.05***
TE–metafrontier	0.86	0.08	0.80	0.07	0.06***
Matched sample					
Conventional SPF					
TE	0.91	0.05	0.90	0.06	0.01
MTR	0.92	0.07	0.96	0.03	−0.03***
TE–metafrontier	0.84	0.08	0.86	0.07	−0.02
Sample-selection SPF					
TE	0.93	0.04	0.90	0.06	0.03***
MTR	0.95	0.06	0.91	0.06	0.05***
TE–metafrontier	0.89	0.06	0.81	0.08	0.07***

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Table 9. Average Treatment Effects after Controlling for Observables

	Pooled		Adopters		Nonadopters		Difference in Means
	Mean	SD	Mean	SD	Mean	SD	Mean
Yield (kg/acre)	1,040.0	148.6	1,042.2	142.1	1,037.8	155.7	4.5
Seeds used (kg/acre)	10.0	1.0	10.1	0.6	9.8	1.3	0.3*
Fertilizer expenditures (Rs./acre)	2,390.6	528.3	2,285.6	483.6	2,492.3	553.3	−206.7**
Marketing expenditures (Rs./acre)[a]	4,746.6	3,181.6	2,541.8	2,341.8	6,879.2	2,317.7	−4,337.4***
Price of baby corn (Rs./kg)	55.6	4.8	54.0	4.3	57.1	4.7	−3.1***
Profits (Rs./acre)b[b]	28,214.0	9,348.3	30,661.7	10,592.4	25,846.6	7,299.1	4,815.1***
No. of obs.	120	59	61				

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Exchange rate at the time of survey was 1 U.S. dollar = 66 Indian rupees (Rs.).
[a]Marketing expenditure do not include total wages paid for marketing labor, which are statistically not different for adopters and nonadopters.
[b]Our definition of profits does not include the expenses of renting leased-in land.

corn production. Specifically, results in Table 9 reveal that contracted baby corn farmers spend about 63% less on marketing than independent producers. Our finding is consistent with Birthal, Joshi, and Gulati (2005), who found that contract farmers in high-value crops in India increased gross margins primarily due to lower total production and marketing costs. We also find that contract farmers receive lower prices for their output than independent producers, which may explain why risk-loving farmers are less likely to engage in CF.[15]

The lower expenditures on fertilizer and marketing more than compensate for losses stemming from lower output prices. Findings in Table 9 show that contracted baby corn producers received lower output prices, about 3 Rs./kg less, relative to independent baby corn growers. In other words, the price received by contracted baby corn growers was 5% lower than that received by independent growers. Our finding is in contrast with Makki and Somwaru (2001), Sivramkrishna and Jyotishi (2008), Huh and Lall (2013), and Saenger et al. (2013), who argued that price premiums stimulate producers to partake in contractual agreements.[16] However, contracted producers' profits were significantly higher (18.6%) than those reported by independent producers.[17] The finding that contract farming is associated with higher profits is consistent with the literature about the effects of contract farming in developing economies (see Wang, Wang, and Delgado, 2014; Mishra et al., 2018a).

Conclusions and Policy Implications

Once the champion of the Green Revolution, India has experienced falling productivity in rice and wheat, overexploitation of natural resources, and lower incomes for smallholders (Sidhu and Byerlee, 1992). Over the past 2 decades, groundwater tables have declined at an alarming rate of about 23 cm/year in the Indian states of Punjab and Haryana, the epicenter of the Green Revolution. Farmers in these states have sought other crops to increase income and secure their livelihoods. Adding value to traditional maize, "specialty corn" has recently been popularized and cultivated by large numbers of farmers. Baby corn, a "specialty corn" crop, has potential in both domestic and international markets because of its high value for nutrition, industrial use, and cattle fodder. Using farm-level data on baby corn producers from the states of Punjab and Haryana in India, this study used an innovative framework that combined sample-selection corrected stochastic production frontier (SPF) and PSM method to measure technical efficiency and separate the technology and managerial gaps. Additionally, it investigated how contract farming (CF) has affected farm performance.

Results revealed that technological efficiency (TE) is higher for contracted farmers than for the control group. The study identified the presence of selectivity bias and found significant differences in technological and managerial gaps between contracted and independent baby corn producers. Specifically, the gaps between contracted baby corn producers and independent producers seemed to be more noticeable after accounting for selection bias. Moreover, findings from this study reveal that, compared to independent baby corn farmers, baby corn CF producers with contracts received a lower price for their produce (5% lower) but garnered higher profits (about 19% higher). Contracted baby corn CF growers also spent less on marketing (63%) and fertilizer compared to independent baby corn growers. Fertilizer costs were comparatively lower for contracted baby corn farmers (by about Rs. 207/acre) than for independent baby corn producers. One can surmise that reduced fertilizer

[15] Similarly, Mishra, Rezitis, and Tsionas (2019) found that risk-averse producers are more likely to engage in contract farming.

[16] Also, Warning and Key (2002) found that the contracting firm offered a higher contracted peanut price than the market price for Senegalese peanut farmers.

[17] We do not include the expenses of renting leased-in land to calculate the profits per acre, as our data show the total rental costs of leased-in land but not the rental payments for leased-in land dedicated to baby corn farming. About 30 farms in our matched sample pay rent for leased-in land; excluding them from the mean profit calculations does not affect this result.

expenditures translated to less use of fertilizer, which is environmentally beneficial for farmers, overall soil health, and general public well-being.

Contract farming in baby corn production may be a suitable replacement for rice cultivation in high-stress areas like Punjab and Haryana. Findings from this study show that markets can be used to ensure the benefit of more sustainable agricultural practices (e.g., lower usage of fertilizers and pesticides). The findings are particularly relevant to policy makers in designing incentives for the effective adoption of CF in baby corn production with potential impacts on productivity, efficiency, and marketing and fertilizer costs. Public policies, especially in a developing country like India, can play a major role in helping smallholders adopt CF. CF can provide smallholders with the transfer of technology, credit and extension services, and links to international markets. This research identifies the extent to which smallholders, including those involved in CF, are more productive, efficient, and profitable than independent producers. Smallholders that participate in CF are better positioned to address the issue of agricultural sustainability without compromising yield or income stability.

[First submitted August 2020; accepted for publication November 2020.]

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