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Collective Marketing and Cocoa Farmer's Price in Cameroon

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Abstract

This study aims to evaluate the effects of collective marketing by farmer organizations (FOs) on cocoa farmer's price in Cameroon. This is done through the quasi-experimental method, which uses the techniques of "Propensity Score Matching". Data used come from 2006 International Institute of Tropical Agriculture (IITA) cocoa baseline survey and concern601 cocoa farmers in Centre region in Cameroon. Results show that, collective marketing has a positive and statistically significant effect on the net price received by farmers. This effect is estimated at 6% increase on the individual sale price. The main recommendation is to promote the development of FOs and collective marketing within FOs. The development of FOs requires a government policy to support the creation of FOs and by extension the effects of collective sales. Development of collective marketing can be done through creation of credit systems by FOs to encourage farmers who sell to individual buyers under the constraint of credit received. This probably would increase, significantly, the share of supply captured by FOs.

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1. Introduction

Smallholder's access to the market is a permanent concern for development actors in developing countries. Indeed, various studies proved that the smallholder remains poorly connected to the agricultural market (Key et al. 2000; Gabre-Madhin, 2001; Gabre-Madhin, 2009). One of the solutions to improve their access to the market involves promoting collective marketing through farmers' organizations (FOs). However, it is noted that very few studies have so far been carried to point out the importance of FOs in the collective marketing of members' products in developing countries. Collective marketing can also be viewed as a response of market liberalization. To accompany market liberalization, the Cameroonian State gradually installed the legal framework necessary for the creation and operation of FOs. Thus, cooperatives, Common Initiative Groups (CIGs) and their unions are structures which are formalized in the framework of the law No.92/006 of August 14, 1992, relating to cooperative organizations and Common Initiatives Groups. These organizations are created to solve their members' socio-economic problems. This study focuses on collective marketing of cocoa by FOs in Cameroon. According to Kamdem et al. (2010), Cocoa plays an important economic and social role in Cameroon, accounting for 6% of export earnings in 2006 and contributing 115 billion CFA francs to the national economy. There are approximately 260,000 producers and a total of 400,000 hectares is planted to cocoa. With regard to cocoa chain, liberalization began in 1991 by dissolution of Office National de Commercialization des Produits de Base (ONCPB) on January 28, 1991, and the creation of Office National du Cacao et du Café (ONCC) concomitantly with the Conseil Interprofessionnel du Café et du Cacao (CICC) on July 12, 1991. One of the objectives of liberalization was to "professionalize" the operators of cocoa chain. On the one side, the tradesmen should organize themselves to be able to negotiate for themselves contracts with importers, to negotiate financing means with the banks and to ensure marketing of products in strict compliance with international rules. On the other side, producers should organize themselves to ensure efficient negotiations with tradesmen through grouped sales, to control the quality of their products and to supply themselves with inputs by open market offer. Within this framework, the ONCC and the CICC had the role of guaranteeing the environment of this "professionalization" of actors. In parallel, the Société de Développement du Cacao (SODECAO) and the Programme Semencier Cacao Café (PSCC) were withdrawn gradually from the direct functions which they exerted in support of cocoa chain to transfer their duties (commercial, drying, storage, treatment, research/development, technical vulgarization/ technical advises) to farmers organizations. Their activities were reduced to only minimum production of planting material, since the capacities to produce are not exploited whereas supply always remained much lower than the demand. Beyond this institutional cocoa farming, FOs pain to create a unique framework dialogue at the national level for all products. In Cameroon, Center and South-west regions constitutes the highest percentage (85%) of national cocoa production in Cameroon. In the "Southwest" region, former cooperatives (such as the *Southwest Farmer Cooperative Union* based in Kumba) have been passed over to cocoa buyers (who are often producers). Even if they sometimes seem to be FOs, those CIGs and "purchasers cooperatives", pre-financed by official partners or exporters, they are in fact purchasing centres acting on behalf of the buyers. In the absence of projects to support producers' initiatives, no collective marketing organized by FO has been able to emerge in the Southwest region. The existence of FOs in the Centre region of Cameroon can be explained as an attempt to fill the gap left by the State in supplying farmers with inputs and marketing operations. But, according to Folefack and Gockowski (2004), only 40% of cocoa farmers in the Centre region effectively take part in collective sales organized by FOs.One can thus wonder why in spite of the existence of FOs, some cocoa farmers attend to the collective marketing while others do not. This implies the following main question, which justifies our study: what are the effects of collective marketing through FOs on cocoa farmer's price in Cameroon? This question refers to the control of functional and operational costs of cocoa market in Cameroon through collective sales by FOs. Many studies which highlight the effects of collective marketing on farmers are generally biased (Bernard et al. 2008). The impact analysis, which arouses the interest of many economists, has an important methodology debate. The particularity of this study is to try to isolate this bias by comparing cocoa farmers in Cameroon who sell collectively (treatment group) with those who sell individually (control group) in the Centre region which have some common characteristics.

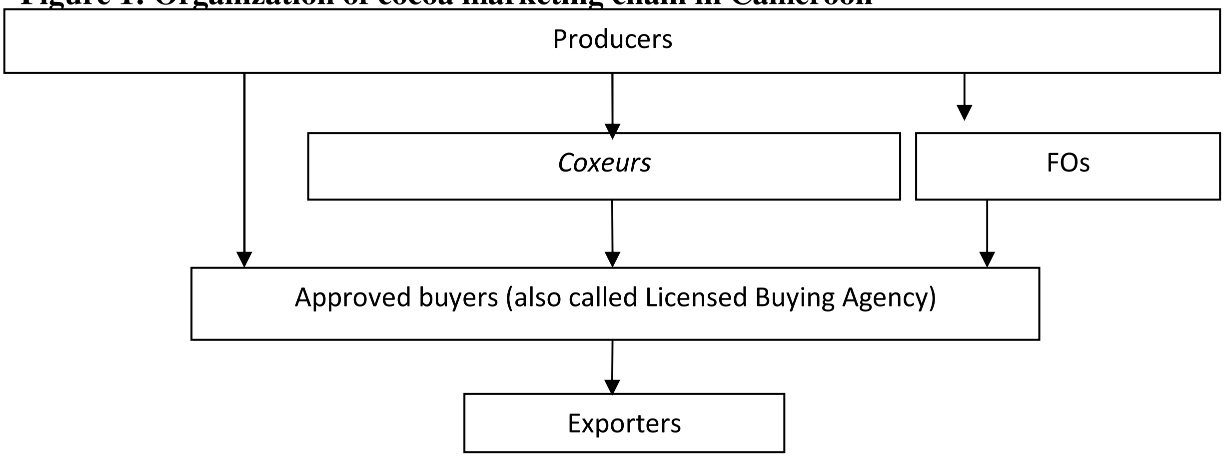
1.2. Empirical Evidence of the impact of farmers' organizations

The impact analysis of farmers'organizations is relatively new. Thus, a certain number of studies has been carried out on the importance of FOs to market the product of their members (Gadzikwa et al. 2006; Hellin et al. 2009; Devaux et al., 2009; Kruijssen et al. 2009; Catacutan al. 2008; Barham and Chitemi, 2009). However, very few studies use the impact methods analysis (randomized evaluations, matching methods specifically propensity score matching, double-difference methods, instrumental variable methods, regression discontinuity design and pipeline methods, distributional impacts and structural approaches) to highlight the existence of bias in the impact analysis of FOs on marketing. Hence, the studies of Bernard, al. (2008) use the method of Propensity Score Matching (PSM) to show the impact of cooperatives on smallholders' commercialization behaviour in Ethiopia. The use this method enable to reduce biases due to the location of cooperatives and members' self-selection into them and find that in spite of the fact that FOs enables to negotiate better prices for their members, these FOs don't always succeed in increasing the quantity of products marketed. In addition, the studies of Verhofstadt and Maertens (2014) in Rwanda using the same method to reduce bias arising from failure to control for heterogeneity in observed household characteristics show that cooperative membership in general has a positive impact on farm performance. In the same logic, the studies of Verhofstadt and Maertens (2015) in Rwanda using propensity score matching techniques to reduce bias from cooperative membership and certain types of households, reach to the results that cooperative membership in general increases income and reduces poverty.

1.2. Organization of cocoa marketing chain in Cameroon

The cocoa marketing chain is organized in a fairly simple way [Figure 1 from Kamdem et al. (2010)]. Thus, according to the study of Kamdem et al. (2010), farmers can either sell to "*coxeurs*" (who usually come to buy cocoa from farmers), or directly sale to approved buyers (though this often requires a long trip) or sell through FO (in the Centre region only because there is really no FO in the other region of production, the Southwest region).

Figure 1: Organization of cocoa marketing chain in Cameroon



Source: Kamdem et al. (2010)

The first channel of marketing (direct sale to approved buyers) is mostly by the large farmers. It is not very common in the Centre region, but very widespread in the Southwest region. The second channel (sale to *coxeurs*) is very widespread in the Centre region as well as in the Southwest region. The third channel (sale via FO) exists only in the Centre region. The approved buyers resell the cocoa bought to the exporters. Faced with this multiple channels of marketing, it arises that farmers generally need to choose between selling collectively or selling individually. Faced with this choice, many farmers still chooses to sell their cocoa individually. If the principal reason remains the comparison of satisfaction that they draw from the two options, many studies show that, beyond this satisfaction, many factors determine the choice of farmer. Indeed, Bernard et al. (2007) show that the higher the level of education of the farmer and the size of the farm (in hectare), the higher is the probability of selling to FO. In addition, the study of Sinja et al. (2006) on the milk farmers in Kenya show that the probability of taking part in collective marketing is identical when one considers the sex, the age and the level of education. Moreover, the results of the study carried out by Gadzikwa et al. (2006) show that the participation at FO in the province of KwaZulu-Natal in South Africa is positively determined by the growth of net benefit and negatively determined by the growth of household size. Thus, the consideration of various variables suitable for assigning the farmer participation to FO generally reduces bias of impact evaluation. For this reason, in this study, we deployed the technique of "Propensity Score Matching" in order to reduce the possible effect of bias in the results.

2. Methodology

The impact evaluation method presents empirical difficulties. Indeed, the alternative situation to the design (the "counterfactual") is difficult to define Heckman et al. (1998). This can be explained by the fact that individuals in the control group can also participate in other equivalent programs as those provided by the studied design. This difficulty reinforces the necessity to better understand the mechanism of design. Moreover, the control group is built with the objective that, on the average, the non-participants have identical characteristics as those of the participants. But it also presents heterogeneous elements unobserved by the evaluator which can have an influence on their probability of participating in the evaluated program. This is the problem of selectivity bias. It makes the identification and correction of selection mechanisms to the design participation necessary, since one could produce bias estimations of participation effects to the program by directly comparing the situations of the two groups (participants and non-participants to the program) if one does not consider these selectivity bias. To avoid these difficulties, the method of “Propensity Score Matching”, which is one of the impact evaluation methods, is used.

2.1. Propensity Score Matching assumptions

Assumption 1: O*bservable selection and conditional independence*. The matching based on the assumption that all the variables producing selection bias (control variables) are observed (Rosenbaum and Rubin, 1983; Rubin and Thomas, 1996; Imbens, 2004; Dehejia, 2003; Smith and Todd, 2005). Given *Xi,* the vector of observed variables, the assumption of selection on observables means that the latent result variables (Y_{NT}, Y_T) are orthogonal to the conditional participation of characteristics (X). Under this assumption, it is possible to cancel selection bias by comparing individuals with identical observed characteristics.

Assumption 2: *Existence of common support*. The application of matching techniques is only possible if there exists untreated individuals with characteristics identical to those of treated individuals $0 < P(T = 1|X) < 1$. The test of this assumption is based on the estimation of common support zone (Todd, 2007). The assumption of common support means that the probability associated to the participation, noted $P(T = 1|X) < 1$ is not zero: for any *i*, there exists a positive probability to participate.

Assumption 3: *SUTVA (stable unit value assumption).* This assumption assumes that the treatment only affects the outcome variable of those who participate. This means that there are no indirect effects from the participants at collective sales to farmers who sell individually (control group).

2.2. Estimating method

The principle of estimating method is to use collected information about untreated individuals to build a counterfactual for each treated individual. Considering the selection bias as a sample selection problem, we apply PSM to estimate the average treatment effect (ATE) of participants at collective sales. This involves matching treated farmers (participants at collective sales) with control farmers (participants at individual sales) that are similar in terms of observable characteristics. Equation (1) explains the evaluation problem comparing outcomes Y across treated and control individuals. $Y_i = \alpha X_i + \beta T_i + \varepsilon_i$ (1).

T is a dummy equal to 1 for those who participate and 0 for those who do not participate; X is set of other observed characteristics. ε is an error term reflecting unobserved characteristics that also affect Y. We estimate the propensity score (PS) as the probability of being a participants at collective sales, using the vector X as conditioning factors. The ATE is calculated as the average of the outcome differences between treated $Y(1)$ and controls $Y(0)$.

$$PS = P(T = 1|X) \quad (2)$$

$$ATE = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)] \quad (3)$$

The estimator Δ^{ATT} is obtained as the average of all differences between the situation of treated individuals and the built counterfactual.

The problem becomes estimating $E[Y(1) - Y(0)]$ for each treated individual with characteristics X_i. To reach the result, one must first make pairings on the base of "Propensity Score Matching". Then the next step will just be a question of defining the common support and calculating the variations.

2.2.1. Propensity score estimation

Propensity Score Matching is used to select observable characteristics under the assumption of conditional inter-dependence. Hence this estimation is made from probit or logit model of participation in the program, by controlling all the variables X which affect, in the meantime, the "participation" and "result" variables. Indeed, estimators of PSM are less biased when X include variables which both affect the participation in the program and its result (Heckman et al., 1998). Predicted values (*propensity score:* $PS_i = P(T = 1|X)$) are then obtained. These values of propensity score represent the probability distribution for each farmer and for each transaction to participate in the program, i.e. selling through FOs. This predicted probability of participation is conditional to exogenous characteristics. The interest in estimating this predicted probability to take part in the program is to make the pairing of individuals having "propensity score", which are close; this explains the necessity to build a common support.

2.2.2. Common support determination

After the estimation of propensity score for all individuals in the sample, one determines the common support to make sure that, for each individual who participate in the program, one can find at least an individual who did not participate and who has the same propensity score. To build the common support of propensity score, two approaches can be adopted. The initial method of pairing is from (Rubin, 1977). Though it looks simple, many critics point out the problems of dimensionality, the nature of process and the unknown properties of its estimators. More details can be found in(Crepon, 2000). This method corresponds to the method of pairing of nearest neighbour. The studies of (Heckman et al., 1998) enable to wipe out the limits of (Rubin, 1977) method, through the method of Kernel and locally weighted regressions. This method consists in generating, for each observation of the group of treatment, an observation which is a weighted average of control group observations (either the unit, or a given interval). These weightings are inversely proportional to the distance between observation *i* (in terms of Pi) and control group observations. The results can be sensitive to the choice of interval and the weighting function. It is this method which is used in this study.

3.4.3. Estimating of standard error

The standard error estimation is obtained by applying the methods of "bootstrap", which consists in replicating the entire estimation procedure on a random sample with handing-over in the initial sample and determining the standard error of the entire distribution of estimators obtained. This estimation of standard error considers the fact that the "propensity score" has been estimated. Hence, each bootstrap must take into consideration, not only the pairing on the random sample, but also the estimation of the score.

2.3. Data

This study uses data collected through a questionnaire administrated by IITA for a "baseline survey" of STCP[1] program. This survey covered the period running from March15 toApril15, 2006 and concerned cocoa farmers. Data were collected on farmers as well as their transactions characteristics. From both regions, data were collected on 904 producers having carried out 2487 cocoa transactions. To better apprehend the impact of collective marketing, we exploited only the data on 601 farmers from the Centre region where there exist individual and collective sales at the same time. Data collected have helped to make a description of variables on farmer's characteristic transactions, as well as variable result (Table 1).

Table1: Statistics of data collected by region and selling channel

Titles	Farmers			
	Individual sales	Collective sales	Individual and collective sales	Total
Number	369	214	18	601
Price mean (FCFA/kg)	529.000	592.000	549.000	552.000
Price standard deviation	54.810	55.790	39.530	62.350
Quantity per transaction	224.500	272.100	295.400	243.600
Total quantity	515.800	642.700	844.800	570.800

[1]Sustainable Tree Crop Program.

Number of farmers who have received credit from anyone than cocoa buyer	0	61	8	69
Number of farmers who have received credit from cocoa buyer	113	0	8	121
Distance to market (km)	0.300	0.700	0.800	0.500

Source: IITA survey 2006

From the distribution of farmers by sales category, we joint other statistics such as mean price and standard deviation of price (Table 1). In this table, we have distinguished number of farmers who have received credit from anyone than cocoa buyer and number of farmers who have received credit from cocoa buyer. We can observe that some farmers who sell individually (113 farmers) receive their credit from cocoa buyer while some farmers who sell collectively (61 farmers) receive their credit from anyone than cocoa buyer.

Data collected have helped to make a description of variables on farmer's characteristic transactions, as well as variable result (Table 2).Thus, one can distinguish the variable result (OUT) from the farmers and transactions characteristic variables (CAR) as well as participation variable for logit regression (PART). In this study, the participation variable is collective sale or not, while the result variable is farmer's price. Concerning result variable, other variables (the inputs supplied by FO, training facilitated by FO) could be associated. But the fact that we only have data on farmer's price forces us to use only this variable as a result variable. It is important to note that the question of collective marketing effects on cocoa farmer's price implies also world market instability. These influences, in a decisive and exogenous way, the price receive by cocoa farmers (both in collective and individual sales). This can also substantially decrease the significance of PSM method, when it is not taken into account in the analysis. Indeed, FOs do not have any control on international cocoa market trends. Thus, this method integrated instability of international cocoa market price by the variable "Monthly Variation Coefficient of international cocoa market prize (CIF[2] price) for the corresponding monthly cocoa farmer's price". In fact, price instability can affect differently individual famers and FO. FO received price information from ONCC while individual farmer does not. Thus, individual farmers have less price information and high prices are insufficiently transmitted.

Table 2: Description of the variables used in the analysis

[2]Cost, Insurance and Freight.

Variables	Description of the variable	Unit	Categories
Pp	Price received by the farmer	FCFA/kg	OUT
TypeTransac	Type of sales: via a PO versus individual exclusively	1= if Collective	PART
Gender	Gender of farmer	1=if Male	CAR
Age	Farmer age		CAR
Educ	Farmer level of education	1=if has been in school	CAR
Farmsize	Farm size of farmer	in hectare	CAR
(Farmsize)2	Farm size of farmer square	in hectare	CAR
Hseholdsize	Household size		CAR
(Hseholdsize)2	Household size square		CAR
RentScol	Selling during the period of start of the school year	1= if Yes	CAR
Cred1	Credit received from anyone (either for individual or collective sales)	1= if Yes	CAR
Cred2	Credit received from buyer (either for individual or collective sales)	1= if Yes	CAR
TotInc	Farmer total income	in 10000 FCFA	CAR
IndDivers	Index of the producer's income diversification (the smaller the index, the more the producer is diversified)	between 0 and 1	CAR
DistProd	Distance from the house to the point of sale	Km	CAR
QTransac	Quantity per transaction	Kg	CAR
NbTransac	Number of transactions per producer during the campaign		CAR
NbBuyers	Number of approved buyers in the village		CAR
HarvestSeason	Season of abundance	1= if Yes	CAR
QTot	Producer's production	Kg	CAR
(QTot)2	Producer's production square	Kg	CAR
InfoP	Information about the CIF price (international market price)	1= if Yes	CAR
DistBuyer2_	Number of non-tarmac km between the point of sale and the port of Douala	Km	CAR
CVPCaf	Monthly Variation Coefficient of CIF price		CAR
DumLékié	Dummy for Lékié Division	1= if Yes	CAR
DumMbam	Dummy for Mbam Division	1= if Yes	CAR
DumMefou	Dummy for Mefou Division	1= if Yes	CAR
DumNyong	Dummy for Nyong Division	1= if Yes	CAR

3. Empirical results

This study aims at measuring, in a robust way, the effect of farmers' organizations through collective sales on cocoa farmer's selling price. The challenge faced here consists in reducing considerably the measurement bias by using the technique of "propensity score matching". Our study enables us to quantify, by minimizing bias, the impact of collective sales of farmers' organizations on cocoa farmer's price in Cameroon. Table 3 presents descriptive statistics of variables used in the analysis.

Table3: Descriptive statistics of variables used in the analysis

Variables	Individual sales(369)				Collective sales(214)			
Variables	Mean	Std. Dev	Min	Max	Mean	Std-Dev	Min	Max
Gender	0.880	0.318	0.000	1.000	0.957	0.201	0.000	1.000
Age	51.910	14.750	19.000	100.000	47.453	14.108	20.000	88.000
Educ	0.910	0.277	0.000	1.000	0.950	0.211	0.000	1.000
Farmsize	1.760	1.619	0.500	22.000	2.177	1.997	0.500	22.000
(Farmsize)2	5.730	26.780	0.250	484.000	8.7137	34.730	0.250	484.000
Hseholdsize	4.460	1.900	1.000	7.000	4.710	1.906	1.000	7.000
(Hseholdsize)2	23.510	16.910	1.000	49.000	25.803	16.755	1.000	49.000
Cred1	0.300	0.461	0.000	1.000	0.285	0.452	0.000	1.000
Cred2	0.300	0.461	0.000	1.000	0.000	0.000	0.000	0.000
RentScol	0.560	0.496	0.000	1.000	0.610	0.487	0.000	1.000
TotInc	41.790	32.220	7.500	300.000	49.750	32.066	7.500	185.000
IndDivers	0.580	0.307	0.000	1.000	0.610	0.238	0.000	1.000
DistProd	0.340	2.010	0.000	32.000	0.665	1.456	0.000	10.000
QTransac	224.400	229.500	17.500	2000.000	272.060	249.588	16.500	2000.000
NbTransac	2.170	0.990	1.000	6.000	2.800	1.152	1.000	7.000
NbBuyers	3.290	2.550	1.000	10.000	6.574	3.716	1.000	10.000
HarvestSeason	0.780	0.410	0.000	1.000	0.836	0.370	0.000	1.000
QTot	515.700	650.00	40.000	6320.000	642.650	503.604	40.500	3315.000
(QTot)2	687473.500	2837148.000	1600.000	39900000.000	665431.200	1239015.000	1640.200	1.10E+07
InfoP	0.330	0.472	0.000	1.000	0.462	0.499	0.000	1.000
DistBuyer2_	21.570	32.950	1.000	90.000	18.574	24.945	1.000	90.000
CVPCaf	0.019	0.012	0.009	0.046	0.0212	0.013	0.009	0.046
DumLekié	0.371	0.483	0.000	1.000	0.228	0.421	0.000	1.000
DumMbam	0.078	0.269	0.000	1.000	0.5420	0.421	0.000	1.000
DumMefou	0.067	0.251	0.000	1.000	0.1308	0.338	0.000	1.000
DumNyong	0.482	0.500	0.000	1.000	0.098	0.298	0.000	1.000

3.1. Estimation of the probability propensity score

The results of probit estimation of collective marketing participation are presented in Table 4. These results show that, household size, average quantity per transaction, number of transaction, total quantity sold and information received by farmer on the international price significantly influence cocoa farmer's participation in collective marketing.

Table 4: Probit estimation of determinants of collective marketing participation

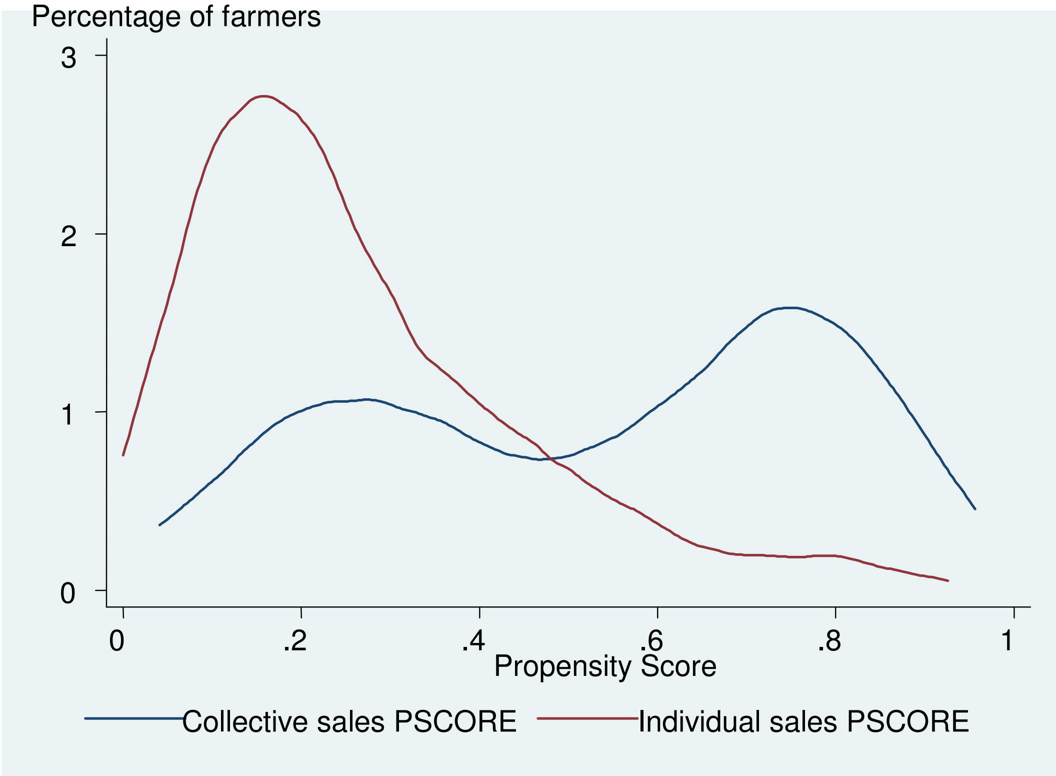
Variables	Coefficients	P-value
Gender	0.160	0.490
Age	-0.0009	0.839
Educ	0.056	0.836
Farmsize	-0.068	0.360
(Farmsize)2	0.002	0.434
Hseholdsize	-0.075	0.646
(Hseholdsize)2	0.004	0.816
RentScol	-0.116	0.469
TotInc	0.004	0.035**
IndDivers	-0.014	0.951

QTransac	0.0004	0.087*
NbTransac	0.153	0.030**
NbBuyers	-0.042	0.503
HarvestSeason	0.031	0.870
InfoP	0.224	0.086*
DistBuyer2_	-0.006	0.050**
CVPCaf	2.723	0.583
DumLekié	-0.520	0.060*
DumMbam	1.133	0.062*
DumNyong	-1.279	0.000***
Constante	-0.353	0.543
Observations		583.000
Pseudo-R^2		0.300

***Significant at 1% level, **significant at 5% level, and *significant at 10% level

The distribution of "propensity scores" between treatment and control groups is shown in Figure 2. This figure clearly shows that the two distributions are different.

Figure2: Propensity scores distribution among treatment and control groups



To ensure the robustness of our estimations, several techniques can be used. We focus on two commonly used methods: non-parametric Kernel regression matching proposed by (Heckman et al., 1998) and five nearest neighbours matching. In the first technique, each treated producer is matched with the entire sample of comparison. However, for each observation in the treatment group, an observation which is the weighted average of observations in the control group is generated. Those weights are made inversely proportional to the distance between each observation concerned and the control group observations, on the base of “propensity score" distribution. In the second technique, each treated observation is paired with the average of its five nearest neighbours of comparison sample, always based on "propensity score" distribution. To ensure maximum comparability of treatment and comparison group, the sample is restricted to the region of common support defined by the values in the range of "propensity score" in which treatment and control observations can be found.

Table 5: Balancing test of samples

Variables	Unmatched sample			Kernel-based matching			5 nearest neighbours matching		
	Means		P-value	Means		P-value	Means		
	Treated	Control		Treated	Control		Treated	Control	P-value
Gender	0.957	0.886	0.003	0.956	0.945	0.604	0.956	0.938	0.404
Age	47.453	51.913	0.000	47.585	48.082	0.728	47.585	49.013	0.329
Educ	0.953	0.915	0.090	0.951	0.968	0.373	0.951	0.978	0.134
Farmsize	2.177	1.765	0.007	2.181	2.535	0.114	2.181	2.372	0.378
Hseholdsize	4.710	4.460	0.128	4.676	4.422	0.180	4.676	4.308	0.047
RentScol	0.616	0.560	0.188	0.613	0.496	0.017	0.613	0.547	0.176
TotInc	49.757	41.792	0.004	48.444	54.718	0.076	48.444	52.383	0.248
IndDivers	0.618	0.588	0.216	0.617	0.601	0.565	0.617	0.607	0.698
QTransac	272.060	224.490	0.020	272.920	270.650	0.931	272.920	284.440	0.658
NbTransac	2.808	2.176	0.000	2.724	2.778	0.608	2.724	2.742	0.866
NbBuyers	6.574	3.298	0.000	6.458	6.608	0.684	6.458	6.699	0.510
HarvestSeason	0.836	0.780	0.103	0.835	0.700	0.001	0.835	0.727	0.008
InfoP	0.462	0.333	0.002	0.449	0.476	0.576	0.449	0.462	0.783
DistBuyer2_	18.575	21.577	0.249	19.169	26.439	0.003	19.169	26.754	0.002
CVPCaf	0.021	0.019	0.048	0.021	0.020	0.506	0.021	0.019	0.354
DumLekié	0.228	0.371	0.000	0.236	0.242	0.891	0.236	0.263	0.526
DumMbam	0.542	0.078	0.000	0.526	0.536	0.837	0.526	0.535	0.860
DumMefou	0.130	0.067	0.011	0.135	0.107	0.386	0.135	0.102	0.303
DumNyong	0.098	0.482	0.000	0.101	0.113	0.695	0.101	0.098	0.922

The right way to test the validity of matching is to compare average characteristics of farmers in the treated sample with the corresponding characteristics of control group generated. Therefore, the absence of significant differences between treatment and control groups confirms the validity of matching. Thus, we undertook a series of statistical tests of farmer's characteristics and trading difference in three samples: the sample of unmatched farmers, the sample of farmers matched with Kernel technique, and the sample of farmers matched with five nearest neighbours technique. Table 5 shows the significant difference in the vast majority of characteristics in farmers sample unmatched (collective sales with those who sell individually). In the unmatched sample, we have fourteen (14) farmers' characteristics which differ between collective and individual sales. After matching, it remain only four for fourteen farmers' characteristics for *Kernel-based matching* and three for five *nearest neighbours matching* which differ between collective and individual sales. In summary, matched samples ensure the validity of comparability required to minimize bias, but cannot erase the bias.

3.2. Average effect of collective marketing

The indicator of cocoa collective marketing impact is the net price received by farmers. The impact of collective marketing on the net price paid to farmers shows whether collective sales (compared to individual sales) enable farmers to have a higher price. This certainly goes through the reduction of transaction costs and the increase of bargaining power. Table 6 presents the results of average treatment effects estimation for collective marketing in terms of price received by cocoa farmers. To ensure the robustness of this estimation, we first calculated the difference in the output variable (net farmer cocoa price) between treatment group and the control group. Then, for the standard error, we made 100 replications bootstrap using Stata Software.

Table 6: Average effect of collective marketing on price after two stapes replication (Outcome variable: Net price received by the farmers)

	Kernel-based matching	5 nearest neighbours matching
ATT	32.048	34.287
Std. error	6.112***	6.628***
Number of observations of treated group	214(7)	214(7)
Number of observations of control group	369	369
Total number of observations	583(7)	583(7)

Note: Observations in parentheses were not used in the estimate due to the common support condition stratified. Bootstrap with 100 replications are used to estimate the standard errors.
***Significant at 1% level, **significant at 5% level, and *significant at 10% level

The results of average effects estimation for both methods (for Kernel matching and matching five nearest neighbours) show that farmers who sell collectively receive about 33 FCFA per kilogram more than those who sell individually, which represents a premium of 6%. This effect is statistically significant at 1% and robust across the two forms of matching. Given these estimations, we find that the two matching methods (for Kernel matching and five nearest neighbors matching) lead to similar results as much in the matching test as in the average effects estimation.

Moreover, whatever the matching technique used, a comparison of Propensity Score Matching method with the Naïve method is necessary to better assess the contribution of this method to impact evaluation of collective sales' (Table 7).

Table 7: Comparison of the average effects using Naïve and PSM methods

Titles	Values
Average Price in individual sales (FCFA per kg)	529
Average Price in collective sales (FCFA per kg)	592
Average effects usingNaïvemethod (FCFA per kg)	63
Average effects using PSM method (FCFA per kg)	33
Average effects difference of two methods used (FCFA per kg)	30

The results in Table 7 show that the difference between the average effect by Naïve method and Propensity Score Matching method is 30 CFA francs per kg. Application of Naïve method is biased because of non-consideration of individual characteristics of farmers and transactions. This difference is the result of bias reduction by applying Propensity Score Matching method. It is possible to test the significant of difference between the two methods by the following way: H0: $\mu = \mu 0$; H1: $\mu \neq \mu 0$. Since the average effects are obtained from large sample, distribution can be approximated by a normal distribution. Thus, we use the statistic Z to conclude:

$Z = \frac{\mu - \mu_0}{\sqrt{\frac{S^2}{n}}} = \frac{63-33}{3.7}$ =8.08 >1.96. H0 is rejected. 63 FCFA is significantly different to 33 FCFA. Testing the significance of the two methods lead to the evidence that the bias reduce by using the propensity score technique is 30 FCFA. Since the impact of collective marketing is positive and significant, what could be the source of this impact?

3.3. What explain the high price of FOs?

The fact that the price is high in collective sales by FOs compared to individual sales can be explained by some specific variables such as input supply, training organized by FOs, the speed of payment to the farmers, credit received and distance to the sale point. Given the non-existence of data on all these variables, we will focus only on two of them: the credit and the distance to the sale point. Thus we consider each of these two variables as outcome variable and we apply the PSM.

3.3.1. Are high prices of FOs explained by distance to the sale point?

The application of PSM on the data using the distance to the sale point as a variable result allows us to obtain the results contained in Table 8.

Table 8: Average effect of collective marketing on distance after two stapes replication (Outcome variable: Distance to the sele point)

	Kernel-based matching	5 nearest neighbours matching
ATT	-0.039	0.015
Std. error	0.569	0.834
Number of observations of treated group	213(7)	213(7)
Number of observations of control group	369	369
Total number of observations	582(7)	582(7)

Note: Observations in parentheses were not used in the estimate due to the common support condition stratified.Bootstrap with 100 replications are used to estimate the standard errors.

***Significant at 1% level, **significant at 5% level, and *significant at 10% level.

This table allows us to conclude that the distance from the sale point has no effect on collective sales.

What about credit?

3.3.2. Are high prices of FOs explained by credit?

The application of PSM on the data using credit as a variable result allows us to obtain the results contained in tables9 and 110.

Table 9: Average effect of collective marketing on credit from anyone than cocoa buyer after two stapes replication (Outcome variable: Credit received by farmers from anyone)

	Kernel-based matching	5 nearest neighbours matching
ATT	0.111	0.124
Std. error	0.537**	0.054**
Number of observations of treated group	214(7)	214(7)
Number of observations of control group	369	369
Total number of observations	583(7)	583(7)

Note: Observations in parentheses were not used in the estimate due to the common support condition stratified.Bootstrap with 100 replications are used to estimate the standard errors. ***Significant at 1% level, **significant at 5% level, and *significant at 10% level

This table allows us to conclude that the credit received by producers from anyone has a significant and positive effect on collective sales.

Table 10: Average effect of collective marketing on credit from cocoa buyer after two stapes replication (Outcome variable: Credit received by farmers from buyer)

	Kernel-based matching	5 nearest neighbours matching
ATT	-0.168	-0.155
Std. error	0.030***	0.032***
Number of observations of treated group	214(7)	214(7)
Number of observations of control group	369	369
Total number of observations	583(7)	583(7)

Note: Observations in parentheses were not used in the estimate due to the common support condition stratified.Bootstrap with 100 replications are used to estimate the standard errors ***Significant at 1% level, **significant at 5% level, and *significant at 10% level.

This table allows us to conclude that the credit received by producers from buyer has a significant and negative effect on collective sales.

4. Conclusion and recommendations

The importance of collective marketing carried out by farmers' organizations (FOs) is to have farmer's positive benefit generated from externalities for those who participate. The objective was to assess the impact of cocoa collective marketing on the net price received by the farmers. Analysis of data collected by STCP-IITA in 2006 enables us to draw the main conclusion: the impact of collective marketing on price received by cocoa farmers in the Centre region of Cameroon is a reality. This effect is positive and statistically significant. It is estimated at 33 FCFA per kilogram by PSM method, and representing an increase of 6% of average sale price (comparing collective with individual sale). This increase is the same order of magnitude as that found in other countries for other farmers (Bernard et al. 2008). Furthermore, the use of naïve method enables to be aware of the bias that this method contain. Thus, we note that there is a difference of 30 FCFA per kilogram between the two methods. This difference can be attributed to the existence of bias in the naïve method. However, applying PSM enables to minimize only bias due to observed characteristics, while bias due to non-observed characteristics cannot be minimized. In spite of the fact that all the biases cannot be minimized, this does not affect the importance of collective marketing impact. In addition, other results variables out of price can explain the participation of farmers in FO. Examples are input supply, credit, and training facilitated by the FOs.

Given this conclusion, the main recommendation is to promote the development of collective marketing by FOs. The reason that some farmers do not sell through FOs (although this would allow them to get a better price) may be partly related to credit access (Kamdem et al., 2010). Indeed, one can assume that farmers who need urgent cash advance cannot sell to FOs because they need credit (private buyers only offer them for individual sales) or because they cannot wait for market days to sell their cocoa to the FOs. We have estimated PSM on effect of collective sales on credit received from anyone and from buyer. The evidence is that the effect is positive for credit received from anyone and negative for credit received from buyer. This confirms the fact that the reason that some farmers do not sell through FOs may be partly related to credit access. The development of credit system available to farmers (or the creation of credit systems by FOs) obviously would increase significantly the share of supply captured by FOs.

In addition, future studies may be conducted to analyse the conditions for the emergence of FOs to understand why they appeared in some areas and not in others. Indeed, the creation of FOs definitely needs to support a number of costs and constraints (awareness, logistics cost for office, headquarters of FO, etc.). These costs and constraints can be different depending on whether the creation of FOs is exogenous or endogenous. It is exogenous when creating the FO is an initiative of one or more external(s) elite (s) of the area or an NGO. In this case, costs and constraints set up are almost entirely supported by the donor. Regarding an endogenous creation of FO, it is initiated by one or more members of the locality. In this case, costs and constraints are supported by members. Moreover, the legal framework supports the creation of FOs (Law No. 92/006 of 14 August 1992 relating to cooperative and CIGs). Thus, the challenges in creating FOs need to be known more in future studies. It would also be appreciable in future studies to identify factors that lead farmers to join or not join the FO. This may also help to identify the factors that guide farmers who are members of FO to choose selling through FOs or not. Such studies would help to guide policies to facilitate the development of FOs and strengthen their impact on prices received by farmers. However, to make a robust conclusion on the impact of FOs marketing on cocoa price, we suggest further research must be based on a panel data (before and after). In fact, cross-sectional data survey may not clearly show cocoa price effects from FOs marketing.

5. References

Barham, J., & Chitemi, C. (2009) "Collective action initiatives to improve marketing performance: Lessons from farmer groups in Tanzania", Food Policy, 34(1), 53–59.

Bernard, T., Gabre-Madhin, E., and Taffesse, A. S. (2008) "Heterogeneous Impacts Of Cooperatives On Smallholders' Commercialization Behavior: Evidence From Ethiopia", African Association of Agricultural Economists (AAAE).

Bernard, T., Gabre-Madhin, E. Z., and Taffesse, A. S. (2007) "Smallholders' commercialization through cooperatives: A diagnostic for Ethiopia", IFPRI discussion paper No. 722, International Food Policy Research Institute (IFPRI).

Bernard, T., Taffesse, A. S., and Gabre-Madhin, E. (2008) "Impact of cooperatives on smallholders' commercialization behavior: evidence from Ethiopia", Agricultural Economics, 39(2), 147–161.

Catacutan, D., Bertomeu, M., Arbes, L., Duque, C., and Butra, N. (2008) "Fluctuating Fortunes of a Collective Enterprise: The Case of the Agroforestry Tree Seeds Association of Lantapan (ATSAL) in the Philippines", Small-Scale Forestry, 7(3-4), 353–368.

Crepon, B. (2000) "Méthodes d'appariement dans l'évaluation des politiques de l'emploi". Presented at the Communication aux Journées de Méthodologie Statistique, mimeo INSEE.

Dehejia, R. H. (2003) "Was There a Riverside Miracle? A Hierarchical Framework for Evaluating Programs with Grouped Data", Journal of Business & Economic Statistics, 21(1), 1–11.

Devaux, A., Horton, D., Velasco, C., Thiele, G., López, G., Bernet, T., and Ordinola, M. (2009) "Collective action for market chain innovation in the Andes", Food Policy, 34(1), 31–38.

Folefack, D. P., and Gockowski, J. (2004) Libéralisation et système de commercialisation du cacao", Forum sur le commerce des produits agricoles, www.forum1.interreseaux.net, Accessed 12 August 2008.

Gabre-Madhin, E. (2009) "A Market for all Farmers: Market Institutions and Smallholder Participation", Center of Evaluation for Global Action.

Gabre-Madhin, E. Z. (2001) "Market institutions, transaction costs, and social capital in the Ethiopian grain market" Washington, D.C.: International Food Policy Research Institute.

Gadzikwa, L., Lyne, M. C., and Hendriks, S. L. (2006) "collective action in smallholder organic farming: a study of the ezemvelo farmers'organization in kwazulu-natal", South African Journal of Economics, 74(2), 344–358.

Heckman, J., Ichimura, H., Smith, J., and Todd, P. (1998) "Characterizing Selection Bias Using Experimental Data", Econometrica, 66(5), 1017.

Hellin, J., Lundy, M., and Meijer, M. (2009) "Farmer organization, collective action and market access in Meso-America". Food Policy, 34(1), 16–22.

Imbens, G. W. (2004) "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review", The Review of Economics and Statistics, 86(1), 4–29.

Kamdem, C., Galtier, F., Gockowski, J., David-Benz, H., Egg, J., and Kamgnia Dia, B. (2010) "What determines the price received by cocoa farmers in Cameroon? An empirical analysis based on bargaining theory", African Journal of Agricultural and Resource Economics, 6(1).

Key, N., Sadoulet, E., and De Janvry, A. (2000) "Transactions costs and agricultural household supply response", American Journal of Agricultural Economics, 82(2), 245–259.

Kruijssen, F., Keizer, M., and Giuliani, A. (2009) "Collective action for small-scale producers of agricultural biodiversity products", Food Policy, 34(1), 46–52.

Rosenbaum, P. R., and Rubin, D. B. (1983) "The Central Role of the Propensity Score in Observational Studies for Causal Effects", Biometrika, 70(1), 41.

Rubin, D. B. (1977) "Assignment to Treatment Group on the Basis of a Covariate", Journal of Educational Statistics, 2(1), 1–26.

Rubin, D. B., and Thomas, N. (1996) "Matching Using Estimated Propensity Scores: Relating Theory to Practice", Biometrics, 52(1), 249–264.

Sinja, J., Njoroge, L., Mbaya, H., Magara, H., Mwangi, E., Baltenweck, I., and Omore, A. (2006) "Milk market access for smallholders: a case of informal milk trader groups in Kenya", CGIAR systemwide program on collective action and property rights (CAPRi).

Smith, J. A., and Todd, P. E. (2005) "Does matching overcome LaLonde's critique of nonexperimental estimators?", Journal of Econometrics, 125(1–2), 305–353.

Verhofstadt, E., and Maertens, M. (2014) "Smallholder cooperatives and agricultural performance in Rwanda: do organizational differences matter?", Agricultural Economics, 45(S1), 39–52.

Verhofstadt, E., and Maertens, M. (2015) "Can Agricultural Cooperatives Reduce Poverty? Heterogeneous Impact of Cooperative Membership on Farmers' Welfare in Rwanda", Applied Economic Perspectives and Policy, 37(1), 86–106.