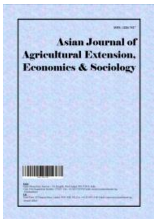

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Mechanical Drying System' Adoption and its Impact on Cocoa Beans Quality and Household Incomes at Farm Level: A Case Study of Central and South-West Cameroon

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Authors' contributions

This work was carried out in collaboration among all authors. Authors EWO and YY designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors EWO, MOA, and FMF managed the literature searches and analyses of the study. Authors EWO and YY reviewed and approved the final manuscript.

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ABSTRACT

Drying has been considered as a key farm-based, quality determining unit operation in the cocoa processing chain which can have an integral effect on the bean quality. In recent years, minimal attention has been directed to this process mainly because of the outdated methods and lack of technical know-how with regards to the modern technology adoption by producers. This article therefore aimed to analyze the adoption and welfare impacts of the Mechanical Drying System in Cameroon using data from a sample of 128 farm households. Using well-structured questionnaires, six villages were included in our study, and about 19 farmers from each village were approached and interviewed. The survey collected valuable information on several issues at the farm level: the data on farmer resources, drying activities, technology choices, constraints, socio-economic profiles,

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input markets, and cocoa beans processing markets. Using various treatment effect estimators, such as Endogenous Switching Regression, Propensity Score Matching, and Inverse Probability Weighting, our results revealed that adoption of the Mechanical Drying System leads to substantial gains in crop quality, and household incomes. For asset value, households that adopted the MDS technology had a per capita asset value of XAF2608.22 compared to those households that did not adopt the MDS who had a per capita asset value of about XAF412.83 less. Our ESR results further depicted that the adoption of MDS lowered the probability of poverty by 9.29% points for adopters compared to non-adopters. Also, ESR results indicated that the adoption of MDS increased the probability of MDS security for adopters by 37.68% points compared to non-adopters. On average, our PSM results depicted that, MDS adoption increased yield in the range of 614.74 to 679.04 kg/ha for adopters compared to non-adopters and the household income per capita from 86.21 XAF to 108.95 XAF for adopters compared to non-adopters. ATT results also demonstrated that farmers who adopted MDS had higher yields 679.04Kg/ha compared to those who did not adopt the MDS technology which resulted in higher household incomes, and decreased risk of high levels of poverty. Although the magnitude of the estimated effects varied between the three econometric models, the qualitative results were consistent and like the descriptive statistics. Hence, we concluded from our study that, the adoption of MDS by farm producers led to substantial gains in crop quality, and household incomes. Therefore, stimulating agricultural growth depends largely on policies that promote technology adoption at the farm level.

Keywords: Adoption; mechanical drying system; Cocoa beans quality; treatment effect estimators; household welfare; Cameroon.

1. INTRODUCTION

In Cameroon, agriculture, which employs more than 75% of the nation's population, is vital for achieving the development goals of alleviating poverty. Cocoa beans amongst coffee, rubber, banana, cotton, tea, etc., are one of the major cash crops in Cameroon. Cameroon is the world's fifth-biggest cocoa beans producer, behind the Ivory Coast, Ghana, Indonesia, and Nigeria, according to the UN Food and Agriculture Organization, [1]. This marketable crop accounts for more than half of the country's exports of basic items (58.7%), such as oil, wood, and minerals (as revealed by government statistics, CMR 2017 [2].

Cocoa beans sales contribute about 250 billion XAF ($426 million) per year with an average annual production up to 300 000 tons (382 000 tons of cocoa beans produces in 2017; [2] *CMR,2017*). Cameroon cocoa beans sector also accounts for approximately 2% of the national GDP, 6% of the primary GDP, and approximately 30% of the GDP of agricultural products subsector for export and processing [3]. The cocoa sector in Cameroon is largely dominated by exporters of unfinished products, especially raw cocoa beans. The plant is commonly grown in the South-west, North-West, littoral, West, East, and Central regions of the country.

Despite being the country's main producer of cocoa beans, producers in the South-West and Central regions in Cameroon are still struggling on how to improve the quality of their products. The producers, despite having $11 million in investments between 2010 and 2015, have not been able to achieve the expected results.

One of the biggest problems contributing to low cocoa beans quality is moisture, which subsequently affects its drying quality. In response to this problem, cocoa beans producers in Cameroon have tried different approaches and this includes proper drying techniques.

In Cameroon, two techniques of drying are used: natural drying (sun) which is very widespread, and artificial drying (mechanical drying) which on the other hand is less commonly used. It is necessary to distinguish artificial complete drying from the artificial drying occurring after pre-drying or solar drying.

From a current survey conducted, the current adoption rate for MDS were very low and as such farmers were unable to achieve full yield from the selling of their cocoa beans. This means that most farmers still used traditional methods to dry their cocoa beans, such as solar drying. Continuous use of solar drying has led to poor quality of cocoa beans, and the introduction of MDS was also low and slow in terms of farmers adapting to this new technology. Therefore, efforts aimed to improve smallholder agricultural practices and incomes, require that we understand and identify the constraints and incentives which influence MDS adoption.

Table 1. MDS in Cameroon: Characteristics and adoption rates (% of households)

Types	Attributes for MDS					Adoption rates (% of household)					
						Districts					
	Years of release	Yield (%)	Drying phase (hours)	quality	Temperature (°c)	KI	KII	KIII	OI	S	All
						25	15	18	40	30	128
All MDS						5	3	0	11	3	22
Static dryer	1990	55 -7	20	GI	60-68	60	66.66	0	66.63	33.33	10.74
Rotary dryer	2000	60 -8	30	GI	-	0	0	0	0	33.33	1.46
Vertical dryer	2010	60- 7	16	GI	103	40	33.33	0	36.36	33.33	4.56
Other (solar)	always	70-12	2-3 weeks	FS	Sun	80	80	100	75.5	90	82.81

Note: Adoption rates were computed by authors using survey data and major attributes were drawn from LEKIE and MEME (2019)

Therefore, the main objective of this paper is to assess the impacts of MDS adoption on household incomes, asset, poverty, and MDS yield using various models: Endogenous Switching Regression (ESR), Propensity Score Matching (PSM), and Inverse Probability Weighting (IPW); Tobit model will be used to estimate the adoption rate of MDS, and to access the factors affecting MDS adoption at farm level. Different estimators of the adoption effect will be used to isolate the effects of adoption on different outcome variables such as MDS yields, household incomes, asset, and poverty. This will help to provide robust empirical evidence on the adoption and economic impacts of MDS.

2. COCOA BEANS RESEARCH IN CAMEROON

2.1 Background

Cocoa is one of the main cash crops in Cameroon, offering employment to more than 600,000 peoples all over the country, which benefits about 3 million people either directly or indirectly [4]. Cameroon is the world's fifth-biggest cocoa grower after the Ivory Coast, Ghana, Indonesia, and Nigeria as noted earlier. The prices paid to cocoa farmers are much lower than those on the world market, but buyers impose strict quality demands on producers. These conditions lower prices paid to producers. Smallholders, farmer cooperatives, individual buyers, License Buying Companies (LBCs), unfinished product exporters, semi-finished product exporters, chocolate, and other cocoa products manufacturers, pharmaceutical companies, and cosmetics manufacturers are the main players in the global value chain in Cameroon.

The South-west and central regions are among the six cocoa producing areas in Cameroon. South-west region includes the MEME districts (1st producing area at the national level). The South-West also has about 36,750 cocoa farmers occupying an area of 103,900 Acres [2]; on the other hand, the Central region includes the LEKIE district (2nd producing area at the national level), which also records seventy (70) cocoa farmers occupying an area of one hundred and fifty-eight (158) Acres (Table 3). The production is mainly carried out by peasant farmers who, even though they are the main producers of this high-demand crop, do not earn sufficient income to meet their daily needs and sustain a modest standard of living.

On adoption, overall, 17.18% of farmers have adopted MDS and this higher adoption rates are observed at OBALA (50%) as compared to other districts such as SA'A and KUMBA II with the lowest adoption rate of 13.63% (see Table 1). Although a total of three MDS were released, only two types —*Vertical dryer* (36.36%) and *static dryer* (59.09%) are the most used MDS in Cameroon (Table 1). [1]

3. MATERIALS AND METHODS

3.1 Sample Area of the Survey

The MEME district is situated in the forest zone. Agriculture, trade/commerce, and small-scale mining are the main occupations of its inhabitants. With an average annual rainfall of about 3 000 mm characterizing the climate of the region, the district is suitable for production of cocoa beans. The total MEME population is about 384, 286 people [5] representing about 1.53% of the national population; the MEME land area is 3105 km^2 [2]. On the other hand, LEKIE is well noted for different characteristics: less rainfall (around 1,500 mm), a better and longer dry season. The main differentiation related to altitude is the region that corresponds to the plateau. The altitude is generally greater than 700m which is the last zone best suited for cocoa and consists of ferritic soils from the decomposition of metamorphic rocks [6].

The data used in this paper were from a survey of 128 farmers, randomly selected and interviewed using well-structured questionnaires. These total sample of 128 farm households were selected randomly from the six districts with the number of households from each selected village being proportional to the size of the district. These were the people using MDS to dry their cocoa beans. The survey collected valuable information on several issues at the farm level: the data on the farmers' resource, drying activities, technology choices and preferences, constraints, socio-economic profiles, input markets, and cocoa beans processing markets.
The survey was conducted between June and September 2019, and specifically, it covered the South-West region, MEME districts (KUMBA I, KUMBA II, and KUMBA III), and Central region, LEKIE district (Obala, SA'A). These were the

[1] Adoption was measured by the percentage of households who used MDS between 2018-2019 growing season. Adoption intensity was measured as the total of people using MDS for drying. We used both variables in econometric analysis.

targeted areas for the research as they are the major cocoa beans growing areas. Seven regions were designated as cocoa beans growing regions, and two regions were purposively chosen as primary sampling units. Three villages were conveniently selected from each sampled region. The data obtained in the study were coded and analyzed using Statistical Package for Social Sciences (SPSS, 2007), and the results were presented in tables.

3.2 Econometric Framework and Estimation Technique

3.2.1 Evaluation of MDS adoption and its utilization rate

Adoption was defined as the percentage of households who reported using any of the MDS in the 2018/2019 growing season, while utilization rate was defined as the period, households used mechanical dryer to dry cocoa beans.

Adoption behavior at the farm level and factors influencing technology adoption were studied and identified by numerous econometric models as illustrated by Dorfman [7]; Mwangi, [8]; Makaiko Khonje et al [9]; Obayelu [10]; and Julius Manda, [11]. Technology adoption was modeled in a random utility framework. In this regard, let Q* denote the difference between the utility from adoption (U_{iA}) and the utility from non-adoption (U_{iN}) of MDS. If $Q^*=U_{iA} - U_{iN}>0$, a household will opt to adopt the MDS. However, the two utilities by being unobservable, it can be expressed as a function of observable components in the latent variable model below:

$$Q_i^* = K_i\alpha + \varepsilon_i \quad \text{with } Q_i = \begin{cases} 1 & if\ Q_i^* > 0 \\ 0 & otherwise \end{cases}$$

Where *Q* is a binary variable
Q= 1 if the technology is adopted
Q= 0 otherwise.
Alpha (α) is a vector of parameters to be estimated,
K is a vector that represents household-and farm-level characteristics.
ε is the random error term.

We used Tobit model proposed by Tobin [12] (1958) for a solution to estimate factors that affect the utilization of MDS. It is required by Tobit that, the decision to adopt MDS and its utilization be determined by the same process because Tobit is restrictive.

3.3 Technology Adoption: Impact Evaluation

Centered on non-experimental observations, it is unrealistic to evaluate the impact of technology adoption on household welfare. Two variables cannot be observed: first, the outcome variable for adopters, in the case that they did not adopt MDS; On the other hand, the outcome variable for non-adopters, in the case they did adopt MDS. In trial studies, adoption was randomly attributed to treatment and control status to ensure that, the outcome variables observed in households that did not adopt statistically reflect what would have happened without adoption. Adoption was randomly distributed to the household itself deciding to adopt based on the information it has, but not between adopters and non-adopters, therefore, the two groups may be systematically different [8].

For the impact analysis, we used the recent (2019) data and three different econometric approaches: Endogenous Switching Regression (ESR), Propensity Score Matching (PSM) and Inverse Probability Weighting (IPW) models.

3.3.1 Endogenous switching regression

The mean treatment on the treated (ATT) measures the average difference in the results of the category of adopters with and without technology. The most frequently used methods for calculating ATT such as PSM ignored unobservable factors that could affect the adoption process and assumed that the return (coefficient) of characteristics was the same for adopters and non-adopters, which is not the case in many recent empirical studies [13-16]. The ESR framework took place in two stages:

1. The decision to adopt MDS (Eqn. 1), was estimated by using a Probit model.
2. An Ordinary Least Squares (OLS) regression with selectivity correction was used to examine the relationship between the outcome variable and a set of explanatory variables conditional on the adoption decision.

The two regression equations of the results, conditional on adoption, could be expressed as follows:

Group 1 (Adopters): $y_{1i}=x_{1i}\beta_1+w_{1i}$ if Q=1 (2a)

Group 2 (Non-adopters): $y_{2i}=x_{2i}\beta_2+w_{2i}$ if Q=0 (2b)

Where:

y_{1i} and y_{2i} represent welfare outcome variables such as yield, asset value, household income, MDS utilization, and poverty ;
x_{1i} and x_{2i} are vectors of exogenous covariates ;
β_1 and β_2 are vectors of parameters ;
w_{1i} and w_{2i} are random disturbance terms.

According to Dorfman, 1996 [7] and Guy Martial Takam-Fongang et al, [17], for the ESR model to be identified, the K variables in the adoption model (Eqn.1) must contain a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption. The selection instruments we used included the following: access to credit (yes=1) and longevity in use (years). Following Di Falco et al. [18] and Julius Manda, 2019 [19], a simple falsification test was performed to select the instruments. The technology adoption decision is affected in case the variable is a valid selection instrument but will not affect the welfare outcome variable. Following the results, the selected instruments can be considered as valid, as they are jointly statistically significant in explaining adoption decision [LR χ^2= 119 (p= 0.000)] but are not statistically significant in explaining the outcome equation [F= 1.60 (p= 0.07)][5].

The error terms in Eqns.1 and 2 is assumed to have a tri-variate normal distribution with the mean vector zero and covariance matrix:

$$\Omega = \text{cov}\,(\varepsilon, w_1, w_2) = \begin{vmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_\varepsilon^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{vmatrix} \qquad (3)$$

Let us suppose that σ_ε^2 = 1 as the coefficients in the selection model are estimable up to a scale factor. Since y_1 and y_2 are never observed simultaneously, the covariance between w_1 and w_2 is not defined Maddala, 1983 [20]. The error term of the selection Eqn. 1, εi by being correlated with the error terms of the welfare outcome functions (2) (w_1 and w_2), the expected values of w_1 and w_2 conditional on the sample selection are non-zero. (Acheampong et al, [21];

E (w_{1i} |Q =1) = $\sigma_{\varepsilon 1}$ [$\phi(K_i\alpha)$ / $\Phi(K_i\alpha)$ ≡ $\sigma_{\varepsilon 1}\lambda_1$ (4)
E (w_{2i} |Q =0) = $\sigma_{\varepsilon 2}$ [$\phi(K_i\alpha)$ / 1−$\Phi(K_i\alpha)$ ≡ $\sigma_{\varepsilon 2}\lambda_2$ (5)
ϕ is the standard normal probability density function,
Φ the standard normal cumulative density function,
λ_{1i} = $\phi(K_i\alpha)$ / $\Phi((K_i\alpha)$ and
λ_{2i} = $\phi(K_i\alpha)$ / 1−$\Phi(K_i\alpha)$
λ_1 and λ_2 are the inverse mills ratio calculated from the selection equation

To correct for selection bias in the two-step estimation procedure i.e., ESR model, λ_1 and λ_2 will be included in 2a and 2b. To estimate the mean treatment effect of the treated (ATT), and the non-treated (ATU), The above ESR framework can be used by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios. Following Acheampong et al,[21]; we calculated the ATT and ATU as follows:
Adopters with adoption (noticed in the sample)

$$(y_{i1}|Q=1;)=x_{i1}\beta_1+\sigma_{\varepsilon 1}\lambda_{i1} \qquad (6a)$$

Non-adopters without adoption (noticed in the sample)

$$(y_{i2}|Q=0;)=x_{i2}\beta_2+\sigma_{\varepsilon 2}\lambda_{i2} \qquad (6b)$$

Adopters had decided not to adopt (contrary to fact)

$$(y_{i2}|Q=1;)=x_{i1}\beta_2+\sigma_{\varepsilon 2}\lambda_{i1} \qquad (6c)$$

Non-adopters had decided to adopt (contrary to fact)

$$(y_{i1}|Q=0;)=x_{i2}\beta_1+\sigma_{\varepsilon 1}\lambda_{i2} \qquad (6d)$$

The mean treatment effect on the treated (ATT) is computed as the difference between (6a) and (6c);

$$ATT = (y_{i1}|Q=1;\, x) - (y_{i2}|Q=1;\, x) = x_{i1}(\beta_1-\beta_2) + \lambda_{i1}(\sigma_{\varepsilon 1}-\sigma_{\varepsilon 2}) \qquad (7)$$

The mean treatment effect on the non-treated (ATU) is given by the difference between (6d) and (6b);

$$ATU = (y_{i1}|Q=0;\, x) - (y_{i2}|Q=0;\, x) = x_{i2}(\beta_1-\beta_2) + \lambda_{i2}(\sigma_{\varepsilon 1}-\sigma_{\varepsilon 2}) \qquad (8)$$

If the cocoa beans of adopters (those who adopt MDS) or non-adopters (those who did not adopt MDS) had the same characteristics with the cocoa beans of non-adopters (if they decided to adopt) or adopters (if they decided not to adopt), the expected change in the mean outcome of adopters is captured by the first term on the right of Eqns. (7) and (8). All potential effects of the difference in unobserved variables are captured by the second term (λ). In Stata 13, the model was calculated for continuous and binary outcome variables by move-stay and switch probit commands, respectively.

3.3.2 Propensity score matching

Since the ESR results may be responsive to its model assumption i.e., the selection of instrumental variables, we have used PSM and IPW approaches to check the sturdiness of the estimated income effect. Following Heckman et al. [22], let Y_1 be the value of the welfare outcome variable when the household *i* is subject to treatment (Q=1) and Y_0 the same variable when the household does not adopt MDS (Q=0). Following Mariapia Mendola, 2007 [13], the ATT can be defined as:

ATT= $\{Y_1 - Y_0|$Q=1$\}$ = E ($Y_1|$Q=1) – E ($Y_0|$Q=1 (9)

We can observe the outcome variable of adopters *E* ($Y_1|$ Q = 1), but we cannot observe the outcome of the adopters if they did not adopt *E* (Y_0 | Q = 1), and the estimation of ATT using Eqn. (9) may therefore, lead to biased estimations. PSM relies on conditional independence, depending on the probability of adoption given observable covariates, Y_1 and adoption status (Q) are statistically independent of the outcome of interest in the absence of adoption (Mariapia Mendola, 2007 [13]. The propensity score or probability of receiving treatment is defined by Rosenbaum and Rubin 1983 [23] as:

(X)=pr (Q= 1) $|X$ (10)

The common support condition requiring significant overlap in covariates between adopters and non-adopters is another relevant assumption of PSM, such that the producers being compared have a common likelihood of being both an adopter and a non-adopter, which requires substantial overlap in covariates between adopters and non-adopters, so that 0 < (X) < 1 as pointed out by Takahashi 2014 [24] and Acheampong et al, [21]. If the two assumptions are met, then the PSM estimator for ATT can be specified as the mean difference adopters matched with non-adopters balanced on propensity scores and falling within the common support region, expressed as:

$$\text{ATT} = E\ (Y_1|\text{Q=1},\ (X)) - E\ (Y_0|\text{Q=1},\ (X). \quad (11)$$

The PSM method is a two-step procedure: first, a probability (logit or probit) model for MDS adoption is calculated to measure the propensity score for each observation; second, an estimation of the ATT score, where each adopter is matched to a non-adopter with similar propensity score values. Although PSM aims to compare the difference in quantity between the outcome variables of adopters and non-adopters with identical characteristics, it does not correct non-observable bias because it only monitors observed variables (to the extent that they are perfectly measured). We calculated PSM using *teffects psmatch* command in Stata 13 which implements nearest-neighbor matching in the estimation process.[2],[3]

3.4 Inverse Probability Weighting (IPW)

The effect of parameters using the means of the results observed is calculated by IPW weighted by the inverse probability of treatment. There is no outcome model. To estimate the parameters of the conditional probability model, the IPW estimators use the quasi-maximum likelihood (QML). The estimation function vector is the combination of the estimation functions for the impact parameters with the estimation functions for the conditional probability parameters (Acheampong et al, [21] and Julius [25]. Functions of the sample calculation used by the IPW estimate are:

$$s_{ipw,\,i}(x_i,\hat{\theta})' = s_{ipw,e,i}(x_i,\hat{\theta},\hat{\gamma})', s_{tm,i}(\text{k}_i, 1, \hat{\gamma})' \quad (12)$$

The estimation functions $s_{ipw,\,\text{I}}(\text{k}_i,\hat{\theta},\hat{\gamma})'$ differ from one effect parameter to another. The normalized

[2] The use of ESR models helped to eliminate the bias and as such results were more robust.

[3] Adopters and non-adopters can have the same average education, but this does not necessarily mean education has the same return (coefficient) on outcome variable for both groups of households as the quality of education may vary across the group.

inverse-probability weights are used by all the IPW estimators. The practical shape for the normalized inverse-probability weights differs with the possible outcome means (POM) effect parameters, average treatment effects (ATE), and average treatment on the treated (ATT). We used teffects ipw command in Stata 13 in the estimation process. With a measured probability that closely matches those of the participants, PSM gives greater weight to comparison group subjects. On the other hand, IPW gives greater weight to members of the comparison-group with higher estimated participation probabilities. The IPW solution is even more intuitively appealing Handouyahia et al. [26].

4. RESULTS AND DISCUSSION

4.1 Households Sample: Socio-economic Characteristics

The socio-economic characteristics of selected variables by district and adoption group are presented in Table 3. The results revealed that the level of household head education in Obala I district (9.8 years) was substantially higher when compared to farmers in other districts. The findings indicated that in terms of household characteristics such as age, education, and household size, adopters were distinguishable. Adopters had a higher level of education of 9.9 years than non-adopters who had an average of 7.5 years. This helped farmers to better understand the significance of new agricultural technologies being implemented. Similar to this finding, training is projected to have a positive effect on the adoption of technology (Huffman 2001 [27]. This is consistent with the expectation that due to the greater understanding of the availability and benefits of new agricultural technologies, the probability of implementing new agricultural technologies such as MDS increases with the level of education of the household heads. Education not only encourages adoption but also increases productivity, especially among adopters of advanced technology. Furthermore, adopters were comparatively younger than non-adopters. On average, farm households had more land in Obala I (88 hectares) and Sa'a (70 hectares) than those in other districts. Results also indicated that adopters owned more land (140 hectares) compared to the 109.1 hectares of non-adopters who owned less land.

If they have sufficient credit, farmers can allocate more money to the adoption of mechanical dryers, and those who own more credit are expected to have a comparative advantage when it comes to MDS adoption. Compared with other districts, farmers in the Obala district had the highest asset value per capita (XAF14 850), and tropical livestock units (1.11). Adopters are distinct in terms of asset holdings—asset value per capita (XAF12 1250 *vs*. XAF7 000) and tropical livestock units (0.21 *vs*. 0.1) and have more assets than non-adopters. This means that farmers with a wider resource base (assets) are more likely to experiment with MDS options because they better hedge against the technology associated risks. To fund inputs such as fuel or electricity for MDS, they may also use the asset-based profits. From our findings, at Obala district, more static dryers (SD) were used compared to the other four districts where the survey was carried out. On average, adopters used more MDS than non-adopters. The average moisture in the study area was 8% of water volume. In Obala, farmers had the highest quality of cocoa beans compared to other districts. Adopters had a higher quality of cocoa beans having 7% moisture compared to 10% for non-adopters.

Compared with other districts, farmers in Obala and Sa'a districts had more access to institutional support services (subsidies) and credit, respectively. Similarly, both subsidies and credit were more available to adopters than non-adopters. On the other hand, credit provides the much-needed capital to address challenges that come with the adoption of MDS. In most cases, MDS adoption was associated with high input costs that can hardly be funded by farmer's resources. As noted *by* Abdulai and Huffman 2014 [28], in the diffusion of new technologies, institutional support services such as access to extension services are relevant and consequently affect their effect on household welfare. Farmers can only adopt MDS if they are aware of their inherent features as reported by Adegbola and Gardebroek, 2007 [29].

Compared with other districts, farmers in the Obala district had the highest household income per capita of XAF550. Adopters had a higher household income per capita of XAF450 compared to XAF350 for non-adopters (Table 3). It means that adopters were better off than non-adopters. Consumption expenditure is considered a stronger indicator of household well-being than real income as a proxy for household income since real incomes are seasonal, difficult to measure for a variety of reasons, and are more likely to be under-reported in household surveys. On the poverty status in the districts, more people in Kumba III district (98.98%) were poorer than other districts and adopters (73%) were less poor than non-adopters (82.81); this is measured by the correlation between household daily consumption and the United Nation statistics on poverty (1.90 dollars/day). MDS security results also indicated that farmers in Koumba I district were more resourceful and yielding (100%) than those in other districts. Ea =====

4.2 Adoption and Utilization Intensity of MDS: The Determinants

Table 4 presents the estimates of the factors influencing MDS adoption and utilization intensity in Cameroon.

Tobit estimates factors influenced the intensity of MDS adoption. The Tobit estimates results revealed that access to subsidies had a positive and significant effect on the amount allocated to MDS. Because of their increased visibility and awareness, farmers who were frequently visited by extension government service staff and those who attended field days, hosted demonstrations, or had media extension messages, were likely to adopt MDS and increase the amount allocated to the MDS. MDS can only be approved by a farmer if he is aware of the availability and benefits of these machines and their characteristics.

Access to credit was found to be significant and had a positive effect on the amount allocated to MDS adoption. Access to credit for various inputs helped farmers to quickly implement new agricultural technologies, unlike where there was a constraint. Increased access to government support services such as subsidies, credits, and supply of inputs, infrastructures development (electricity grid) i.e., markets access and road networks should therefore be an important part of efforts to encourage MDS adoption. Age of household head, education and belonging to a member of a group of farmers plays a part in adopting MDS. The results also showed that the relationship between Tropical livestock units (TLU) and funds allocated to MDS was positive and significant. Farmer's livestock helped them to provide extra resources that could be used in funding and improving post-harvest practices.

It was found that overall household size affects negatively the amount allocated to MDS. This means that as the number of household size increases, fewer numbers of households get access to the cocoa bean's dryer in terms of adopting and allocating more resources to MDS. The family appears to be resource constrained.

4.3 Impacts of MDS on Outcome Variables

4.3.1 Endogenous switching regression estimation results

The ESR-based average income effects of MDS adoption on outcome variables are summarized in Table 5; yield (XAF/Kg), asset value (XAF/capita), household income (XAF/capita), MDS security, and poverty status under real and counterfactual conditions. To normalize the distribution of the data, key continuous outcome variables such as moisture, asset value, and household income were transformed into a natural logarithm. Due to space limitations, the detailed determinants of the ESR model are not addressed, but it is important to notice that the estimated coefficients on the selection terms were significantly different from zero, indicating that there was self-selection in MDS adoption in Cameroon.

As we see from Table 5, the adoption of MDS will greatly favored both adopters and non-adopters. On yield, if they did not adopt, households that adopted the MDS would have had a yield loss of 564Kg/ha. On the other hand, households that did not adopt MDS would have had a gain of 239Kg/ha if they had adopted. Since most MDS have high yields, proper drying, continuous work, and many more advantages, efficiency and higher revenues are likely to be obtained by adopters of such drying systems. For asset value, households that have currently adopted MDS would have had a per capita asset value of XAF2608.22 less if they did not adopt.

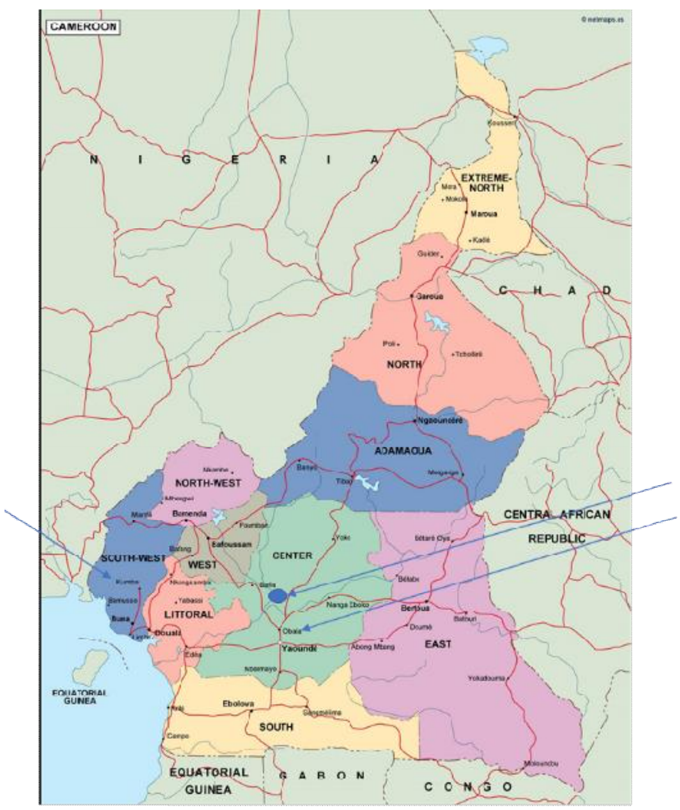
On the opposite, households that did not adopt would have a per capita asset value of about XAF412.83 less if they adopted. This may be due to the asset measure that includes water that heavily destroys the cocoa beans. This means that if you are a non-adopter and you want to adopt, you need to decrease cocoa beans exposure to water and invest significantly in new technology to dry your cocoa beans. MDS adopters will lose a per capita household income of XAF86.21 if they did not adopt. Similarly, households that did not adopt would have a per capita household income of XAF246.39 more if they adopted MDS.

ESR results depicted that the adoption of MDS lowered the probability of poverty by 9.29% points for adopters if they had not adopted it. Furthermore, ESR results indicated that the adoption of MDS would also increase the probability of MDS security for adopters by 37.68% points if they did not adopt. The results of the ESR also showed that the adoption of MDS decreased moisture; increased the value of the capital asset, household income, yield, and reduced poverty for adopters. Households that have not adopted would also have benefited significantly if they adopted MDS.

Table 2. Households sample distribution by district and gender

District	Province	Gender of household head		All
		Female	Male	
KI		1	24	25
KII	SW	1	14	15
KIII		0	18	18
OI		0	40	40
S	Central	0	30	30
All		2	126	128

Source: Author's calculations using the survey data [4]



Source: NIS, 2008

: SA'A

Fig. 1. A map showing the main study area (Meme and Kumba district)

[4] *Agricultural place is a catchment area made up of five different zones comprising villages.*

Table 3. Sample households by district and adoption group: Socio-economic characteristics

Variable	District					Adoption Category		All
	KI N=25	KII N=15	KIII N=18	OI N=40	S N=30	Non- adopter N=106	Adopters N=22	N=128
Household income (XAF/c)	400	350	350	550	400	350	450	410
Yield (XAF/Kg)	1100	1095	1000	1138	1050	1000	1500	1 077
Asset value (XAF/c)	10 000	7 000	7 000	14 850	10 000	7 000	12 150	9 770
Poverty headcount (%)	80	81.25	98.98	72.5	90	82.81	73	86
MDS security (%)	100	66.66	-	72.72	-	-	81.81	48
Gender of household head (1=male)	0.96	0.93	1	1	1	0.98	1	1
Age of household head (year)	48	51	62	46	50	55	47	51
Education level (years)	9.3	8.5	7.6	9.8	8.1	7.5	9.9	9
Total household size	5.16	6.08	8.10	6.08	7.15	7.14	5.6	6
Farmers group association	0.6	-	0.36	0.55	0.26	0.66	0.31	0.34
Size of land owned (Ha)	39	26.3	25.8	88	70	109.1	140	50
Access to extension	0.2	0.25	0.15	0.25	0.26	0.22	0.27	0.22
Access to credit	0.16	0.06	0.00	0.4	0.1	0.17	0.22	0.14
MDS experience (years)	12.8	16.3	0.00	11.90	9.66	0.00	12.66	
Tropical livestock unit (TLU)	0.1	0.16	0.09	1.11	0.13	0.1	0.21	0.31
Moisture (%)	8	10	12	8	10	10	7	9

Source: Author's calculations using the survey data XAF denotes Central African CFA Franc and US$1= XAF593.607 at the time of the survey[5]

[5] *In Cameroon, on average most farmers own large farm size (5 hectares) but only 80% of the total was under the Cocoa beans production.*

Table 4. Estimated results from Tobit for MDS adoption and utilization intensity in Cameroon

Variable	One-stage Tobit with decomposition						
			Average marginal effects	Marginal effects	Marginal effects for adopters		
	Coefficient	Standard error	Coefficient	Coefficient	t-statistic	Coefficient	z-value
Value of assets per capita (XAF)	-0,014	0,142	-0,014	-0,014	38,571	0,02	100,906
Land ownership (ha)	0,013	0,013	0,001	0,013	8,408	-0,006	6,398
Tropical livestock units (TLU)	0,018	0,025	0,005	0,018	0,231	0,083	1,082**
Farmer's group membership (1=yes)	0,158	0,184	0,046	0,158	0,738	0,044	0,243
Access to credit (1=yes)	0,005	1,066	0,592	0,005	0,050*	0,182	0,172
Gender of household head (1=Male)	-0,093	0,298	-0,027	-0,093	0,357	0,334	1,647
Age of household head (years)	0,008	0,007	0,002	0,008	1,254	0,057	0,93
Education of household head (years)	-0,012	0,037	-0,003	-0,012	0,365	-0,037	1,315
Total household size (number)	-0,089	0,043	-0,026	-0,089	1,925**	-0,001	0,031
Extension contacts	0,131	0,043	0,08	0,131	3,055***	0.036	1,174
MDS Experience (years)	-0,013	0,01	-0,004	-0,013	1,25	0.007	0,791
Province dummy (southwest as reference)							
Kumba	0,081	0,013	0,024	0,081	0,223***	-0,057	0,141
Obala	0,643	0,455	0,189	0,643	1,551	0,013	0,028
Sa'a	0,15	0,022	0,044	0,15	0,381***	-0,012	0,275
Constant	2,098	0,454			3,380***		
Number of observations	128				22		

*Notes: *Significant at 10%; ** Significant at 5%; and ***Significant at 1%; Source: Author's calculations using the survey data*[6]

[6] *Poverty was generated based on the international poverty line of US$1.90/capita/day with a purchasing power exchange rate of XAF593.607 using consumption expenditure (proxy for household income in this study) data.* [6]*However the definition of an adoption could be further improved if we had panel data set so that adoption rate is applicable for more than two growing seasons or year.*

Table 5. ESR-based average treatment effects of MDS adoption on welfare outcome variables

Means of outcome variable	Farm households' type and treatment effects	Decision stage		Average treatment effects (ATE)
		To adopt	Not to adopt	
Yield (kg/ha)	Farm households that adopted (ATT)	903	339	564***(6,367)
	Farm households that did not adopt (ATU)	598	359	239***(3,226)
Asset value (XAF/capita)	Farm households that adopted (ATT)	3994.08	1,386	2608,22***(5015,80)
	Farm households that did not adopt (ATU)	3748.88	4161.71	-412.83
Household income (XAF/capita)	Farm households that adopted (ATT)	306.33	220.12	86,21***(2052,61)
	Farm households that did not adopt (ATU)	290.69	44.3	246,39***(10266,25)
MDS security (%)	Farm households that adopted (ATT)	37.68	_	37,68***(10,309)
	Farm households that did not adopt (ATU)	40.4	_	40,4***(11,04)
Poverty headcount (%)	Farm households that adopted (ATT)	-10.28	-0.99	-9.29
	Farm households that did not adopt (ATU)	35.43	22.99	12,44***(6,557)

Nb. Standard errors in brackets; Source: Author's calculations using the survey data. [8]We only accounted for additional benefits due to increased yield from the adoption of MDS

Table 6. Treatment effect estimates of the impact of MDS adoption on welfare outcome variables

Means of outcome variable	treatment effects type	treatment effect estimator	treatment effect estimator
		Inverse probability weight (IPW)	Propensity score matching (PSM)
Yield (kg/ha)	ATEs on the treated (ATT)	679,04***(1,08)	614,75**(0,87)
Asset value (XAF/capita)	ATEs on the treated (ATT)	-3478.38	1057,24(46,28)
Household income (XAF/capita)	ATEs on the treated (ATT)	67,9(241,63)	108,95**(36316,66)
MDS security (%)	ATEs on the treated (ATT)	-8.37	-11.16
Poverty headcount (%)	ATEs on the treated (ATT)	-1.04	3,3(0,52)

*Notes: Absolute values of Z-statistics in parentheses. ** Significant at 5% and ***Significant at 1%; Source: Author's calculations using the survey data*

4.3.2 Propensity score matching estimation results

Because ESR results may be responsive to its model assumption i.e., selection of instrumental variables, IPW and PSM approaches were also used to verify the sturdiness of estimated income effects. The PSM estimated that the effects of adoption on yield (XAF/Kg) and household income (XAF/capita) were isolated (Table 6, Column 4). The average treatment effects on the treated (ATT) suggested that MDS adoption positively and significantly increased yield and capita household income. Farmers who adopted MDS had higher yields of 614.75Kg/ha and per capita household income of XAF108.95 than non-adopters. MDS adoption helped to improve crop quality and income. Thus, to reduce poverty and attain yielding, it is crucial perhaps even essential to adopt technologies that increased crop yielding and address quality and marketing constraints.

4.3.3 Inverse probability weighting estimation results

IPW evaluated average treatment effects on treated (ATT) which is presented in Table 6, column 3, and revealed that MDS adoption had a positive and significant yield effect (Kg/ha). ATT results, therefore, demonstrated that farmers who adopted MDS had higher yields 679.04Kg/ha. The adoption of MDS, while not statistically significant under IPW, contributed to higher household incomes, and decreased the risk of high levels of poverty.

5. CONCLUSION

This article used a sample of 128 farm households to access agricultural practices, MDS impact on cocoa beans quality, and household welfare in Central and South-west Cameroon. Estimation from the Tobit model showed that MDS adoption was largely influenced by several factors namely: access to credit/subsidies, extension, household size, education level, etc. However, an effort remains to be made so that households have easier access to credit and subsidies. Using the three estimators' effect (Endogenous Switching Regression, Inverse Probability Weighting, and Propensity Score Matching models), the study further revealed that MDS adoption improved gain in yield, increased household incomes, and improved cocoa beans quality. The results also revealed that MDS had a significant impact on income for adopters. Although the magnitude of the estimated effects varies between the three econometric models, the qualitative results were consistent and like the descriptive statistics. The adoption process also reduced the risk of poverty for adopters by 9% and increased household welfare by a probability of 9% and about 12% respectively. On average, MDS adoption increased the yield in the range of 614.74 to 679.04 kg/ha, and the household income per capita from 86.21 XAF to 108.95 XAF. The higher MDS adoption rate was associated with improved cocoa beans quality and higher income if most farmers earned more from their product. Adopters would had lost considerably if they had not adopted MDS while non-adopters would have benefited more if they had adopted MDS. Therefore, encouraging new technologies such as MDS should be the government's mission. It also highlights the need for policies to improve the uptake of MDS among non-adopters through more efficient extension, credits, and input supply systems. For further research, a larger group of farmers should be accessed such that we can have a result, representative of the whole country. Also, we can also involve the government in the study to facilitate access to information and obtaining a fund support. The sampling method can vary, and the results might be robust depending on the sampling method chosen.

CONSENT

As per international standard or university standard, Participants' written consent has been collected and preserved by the author(s).

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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