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

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Supply chain upgrading in domestic and staple food chains in developing countries is important for a more efficient supply to growing urban markets. Little research is done on institutional innovations, such as contract-farming, in these chains. Research on the impact of smallholder contract-farming largely focuses on export-oriented high-value commodities. In this paper, we assess the welfare implications of smallholder contract-farming in the rice sector in Benin, using farm-household survey data and applying propensity score matching and difference-in-difference estimation. We find that contract-farming is associated with higher rice incomes, higher yields, higher input use, increased commercialization and higher farm-gate prices.

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1 Introduction

Supply chain upgrading and institutional innovations in domestic and staple food chains in developing countries is recognized to be particularly important (Gómez et al., 2011). Increasing efficiency in these chains has the potential to benefit a large number of smallholder farmers; as opposed to high-value and export chains that are often exclusive and more limited in terms of the number of farmers involved (Reardon et al., 2012). Upgrading staple and domestic food supply chains is needed for a more efficient supply to fast growing urban markets and to sustain access to affordable food for urban consumers (Minten et al., 2013). It has been argued that the development of staple food chains can contribute more to poverty reduction and food security in poor countries than the development of high-value export chains (Diao et al., 2012). The 2008 food price crisis has created concerns about the dependence of African cities on food imports and pushed governments and donors to invest in the development and upgrading of domestic and staple food supply chains (Christiaensen and Devarajan, 2011). The sharply increased prices for staple foods might also attract private investors and create possibilities for institutional innovations such as contract-farming.

In the recent literature, contract-farming is put forward as an institutional innovation that can reduce transaction costs in food supply chains and solve market imperfections in linking smallholder farmers to markets (Key and Runsten, 1999; Oya, 2012; Swinnen and Maertens, 2007). Contract-farming can improve farmers' access to inputs, credit and technology, and ultimately benefit farm productivity and incomes. Contract-farming can reduce the risk faced by farmers as contracts offer a guaranteed market outlet and, depending on the type of contract, share production risks between farmers and buyers.

There is a growing body of recent empirical literature, based on case-studies from around the world, that documents positive welfare effects of contract-farming. It has been shown that contract-farming leads to higher productivity, higher profits and higher net farm incomes; that it reduces price variability and leads to higher income stability; that it increases farmers' subjective wellbeing; and that it can create productivity spillover effects to other crops. However, most of this evidence comes from high-value supply chains, mostly fruits, vegetables and products from animal origin destined for export markets or supermarket retail in urban high-value market segments – e.g. Birthal et al. (2005) for milk, broiler and vegetable production in India; Maertens and Swinnen (2009) and Dedehouanou et al. (2013) for vegetable production in Senegal; McCulloch and Ota (2002) for horticulture production in

Kenya; Minten et al. (2009) for vegetable production in Madagascar; Miyata et al. (2009) for fruit and vegetable production in China; Ramaswami et al. (2009) for poultry production in India; Rao and Qaim (2011) for vegetable production in Kenya; Singh (2007) for vegetable farming in India; Barrett et al. (2012) for fruit and vegetables in Nicaragua, Madagascar, Mozambique and India.

There is very few evidence on contract-farming in staple food chains and chains connecting farmers to domestic markets. Theoretical considerations have pointed towards difficulties for contracting in staple food sectors (Swinnen et al., 2010). Contract enforcement would be particularly difficult in staple food chains because the low value in the chain and the limited possibilities for quality upgrading and value adding impede the use of a price premium as contract enforcement mechanism. The large number of small buyers in staple food chains and the fact that staples are bulky and not highly perishable and therefore relatively easy to store and transport, further increases the likelihood of opportunistic sales and contract breach. There are a few empirical studies that document successes of contract-farming in staple food sectors. Bellemare (2010) shows that contract-farming in the rice sector in Madagascar has a positive impact on farm income. Simmons et al. (2005) document that contracting increases gross margins in the seed corn sector but not in the seed rice sector in Indonesia.

In this paper, we assess the welfare implications of contract-farming in the rice sector in Benin. We use data from a farm-household survey, and propensity score matching and difference-in-difference estimation to reveal how contract-farming affects the performance of smallholder rice farms. We find that contract-farming is associated with higher rice incomes, higher yields, higher input use, increased commercialization and higher farm-gate prices.

2 Case study: Rice in Benin

As in other countries in Western Africa, the consumption of rice in Benin has increased sharply during the past decade, especially in urban areas. Rice production has quadrupled during the past decade, from 37 thousand ton of milled rice equivalent in 2001 to 147 thousand ton in 2011 (Figure 1). The largest share of rice available in the country comes from imports. Rice imports have increased tremendously in the past decade, from 72 thousand ton in 2001 to 600 thousand ton and more from 2006 onwards, but dropped quite sharply, to 368 thousand ton, in 2011. Rice production increased most sharply in 2011. The dependency on rice imports has decreased over the last years. While the share of imported rice was 94% in 2006, this reduced to 71% in 2011. 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).

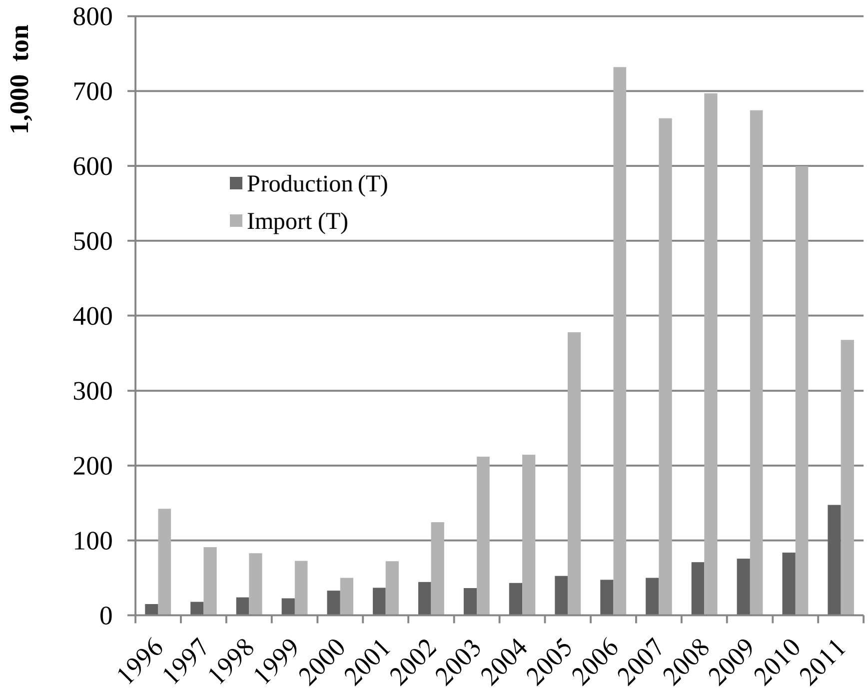

Figure 1. Rice production and import in Benin (milled rice equivalent), 1996 - 2011
Source: authors' calculation based on FAOSTAT (2014) taking into account a paddy to milled rice conversion factor of 0.67.

Despite the increasing production and the growing market potential for a local high-quality rice, the sector largely remains characterized by low quality, low value added, lack of investment and adequate infrastructure, and inefficient spot market exchange. An exception to this is the ESOP (*Entreprises de Services et Organisations de Producteurs)* contract-farming approach that aims at connecting farmers to the market in a sustainable way. An ESOP is a private social economic enterprise that works with a contract-farming approach. The approach entails a contract between groups of producers and the ESOP for the delivery of high-quality rice. The ESOP provides training and other services to the farmer groups in order to improve production and quality. The ESOP approach recognizes that value adding is key to the sustainability of this type of initiative (ETD, 2012). The ESOP initiative has been promoted by the *Centre International de Développement et de Recherche* (CIDR) as supervising and financial partner and the regional NGO ETD as technical partner.

Benin's central Collines region and more specifically the municipalities Glazoué, Bantè and Savalou compose the country's most important area for lowland rice production. Cultivation is rain-fed with only one rice harvest per year. Farmers usually commercialize rice through spot market exchanges, either with traders collecting paddy rice at the farm-gate, or at the nearest markets. In Savalou an ESOP unit established in 2006 and is fully operational since 2008. The ESOP works with groups of 10 to 15 farmers and being organized in such a group is the only condition for being eligible to enter in a contract. Contracts are written and signed before the start of the agricultural season. They specify a fixed price 150 FCFA per kg paddy rice in 2012 - the payment modalities and some quality specifications such as rice variety, impurity and humidity thresholds. In return, the farmers receive the needed inputs (seeds, fertilizer and herbicides) on credit and technical assistance throughout the growing period. The procured paddy rice is processed (dehusked, polished and sorted on grain size) in the ESOP facility, packaged and branded as a local quality rice *riz Délice*, and sold in domestic urban markets.

3 Methods

3.1 Data collection

We use primary farm-household survey data collected between April and May 2013 in the municipality of Savalou in central Benin. We focus on four districts (Tchetti, Doume, Kpataba and Ouesse) where rice production is most prevalent and the ESOP contract-farming approach is present. A two-stage stratified random sample was drawn. In the first stage, 21 villages were selected in the four districts according to the presence of contract-farming. In the second stage, rice-farming households were stratified according to whether they participate in the ESOP scheme or not. In total 396 households were sampled in the selected villages. Contract farmers were oversampled in order to have sufficient observations to make inferences. The ESOP contract scheme is still small and the large majority of rice farmers in the area are not involved in contract-farming. The sample includes 89 contract farmers and 307 non-contract farmers.

A quantitative structured questionnaire was used, including various modules on household demographics, land and non-land assets, agricultural production and commercialization, off-farm employment and income, food security, and credit. This resulted in detailed data on rice production and income, rice contracting experience and agricultural practices. The household survey data were complemented with information on infrastructure, accessibility, market access and rice farmer groups from a village survey.

3.2 Econometric Approach

Besides a comparison of means across contract and non-contract farmers, we use three different methods to reveal whether contract-farming is associated with improved farm performance. First, we use OLS to estimate linear regression models of the following type:

$$Y_i = \alpha_i + \beta C_i + \gamma X_i + \varepsilon_i \quad (1)$$

The dependent variable Y_i represents farm performance. We estimate multiple models with several indicators representing different aspects of farm performance: 1/ net income from rice farming (INCRI); 2/ net income from rice farming per hectare (INCRIHA); 3/ rice yield (YIELD); 4/ total value of inputs used for rice production, including seeds, fertilizer and herbi/pesticides (INPUT); 5/ the share of produced rice sold in the market (%SOLD); 6/ the sales price, measured as a weighted average price received for unpeeled rice, weighted by the volume share sold (PRICE); 7/ the cultivated rice area (AREA); and 8/ the total quantity of rice produced (QTYPROD). These are all continuous variables, and hence linear regression and OLS are used.

The main variable of interest, C_i, is a dummy variable for participation in an ESOP contract. To control for possible selection bias from observed heterogeneity, we include a large set of observable household and farm characteristics. The vector X_i includes indicators of human, social and physical capital as listed in Table 1. We also include four variables that proxy for specific unobserved farm and farmer characteristics. This includes a dummy variable for having experience with cotton cultivation as a proxy for farmers' management experience. Cotton used to be the main cash crop in the area and cotton cultivation gave farmers some experience in commercial agriculture. Risk and time preferences were assessed using multi price level games (Coller and Williams, 1999; Holt and Laury, 2002). In a first game, respondents were given the hypothetical choice between receiving 30.000 FCFA (approx. 45 Euro) now or receiving a higher amount within a year. The game was repeated 10 times, each time increasing the alternative amount up to 90.000 FCFA (approx. 130 Euro). In a second game, the respondents were asked to make a hypothetical investment choice, investing 150.000 FCFA (approx. 230 Euro) with 50% probability of gaining a certain amount and 50% probability of losing a smaller amount. The game was repeated 5 times with different amounts for profits and losses but without changing the probability of gaining and losing. From these data dummy variables were constructed for the 25% most risk-seeking and the 25% most future-oriented households in the sample, based on the number of risky and future-oriented choices made in the games.

Table 1. Description of independent variables used in the linear regression models

Variables	Description
Human capital	
Male HH head	Dummy for male headed households
Age HH head	Age of the household head in years
Education HH head	Dummy for HH head having at least one year of education
Adults	Number of adults (≥18 yrs old) in the household
Children	Number of children (<18 yrs old) in the household
Social capital	
FO member	Dummy for household being member of a farmer organization (FO)
Public function	Dummy for a household member holding a public function in the village or community (e.g. village head, farmer group leader,…)
Physical capital	
Land owned in 2012	Total area owned by the household in 2012, in ha
Land owned squared	The square of the total area owned by the household
Livestock	Number of tropical livestock units (TLU) owned by the household
Asset deprivation	Dummy for asset deprivation: 1= 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
Distance to market	Distance to the nearest market in km
Proxy variables for unobserved characteristics	
Risk attitude	Dummy for risk loving HH
Time preference	Dummy for future-oriented HH
Cotton experience	Dummy for experience with cotton growing

Second, we apply propensity score matching (PSM) and estimate an average treatment effect (ATE) of contract participation. We estimate the propensity score (PS), the probability of participating in the ESOP contract, using a probit model with the same set of control variables (Table 1) and one additional variable, maize yield. Maize is the main staple crop in Benin and all households in our sample cultivate maize. Maize yields are an indication of overall farm productivity, capturing observable as well as unobservable factors. To match households according to their propensity score, we apply kernel matching, with the default Gaussian kernel and bootstrapped 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).

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

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

The reliability of propensity score matching estimators depends on two crucial assumptions. First, the conditional independence assumption requires that given observable variables, potential outcomes are independent of treatment assignment (Imbens, 2004). This implies that selection into treatment is based entirely on observable covariates, which is a strong assumption. Second, the common support or overlap condition requires that treatment observations have comparison control observations nearby in the propensity score distribution (Caliendo and Kopeinig, 2008). We address these assumptions by analyzing balancing properties (Table A3), the propensity score overlap (Figure A4) and a simulation-based sensitivity analysis for PSM estimates (Table A5).

Third, we use a difference-in-difference (D-i-D) estimator for the outcome variable AREA for which recall data are available (Table 3). 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. We use the D-i-D result as a robustness check. 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).

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

$$\text{Y}_\text{i} = \alpha_\text{i} + \beta\text{post}_\text{i} + \gamma\text{C}_\text{i} + \delta\text{post}_\text{i} * \text{C}_\text{i} + \varepsilon_\text{i} \tag{3}$$

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 is then found as the coefficient for the interaction term of C_i with *post*.

4 Results and Discussion

4.1 Household characteristics

Table 2 presents t-test comparison of means for contract versus non-contract farmers for human, social and physical capital indicators and proxy variables. The average age of a household head is 42 years and 7% of sampled households is female-headed. Contract-farming households have slightly less adults, 2.45 compared to 2.67 for non-contract households, but significantly more children, 3.93 compared to 3.36 for non-contract households. Education is very low in the area and only 36% of household heads in the sample received some schooling. Education is significantly and substantially lower for contract households than for non-contract households, with 26% of schooled household heads compared to 38%.

All contract farmers are member of a farmers' organization; which reflects the fact that organizing themselves in small groups is a prerequisite for contracting with the ESOP. Also for non-contract households, group membership is high at 79%. Around 8% of households, whether contract or non-contract, have a member with a public or leadership function.

Landholdings are quite large, on average 14 ha per household, and land is not a constraining factor in the area. The cultivation system is quite extensive and farmers usually leave a certain part of their land fallow. The average cultivated area for the 2012 season in the sample is 7.96 ha. Contract households have slightly more land, 15 ha, than non-contract household, 13 ha, and also cultivate a larger area (9.81 ha on average for contract farmers versus 7.42 ha for non-contract farmers). Contract households also own more livestock, 3.74 tropical livestock units (TLU) on average, than non-contract households, 2.33 TLU; and are less deprived of assets. Contract farmers live at a larger distance from the market, 7.45 km, than non-contract farmers, 5.58 km.

The comparison of the proxies for unobserved characteristics shows that there is an equal proportion of risk-loving households in the two groups. However, contract-farming households are more often future-oriented and have more experience with cotton farming Maize yields, as a measure of overall productivity, do not differ between the two groups.

Table 2. Household and farm characteristics for contract and non-contract households

Variable	Total sample (N=396)		Non-contract households (N=307)		Contract households (N=89)		T-test t-value	
Human capital								
Male HH head (dummy)	0.93	*(0.26)*	0.92	*(0.27)*	0.94	*(0.23)*	-0.70	
Age HH head (yrs)	42.35	*(12.58)*	42.63	*(12.85)*	41.39	*(11.63)*	0.82	
Education HH head (dummy)	0.36	*(0.48)*	0.38	*(0.49)*	0.26	*(0.44)*	2.19	**
Adults (#)	2.62	*(1.07)*	2.67	*(1.13)*	2.45	*(0.81)*	1.73	*
Children (#)	3.49	*(2.19)*	3.36	*(2.14)*	3.93	*(2.31)*	-2.17	**
Social capital								
FO member (dummy)	0.84	*(0.37)*	0.79	*(0.40)*	1.00	*(0.00)*	-4.78	***
Public function (dummy)	0.08	*(0.26)*	0.08	*(0.27)*	0.07	*(0.25)*	0.34	
Physical capital								
Land owned in 2012 (ha)	13.73	*(11.82)*	13.28	*(11.25)*	15.29	*(13.58)*	-1.00	*
Livestock (TLU)	2.65	*(5.19)*	2.33	*(4.35)*	3.74	*(7.34)*	-2.38	**
Asset deprivation (dummy)	0.13	*(0.34)*	0.15	*(0.36)*	0.08	*(0.27)*	1.74	*
Distance to market (km)	6.00	*(5.05)*	5.58	*(5.36)*	7.45	*(3.47)*	-3.11	***

Unobserved characteristics proxies								
Risk attitude (dummy)	0.22	*(0.41)*	0.22	*(0.42)*	0.20	*(0.40)*	0.45	
Time preference (dummy)	0.21	*(0.41)*	0.19	*(0.39)*	0.29	*(0.46)*	-2.03	**
Cotton experience (dummy)	0.67	*(0.47)*	0.63	*(0.48)*	0.80	*(0.40)*	-3.01	***
Maize yield (t/ha)	0.96	*(0.57)*	0.95	*(0.56)*	0.97	*(0.63)*	-0.26	

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

Source: Estimated from survey data

4.2 Contract farming and farm performance

Looking at the comparison of means for the different farm performance indicators (Table 3), we observe that contract-farming households perform better for all indicators. Contract farmers have a net rice income that is around 2.5 times higher than for non-contract households, and a net rice income per ha that is 2 times higher. Contract households cultivate a significantly larger area with rice, 0.92 ha compared to 0.69 ha for non-contract households in 2012; while for 2008 there is no difference in the area cultivated between the two groups. Contract farmers use significantly more inputs and their total rice production is 80% higher than the production of non-contract farmers. Rice yield is generally low[1] at only 1.89 ton/ha on average for the sample but contract farmers have significantly higher yields, 2.09 ton/ha compared to 1.83 ton/ha. Contract-farmers commercialize a higher share of their rice produce, 71% compared to 61% for non-contract households, and they receive an average price that is about 10% higher than the average price non-contract farmers receive.

Table 3. Mean comparison for outcome variables according to participation in contract-farming

Dependent variable	Total sample (N=396)	Non-contract households (N=307)	Contract households (N=89)
INCRI (Euro)	165.16 *(281.22)*	122.78 *(227.33)*	311.34 *** *(383.94)*
INCRIHA (Euro)	234.85 *(396.97)*	189.58 *(360.24)*	391.00 *** *(473.60)*
PRICE (FCFA/kg)	147.89 *(78.67)*	144.70 *(86.69)*	158.91 * *(38.55)*
%SOLD	0.64 *(0.24)*	0.61 *(0.25)*	0.71 *** *(0.19)*
QTYPROD (kg)	1319.86 *(1306.09)*	1116.53 *(1074.14)*	2021.24 *** *(1733.01)*
AREA (2012) (ha)	0.74 *(0.62)*	0.69 *(0.61)*	0.92 *** *(0.64)*
AREA (2008) (ha)	0.48 *(0.51)*	0.47 *(0.52)*	0.52 *(0.45)*
YIELD (ton/ha)	1.89 *(1.12)*	1.83 *(1.10)*	2.09 ** *(1.18)*
INPUT (Euro)	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

[1] 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.

4.3 Econometric results

The estimated treatment effects of contract-farming on the different farm performance indicators are summarized in Table 4. Results from linear regressions, propensity score matching, and the difference-in-difference estimation are reported. We see that for all farm performance indicators the effect of contract-farming is significantly positive and estimates have the same sign and are of comparable magnitude and significance level across the different estimation methods. This is a first indication of robustness of the results. The fact that the D-i-D estimation on area gives the same results as the OLS and PSM estimation, points to a low bias from unobserved time-constant heterogeneity in the sample.

The full OLS regression results and the results from the propensity score matching estimation are reported in Annex 1 and 2 respectively. The balancing properties and propensity score distribution and overlap are given in Annex 3 and 4. In Annex 5, we further elaborate on the robustness of the PSM estimates with a simulation-based sensitivity analysis.

Table 4. Estimated effects of participation in contract-farming on rice farm performance

Outcome variable	OLS	PSM	D-i-D
INCRI	179.82***	181.80***	
	45.15	*39.39*	
INCRIHA	199.07***	232.03***	
	55.21	*49.41*	
PRICE	12.32**	11.36*	
	6.26	*6.16*	
%SOLD	0.08***	0.06**	
	0.03	*0.03*	
QTYPROD	816.77***	842.90***	
	193.56	*188.58*	
AREA	0.18**	0.20***	0.19**
	0.08	*0.07*	*0.09*
YIELD	0.26*	0.29*	
	0.14	*0.15*	
INPUT	40.50***	39.41***	
	8.80	*8.03*	

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

We find that participation in contract-farming significantly increases rice income. While the absolute effect is rather small – the point estimates are around 180 Euro – it is an important effect in the light of the large incidence of poverty in the area. In addition, relative to the average rice income in the sample (which is 165 Euro, Table 3), the effect implies an increase of 110%. These results are in line with most empirical studies showing a positive effect of participation in contract-farming on farm income; in high-value sectors (e.g. Maertens and Swinnen, 2009; Rao and Qaim, 2011) as well as in staple food sectors (e.g. Bellemare, 2010; Simmons et al., 2005). Our estimated effect of contract-farming on rice income of 110% compares to the overall income effect of 110% for contract-farming in the horticultural export sector in Senegal by Maertens and Swinnen (2009) but is larger than the income effect of 18% estimated by Bellemare (2010) for the case of rice farmers in Madagascar. Such differences in findings follow from the very nature of these studies that are by definition case-specific, and from difficulties in estimating unbiased causal effects in this type of studies.

In addition to pointing to an overall positive effect of contract-farming on farm income, our results on the different farm performance indicators allow to disentangle to some extent the channels through which the positive income effect comes about. Our results indicate that a combination of effects play and that contract-farming results in area expansion, increased intensification and yield improvements, output growth as well as improved commercialization. First, we find that contract-farming results in a significantly larger rice area – an effect that is consistent across the OLS, PSM and D-i-D methods. The rice area increases with about 0.2 ha, which is 27% of the average rice area in the sample. While land is not a scarce factor in the research region, preparing a plot of land for rice cultivation requires quite some investment (e.g. for clean-up, leveling, and tillage), especially in comparison with land preparation for other staple crops such as maize. Hence, the estimated effect points to an investment effect, that might result in growth in the rice sector in the region in the long run.

Second, we find that contract-farming leads to using more (a higher value of) inputs in rice farming and higher rice yields. We find that input use increases with about 40 Euro, which is an increase of 70% compared to the average value of inputs used in rice farming in the research area. Yields are found to increase with 0.29 ton/ha. Given that rice yields are on average very low in the area (1.89 ton/ha, Table 3), this is an important effect. Improving access to inputs and technology, and creating productivity increases are among the most documented and discussed effects of contract-farming in high-value sectors and export chains (e.g. Dries and Swinnen, 2004; Dries et al., 2009; Minten et al., 2009). Our results imply that also in staple food sectors contract-farming can be an important instrument for stimulating technological improvements and increasing yields.

Third, the combined effect of area expansion on the one hand and intensification and yield improvements on the other hand, results in a larger rice output and higher net rice incomes per hectare. We find that contract-farming is associated with an output increase of about 840 kg of unpeeled rice or 64% of the average rice output, and with an increase in net rice revenue per ha of about 200 Euro/ha or a doubling of per ha revenue.

Fourth, we find significant positive effects of contract-farming on rice commercialization and on farm-gate prices. Contract farming increases the share of rice that is commercialized with 9% points or 5%, and increases the average price farmers receive for their rice with about 12 Euro/ton or 8%. Respondents in the survey mentioned a guaranteed market outlet (89% of respondents) and a higher price (39%) among the main reasons to enter into an ESOP contract. Contract-farming is often put forward as an intuitional tool to better link farmers to markets and many empirical studies, including this one, show that contract-farming can indeed improve market access for smallholder farmers and result in increased commercialization and market participation (e.g. Barrett et al., 2012; Masakure and Henson, 2005). In addition, theoretical insights by Swinnen et al. (2010) and Swinnen and Vandeplas (2012) predict that a price premium is essential for avoiding holdup problems and contract breach – especially in developing countries where contract-enforcement institutions are weak – and hence for sustainable contract-farming. There is however very few evidence on the price effect of contract-farming. In studies focussing on export chains, the price effect of contract-farming is difficult to disentangle from the effect of supplying international markets where prices are higher. Other studies on contract-farming in staple food sectors have not analyzed the effect on producer prices. Our estimated price effect of 8% seems to suggest that a rather modest price premium can result in sustained contract-farming.

5 Conclusion

In this paper, we analyze the welfare effects of smallholder contract-farming in the rice sector in Benin. We use data from a farm-household survey, and propensity score matching and difference-in-difference estimation to reveal how contract-farming affects the performance of smallholder rice farms. We find that contract-farming is associated with a higher income from rice production. This income increase comes about through a combination of effects as contract-farming is found to result in larger areas allocated to rice production, in higher input use and increased intensification, in higher yields and higher rice production, in increased commercialization and in higher producer prices.

This case study contributes to the scarce empirical evidence on contract-farming in staple food chains and chains connecting farmers to domestic markets. Theoretical considerations point towards difficulties for sustained contract-farming in staple food chains due to the limited possibilities for creating added-value in staple food products and due to the higher likelihood of side-selling in markets with a large number of buyers. The positive effect we find on farm income and productivity indicates that contract-farming in domestic rice supply chains in Benin could be sustainable. Rice might be a special case as it is a staple crop that allows for some quality differentiation and associated added-value. This quality differentiation might be important in enabling the payment of a price premium in contract-farming schemes and in avoiding side-selling. The rice sector in Benin is still quite small with underdeveloped supply chains. Competition is limited, which makes side-selling a less important issue and which may further explain the success in contract enforcement. In recent years, food prices, and especially rice prices, increased dramatically. Higher prices increase the value in the food chains and this might have contributed to increase the feasibility of contract-farming in the rice chain in Benin. The possibilities for upgrading food chains through contract-farming might be different for other staple food crops and in other market conditions and institutional settings.

Rice is still a relatively small albeit fast-growing sector in Benin and the process of supply chain upgrading is still in its infancy in the sector We estimated the effects of contract-farming in a quite early stage in this process. Given the current trend of increased rice production and the policy focus on rice self-sufficiency in Benin – as in many other West-African countries - rice production is likely to expand further. Our results show that expansion of the sector through contract-farming schemes may improve rural incomes and productivity, and thereby contribute to poverty alleviation and food security.

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Annex 1. Full OLS results

Variables	INCRI	INCRIHA	AREA	INPUT	QTYPROD	YIELD	SOLD	PRICE
Contract participation (dummy)	179.82***	199.07***	0.18**	40.50***	816.77***	0.26*	0.08***	12.32**
	45.15	*55.21*	*0.08*	*8.80*	*193.56*	*0.14*	*0.03*	*6.26*
Male HH head (dummy)	-5.83	2.50	-0.14	10.91	-105.91	-0.16	-0.08*	-16.16
	35.38	*63.98*	*0.16*	*7.15*	*144.08*	*0.20*	*0.04*	*14.57*
Age HH head (yrs)	-0.14	-0.51	0.00	-0.18	-1.82	-0.01	-0.00***	-0.63*
	1.61	*1.93*	*0.00*	*0.30*	*7.40*	*0.01*	*0.00*	*0.37*
Education HH head (dummy)	91.38***	122.24***	0.08	9.98	499.53***	0.24**	-0.05*	8.99
	35.08	*45.12*	*0.06*	*6.10*	*151.19*	*0.12*	*0.03*	*10.89*
Adults >=18yrs (#)	-12.21	-31.47	-0.02	-1.00	-14.13	0.01	-0.02	-3.70
	12.72	*21.55*	*0.03*	*2.43*	*57.88*	*0.06*	*0.02*	*3.66*
Children (#)	0.49	-2.59	0.02*	3.05**	10.34	-0.08***	-0.02***	-3.38**
	6.41	*10.30*	*0.01*	*1.47*	*28.52*	*0.03*	*0.01*	*1.40*
FO member (dummy)	37.21	99.85**	0.03	-8.07	80.50	0.12	-0.03	1.06
	26.60	*43.27*	*0.08*	*7.24*	*128.31*	*0.14*	*0.03*	*6.77*
Public function (dummy)	24.90	-109.90	0.08	24.77	321.36	0.18	0.05	-1.04
	68.62	*72.98*	*0.15*	*15.35*	*341.71*	*0.20*	*0.04*	*10.24*
Land owned in 2012 (Ha)	2.96	-3.92	0.02***	2.59***	39.70***	-0.01	0.01***	0.41
	2.22	*3.71*	*0.01*	*0.65*	*9.91*	*0.01*	*0.00*	*0.94*
Square of land	-0.05*	0.01	0.00	-0.02**	-0.37***	0.00	-0.00***	-0.01
	0.02	*0.04*	*0.00*	*0.01*	*0.11*	*0.00*	*0.00*	*0.01*
Livestock (TLU)	7.43**	2.97	0.02**	1.07	46.61**	0.02*	0.00***	0.52
	3.17	*3.03*	*0.01*	*0.78*	*18.54*	*0.01*	*0.00*	*0.40*
Asset deprivation (dummy)	-38.26	3.04	-0.06	0.19	-326.69**	-0.22	-0.08*	-18.94
	37.55	*69.60*	*0.09*	*6.37*	*128.32*	*0.18*	*0.05*	*13.45*
Distance to market (km)	1.28	1.88	0.00	-1.82***	5.69	-0.01	0.00	0.53
	2.68	*3.96*	*0.01*	*0.50*	*11.80*	*0.01*	*0.00*	*0.52*
Risk attitude (dummy)	-0.42	125.79**	-0.21***	-4.77	50.50	0.48***	-0.03	-9.12
	30.78	*55.77*	*0.05*	*5.55*	*141.77*	*0.16*	*0.03*	*7.59*
Time preference (dummy)	-48.83	-49.51	-0.06	-3.82	-157.86	-0.12	-0.03	4.46
	35.41	*45.50*	*0.07*	*7.34*	*171.86*	*0.13*	*0.03*	*7.18*
Cotton experience (dummy)	-9.16	-16.20	-0.08	-4.20	48.92	0.31***	0.04	-2.29
	31.70	*37.46*	*0.07*	*7.81*	*127.35*	*0.12*	*0.03*	*9.87*
Constant	69.78	207.47**	0.55***	24.02*	495.96	2.16***	0.92***	201.31***
	68.95	*104.28*	*0.19*	*13.84*	*326.11*	*0.32*	*0.06*	*17.80*

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

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: Balancing properties in the matched sample

Annex 3: Balancing properties in the matched sample

shows the results of the propensity score balancing test for the matched sample, showing that conditional on the propensity score the two groups do not show significant differences anymore for any of the included characteristics. The balancing property shows that differences between the groups in observed factors that could explain both selection into contract-farming as well as higher values for the outcome variables are properly controlled for before calculating the treatment effect. We also include the proxies for unobserved factors that could be of importance for selection into contract-farming such as risk attitude, time preference, managerial experience and overall farm productivity, as explained in section 3.2.

Table A3. Balancing properties in the matched sample

Variable	Non-contracting households (N=271)		Contracting households (N=87)		Ttest t-value
Human capital					
Male HH head (dummy)					
Age HH head (yrs)	40.44	*(11.24)*	40.58	*(10.96)*	0.03
Education HH head (dummy)	0.24	*(0.43)*	0.26	*(0.44)*	0.16
Adults (#)	2.39	*(0.71)*	2.44	*(0.79)*	0.32
Children (#)	3.85	*(2.33)*	3.94	*(2.33)*	0.30
Social capital					
FO member (dummy)					
Public function (dummy)	0.07	*(0.25)*	0.07	*(0.26)*	0.07
Physical capital					
Land owned in 2012 (Ha)	14.15	*(11.06)*	15.34	*(13.80)*	0.63
Livestock (TLU)	2.55	*(3.59)*	3.11	*(4.03)*	0.97
Asset deprivation (dummy)	0.07	*(0.26)*	0.08	*(0.28)*	0.22
Distance to market (km)	7.23	*(5.49)*	7.33	*(3.46)*	0.18
Unobserved characteristics proxies					
Risk attitude (dummy)	0.18	*(0.39)*	0.21	*(0.41)*	0.41
Time preference (dummy)	0.29	*(0.45)*	0.29	*(0.46)*	0.04
Cotton experience (dummy)	0.80	*(0.40)*	0.81	*(0.39)*	0.25
Maize yield (t/Ha)	0.97	*(0.55)*	0.98	*(0.63)*	0.08

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

Annex 4: Common support property for PSM

Figure A4 illustrates another important aspect of the PSM analysis. The ATE is only defined in the region of common support or overlap. 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. This is addressed by only using observations in the common support region for the matching procedure, which resulted in 87 out of 89 contract-farming Households being matched with 271 out of 307 non-participating Households.

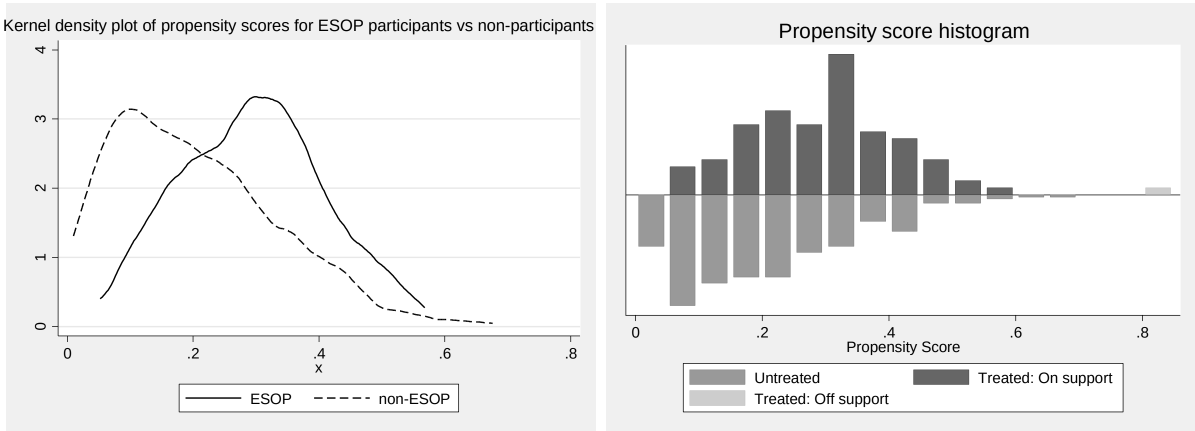

Figure A4. Kernel density plot and histogram of propensity scores

Annex 5: Simulation-based sensitivity analysis for PSM 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 simulation-based sensitivity analysis for PSM kernel estimates 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 could affect 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 calculate a new propensity score

$$\mathrm{PS_U} = \mathrm{P(C} = 1|\mathrm{X, U)}$$

which is then used for matching 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 Table A5. We use a neutral confounder U_n and two binary confounders respectively set up to 1/ have both a very high selection and outcome effect, which is the most threatening situation for the validity of PSM estimates (worst confounder, U_w) and 2/ a more moderate selection and outcome effect (moderate confounder, U_m).

We see that under the neutral confounder the estimate value barely changes, as expected. The largest effect on the estimates is seen at inclusion of U_w but nevertheless since the treatment effects as shown in section 4.2 are very large, even if the effect reduces with 9.80% to 27.98% the treatment effect is still large and positive (simulated treatment effect values not shown in the table). The treatment effect for AREA is least robust to the inclusion of this confounder, but for this outcome variable the inclusion of a D-i-D analysis provides clear confirmation of its robustness.

Any confounder of similar nature as the moderate confounder U_m, with smaller impact on the relative probability of being participating in contract-farming, would have small effects on the estimates with impacts between -4.3% and +10.8%, and also still results in large positive ATE estimator values (not shown in table). We see that the treatment effect for PRICE is least robust to inclusion of this confounder thus this result should be interpreted with caution.

Table A5. Simulation-based sensitivity analysis for PSM estimates

	neutral confounder U_n			worst confounder U_w			moderate confounder U_m		
	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
PRICE	1.97%	1.06	1.00	-27.01%	1.92	6.84	10.84%	0.75	2.76
%SOLD	0.02%	1.00	1.01	-1.98%	1.85	9.69	-0.33%	1.52	2.57
QTYPROD	-0.33%	1.10	1.03	-11.34%	1.83	10.05	-1.26%	1.71	2.57
AREA	-0.14%	1.07	1.05	-27.98%	1.82	10.65	-3.51%	1.28	2.63
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

[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