Contract Farming, Productivity and Fertilizer Usage
Empirical Evidence from Specialty Crop Production

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ABSTRACT

This study investigates the impact of contract farming (CF) in baby corn production on yield, irrigation costs, fertilizer costs and usage of chemical fertilizer. We find that adoption of CF by baby corn smallholders, after controlling for characteristics of both control and treatment groups, leads to higher yields and lower spending on fertilizers and irrigation. Additionally, CF in baby corn farming leads to a reduction in the use of chemical fertilizers (Urea and DAP). Thus, CF intervention benefits the livelihood of smallholders, reduces environmental degradation and reduces stress on groundwater without compromising yield.

**Keyword:** Contract farming, fertilizer usage, marginal mean weighting through stratification (MMWS), water usage

**JEL codes:** C21, Q12, Q5
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# ACRONYMS

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>CF</td>
<td>Contract Farming</td>
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<td>DAP</td>
<td>Diammonium Phosphate</td>
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<td>DR-MMWS</td>
<td>Doubly Robust Marginal Mean Weighting through Stratification</td>
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<td>IPTW</td>
<td>Inverse Probability of Treatment Weighting</td>
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<td>MMWS</td>
<td>Marginal Mean Weighting through Stratification</td>
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<tr>
<td>OLS</td>
<td>Ordinary Least Squares</td>
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<td>PSM</td>
<td>Propensity Score Matching</td>
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<td>PSW</td>
<td>Propensity Score Weighting</td>
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<td>RA</td>
<td>Regression Adjusted</td>
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1. Introduction

The Green Revolution 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 in farmland holdings. However, after five decades of overusing water, electricity, subsidized fertilizer and pesticides, farmers in the northwestern states face significant declines in growth rates of agricultural productivity. For example, in one assessment, agricultural productivity growth rates declined from 5.1% in 1981–82 to 2.4% in 2013–14 in Punjab and from about 4% in 1981–82 to 2.5% in 2013–14 in Haryana (Binswanger-Mkhize and D’Souza 2015). In this assessment, agricultural growth rates were significantly lower for Punjab and Haryana than for a majority of other states. The declining growth rates have been attributed to limited expansion of cropped areas and lower productivity of major crops (Chand et al. 2007). Additionally, Feola and Binder (2010) argue that unsustainable cropping practices are causing water shortages, soil erosion, increased soil salinity and ecosystem damage in marginal areas of the developing world.

The Green Revolution introduced high-yielding varieties of rice and wheat to the developing world. It also introduced modern agricultural technologies, including new irrigation technologies and heavy doses of chemical fertilizer (Binswanger et al. 1993; Saifi and Drake 2008). In India, farmers in major grain-producing states, including Punjab and Haryana, adopted rice-wheat crop rotation. Because rice and wheat 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 et al. 2008). Removal of nutrients has adversely impacted both rice and wheat yields in
Punjab (Government of Punjab 2012). Vagneron (2007) also notes that chemical fertilizers may lead to surface and groundwater pollution (e.g., through run-off and leaching), and the discharge of saline water into rivers and watersheds could further increase farmland soil salinity and destroy crops (Sharpley et al. 2001).

As a result, farmers in Punjab and Haryana are adopting maize as an alternative crop for income and livelihood security (Gulati et al. 2017; Bhatt et al. 2016). An interesting recent development is that of growing maize for vegetable purposes (Dass et al. 2008). Adding value to the traditional maize, niche crops of ‘specialty corn’ recently have been popularized and cultivated by large numbers of farmers (Parihar et al. 2011). Urbanization, rising incomes and greater interest in convenience foods are increasing consumer demands for certain kinds of specialty corn (Yadav et al. 2014). One such specialty corn product is baby corn. Many common sweet corn and field corn cultivars can be used to grow baby corn. 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 income level 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 baby corn and its tremendous potential for improving the income and livelihood of smallholders in India, especially in regions (Punjab and Haryana) facing environmental degradation. Baby corn provides income from direct sales within two months of

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1 Baby corn is a short-duration crop of 50 to 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.
sowing, (Chaudhary *et al.* 2012). 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\(^2\) of baby corn and legumes can improve soil health and reduce the use of weedicide. Finally, as noted by Lamichhane *et al.* (2015), 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.

Baby corn is becoming popular in domestic and foreign markets and has enormous processing and export potential. Joshi *et al.* (2005) concluded that with changing food preferences, demand for quality protein maize like baby corn will increase rapidly, and that 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 also has 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 policymakers in India are interested in self-sustaining, low-input, energy-efficient agricultural systems.\(^3\)

This study will assess the impact of CF on the productivity, irrigation costs and fertilizer costs involved in growing baby corn. Additionally, it will investigate how CF affects farmers’

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\(^2\) Intercropping is a way to increase diversity in an agricultural ecosystem. Intercropping not only enhances the productivity but also provides security against the potential risk 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).
use of chemical fertilizers, specifically urea and DAP (diammonium phosphate). Unlike previous studies, it uses reweighting estimators—in this case, the inverse probability of treatment weighting (IPTW) and doubly robust marginal mean weighting through stratification (DR-MMWS) methods—to evaluate the treatment effects of CF on outcome variables. IPTW matching is preferred for small sample sizes and control groups. DR-MMWS overcomes any misspecification of the functional form, propensity score and outcome models. The study data are from a farm-level survey of smallholders in two Indian states, Punjab and Haryana, which have been on the forefront of the Green Revolution but now face significant productivity, soil and environmental problems.

This study contributes to the literature on several fronts. It investigates the effects of CF on both outcome variables and fertilizer usage. Fertilizer usage is directly linked to groundwater contamination and soil degradation. If private market intervention, like CF, can increase yield and at the same time decrease both irrigation costs and fertilizer usage, it bodes well for farmers and policymakers and provides environmental benefits for society at large. This assessment also use propensity score weighting matching to account for all observations and to match the control and treatment groups. This method overcomes the problems of a lack of common support and of the large sample required in the propensity score method.

The rest of this paper is organized into five sections. Section 2 covers background information on the crisis in northwestern Indian agriculture and examines the advantages of

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4 Urea, a white crystalline solid containing 46% nitrogen, is a widely used animal feed additive and fertilizer. DAP is the world’s most widely used phosphorus fertilizer, with a relatively high nutrient content and excellent physical properties that make it popular in farming and other industries.

5 A potential drawback of the propensity scores when used for matching is that a large number of subjects may be needed, especially in the control group.

6 We also compare the estimates obtained from IPTW and DR-MMWS with regression adjusted (RA) and marginal mean weighting (MMW) methods.

7 As Aldy et al. (1998) and Ruttan (1994) point out, market failure constrains the development of more sustainable practices. Society underinvests in more sustainable agricultural practices.
maize cultivation and maize-wheat cropping patterns. Section 3 describes the methodology. Section 4 describes survey data. Section 5 covers the evaluation approach used for the study and results and discussion, and the final section provides the study’s key findings and discusses policy recommendations.

2. Background

High-yielding seed varieties, 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 output has resulted in higher incomes for Indian farmers who specialize in rice and wheat crops, especially in Punjab and Haryana—the epicentre of the Green Revolution (Binswanger-Mkhize and D’Souza 2015). Conventionally, rice and wheat crops have been water-, capital- and energy-intensive, and as a result have adversely affected natural resources. Recent data reveal that yield growth\(^8\) 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). Another issue facing Indian farmers is the excessive use of chemical fertilizers. One-third of farmers in areas dominated by rice and wheat crops apply an average of 180 kilograms per hectare (kg/ha) of nitrogen fertilizer to each of the rice and wheat crops combined, compared to the recommended dosage of about 120 kg/ha (Ladha et al. 2008). These actions have led to increased soil salinity, leaching of nitrates into the groundwater, reduced water quality and compromised drinking water (Bhatt et al. 2016; Singh et al. 2010).

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\(^8\) Declining diversity in crops, resulting from an overuse of natural resources and ecological, is reasons for the deceleration in agricultural growth (Singh and Sidhu 2004).
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\(^9\) 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 byproduct 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. 2012). 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. Yet even though baby corn production in India is likely to have multiple benefits, both economic and environmental,\(^{10}\) the literature falls short in quantifying either the reduction in irrigation and fertilizer costs or the reduction in chemical fertilizer usage. This study intends to fill this gap.

With looming budget deficits, loss in agricultural productivity and increased food security goals, the Government of India’s National Agriculture Policy has encouraged private sector investments through contract farming (CF).\(^{11}\) CF can help accelerate technology transfer, secure capital inflow and ensure markets for crop production, especially for high-value horticultural crops like baby 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

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\(^9\) Exchange rate at the time of survey was 1$US=66 Indian rupees (Rs.).

\(^{10}\) Reduction in usage of water and chemical fertilizer, compared to water-intensive rice crop (Sharma and Banik 2013).

\(^{11}\) Contract farming is a system for producing and supplying agricultural/horticultural produce under forward contracts between producers/suppliers and buyers. It has different names for different variants, such as the centralized model (a company-farmer arrangement) and outgrower 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.
production and marketing risks (Allen and Lueck 1995) through the provision of 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 et al. 2016). The role and impact of CF in developing countries has prompted extensive debate (see Masakure and Henson 2005; Simmons et al. 2005; Oya 2012; Prowse 2012). Most of the empirical literature on the topic investigates two primary aspects of CF: (1) drivers of CF participation, and (2) 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 depicts a mixed picture with both successes and failures (see Little and Watts 1994; Opondo 2000; Morvaridi 1995; Baumann 2000; Key and Rusten 1999; Glover and Kusterer 1990; Goldsmith 1985; Glover 1984; Simmons et al. 2005; Porter and Howard 1997). Researchers have studied the impact of CF on income and employment (see Glover and Kusterer 1990; Key and Rusten 1999; Goldsmith 1985; Glover 1984) and found that CF helps to improve the income of farmers and to generate employment for poor rural workers (Wainaina et al. 2012; Kalamkar 2012; Ramaswami et al. 2006; Tripathi et al. 2005; Birthal et al. 2005; Singh 2002; Warning and Key 2002; Leung et al. 2008; Bellemare 2012; Michelson 2013; Miyata et al. 2009; Xu and Wang 2009; Zhu 2007; Simmons et al. 2005). Evidence of the impact of CF in India is also mixed. A set of Indian studies—see Dev and Rao (2005), Nagraj et al. (2008), Kumar and Kumar (2008), Ramaswami et al. (2006), Tripathi et al. (2005), Birthal et al. (2005), Kalamkar (2012), Kumar (2006), and Dileep et al. (2002)—found that contract producers earned almost three times the profits of independent producers owing to higher yields and assured output prices. Contrary to popular belief, studies have found that CF in labour-intensive and
perishable crops generated more employment. These studies include examinations of gherkin cultivation in India (Dev and Rao 2005; Nagaraj et al. 2008; Kumar and Kumar, 2008), tomato cultivation in Punjab (Singh 2002; Dileep et al. 2002) and milk production in Punjab and Rajasthan (Birthal et al. 2005; Birthal et al. 2008). Nevertheless, researchers have found that CF can have a negative impact on the environment, the welfare of farmers, and the power structure between contractors and farmers (see Singh 2002; Opondo 2000; Key and Runsten 1999; Morvaridi 1995; Little and Watts 1994). For instance, Little and Watts (1994) dispute the positive welfare impact of CF on the income of beneficiaries, and Singh (2002) highlights the exploitative nature of CF—namely, the monopsonistic power of CF companies. Similarly, Key and Runsten (1999) attribute rural inequalities in income to be a negative outcome of CF. They argue that contracting firms that make decisions on production and land management overlook the long-term land and environmental impact. The present study departs from the above literature by quantifying the impact of CF on both farm performance (productivity and costs savings) and input usage—those having a negative impact on the environment (water and salinity).

3. Conceptual and empirical framework

3.1. CF adoption decision

Consider a risk neutral smallholder facing a binary choice to choose whether or not to adopt CF for baby corn production. The adoption decision-making process, considering the impact of CF on farm productivity, other outcome variables (irrigation costs, fertilizer costs) and urea and DAP usage, can be modelled in a simple optimization framework. The smallholder will evaluate the net welfare associated with adoption and non-adoption of CF. The difference between the net benefit of adoption and non-adoption may be given as $NBCF^*$, such that $NBCF^* > 0$ indicating that the
net benefits from adoption of CF exceed those of non-adoption. Although $CF_{NB}$ is not observable, it can be expressed as a function of observable factors in the following latent variable model:

$$CF_{NB} = \beta \Phi_i + \zeta_i, \quad CF_{NB} = I(CF_{NB} > 0) \tag{1}$$

where $CF_{NB}$ is a binary variable, with 1 for a smallholder farmer who adopted CF and 0 otherwise; $\beta$ is a vector of parameters to be estimated; $\Phi_i$ is a vector of farm, operator, household and other local attributes; and $\zeta_i$ is an error term assumed to be normally distributed.

Therefore, the probability of adoption of CF can be represented as:

$$\Pr(CF_{NB} = 1) = \Pr(CF_{NB} > 0) = \Pr(\zeta_i < -\beta \Phi_i) = 1 - F(-\beta \Phi_i) \tag{2}$$

where $F$ is the cumulative distribution function for $\zeta_i$. Recall that the adoption of CF is expected to affect the demand for inputs such as fertilizer and pesticides, productivity and net returns. To link the decision to adopt or not adopt CF for baby corn with potential outcomes, such as net profits, assume that smallholder maximizes net returns (profits), $\pi$, subject to competitive input and output markets, and a single-output technology that is quasi-concave in the vector of variable inputs, $VI$, and can be expressed as:

$$\max \pi = PQ(I, \Phi) - \omega I, \tag{3}$$

where $P$ is the output price and $Q$ is expected output level; $\omega$ is a column of input prices including fertilizer; $I$ is a vector of input; and $\Phi$ is a vector of farm, operator, household and other local attributes. From Equation 3, one may conclude that $\pi$, a function of variable inputs, output prices, smallholder, farm and household attributes, can have net returns expressed as:

$$\pi = \pi(CF_{NB}, \omega, P, \Phi). \tag{4}$$
Using Hotelling’s lemma in Equation 4 yields a reduced-form equation for input demand and output supply:

\[ \omega = \omega(CF_{NB}, I, P, \Phi) \]  \hspace{1cm} (5)  
\[ Q = Q(CF_{NB}, I, P, \Phi) \]  \hspace{1cm} (6) 

Equations 4 through 6 indicate that CF inputs and outprices, as well as farm, operator and household characteristics, tend to influence net returns, demand for inputs and farm-level productivity.

3.2 Outcome impact evaluation and selection bias

As stated earlier, the study objective is to investigate the extent and degree to which CF adoption affects smallholders’ outcomes—farm productivity (yield) of baby corn, costs (irrigation and fertilizer) and amount of chemical fertilizer (Urea and DAP). The vector of outcomes is a linear function of a vector of smallholder and household attributes, and the outcome variables can be expressed as:

\[ Y_i = \Phi_i \alpha + CF_{NB} \lambda + \vartheta_i \]  \hspace{1cm} (7) 

where \( Y_i \) represents a vector of outcome variables; \( \Phi_i \) is a vector of farm, smallholder and household attributes (e.g., age and education of smallholders, household size, risk preferences); \( CF_{NB} \) is an indicator of a smallholder’s adoption of CF status; \( \vartheta_i \) is a random error term; and \( \alpha \) and \( \lambda \) are vectors of parameters to be estimated. To elicit risk preferences for farmers, several questions on farmers’ perception about their willingness to take risk were asked based-on a Likert scale; the risk preference elicitation approach using hypothetical payoff matrix and games were also employed. For example, farmers’ perceptions on risks related to quality of produce, weather, pests & insects were rated on a Likert scale; and their subjective risk aversion capacity was tested through questions like whether they loved to take risk and to what extent.
Recall that in impact evaluation, only certain smallholder attributes can be observed. Unobserved attributes, such as innate technical skills, social networking connections or managerial abilities, are known only to the smallholder. Therefore, a potential selection bias arises where implicit factors $\theta$ in the outcome of Equation (7) affect $\zeta$ in Equation (1); as a result, ordinary least squares (OLS) would yield bias estimates. Random control trials are necessary to evaluate programs and policies. However, it is difficult to conduct random control trials. Instead, researchers use quasi-experimental data and ensure that both control and treatment groups can be compared as closely as possible (Linden 2014). To this end, approaches such as matching, stratification and weighting (Stuart 2010; Austin 2007; Sturmer et al. 2006) are used to evaluate impacts. Economists often use propensity score matching (PSM) to evaluate the impacts of technology adoption and market interventions on household welfare. However, PSM suffers from the so-called curse of dimensionality, meaning that it is difficult to find matches unless the dataset is large. PSM also suffers from lack of common support (Caliendo and Kopeinig 2005), which may bias results (Linden et al. 2016). Finally, PSM requires large sample sizes, since a significant amount of data that cannot be matched may be wasted. This problem becomes important when the sample size is small.

If a significant number of treated subjects are excluded from the assessment, the results may be biased (Austin 2013). Moreover, the treatment effect’s internal consistency and generalisability may be compromised if individuals are dropped from the treatment group, particularly when the sample size is small. This issue is resolved by using the propensity score weighting (PSW) technique. In the PSW technique, no individual is excluded from the analysis, which avoids compromising the statistical power of assessing the treatment effect (Stone and Tang 2013). Impact elevation studies commonly use two particular weighting techniques: the
inverse probability treatment weighting (IPTW) and the marginal mean weighting stratification (MMWS). The IPTW method standardizes the treatment groups to the population for which the treatment is intended (Rubin et al. 2000; Rosenbaum 1987). In IPTW, the treated individuals receive a weight equal to the inverse of the estimated propensity score; non-treated individuals, by contrast, receive a weight of the inverse of the 1 minus the estimated propensity score.

Several studies, such as Wooldridge (2010), Bang and Robins (2005), and Linden (2017) found that an extended ‘doubly robust’ method of the IPTW works well for program and policy elevations. The doubly robust-IPTW method utilizes IPTW and covariates within the same outcome model. In case of the doubly robust-IPTW estimator, the propensity score model to the outcome model is correctly specified.

The MMWS is a more robust approach that combines stratification and weighting methods. It has been used for health policy studies, epidemiology and medical care. The MMWS method takes the investigative sample, stratifies it into quantiles of propensity scores, and then assigns all members of the study population a weight corresponding to each stratum and treatment assignment (Linden 2014, 2017). The MMWS method is preferred because it is more flexible and can be applied to a broad range of experimental conditions, including binary, ordinal and nominal treatments (Hong 2010, 2012). The IPTW method tends to introduce additional bias when only a portion of the population provides support for causal inference, whereas the MMWS avoids this problem (Hong 2010). MMWS tends to provide more robustness compared to IPTW because of its non-parametric approach, which usually provides a better approximation of non-linear relationships between treatment assignment and pre-treatment covariates (Hong 2010). Therefore, considering the drawbacks of the PSM method and a small treatment group, this study
compares IPTW and MMWS estimates with DR-MMWS with regression adjusted (RA) and marginal mean weighting (MMW) methods.

3.3 Model Specification

Assume that K units are drawn from a large population. For each \( i, i=1,\ldots, K \) in the sample \((Y_i, T_i, \Phi_i)\) is observed. \( Y_i \) is the outcome variable; \( T_i \) is the treatment variable \((T_i)\), which takes integer values between 0 and 1 in the binary treatment case; and \( \Phi_i \) is the set of pre-treatment covariates. According to Imbens (2000), if the pre-treatment differences are adjusted, the issue of deriving causal inferences could be solved. This is overcome by the formulation of unconfoundedness. Let \( D_a(T_a) \) represent the indicator of receiving the treatment \( t \):

\[
D_a = \begin{cases} 
1, & \text{if } T_i = t \\
0, & \text{otherwise}
\end{cases}
\]

(8)

The potential set of outcomes for each individual is represented by \((Y_{0i}, Y_{1i})\). The potential outcome for each individual \( i \) is represented by \( Y_{it} \), for which \( T_i = t \) where \( t \in \{0,1\} \). However, only one potential outcome is observed depending on the status of the treatment (Linden et al. 2016). The observed outcome \( Y_i \) could be specified in terms of treatment indicator \( D_a(T_a) \) and the potential outcomes \( Y_{it} \) as:

\[
Y_i = D_{0i}(T_{0i})Y_{0i} + D_{1i}(T_{1i})Y_{1i}
\]

(9)

Therefore, individual-level treatment effects of treatment level 0 versus 1 could be represented by \( Y_{0i} - Y_{1i} \), or the differences of potential outcomes. The population average treatment effect is obtained by taking differences of the means of these two potential outcomes (Linden et al. 2016):

\[
\Delta_{i1} = E[Y_{0i} - Y_{1i}] = \mu_0 - \mu_1
\]

(10)

In a quasi-experimental setting, the estimation of \( \Delta_{it} \) requires additional conditioning on \( \Phi_i \), which is assumed to contain all confounders with the treatment assignment process and the
potential outcomes. By conditioning on $\Phi_i$, we assume that the treatment assignment is randomly assigned, as in the randomized experimental design. The conditional expectation of the potential outcome for treatment $t$ is identified by the conditional expectation of the observed outcome of an individual receiving the treatment (Imbens and Woolridge 2009).

$$
E[Y_i|\Phi_i] = E[Y_i|D_n(T_i) = 1, \Phi_i] = E[Y_i|D_n(T_i) = 1, \Phi_i]
$$

$$
= E[Y_i|T_i = t, \Phi_i]
$$

(9)

Thereafter, averages of these conditional means are calculated to derive the average outcome (Imbens 2000). In the binary treatment case, Rosenbaum and Rubin (1983) define the propensity score as the conditional probability of receiving treatment given pre-treatment covariates, implying that instead of having to adjust for all pre-treatment covariates, it is sufficient to adjust the propensity score $e(t, \phi)$. Specifically,

$$
e(t, \phi) = Pr[T_i = 1|\Phi_i = \phi] = E[D_n(T_i) = 1|\Phi_i = \phi]
$$

(10)

Following Imbens (2000), the mean for the potential outcomes can be obtained by weighting observed outcomes by the conditional probability of receiving the treatment actually received, defined as:

$$
E\left[\frac{Y_iD_n(T_i)}{e(t, \Phi_i)}\right] = E(Y_i)
$$

(11)

This can be used to estimate the average causal effect $E[(Y_{it} - (Y_{it}))]$. In the case of IPTW, the treatment effect estimator based on the normalized weights, Equation 11, can be specified as:

$$
\hat{\tau}_{ml}^{\text{IPTW}} = \frac{\sum_{i=1}^{n} Y_iD_m(T_i)}{\sum_{i=1}^{n} \hat{e}(m, \Phi_i)} - \frac{\sum_{i=1}^{n} Y_iD_l(T_i)}{\sum_{i=1}^{n} \hat{e}(l, \Phi_i)}
$$

(12)

where $m$ and $l$ denote the treated and non-treated (or control) groups.
The MMWS approach includes the following steps: (1) estimate propensity score by either a logistic or a probit model; (2) stratify the propensity scores into equally sized quantile categories—five categories (Rosenbaum and Rubin 1984) usually removes 90% of the selection bias—and then (3) construct marginal mean weights for individuals using the following formula:

$$MMWS = \frac{n_s \times \hat{P}_r(T = t)}{n_{T=1,s}}$$

(13)

where \( \hat{P}_r(T = t) \) represents the estimated probability of being assigned to the treatment group \( t \); \( n_s \) is the number of individuals in \( s \), which is obtained from the estimated probability treatment level \( t \); and \( n_{T=1,s} \) is the total number of individuals in stratum \( s \) who actually were assigned to treatment group \( t \), (Linden et al. 2016). The unconditional mean is estimated by:

$$\mu_{MMWS} = \frac{\sum_{i=1}^{K} \Delta_{MMWS,i,T,D}(t)}{\sum_{i=1}^{K} \Delta_{MMWS,i,D}(t)}$$

(14)

The average treatment effect can be estimated by contrasting estimated potential outcome means between any two treatment levels. The estimation of equations 12 and 14 and other estimators can be performed using a STATA package.

4. Data

This study is based on a primary survey of smallholder households. The survey was conducted during March and April 2016 in the states of Punjab and Haryana of the Indian subcontinent. We surveyed 76 contract baby corn farmers and 84 independent baby corn farmers. All contract farmers had formal contracts with two different agribusiness firms, namely Aterna Baby Corn Production and Marketing Cooperative Society Limited (ABCPMCSL) and Field Fresh Foods Private Limited. The ABCPMCSL is an agribusiness cooperative firm, registered in 2009 and
based in the Aterna village of Sonipat district in Haryana. The ABCPMCSL has three processing units for baby corn and other commodities like tomatoes, mushroom and sweet corn. The contract between ABCPMCSL and farmers was a marketing contract; in other words, farmers would be able to sell their produce to the firm but would have to sell it at spot prices. The contract farmers were assured that their produce would be purchased at a minimum price of Rs. 50 per kg. The contract price of baby corn was based on the spot price of baby corn in the Azad Pur Fruit and Vegetable Market in Delhi, not far from the village. ABCPMCSL did not provide any services, farm inputs or credit to the contracting farmers. But, farmers received training-cum-consultation pertaining to cultivation practices of baby corn from the firm. The farmers had to supply peeled baby corn to the firm to facilitate quality assessment by firm before accepting produce. The firm accepted good quality of produce as per contract specification and rejected the poor quality. The farmers delivered the produce to the premises of the processing unit. They could bring any quantity of harvested produce daily. ABCPMCSL, the contracting firm, exported fresh baby corn produce to the United Kingdom and sold processed baby corn in India to the hotel and restaurant industry and to corporations like Del Monte, Holyland Group and Birla foods. Contracts were renewed every year. 64 of the sample contract farmers contracted with the ABCPMCSL. The Field Fresh Foods Private Limited (FFFPL), another contracting firm, is a private corporate firm established in 2004 in Punjab. The contract between FFFPL and farmers included an input contract, besides the marketing contract. The firm provided baby corn seeds for cultivation to the farmers and gave them training on good cultivation practices – from sowing to harvesting. The cost of seed was adjusted in the payment received by farmer on delivery of produce. The firm received unpeeled baby corn from the farmers at a fixed rate of Rs. 8 per kg (equivalent to price of Rs. 80 per kg for peeled baby corn). The overmatured baby corn was
removed by the firm before weighing the produce. The contractor assured farmers of the buyback of the produce. The farmers transported the produce from the fields to the firm’s premises on weekly basis and received payment. Contracts were renewed every year. 12 farmers in the sample contracted with FFFPL. The firm exported fresh baby corn to United Kingdom and other European countries. Independent baby corn growers were chosen randomly from Attena village in Rai block of Sonipat district of Haryana. The survey data collected included farm characteristics (farm size, asset ownership); household and farmer characteristics (age of the operator, household size, education, caste); cropping patterns; economics of cultivation (inputs, costs, yield and output price); marketing channels; risk behaviour; and information on distances to key infrastructures.

We consider baby corn farmers’ contracts with the two firms as one treatment, in our analysis. Both the contracts are formal contracts for purchase of fresh baby corn by firms for export to European countries as well as selling to domestic market in fresh and processed forms.

4.1. Comparison of contract and independent baby corn farmers

Table 4.1 represents the differences between the contract and independent baby corn farmers. There seems to be no statistical difference in age, education and caste status, and no significant difference in household size, access to credit, number of extension visits from government officials, labour costs, pesticide and weedicide costs and distances to roads and cooperatives. However, there are differences in farming experience, total land size cultivated, percentage of membership in a cooperative, cost of seed, availability of irrigation facility and risk preferences.

Contract baby corn farmers on average had 20 years of farming experience, while independent baby corn farmers had 23 years of experience (statistically significant at the 10% level). Contract baby corn farmers cultivated an average of about 21 acres, whereas independent
baby corn farmers cultivated an average of about 15 acres. Almost 28% of contract baby corn farmers had cooperative membership, compared to 14% of independent baby corn farmers.

Contract baby corn farmers also spent significantly less on seed compared to independent baby corn farmers, at the 1% level of significance. Almost 95% of contract baby corn farmers had irrigation available for the previous five years, compared to 84% for independent baby corn farmers, suggesting that having irrigation might be important criteria for being under contract.

Finally, a significantly lower proportion (11%) of contract baby corn farmers were not averse to taking risks, compared to about 23% of independent baby corn farmers—a difference statistically significant at the 10% level, suggesting that contract baby corn farmers are more risk averse.

Although almost 58% of the contract baby corn producers showed risk-averse behaviour, the proportion was lower (albeit not significantly) for independent baby corn farmers (48%).

Table 4.1: Descriptive statistics, all baby corn farmers with and without contracts, India

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total Sample</th>
<th>Smallholders with contract farming</th>
<th>Smallholders without contract farming</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (Std. Dev.)</td>
<td>Mean (Std. Dev.)</td>
<td>Mean (Std. Dev.)</td>
</tr>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yield (Kg/acre)</td>
<td>1330.06 (73.07)</td>
<td>1598.58*** (142.46)</td>
<td>1084.19 (34.24)</td>
</tr>
<tr>
<td>Cost of fertilizer (Rs./acre)</td>
<td>4516.19 (282.66)</td>
<td>4281.74 (345.88)</td>
<td>4728.32 (438.86)</td>
</tr>
<tr>
<td>Irrigation cost (Rs./acre)</td>
<td>2590.86 (115.10)</td>
<td>2659.38 (116.85)</td>
<td>2623.41 (81.83)</td>
</tr>
<tr>
<td>Urea a usage (Kg/acre)</td>
<td>177.46 (4.43)</td>
<td>164.19*** (51.7)</td>
<td>189.47 (6.79)</td>
</tr>
<tr>
<td>DAP b usage (Kg/acre)</td>
<td>51.81 (1.47)</td>
<td>49.17* (1.91)</td>
<td>54.19 (2.18)</td>
</tr>
<tr>
<td><strong>Explanatory Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age, household head (HH) (years)</td>
<td>50.33 (0.94)</td>
<td>50.64 (1.37)</td>
<td>50.06 (1.31)</td>
</tr>
<tr>
<td>Education, HH (years)</td>
<td>10.11 (0.27)</td>
<td>10.05 (0.41)</td>
<td>10.16 (0.37)</td>
</tr>
<tr>
<td>Scheduled Caste/Scheduled Tribes c (%)</td>
<td>96.25 (1.50)</td>
<td>97.36 (1.80)</td>
<td>95.23 (2.33)</td>
</tr>
<tr>
<td>General and Other Backward Castes d (%)</td>
<td>3.75 (1.50)</td>
<td>2.63 (1.84)</td>
<td>4.76 (2.33)</td>
</tr>
<tr>
<td>Variable</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Sample Size</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
<td>--------</td>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>Farming experience, HH (years)</td>
<td>21.36</td>
<td>19.61*</td>
<td>22.94</td>
</tr>
<tr>
<td>(0.96)</td>
<td>(1.25)</td>
<td>(1.42)</td>
<td></td>
</tr>
<tr>
<td>Total land cultivated (acres)</td>
<td>17.66</td>
<td>21.09*</td>
<td>14.56</td>
</tr>
<tr>
<td>(1.78)</td>
<td>(3.31)</td>
<td>(1.53)</td>
<td></td>
</tr>
<tr>
<td>Households size (Nos.)</td>
<td>6.94</td>
<td>6.56</td>
<td>7.28</td>
</tr>
<tr>
<td>(0.28)</td>
<td>(0.39)</td>
<td>(0.41)</td>
<td></td>
</tr>
<tr>
<td>Access to credit in past five years (%)</td>
<td>11.25</td>
<td>13.15</td>
<td>9.52</td>
</tr>
<tr>
<td>(2.50)</td>
<td>(3.90)</td>
<td>(3.22)</td>
<td></td>
</tr>
<tr>
<td>Member of a cooperative (%)</td>
<td>20.62</td>
<td>27.63**</td>
<td>14.28</td>
</tr>
<tr>
<td>(3.20)</td>
<td>(5.16)</td>
<td>(3.84)</td>
<td></td>
</tr>
<tr>
<td>Extension visits, govt. agents (Nos.)</td>
<td>71.87</td>
<td>77.63</td>
<td>66.67</td>
</tr>
<tr>
<td>(6.93)</td>
<td>(11.78)</td>
<td>(7.82)</td>
<td></td>
</tr>
<tr>
<td>Cost of labor (Rs./acre)</td>
<td>7,786.67</td>
<td>7,709.55</td>
<td>7,856.46</td>
</tr>
<tr>
<td>(411.54)</td>
<td>(463.12)</td>
<td>(665.23)</td>
<td></td>
</tr>
<tr>
<td>Cost of seed (Rs./acre)</td>
<td>4,746.57</td>
<td>4,578.19***</td>
<td>4,898.92</td>
</tr>
<tr>
<td>(83.54)</td>
<td>(144.37)</td>
<td>(88.53)</td>
<td></td>
</tr>
<tr>
<td>Cost of pesticide (Rs./acre)</td>
<td>793.64</td>
<td>727.37</td>
<td>853.59</td>
</tr>
<tr>
<td>(55.37)</td>
<td>(62.36)</td>
<td>(88.99)</td>
<td></td>
</tr>
<tr>
<td>Cost of weedicide (Rs./acre)</td>
<td>623.50</td>
<td>532.95</td>
<td>705.43</td>
</tr>
<tr>
<td>(88.23)</td>
<td>(51.39)</td>
<td>(161.48)</td>
<td></td>
</tr>
<tr>
<td>Irrigation available for past five years (%)</td>
<td>89.37</td>
<td>94.73**</td>
<td>84.52</td>
</tr>
<tr>
<td>(2.44)</td>
<td>(2.57)</td>
<td>(3.96)</td>
<td></td>
</tr>
<tr>
<td>Risk averse (%)</td>
<td>52.50</td>
<td>57.89</td>
<td>47.61</td>
</tr>
<tr>
<td>(3.96)</td>
<td>(5.70)</td>
<td>(5.48)</td>
<td></td>
</tr>
<tr>
<td>Risk neutral (%)</td>
<td>30.00</td>
<td>30.26</td>
<td>29.76</td>
</tr>
<tr>
<td>(3.63)</td>
<td>(5.30)</td>
<td>(5.01)</td>
<td></td>
</tr>
<tr>
<td>Risk loving (%)</td>
<td>17.50</td>
<td>11.84*</td>
<td>22.61</td>
</tr>
<tr>
<td>(3.01)</td>
<td>(3.73)</td>
<td>(4.59)</td>
<td></td>
</tr>
<tr>
<td>Distance to road (km)</td>
<td>0.47</td>
<td>0.40</td>
<td>0.54</td>
</tr>
<tr>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.09)</td>
<td></td>
</tr>
<tr>
<td>Distance to cooperative (km)</td>
<td>1.57</td>
<td>1.77</td>
<td>1.38</td>
</tr>
<tr>
<td>(0.20)</td>
<td>(0.41)</td>
<td>(0.13)</td>
<td></td>
</tr>
</tbody>
</table>

Source: IFPRI-India survey. Note: Indian rupee; exchange rate was USD1=Rs. 65 at the time of the survey.

a Urea, a white crystalline solid containing 46% nitrogen, is a widely used animal feed additive and fertilizer.
b DAP= Diammonium phosphate.
c Includes designated groups of historically disadvantaged indigenous people in India, as recognized in the Constitution of India. Since independence, the Scheduled Castes and Scheduled Tribes have been given Reservation status, guaranteeing political representation.
d Includes socially and educationally disadvantaged castes.

* Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.
5. Results and discussion

This section covers the evaluation approach, both pre-intervention and post-intervention, and then discusses results from the treatment effects model.

5.1. Evaluation approach

Table 5.1 and Table 5.2 show the unadjusted and adjusted characteristics of the contract and independent baby corn producers. Following Linden and Samuels (2013), we use the absolute standard mean difference to assess the balancing of the covariates. The absolute standard difference (Column 4, Table 5.1) is greater than zero, and 6 of the 18 covariates have values greater than the 0.25 cut-off limit proposed by Rubin (2001). The weighted characteristics for both treatment and control group variables (Table 5.2) are less than the 0.25 cut-off limit; in many cases, they are close to zero. Figures 5.1 and 5.2 also present graphical representations of the adjustment process. Figure 5.1 shows the mean differences (not absolute) from zero in the unadjusted case, while Figure 5.2 shows the mean differences (not absolute) from zero in the adjusted case. Note that in Figure 5.2 (adjusted), the mean differences have reduced considerably and are around zero.
Table 5.1: Unadjusted characteristics of treatment and control groups

<table>
<thead>
<tr>
<th>Variables</th>
<th>Treatment (N = 76)</th>
<th>Control (N = 84)</th>
<th>Abs. Standardized Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln_age, HH (years)</td>
<td>3.90</td>
<td>3.88</td>
<td>0.044</td>
</tr>
<tr>
<td>Ln_education, HH (years)</td>
<td>1.84</td>
<td>2.16</td>
<td>0.195</td>
</tr>
<tr>
<td>Farming experience, HH (years)</td>
<td>19.62</td>
<td>23.10</td>
<td>2.89</td>
</tr>
<tr>
<td>Ln_household size (Nos.)</td>
<td>1.77</td>
<td>1.89</td>
<td>0.261</td>
</tr>
<tr>
<td>Scheduled Caste/Scheduled Tribes</td>
<td>0.97</td>
<td>0.96</td>
<td>0.115</td>
</tr>
<tr>
<td>Ln_land, cultivated (acres)</td>
<td>2.38</td>
<td>2.33</td>
<td>0.030</td>
</tr>
<tr>
<td>Irrigation available for past five years</td>
<td>0.95</td>
<td>0.86</td>
<td>0.310</td>
</tr>
<tr>
<td>Access to credit in past five years</td>
<td>0.13</td>
<td>0.10</td>
<td>0.110</td>
</tr>
<tr>
<td>Member of cooperatives</td>
<td>0.28</td>
<td>0.14</td>
<td>0.325</td>
</tr>
<tr>
<td>Extension visits, govt. agents (Nos.)</td>
<td>0.78</td>
<td>0.66</td>
<td>0.128</td>
</tr>
<tr>
<td>Ln_cost of pesticide (Rs./acre)</td>
<td>5.91</td>
<td>6.45</td>
<td>0.270</td>
</tr>
<tr>
<td>Ln_cost of weedicide (Rs./acre)</td>
<td>3.82</td>
<td>4.66</td>
<td>0.178</td>
</tr>
<tr>
<td>Ln_cost of seed (Rs./acre)</td>
<td>8.35</td>
<td>8.46</td>
<td>0.248</td>
</tr>
<tr>
<td>Ln_cost of labour (Rs./acre)</td>
<td>8.35</td>
<td>7.08</td>
<td>0.319</td>
</tr>
<tr>
<td>Risk loving (=1 if operator likes taking risks; 0 otherwise)</td>
<td>0.12</td>
<td>0.23</td>
<td>0.293</td>
</tr>
<tr>
<td>Risk averse (=1 if operator dislikes taking risks; 0 otherwise)</td>
<td>0.58</td>
<td>0.47</td>
<td>0.218</td>
</tr>
<tr>
<td>Distance to cooperative (km)</td>
<td>1.78</td>
<td>1.40</td>
<td>0.142</td>
</tr>
<tr>
<td>Distance to road (km)</td>
<td>0.40</td>
<td>0.55</td>
<td>0.197</td>
</tr>
</tbody>
</table>

Source: IFPRI-India survey. Note: Indian rupee; exchange rate was USD1=Rs. 65 at the time of the survey.
## Table 5.2: Weighted characteristics of treatment and control groups

<table>
<thead>
<tr>
<th>Covariates</th>
<th>Treatment (N = 76)</th>
<th>Control (N = 84)</th>
<th>Absolute Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln_age HH (years)</td>
<td>3.90</td>
<td>3.87</td>
<td>0.089</td>
</tr>
<tr>
<td>Ln_education, HH (years)</td>
<td>1.84</td>
<td>2.09</td>
<td>0.153</td>
</tr>
<tr>
<td>Farming experience, HH (years)</td>
<td>19.62</td>
<td>19.19</td>
<td>0.036</td>
</tr>
<tr>
<td>Ln_household size (Nos.)</td>
<td>1.77</td>
<td>1.75</td>
<td>0.028</td>
</tr>
<tr>
<td>Scheduled Castes/Scheduled Tribes</td>
<td>0.97</td>
<td>0.93</td>
<td>0.190</td>
</tr>
<tr>
<td>Ln_land, cultivated (acres)</td>
<td>2.41</td>
<td>2.27</td>
<td>0.082</td>
</tr>
<tr>
<td>Irrigation available in past five years</td>
<td>0.95</td>
<td>0.94</td>
<td>0.022</td>
</tr>
<tr>
<td>Access to credit in past five years</td>
<td>0.13</td>
<td>0.11</td>
<td>0.059</td>
</tr>
<tr>
<td>Member of a cooperative</td>
<td>0.28</td>
<td>0.25</td>
<td>0.074</td>
</tr>
<tr>
<td>Extension visits, govt. agents (Nos.)</td>
<td>0.78</td>
<td>0.65</td>
<td>0.140</td>
</tr>
<tr>
<td>Ln_cost of pesticide (Rs./acre)</td>
<td>5.91</td>
<td>6.38</td>
<td>0.023</td>
</tr>
<tr>
<td>Ln_cost of weedicide (Rs./acre)</td>
<td>3.82</td>
<td>3.82</td>
<td>0.001</td>
</tr>
<tr>
<td>Ln_cost of seed (Rs./acre)</td>
<td>8.35</td>
<td>8.34</td>
<td>0.031</td>
</tr>
<tr>
<td>Ln_cost of labour (Rs./acre)</td>
<td>8.35</td>
<td>8.13</td>
<td>0.057</td>
</tr>
<tr>
<td>Risk loving (=1 if operator likes taking risks; 0 otherwise)</td>
<td>0.12</td>
<td>0.17</td>
<td>0.137</td>
</tr>
<tr>
<td>Risk averse (=1 if operator dislikes taking risks; 0 otherwise)</td>
<td>0.58</td>
<td>0.60</td>
<td>0.051</td>
</tr>
<tr>
<td>Distance to cooperative (km)</td>
<td>1.78</td>
<td>1.08</td>
<td>0.021</td>
</tr>
<tr>
<td>Distance to road (km)</td>
<td>0.40</td>
<td>0.40</td>
<td>0.002</td>
</tr>
</tbody>
</table>

*Source:* IFPRI-India survey. *Note:* Indian rupee; exchange rate was USD1=Rs. 65 at the time of the survey.
Figure 5.1: Unadjusted balance graph for characteristics

Source: IFPRI-India survey.

Figure 5.2: Weighted balance graph for characteristics

Source: IFPRI-India survey.
The above findings show that the two groups (contracted and independent baby corn farmers) with the listed covariates are comparable. Using these covariates, we performed a logistic regression with outcome variables of interest, such as yield (kg/acre), irrigation cost (Rs./acre), fertilizer cost (Rs./acre), urea usage (kg/acre) and DAP usage (kg/acre) as binary treatment variables for adoption of CF in baby corn farming. Following the Linden (2016) implementation of MMSW and DR-MMWS method, based on the estimated propensity scores, we divided the study sample into five strata. For each estimator, we calculated potential outcome means for the respective treatment group (contracted baby corn growers) and control group (independent baby corn growers). To arrive at the treatment effect, we performed a pairwise test. Finally, to assess the robustness of our findings, we also reported on and compared the estimates of the outcome variables using RA and DR-MMWS.

Table 5.3 shows the estimates of the treatment effects for respective outcome variables by each estimator. Column 1 reports estimates of treatment effects, and Columns 2, 3 and 4 report the estimates of yield, irrigation costs and fertilizer costs. Column 2 shows that baby corn producers with CF have significantly higher yields compared to the independent baby corn producers (average around 493 kg/acre). The DR-MMWS estimate is the highest of the estimators, with yield impact ranging from about 461 kg/acre in the RA estimator to about 508 kg/acre in DR-MMWS estimator. Interestingly, all estimates are significant at the 5% level. Table 5.3 reveals that, based on IPTW and MMWS estimates, baby corn producers with CF had higher yields (about 488 kg/acre) compared to the independent baby corn producers. However, with the DR-MMWS robust estimator, baby corn producers with CF had 4% higher yields (about 508 kg/acre). Findings suggest that baby corn growers with CF had significantly higher yields (between 488 and 508 Kg/acre) than independent baby corn growers. Indeed, CF in baby corn
production can increase yield. This finding is consistent with other studies in the literature (Otsuka et al. 2016), and also is consistent with Nagaraj et al. (2008). However, the estimates obtained from this study are much smaller (5 quintals/acre vs. 23 quintals/acre) than those reported by Nagaraj et al. (2008).

Looking at irrigation and fertilizer costs, baby corn growers with CF had significantly lower irrigation and fertilizer costs compared to independent baby corn producers. (Recall that the data used in this study are cross-sectional with almost static input prices.) The irrigation cost impact ranges from about Rs. 312/acre with the MMWS estimator to about Rs. 336/acre with the IPTW estimator.\textsuperscript{12} Interestingly, all estimates are significant at the 10\% or higher level of significance. Table 5.3, Column 3, reveals that under the DR-MMWS robust estimator, irrigation costs were significantly lower (about Rs. 320/acre) for baby corn producers with CF. As this is a cross-sectional study, and assuming that both types of farmers face the same input prices, one may conclude that CF uses significantly less water than independent baby corn production. This finding is consistent with field experiments (Humphreys et al. 2010; Jalota and Arora 2002; Sur et al. 1980; Bhatt et al. 2016) in the maize-wheat cropping system that found similarly lower water requirements. In this light, baby corn production could be more sustainable than the rice-wheat cropping system, which uses more water for rice growing. Table 5.3, Column 4, reports the impact of CF on fertilizer costs associated with baby corn production. CF reduced fertilizer costs within a range of Rs. −12,219/acre (DR-MMWS) to Rs. −14,827/acre (IPTW). Results suggest that baby corn farmers with CF have significantly lower fertilizer costs than independent baby corn producers. For instance, the IPTW estimator in Table 5.3, Column 4, shows that fertilizer costs were significantly lower, by about Rs. −14,827/acre, for baby corn farmers with

\textsuperscript{12} The average (IPTW, MMWS and DR-MMWS) irrigation cost reduction would be about Rs. 323/acre.
CF. These estimates were significant at the 5% level. Finally, Table 5.3, Column 4, reveals that under the DR-MMWS robust estimator, fertilizer costs were significantly lower (about Rs. –12,218/acre) for baby corn producers with CF. This finding is consistent with Chang et al. (2006), who found that Taiwanese rice producers with CF had lower expenditures on chemical fertilizer compared to independent Taiwanese rice growers.

Finally, we also estimated the impact of CF on fertilizer usage: the quantity of chemical fertilizer (urea and DAP) used by farmers. Table 5.3, Columns 5 and 6, report the impact of CF on the physical quantities of chemical fertilizer used in baby corn production. Baby corn producers with CF use about 38 kg/acre less urea (IPTW method) than independent baby corn producers. Based on the estimators used, the urea usage impact ranges from about 28 kg/acre [DR-MMWS] to about 41 kg/acre [MMWS]; all estimates are significant at the 1% level. Similarly, Table 5.3, Column 6, shows the impact of CF on the use of DAP, ranging from about 6 kg/acre (IPTW) to about 8 kg/acre (MMWS); all estimates are significant at the 10% level. We therefore found that baby corn producers with CF use about 6–7 kg/acre less DAP than independent baby corn producers. Indeed, findings here reinforce the notion that the reduction in fertilizer costs observed above may be driven primarily by a reduction in the quantity of chemical fertilizer (urea and DAP) used by contracted baby corn producers. These findings also suggest that CF can be used to incentivise farmers to reduce their use of chemical fertilizers.

Additionally, reductions in the total amount of chemical fertilizer (urea and DAP) used in the production of baby corn (and, by extension, other commodities) under contract could benefit the environment, increase soil health and reduce groundwater contamination.
Table 5.3: Estimated average treatment effects by estimator: yield, irrigation cost, fertilizer cost, urea and DAP usage

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Yield (kg/acre)</th>
<th>Irrigation cost (Rs./acre)</th>
<th>Fertilizer cost (Rs./acre)</th>
<th>Urea usage(^1) (kg/acre)</th>
<th>DAP(^2) usage (kg/acre)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RA(^3)</td>
<td>461.40***</td>
<td>-274.46**</td>
<td>-12,739.82**</td>
<td>-31.02***</td>
<td>-5.34*</td>
</tr>
<tr>
<td></td>
<td>(153.47)</td>
<td>(184.11)</td>
<td>(5,335.73)</td>
<td>(8.97)</td>
<td>(2.96)</td>
</tr>
<tr>
<td>IPTW(^4)</td>
<td>488.44***</td>
<td>-336.26**</td>
<td>-14,827.29**</td>
<td>-37.97***</td>
<td>-6.39*</td>
</tr>
<tr>
<td></td>
<td>(147.84)</td>
<td>(170.85)</td>
<td>(5,721.81)</td>
<td>(11.61)</td>
<td>(3.44)</td>
</tr>
<tr>
<td>MMWS(^5)</td>
<td>484.26***</td>
<td>-312.40*</td>
<td>-13,666.58**</td>
<td>-40.90***</td>
<td>-7.78*</td>
</tr>
<tr>
<td></td>
<td>(146.26)</td>
<td>(167.06)</td>
<td>(5,983.38)</td>
<td>(13.76)</td>
<td>(4.09)</td>
</tr>
<tr>
<td>DR-MMWS(^6)</td>
<td>508.19***</td>
<td>-319.74*</td>
<td>-12,218.64*</td>
<td>-27.79***</td>
<td>-5.90*</td>
</tr>
<tr>
<td></td>
<td>(166.37)</td>
<td>(138.34)</td>
<td>(5,988.88)</td>
<td>(11.47)</td>
<td>(3.50)</td>
</tr>
</tbody>
</table>

Source: IFPRI-India survey. Note: Indian rupee; exchange rate was USD1=Rs. 65 at the time of the survey.

1 Urea, a white crystalline solid containing 46% nitrogen, is a widely used animal feed additive and fertilizer.
2 DAP (diammonium phosphate) is the world’s most widely used phosphorus fertilizer, with a relatively high nutrient content and excellent physical properties that make it a popular choice in farming and other industries.
3 Regression adjustment.
4 Inverse probability of treatment weighting.
5 Marginal mean weighting.
6 Doubly robust marginal mean weighting.
* Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.
6. Conclusions and policy implications

Once the champion of the Green Revolution, India has been experiencing falling productivity in rice and wheat, overexploitation of natural resources and lower incomes for smallholders (Sidhu and Byerlee 1992). Over the past two decades, groundwater tables have declined at an alarming rate of about 23 centimetres per year in the Indian states of Punjab and Haryana, the epicentre of the Green Revolution. Farmers in these states have been seeking other crops to increase income and secure livelihoods for many rural Indian households. Adding value to the traditional maize, ‘specialty corn’ recently has 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.

This study assessed the impact of CF on productivity and the irrigation and fertilizer costs involved in growing baby corn. Additionally, it investigated how CF has affected farmers’ use of chemical fertilizers, specifically urea and DAP. It used farm-level data from the states of Punjab and Haryana in India and PSW matching to evaluate the treatment effect of CF on outcome variables. Data were matched using the IPTW and MMWS matching method, however, the study included estimates obtained from other PSW methods (RA and DR-MMWS).

Findings from this study reveal that, compared to independent baby corn farmers, baby corn CF producers have higher yields by about 593 kg/acre.13 Additionally, baby corn CF growers spend less on irrigation and fertilizer compared to independent baby corn growers. Irrigation costs and fertilizer costs were comparatively lower for contract baby corn farmers by about Rs. 323/acre for irrigation costs and about Rs. 13,571/acre for fertilizer costs. Compared to independent baby corn producers, baby corn CF producers use significantly lower amounts of

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13 Taking average yield obtained via three methods (IPTW, MMWS and DR-MMWS).
urea (36 kg/acre) and DAP (7 kg/acre). Less use of irrigation water and chemical fertilizers is environmentally beneficial for farmers, overall soil health and general public well-being.

We concluded that compared to independent baby corn farmers, contract baby corn growers have higher yield, spend less on fertilizer and irrigation and use less chemical fertilizers such as urea and DAP. Therefore, CF for baby corn production may be a suitable replacement for rice cultivation in high-stress areas like Punjab and Haryana. Further effects of cultivating baby corn are that it reduces the stress on groundwater and reduces soil and environmental degradation without compromising yield. The reduction in use of chemical fertilizers and irrigated water could be attributed to the extensive monitoring by extension staff members working for the contractor and attending to quality standards. Extension staff members ensure that farmers adhere to the requirements concerning the application of inputs such as seeds, fertilizer, pesticides and water. The produce must conform to international market standards in potential export markets like the United States and United Kingdom, among other international markets.

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 policymakers in designing incentives for the effective adoption of CF in baby corn production with potential impacts on productivity, irrigation and fertilizer costs, and chemical fertilizer usage. 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 linkages to international markets. This research identifies the extent to which smallholders, including those involved in CF, are taking sustainable farming seriously. Smallholders that participate in CF are better positioned to address the issue of agricultural sustainability without compromising yield or income stability.
REFERENCES


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