Impact of contract-farming in staple food chains: the case of rice in Benin

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Abstract

Research on the impact of smallholder contract-farming largely focuses on export-oriented high-value commodities. Little is known about the possibility of contract-farming for upgrading in staple food chains. While theoretical insights predict contract-farming to be infeasible for lower-value staple food crops, empirical evidence from such sectors is extremely scarce. In this paper, we provide evidence on smallholder contract-farming in the rice sector in Benin. We use cross-sectional household data and propensity score matching methods to analyze the impact of contract-farming on selected farm performance indicators. The findings indicate that contract-farming has a positive impact on rice productivity and income.

Keywords

contract-farming, farm productivity, staple food, rice, Benin

1. Introduction

Research on the impact of smallholder contract-farming largely focuses on export-oriented high-value commodities. Exports of food products from developing countries have increased tremendously over the past two decades and are no longer confined to the typical tropical export commodities such as coffee, tea, and cocoa for example, but also include higher-value products such as fruits and vegetables, products from animal origin, and even staple crops. These supply chains, especially those of high-value products, are undergoing rapid processes of globalisation and modernisation. Developing countries' participation in these chains has important implications for rural households in those areas where export crops are cultivated. Whether the impact of the participation of smallholders in contract-farming for the supply of high-value produce in export markets is negative or positive remains a debated issue. Some authors note negative factors such as exclusion of smallholder farmers from high-value commodities chains due to barriers such as strict standards, or increased vulnerability of participants with regard to alternative income sources and bargaining power (e.g. Gibbon, 2003; Porter and Phillips-Howard, 1997; Reardon and Barrett, 2000). On the other hand there is a rapidly growing body of literature that documents positive effects, such as income growth, increased farm productivity, creation of employment opportunities, female empowerment, and poverty reduction (e.g. Barrett et al., 2012; Bellemare, 2010; Maertens and Swinnen, 2009; Reardon et al., 2009).

The rapid modernization of high-value export chains however is in sharp contrast with the lack of attention to development in domestic chains for staple food crops. Those supply chains largely remain characterized by low quality, low value added, high inefficiencies in exchange, lack of investment, and unequal rent distribution. These inefficiencies in food supply chains are a main problem in many developing countries, that became more apparent since the 2008 food crisis. A group of well-known authors in the field recognize the gap in literature on how innovations in food value chains can improve the functioning of domestic chains as opposed to only export channels (Gómez et al., 2011). So far however, research has paid little attention to the possibilities for upgrading staple food chains in developing countries and its impact on smallholders' livelihoods, even though the development of staple food chains contributes more to poverty reduction than high-value export (Christiaensen and Devarajan, 2011; Diao et al., 2012). Research on the potential of contract-farming in staple food chains not only complements the existing literature, but moreover has the potential to better entangle the impact of contract-farming from the impact of access to export markets for high-value produce.

Govereh (1999) points out that it seems certain types of commodity-market structure combinations are more likely than others to attract private investment that can catalyze smallholder crop productivity, referencing to the possibilities for companies that want to engage in contract-farming to create the necessary incentives preventing side-selling. Swinnen et al. (2010) provide a more formal framework on contract-farming in different types of value chains explaining the circumstances in which contracts can be feasible and will be honoured by both parties involved. It points out that contract-farming in staple food chains cannot be sustainable due to the lack of sufficient surplus to incentivize both buyers and producers to enter in a contracting arrangement instead of interacting in spot markets. Rice nevertheless is a special case within the staple foods bracket since quality differentiation is possible. According to Swinnen et al.'s model contract-farming could thus turn into a sustainable opportunity for staple food value chains such as rice as long as there is sufficient added value creation.

This paper wants to offer empirical insight in contract-farming applied to staple food chains by identifying a particular instructive case and studying the impact of contract participation on farm performance in the rice value chain in Benin. Potential selection bias is dealt with by using two propensity score matching techniques. We find that contract participation has an overall significantly positive effect on income from and productivity of rice farming, an effect which is channelled through various pathways.

In the remainder of the paper we will first discuss the case study and data collection in section 1.1 followed by the descriptive statistics in section 1.2. Next, the econometric approach is elaborated upon in section 2, the results of which are discussed in section 3. We conclude in section 4.

1.1. Case study and Data Collection

The case of Benin is especially suited to study the impact of contract-farming in a staple food chain. Approximately half of the population of Benin is involved in the agricultural sector which accounts for 32% of the GDP (World Bank, n.d.).While rice previously was considered a luxury food it is increasingly becoming a staple food, especially in urban areas, and already takes a place among the main crops farmed in the country. Nevertheless, the growth in demand offset the growth in local production. In Africa much of the growth in agricultural imports to feed the growing population concerns staple foods such as rice, despite a comparative advantage for their production (Christiaensen and Devarajan, 2011). Indeed also in Benin local rice production has a comparative advantage over imports (Fiamohe et al., 2012). According to the latest available data Benin produced 220 000 tons of paddy rice in 2011 and imported nearly 368,000 tons of milled rice in the same year, roughly equivalent to 512,200 tons of paddy (FAOSTAT, 2014). In the aftermath of the 2008 food crisis with spiking import prices, the country's ambition arose to become self-sufficient in good quality rice by 2014 and to become a rice exporter by 2018, for which a government strategy was launched in 2009 in collaboration with FAO (MAEP, 2011). For now however, the sector still remains characterized by low quality, low value added, lack of investment and adequate infrastructure and inefficient spot market exchange, despite the growing market potential for a local high quality rice.

The ESOP[1] approach introduced by the NGO ETD is aimed at addressing exactly this potential of connecting farmers with the market in a sustainable way. An ESOP is a privately

[1] *Entreprises de Services et Organisations de Producteurs* ; or Enterprises for Services and Organisations of Producers

run social economic enterprise. On the one hand they work on the social axis of organizing farmers in groups and offer training for them to become more efficient market actors. On the other hand they operate in an economic logic, offering services to the farmers and at the same time providing a quality product meeting consumer demand. In line with Swinnen et al.'s (2010) theoretical framework they recognize that the added value generated is key to the sustainability of this type of initiative (ETD, 2012).

Benin's central Collines region and more specifically the municipalities Glazoué, Dassa and Savalou compose the country's most important area for lowland rice production. Since cultivation is rain-fed, only one rice crop is harvested each year. The ESOP unit established in the Savalou municipality since 2006 contracts self-organized groups of 10 to 15 farmers, providing them inputs on credit and technical assistance. In 2012 the contract price was set at 150 CFA[2]/kg unpeeled rice of the IR841 variety. The procured paddy rice is processed in the ESOP facility, packaged and branded as the local quality rice *riz Délice* for urban markets. This setup makes the ESOP case an illustrative example for contract-farming in local market oriented staple food chains and its impact on smallholder farm performance.

We use primary data collected using household (HH) surveys conducted between April and May 2013 in the municipality of Savalou in central Benin where the ESOP contracting approach is present. A two-stage stratified random sampling technique was used, resulting in a selection of 480 households. In the first stage, 21 villages were randomly selected in four districts based on the information provided to us by local authorities and the presence of contract-farming. In the second stage, we selected 480 rice farming households in these villages according to contract participation. Due to our special interest in contracting, contract farmers were oversampled to make sure they were sufficiently represented in the sample[3]. Four households were dropped from the sample as they did not produce rice in the season prior to the survey. For this paper we will focus specifically on the ESOP type of contract-farming, for which a subsample was retained of 396 households either currently or never participating in this contract type.

A quantitative structured questionnaire was developed, including diverse modules on household demographics, land assets and crop production with detail on rice, rice contracting experience, agricultural practices and quality perception, off-farm employment and income, non-land assets, food security, gender aspects, and credit. The household data was complemented with a survey at village level collecting data on infrastructure, accessibility, market access and rice farmer groups.

1.2. Descriptive Statistics

Table 1 and Table 2 present t-test comparison of means for contracting versus non-contracting farmers for selected household and farm characteristics that are also of interest in subsequent analysis. The average age of a household head is 42 years and the vast majority is male headed with only around 7% female-headed households. No significant differences are observable between the two groups in terms of these characteristics. Contract-farmers also do not seem to be different in terms of household size which is 3 adult equivalent on average. Nevertheless, breaking that number down in (absolute) number of adults and children, contracting households have slightly less adults and significantly more children with an average of 3.93 as compared to 3.36 for non-contracting households. Moreover, contracting households' head are significantly more often unschooled with only 26% of HH heads having

[2] The local currency of Benin, CFA francs, has a fixed exchange rate to the euro: 1 euro = 655.957 CFA francs.

[3] As our goal is not to derive population statistics, but to compare contracting versus non-contracting groups, no weights were used in this analysis.

enjoyed at least one year of education, while for non-contracting households 38% has an educated household head[4].

Contracting households are also distinguished by a higher number of livestock owned amounting to 3.74 tropical livestock units (TLU) on average. They are also slightly less asset deprived which indicates they more often own at least one of a number of basic assets such as a radio or telephone (as defined in more detail in Table 3). Market distance also distinguishes the contract farmers as they live further from the market than non-contractors. This could be a factor for them to facilitate market access through contract-farming. Indeed when farmers were asked for the main reasons to participate in the ESOP contract they most often mentioned a guaranteed market for their crop, higher prices, and access to inputs and credit as the main benefits of the contract. This indicates that the presence of contract-farming resolves some input and output market imperfections, that are more pronounced the further from the market place.

In terms of farm characteristics the contracting and non-contracting groups are also distinguishable. Although land ownership does not differentiate between the groups, contracting households do cultivate a larger area, 9.81 Ha on average as compared to 7.42 Ha for non-contracting households. Looking at the details for rice area in Table 2 the difference is marked there as well with cultivation of 0.92 Ha of rice for contracting households while non-contracting farmers only grow 0.69 Ha of rice. The value of inputs used for rice is significantly higher for contract farmers, in line with ESOP providing inputs on credit for participating farmers. Rice yield is generally low[5] at only 1.89 T/Ha on average for the sample but contracting farmers with 2.09 T/Ha do significantly better than their non-contracting counterparts. Their total rice production is thus, not surprisingly seen the differences in area, inputs and yield, higher for farmers participating in the ESOP contract. Nevertheless yields for maize, the most important food crop in Benin, do not differ between the two groups (Table 1) which could be an indication that contract-farmers are not overall more productive than their counterparts. They do sell a higher share of their rice produce, 71%, in comparison to 61% for non-contracting households despite their being further away from the market places, and receive a higher weighted average price for their total rice sales in the market. These factors are reflected in an overall better income from rice production, which is around 2.5 times higher than for non-contracting households. Calculated per hectare as a measure for land productivity for rice, contract-farmers do more than twice as well, with 391 EUR/Ha as compared to 190 EUR/Ha for non-participating households.

[4] The literature is inconclusive on the effect of education level on contract-participation as results seem to vary on a case-to-case basis from a negative to a positive effect, or no significant effect at all (e.g. Arinloye et al., 2012; Barrett et al., 2012; Miet Maertens et al., 2012; Schipmann and Qaim, 2010).

[5] According to FAOSTAT (2014) the average rice yield in Benin for 2012 amounted to 3.3T/Ha. Rice yields in the study region have been reported informally by the rice farmer organization at 2.5 to 3T/Ha, but 2012 was indicated as a bad year for the rice harvest due to irregularities in rainfall with ‘pockets of drought’, this could explain the lower yields observed in the data.

Table 1. Household and farm characteristics according to participation in contract-farming

Variable	Total sample	Non-contracting households	Contracting households	
	(N=396)	(N=307)	(N=89)	
Human capital				
Male HH head (dummy)	0.93 *(0.26)*	0.92 *(0.27)*	0.94	*(0.23)*
Age HH head (yrs)	42.35 *(12.58)*	42.63 *(12.85)*	41.39	*(11.63)*
Education HH head (dummy)	0.36 *(0.48)*	0.38 *(0.49)*	0.26 **	*(0.44)*
HH size (Adult Equivalent)	2.97 *(0.98)*	2.96 *(0.96)*	3.03	*(1.02)*
Adults >=18yrs (#)	2.62 *(1.07)*	2.67 *(1.13)*	2.45 *	*(0.81)*
Children (#)	3.49 *(2.19)*	3.36 *(2.14)*	3.93 **	*(2.31)*
Risk attitude (dummy)	0.22 *(0.41)*	0.22 *(0.42)*	0.20	*(0.40)*
Time preference (dummy)	0.21 *(0.41)*	0.19 *(0.39)*	0.29 **	*(0.46)*
Cotton experience (dummy)	0.67 *(0.47)*	0.63 *(0.48)*	0.80 ***	*(0.40)*
Social capital				
FO member (dummy)	0.84 *(0.37)*	0.79 *(0.40)*	1.00 ***	*(0.00)*
Public function (dummy)	0.08 *(0.26)*	0.08 *(0.27)*	0.07	*(0.25)*
Distance to market (km)	6.00 *(5.05)*	5.58 *(5.36)*	7.45 ***	*(3.47)*
Productive capital				
Land owned in 2012 (Ha)	13.73 *(11.82)*	13.28 *(11.25)*	15.29 *	*(13.58)*
Area cultivated 2012 (Ha)	7.96 *(6.87)*	7.42 *(6.75)*	9.81 ***	*(6.99)*
Livestock (TLU)	2.65 *(5.19)*	2.33 *(4.35)*	3.74 **	*(7.34)*
Asset deprivation (dummy)	0.13 *(0.34)*	0.15 *(0.36)*	0.08 *	*(0.27)*
Maize yield (t/Ha)	0.96 *(0.57)*	0.95 *(0.56)*	0.97	*(0.63)*
Rice area for ESOP rice (Ha)			0.95	*(0.88)*
Value of rice inputs via ESOP (EUR)			62.42	*(78.74)*
Quantity of rice sold to ESOP (kg)			1354.84	*(1213.68)*
Price for ESOP rice 2012 (CFA/kg)			150.00	*(0.00)*
Value of rice sales to ESOP (EUR)			326.02	*(291.63)*

Significant t-test results are indicated as * p<.1; ** p<.05; *** p<.01. Standard errors in parenthesis

Table 2. Mean comparison for outcome variables according to participation in contract-farming

	Dependent variables	Total sample	Non-contracting households	Contracting households
		(N=396)	(N=307)	(N=89)
INCRI	Rice income (EUR)	165.16 *(281.22)*	122.78 *(227.33)*	311.34 *** *(383.94)*
INCRIHA	Rice income per hectare (EUR)	234.85 *(396.97)*	189.58 *(360.24)*	391.00 *** *(473.60)*
PRICE	Weighted average price (FCFA/kg)	147.89 *(78.67)*	144.70 *(86.69)*	158.91 * *(38.55)*
%SOLD	Share of rice produce sold	0.64 *(0.24)*	0.61 *(0.25)*	0.71 *** *(0.19)*
QTYPROD	Total rice production (kg)	1319.86 *(1306.09)*	1116.53 *(1074.14)*	2021.24 *** *(1733.01)*
AREA	Rice area cultivated 2012 (Ha)	0.74 *(0.62)*	0.69 *(0.61)*	0.92 *** *(0.64)*
YIELD	Rice yield (t/Ha)	1.89 *(1.12)*	1.83 *(1.10)*	2.09 ** *(1.18)*
INPUT	Input use for rice (EUR)	58.10 *(60.29)*	49.19 *(50.25)*	88.82 *** *(79.39)*

Significant t-test results are indicated as * p<.1; ** p<.05; *** p<.01. Figures in parentheses are standard errors.

2. Econometric Approach

Descriptive statistics indicate that contracting and non-contracting groups significantly differ with regard to some selected characteristics. To make a more detailed analysis of the impact of participation in ESOP contract on farm performance, we first estimate linear regression models of the following type by ordinary least squares (OLS):

$$Y_i = \alpha_i + \beta C_i + \gamma X_i + \varepsilon_i \tag{1}$$

The dependent variable Y_i is a measure of farm performance for which we use different indicators related to both labour and land productivity. We assess the model separately for each of these indicators: 1) net income from rice farming (INCRI), 2) net income from rice farming per hectare (INCRI), 3) rice yield (YIELD), 4) total value of inputs used for rice including seeds, fertilizer and herbi/pesticides (INPUT), 5) share of rice crop sold in the market (%SOLD), 6) overall weighted average price received for unpeeled rice (PRICE), 7) rice area cultivated (AREA) and 8) Total rice production (QTYPROD). These are all continuous variables estimated using linear regression. As we are mainly interested in the effect of participation in contract-farming, C_i is the main variable of interest, a dummy indicating whether the household is currently engaged in the ESOP type contract or did never participate in it.

In order to take into account possible selection bias, as participation in contract-farming is likely not random, we apply different methods to estimate the effect of contract-farming as accurately as possible. First of all, we include a vector of control variables X_i in the regression to account for observed heterogeneity being correlated with the error term ε_i. These include household demographic characteristics, asset ownership, and a social capital indicator and a market access indicator (Table 3).

Table 3. Control variables

Variable	Description
Demographic characteristics	
Male HH head	Dummy for male headed households
Age HH head (yrs)	Age of the household head in years
Square of Age	
Education HH head (dummy)	Dummy for educated HH head
Children (#)	Number of children (<18yrs old) in the household
Adults (#)	Number of adults (≥18yrs old) in the household
FO member	Dummy for household being member of a farmer organisation (FO)
Risk attitude (dummy)	Dummy for risk loving HH
Time preference (dummy)	Dummy for future-oriented HH
Asset ownership	
Land owned (Ha)	Total area owned by the household, in hectares
Square of Land	
TLU	Number of tropical livestock units (TLU) owned by the household
Asset deprivation	Dummy for asset deprivation, defined as deprived if the household does not own more than one of the following: radio, TV, telephone, bike, motorbike or refrigerator; and does not own a car or tractor
Social capital	
Public function	Dummy for a household member holding a public function in the village or community (e.g. village head, farmer group leader,…)
Market access	
Distance to market (km)	Distance to the nearest market in kilometre

Second, we apply propensity score matching (PSM) to reorder the sample in a way that closer resembles a randomized set-up for which an average treatment effect (ATE) of contract participation can be calculated. Households are grouped according to their similarity in terms of observable characteristics both related to contract participation and the outcome variable of interest, after which within these groups, treated (contracting) households are compared with non-treated households (Caliendo and Kopeinig, 2008; Rosenbaum and Rubin, 1983; Smith and Todd, 2005). First a propensity score (PS) is calculated for each household which is defined as the probability of being involved in contract-farming as based on observables X, the largest subset of control variables (see Table 3) for which a balanced grouping could be achieved and additionally the variables maize yield and cotton experience[6] were used as indicators of general productivity level and relevant experience of the farmer (see Annex 2).

To then match households according to their propensity score, we apply the kernel matching method using the default Gaussian kernel and with bootstrapping of standard errors. This method uses information from all control group households using a weighting function in constructing the counterfactual outcome, thus reducing variance (Caliendo and Kopeinig, 2008). After matching, the ATE is calculated as the average of the outcome differences between treated and matched controls (Dehejia and Wahba, 2002; Imbens, 2004).

$$\mathrm{PS} = \mathrm{P}(\mathrm{C} = 1|\mathrm{X})$$

$$\mathrm{ATE} = \mathrm{E}[\mathrm{Y}(1) - \mathrm{Y}(0)] = \mathrm{E}[\mathrm{Y}(1)] - \mathrm{E}[\mathrm{Y}(0)] \quad (2)$$

This approach is based on two important assumptions. First, as we can see from the definition of the propensity score, it is assumed that conditional on the observables X the treatment is assigned randomly and thus does not depend on unobserved characteristics, which is a strong assumption commonly referred to as the Conditional Independence Assumption (CIA) (Caliendo and Kopeinig, 2008; Heckman et al., 1997). As detailed in Annex 4, we apply a sensitivity analysis of which the results show robustness of the estimates to departures from the CIA.

Second, the ATE is only defined in the region of common support[7], which means that the treated observation should have a counterpart nearby in the propensity score distribution to be matched with (Caliendo and Kopeinig, 2008). These assumptions are addressed by using propensity score balancing tests while we also only use observations in the common support region for matching. The main results of these checks are illustrated in Figure 1 and Table 4.

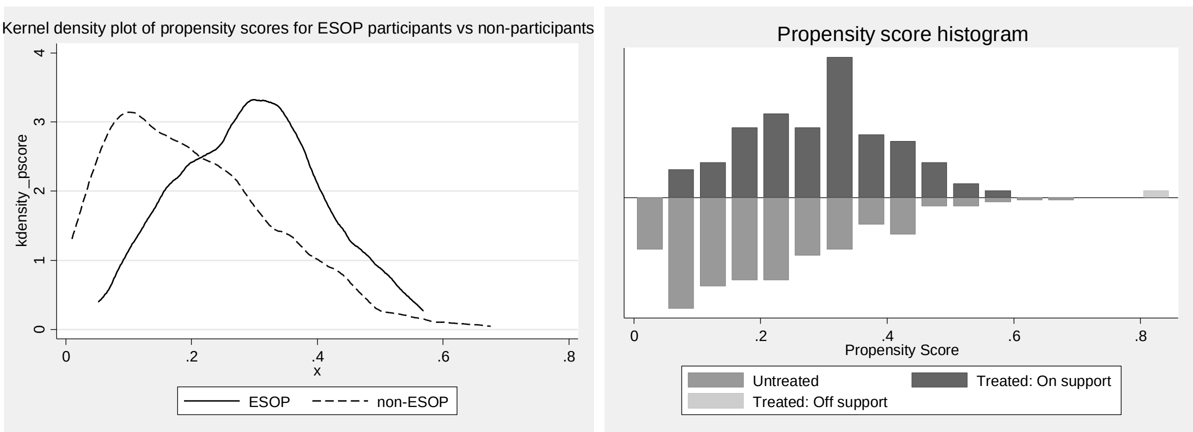

Figure 1. Kernel density plot and histogram of propensity scores

[6] The cotton sector was longtime governed by a parastatal company and subsequently an interprofession organization, taking care of the purchase and distribution of inputs, direct purchase from the farmers, price setting, and processing (Gergely, 2009; Glin et al., 2012). For farmers this meant inputs were provided and produce was purchased at a fixed price.

[7] Common support is defined as the region where the control observations' PS is not smaller than the minimum PS of the treated units; and the PS of treated units not larger than the maximum PS of the controls.

Table 4. PSM Balancing properties

Variable	Unmatched / Matched	Mean Treated	Mean Control	%bias	%reduction of bias	Ttest t	Ttest p>t
Age HH head (yrs)	U	40.862	42.386	-12.7		-1	0.317
	M	40.581	40.535	0.4	97	0.03	0.978
Education HH head (dummy)	U	0.25287	0.38255	-28		-2.23	0.026
	M	0.25581	0.24522	2.3	91.8	0.16	0.874
Children (#)	U	3.9425	3.3859	24.8		2.08	0.039
	M	3.9419	3.8362	4.7	81	0.3	0.767
Adults >=18yrs (#)	U	2.4598	2.6477	-19.4		-1.47	0.142
	M	2.4419	2.404	3.9	79.9	0.32	0.747
Land owned in 2012 (Ha)	U	15.357	13.463	15		1.3	0.193
	M	15.338	14.141	9.5	36.8	0.63	0.531
Maize yield (t/Ha)	U	0.96985	0.95153	3.1		0.26	0.794
	M	0.97531	0.96815	1.2	60.9	0.08	0.937
Livestock (TLU)	U	3.7799	2.3663	23.2		2.22	0.027
	M	3.1099	2.5435	9.3	59.9	0.97	0.332
Distance to market (km)	U	7.3793	5.6443	38.4		2.84	0.005
	M	7.3256	7.2019	2.7	92.9	0.18	0.86
Asset deprivation (dummy)	U	0.08046	0.15101	-22.1		-1.7	0.091
	M	0.0814	0.07243	2.8	87.3	0.22	0.827
Public function (dummy)	U	0.06897	0.08054	-4.4		-0.35	0.724
	M	0.06977	0.06688	1.1	75	0.07	0.941
Cotton experience (dummy)	U	0.81609	0.62081	44.3		3.44	0.001
	M	0.81395	0.79873	3.5	92.2	0.25	0.802
Risk attitude (dummy)	U	0.2069	0.22819	-5.1		-0.42	0.676
	M	0.2093	0.18429	6	-17.5	0.41	0.682
Time preference (dummy)	U	0.29885	0.19799	23.4		2	0.046
	M	0.2907	0.28813	0.6	97.5	0.04	0.971

Third, we use a difference-in-difference (D-i-D) estimator for the outcome variable AREA for which we have recall data available. A main advantage of this approach is that time constant individual effects are differenced out, thus avoiding any bias due to unobserved time-constant heterogeneity. In this way the D-i-D result can be used as a robustness check for the OLS and PSM estimates.

As shown in equation 3 this estimator $\hat{\delta}$ is the difference over time between 2008 and 2012 in the average difference of rice area between the contract-farming (C) and non-contract-farming (nC) groups, and is estimated by OLS in a linear regression on the pooled data for both years (Wooldridge, 2012).

$$\hat{\delta} = \left(\overline{area}_{12,C} - \overline{area}_{12,nC}\right) - \left(\overline{area}_{08,C} - \overline{area}_{08,nC}\right)$$

$$Y_i = \alpha_i + \beta post_i + \gamma C_i + \delta post_i * C_i + \varepsilon_i \quad (3)$$

In this regression, *post* is a dummy taking the value of 1 for the year 2012 and 0 for 2008 data and C_i is the contract dummy as before. The D-i-D estimator then is found as the coefficient for the interaction term of C_i with *post*.

3. Results and Discussion

The results for the estimation of the effect of our main variable of interest contract-farming are summarized in Table 5 for both linear regression and propensity score matching approaches and the difference-in-difference estimator[8]. We see that for all farm performance indicators the effect of contract-farming is significantly positive and estimates are of comparable magnitude for the different estimation methods.

The extent of the overall positive effect[9] of contract-farming on farm performance is clear when comparing the estimates with the descriptive statistics in Table 1. We find that participation in contract-farming significantly increases rice income with a rise of 182 euro or 110% as compared to the sample mean value of 165 euro. Moreover, when expressed as land productivity for rice the increase amounts to 232 euro, which when compared to the sample average of 235 euro means that land productivity approximately doubles as a result of contract participation. Farmers testify that a higher price is one of the main reasons to participate in a contract and this is reflected in the overall weighted mean price they receive for rice sales by the household, with an increase of almost 8% compared to the sample average of 148 FCFA/kg. Contract participants see the share of their rice produce sold increase by 9% as compared to non-contracting households, on a sample average of 63.5% commercialisation of the rice crop. Total rice production is significantly higher for contract-farmers with an increase of 843 kg of unpeeled rice or a 64% rise as compared to the sample mean. Area expansion is one factor feeding into this increased production as contract-farming HHs cultivate around a quarter more rice area than non-participating HHs. OLS and PSM estimates are confirmed in the D-i-D result, which shows robustness of these results with regard to unobserved time-constant heterogeneity. Rice yields were generally low as seen from Table 1 but also increase for contract-farmers and this by a little over 15% when comparing the increase of 0.3 T/Ha to the sample average of 1.89 T/Ha. When looking at the descriptive statistics the contracting households use significantly more inputs for rice production. The estimated effect also arrives at a significant difference of 39 euro more spending on rice inputs by contract farmers, which is again a large effect when compared with the sample mean of 58 euro rice input spending per household.

These results thus indicate that multiple effects of price, commercialisation, area expansion and productivity increase through intensification contribute to the overall increase in income from rice production and rice productivity for contract-farming households.

Table 5. Estimated effects of participation in contract-farming on rice farm performance

	INCRI	INCRIHA	PRICE	%SOLD	QTYPROD	AREA	YIELD	INPUT
OLS	177.980***	195.839***	11.873*	0.084***	826.523***	0.165**	0.326**	39.649***
	(44.34)	*(56.30)*	*(6.70)*	*(0.03)*	*(187.29)*	*(0.08)*	*(0.14)*	*(8.03)*
PSM	181.796***	232.030***	11.358*	0.058**	842.897***	0.203***	0.289*	39.405***
	(39.39)	*(49.41)*	*(6.16)*	*(0.03)*	*(188.58)*	*(0.07)*	*(0.15)*	*(8.03)*
D-i-D						0.186**		
						(0.09)		

Significant effects are indicated as * p<.1; ** p<.05; *** p<.01. Figures in italics are standard errors

[8] Full OLS regression results can be consulted in Annex 1, first-stage results of the propensity score estimation can be found in Annex 2 and full difference-in-difference regression results are provide in Annex 3.

[9] We will base the discussion on the PSM estimate values.

4. Conclusion

In this paper, we analyze the effect of participation in contract-farming for rice production on rice farm performance in Benin. We find that contract-farming has an overall positive effect on a range of performance indicators. Households participating in contract-farming have a higher income from rice production and a higher productivity for rice. This effect is channelled through a combination of pathways including increased prices and commercialisation, area expansion and yield increases through intensification.

These results contribute to the literature that researches the impact of contract-farming by providing empirical indications that contracting in a staple food chain such as rice can contribute to improving smallholders' livelihoods by addressing the gap between rural production and local markets, entangled from the effect of export market access with high-value crops.

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6. Annexes

Annex 1. Full OLS results

Annex 1. Full OLS results

Variables	INCRI	INCRIHA	YIELD	AREA	PRICE	%SOLD	INPUT	QTYPROD
Contract participation	177.980***	195.839***	0.326**	0.165**	11.873*	0.084***	39.649***	826.523***
	44.343	*56.302*	*0.141*	*0.075*	*6.701*	*0.026*	*8.031*	*187.294*
Male HH head	-7.106	10.218	-0.086	-0.186	-10.585	-0.064	5.355	-139.241
	35.257	*62.861*	*0.191*	*0.159*	*14.788*	*0.045*	*7.450*	*146.840*
Age HH head (yrs)	0.067	9.278	0.016	-0.033*	4.981*	0.004	-4.773***	-40.835
	6.903	*10.903*	*0.033*	*0.017*	*2.739*	*0.007*	*1.529*	*30.612*
Square of age	-0.003	-0.111	0.000	0.000*	-0.063**	0.000	0.051***	0.441
	0.083	*0.121*	*0.000*	*0.000*	*0.029*	*0.000*	*0.017*	*0.376*
Education HH head	91.390***	124.980***	0.247**	0.066	10.603	-0.043	8.620	488.502***
	34.530	*44.873*	*0.121*	*0.061*	*11.261*	*0.027*	*5.859*	*146.079*
Children (#)	0.202	-6.461	-0.079***	0.033**	-5.432***	-0.020***	4.580***	25.381
	7.098	*10.953*	*0.028*	*0.015*	*1.842*	*0.006*	*1.476*	*31.869*
Adults >=18yrs (#)	-12.191	-29.672	0.016	-0.025	-2.652	-0.014	-1.872	-21.349
	12.969	*22.131*	*0.055*	*0.028*	*3.665*	*0.015*	*2.463*	*60.766*
Land owned (Ha)	2.837	-4.047	-0.001	0.021***	0.430	0.009***	2.493***	40.014***
	2.228	*3.758*	*0.012*	*0.007*	*1.017*	*0.002*	*0.610*	*9.951*
Square of land	-0.046*	0.008	0.000	0.000	-0.006	-0.000***	-0.020**	-0.374***
	0.025	*0.044*	*0.000*	*0.000*	*0.011*	*0.000*	*0.010*	*0.113*
Livestock (TLU)	7.406**	2.984	0.016*	0.019**	0.545	0.005***	1.038	46.527**
	3.177	*3.044*	*0.009*	*0.008*	*0.353*	*0.001*	*0.821*	*19.088*
Distance to market (km)	1.325	2.399	-0.009	0.000	0.805	0.000	-2.026***	3.672
	2.650	*4.013*	*0.011*	*0.007*	*0.528*	*0.002*	*0.490*	*11.781*
Asset deprivation	-37.157	7.827	-0.250	-0.059	-16.984	-0.082*	-0.725	-343.985***
	37.210	*68.236*	*0.175*	*0.085*	*12.438*	*0.044*	*6.370*	*131.837*
Public function	25.535	-103.877	0.176	0.065	2.015	0.055	22.618	298.229
	67.023	*75.741*	*0.195*	*0.134*	*10.283*	*0.037*	*14.527*	*327.589*
FO member	39.497	99.573**	0.026	0.062	-0.920	-0.045*	-4.871	85.681
	24.142	*44.402*	*0.138*	*0.071*	*7.029*	*0.026*	*6.609*	*115.032*
Risk attitude (dummy)	-0.696	125.236**	0.485***	-0.215***	-9.223	-0.032	-4.876	52.210
	30.859	*55.523*	*0.168*	*0.052*	*7.589*	*0.030*	*5.552*	*142.310*
Time preference	-48.580	-49.071	-0.128	-0.053	4.524	-0.034	-3.707	-159.177
	35.190	*45.382*	*0.135*	*0.066*	*7.071*	*0.026*	*7.282*	*170.504*
Constant	62.144	-2.658	1.789**	1.211***	83.310	0.767***	118.365***	1327.85**
	145.610	*248.791*	*0.761*	*0.375*	*59.460*	*0.149*	*33.657*	*645.000*

Significant effects are indicated as * p<.1; ** p<.05; *** p<.01. Figures in italics are standard errors.

Annex 2. First stage results of propensity score estimation

Annex 2. First stage result of propensity score estimation using a probit model

Variables	ESOP	
Age HH head (yrs)	-0.01	*(0.01)*
Education HH head (dummy)	-0.43**	*(0.17)*
Children (#)	0.05	*(0.04)*
Adults >=18yrs (#)	-0.16*	*(0.09)*
Land owned in 2012 (Ha)	0.00	*(0.01)*
Maize yield (t/Ha)	-0.01	*(0.14)*
Livestock (TLU)	0.02	*(0.01)*
Distance to market (km)	0.03**	*(0.02)*
Asset deprivation (dummy)	-0.26	*(0.25)*
Public function (dummy)	-0.03	*(0.29)*
Cotton experience (dummy)	0.55***	*(0.18)*
Risk attitude (dummy)	-0.10	*(0.19)*
Time preference (dummy)	0.32*	*(0.18)*
Constant	-0.78**	*(0.39)*
pseudo R^2	0.10	

Significant t-test results are indicated as
* p<.1; ** p<.05; *** p<.01

Annex 3. Full difference-in-difference results

Annex 3. Full D-i-D results

Variables	Rice area		
post	0.218	***	*(0.05)*
esop	0.048		*(0.06)*
post*esop	0.186	**	*(0.09)*
constant	0.472	***	*(0.03)*

Significant t-test results are indicated as
* p<.1; ** p<.05; *** p<.01

Annex 4. Simulation-based sensitivity analysis for PSM kernel estimates

The conditional independence assumption (CIA) is a very strong assumption on which the propensity score matching approach is based. In order to test the robustness of the average treatment effects for failures of the CIA assumption, we apply the method as proposed by Ichino et al. (2008) and recently applied e.g. on a contract-farming case study by Maertens et al. (2011). The method aims at assessing the sensitivity of the treatment effect estimates by calculating ATE estimates under different possible departures from the CIA. In order to do this the method uses a binary confounder U that can be defined in different ways to mimic a possible unobserved factor that affects both the likelihood of being selected into treatment (contract participation) and the outcome variable, such as a component of ability, motivation or entrepreneurship. The confounder is then used in the set of matching variables to estimate the ATE in the presence of a confounding factor with these characteristics. The comparison of the baseline estimate with these simulated estimates then gives an idea of the robustness of the baseline result under specific departures from the CIA (Ichino et al., 2008). The results of this analysis for our contract-farming case are reported in Annex 4. We use a neutral confounder and two binary confounders set up to have both high selection and outcome effects as this type of unobserved effect would be the biggest threat to the validity of the PSM estimators; we use respectively a rather extreme 'worst' confounder and one with a more moderate effect. We see that under the neutral confounder the estimate values barely change. As expected, the largest effect on the estimates is seen at inclusion of the 'worst' confounder with estimates decreasing by 2-28%. However, since estimated effects are large as compared to sample mean outcome values, effects remain largely robust. At inclusion of a moderate confounder, still resulting in a probability of selection into treatment varying around 2.5 times higher than without its inclusion, and in most cases also a higher probability of a positive outcome for non-participating HHs, estimate values are affected in a very limited way, showing robustness of the estimates to violations of the CIA.

Annex 4. Simulation-based sensitivity analysis for PSM estimates

	neutral confounder			worst confounder			moderate confounder		
	Estimate effect[a]	Outcome effect[b]	Selection effect[c]	Estimate effect[a]	Outcome effect[b]	Selection effect[c]	Estimate effect[a]	Outcome effect[b]	Selection effect[c]
INCRI	0.33%	1.03	1.10	-9.80%	1.90	9.96	1.65%	0.87	2.49
INCRIHA	0.36%	1.03	1.02	-13.38%	1.86	10.18	1.01%	0.92	2.61
YIELD	0.38%	1.06	1.01	-27.55%	1.85	8.69	-4.30%	1.45	2.50
INPUT	-0.22%	1.03	1.02	-10.39%	1.77	11.23	-1.53%	1.32	2.61
%SOLD	0.02%	1.00	1.01	-1.98%	1.85	9.69	-0.33%	1.52	2.57
PRICE	1.97%	1.06	1.00	-27.01%	1.92	6.84	10.84%	0.75	2.76
AREA	-0.14%	1.07	1.05	-27.98%	1.82	10.65	-3.51%	1.28	2.63
QTYPROD	-0.33%	1.10	1.03	-11.34%	1.83	10.05	-1.26%	1.71	2.57

[a] The estimator effect indicates the extent of change in the estimated treatment effect under the presence of a binary confounder as compared to the baseline estimate

[b] The outcome effect measures the effect of the binary confounder on the untreated outcome

[c] The selection effect measures the effect of the binary confounder on the relative probability of selection into treatment