agriculture

MDPI

Article

Drivers of Mechanization in Cotton Production in Benin, West Africa

Idelphonse O. Saliou [1,*], Afio Zannou [1], Augustin K. N. Aoudji [2] and Albert N. Honlonkou [3]

[1] Laboratoire d'Economie Rurale et de Gestion des Exploitations Agricoles, Faculté des Sciences Agronomiques, Université d'Abomey-Calavi, Abomey-Calavi, Cotonou 01 BP 526, Benin; zannou.afio@gmail.com

[2] Laboratoire d'Etude sur la Pauvreté et la Performance de l'Agriculture, Faculté des Sciences Agronomiques, Université d'Abomey-Calavi, Abomey-Calavi, Cotonou 01 BP 526, Benin; augustin.aoudji@gmail.com

[3] Laboratoire d'Economie des Systèmes Socio-Ecologiques et de la Population, Ecole Nationale d'Economie Appliquée et de Management, Université d'Abomey-Calavi, Cotonou BP 171, Godomey, Benin; meintoh@yahoo.fr

* Correspondence: idelphonse.saliou@gmail.com; Tel.: +229-66007371

Received: 28 September 2020; Accepted: 12 November 2020; Published: 15 November 2020

Abstract: In the context of Africa's farm labor scarcity, the use of mechanization is crucial for agricultural development. In Benin, technological advances, such as animal traction and motorization, are struggling to achieve the success expected by producers. The objective of this research was to analyze the drivers of mechanization in cotton production in Benin. Data collected from 482 cotton producers in three agroecological zones of the country were analyzed using a multinomial Logit model. The results revealed that 34% of cotton producers used hand tools, compared to 31% using draught animals and 35% using tractors. Variables such as education level, area cropped, access to land, access to credit and agroecological zone had a positive influence on the probability of using mechanization in the cotton production. Family labor size per household had a negative influence on the probability of using farm mechanization. Women were more likely to use farm mechanization than men. This research suggests that mechanization policies should adapt agricultural equipment to the specificities of the production systems of each agroecological zone, and strengthen land tenure security and access to credit, particularly for women cotton producers.

Keywords: mechanization; animal traction; farm motorization; labor; gender; land tenure; cotton; Benin

1. Introduction

Farm labor scarcities in sub-Saharan Africa have been a growing problem in recent decades [1]. Elsewhere in the world, faced with rapid increases in real wages caused by labor scarcities, agriculture has been characterized by the substitution of labor with machines and/or draught animals [2–7]. Many development institutions, practitioners and experts believe that support for investments in labor-intensive technologies, such as draught animals and tractors, is necessary to enable Africa to emerge from agricultural stagnation [8].

In Benin, animal traction and farm motorization have experienced a particular boom since 1990 with the revitalization of the Beninese Agricultural Equipment Cooperative (COGEMAG). The China–Africa Agricultural Machinery Center was installed and made it possible to accelerate the farm motorization popularized by the various Rural Promotion Centers (CPR) and Regional Action Centers for Rural Development (CARDER) [9]. Consequently, public authorities are increasingly interested in promoting technological innovations that save farm labor. Despite these public interventions, the expected successes have not yet been achieved. The use of mechanization is still marginal in crop production [10], although producers recognize and declare the need to move from manual activities to mechanization [11]. What are the factors that promote the use of mechanization by producers in Benin?

A recent study in Africa [12] recommended an analysis of the determinants of farm mechanization to define the most appropriate use of machine capital for producers. The present research, carried out in Benin, aims to analyze the drivers of the use of mechanization by producers. The results obtained will contribute to filling a gap in scientific knowledge and will also serve as a guide for public authorities and international institutions in their interventions for agricultural sector modernization in Benin and Africa. This research focuses on cotton, considered a powerful lever in the fight against rural poverty and an instrument of economic growth in Benin [13]. Cotton is the country's main export crop, providing 53% of export earnings and contributing 25% to the gross domestic product [14,15].

2. Theoretical Framework

2.1. Theoretical Perspectives on the Drivers of Farm Mechanization

Different theoretical frameworks have been applied to explain how mechanization unfolds in the course of economic development [16,17]. The economic theory of induced innovation states that changes in the relative scarcity of the production factors leads to the development of technologies that facilitate the substitution of relatively abundant and hence cheap factors for relatively scarce and hence expensive factors of production [18]. Mechanization appears to be a response to farm labor constraints that arise in agriculture [19]. It helps to maintain the viability of agriculture in the face of labor scarcities and rising production costs [20,21], and encompasses the use of draught animals or tractors to perform farming activities.

The presence of a rental service makes it easier for producers to use mechanization without investing in agricultural equipment [22–24]. Researchers studied a number of endogenous and exogenous factors that influence the producers' decisions to contribute to mechanization in their production systems. These factors can act individually or in combination as a catalyst to stimulate the use of farm mechanization [25]. Each of these factors differs between and even within countries [26].

One of the biggest challenges for successful mechanization in Africa is access to finance. It allows producers to invest in the purchase or solicitation of farm equipment location services. Access to credit alleviates the financial constraints that rural households normally face and facilitates their use of farm mechanization [23,27,28].

The land tenure system is also an important driver of farm mechanization. Having a land-use title document is positively and significantly related to the use of mechanization [4,29]. Farm mechanization efforts are reportedly unsuccessful when producers face uncertainties over land ownership [30,31]. The size of farms is positively correlated with the use of farm mechanization. Producers with larger farms are more likely to use mechanization than those with smaller farms [7,32,33]. Land is an important fixed resource in agriculture, and the law of economies of scale applies to the use of farm mechanization services [34].

Kuwornu et al. [35] showed that households with many family members tend to use mechanization services less, as family labor usually replaces activities carried out by tractors. The low literacy rates of producers are predicted to be one of the main deterrents of the use of mechanized equipment. A more educated producer is more likely to understand and easily obtain information about the benefits of mechanization in a shorter period of time than a less educated producer [36–39].

Researchers reported mixed evidence concerning the influence of the gender of the producer on their decision to use farm mechanization. In developing countries, most women are marginalized and have limited access to and control of resources such as land, information, markets, education, extension services and agricultural credit, which harms the mechanization of farms. The authors of [37,40] reported that it is difficult for women to use mini-tillers for socio-cultural reasons. Farms headed by men are more likely to own or use tractors or draught animals than households headed by women because women are less knowledgeable about the benefits of mechanization [24].

Other authors reported that gender-sensitive farm mechanization would not only save women time and energy, but also empower them through improved skills and farm management [25,37,41].

The producer's age has a mixed effect on their decision to use mechanization. Older producers, more often risk-averse, may be reluctant to switch from hand tools to the use of tractors or draught animals, and are less likely to invest in mechanization services than younger ones [33,42]. In contrast, De Groote et al. [43] proved that older producers have accumulated capital due to their production experience and tend to resort to farm mechanization.

It is important to take local conditions and realities into account in order to increase the use of farm mechanization [25]. The choice of agricultural equipment differs according to the agroecological zones and the cropping systems practiced [22,37,40].

Referring to these studies, various hypothesized signs of the coefficients of the explanatory variables are shown in Table 1.

Table 1. Definition of multinomial Logit model variables and expected signs.

Variables	Description	Expected Sign
Gender	1 if the producer is a man and 0 if not	+/−
Primary level	1 if the producer has a primary-level education and 0 if not	+
Secondary level	1 if the producer has a secondary-level education and 0 if not	+
Family labor	Number of family labors in the producer's household	−
Age	Age of the producer (in completed years)	+/−
Experience	Number of years of experience in cotton production (years)	+/−
Area cropped	Area cropped for cotton production (in ha)	+
Credit access	1 if the producer has access to credit and 0 if not	+
Land access	1 if the producer has direct access to land and 0 if not	+
Northern zone	1 if the producer is from the cotton zone of northern Benin and 0 if not	+/−
Western Atacora	1 if the producer is from the western zone of Atacora and 0 if not	+/−

The + and − signs represent the hypothetical positive and negative effects, respectively, of the explanatory variables on the dependent variable.

2.2. Theoretical Models

Logit and Probit models are often used to analyze the determinants of producers' choices to make adjustments to their production systems [23,44]. Considering that producers have a choice between several types of equipment for cotton growing (hoes/daba, draught animals or tractors), the multinomial Logit model is appropriate for this analysis [45,46]. The multinomial Logit model has the advantage of being simple in calculating the choice probabilities, which can be expressed in analytical form [47]. The main limitation of the model is the inherent assumption of the independence of irrelevant alternatives (IIA), which states that the probability ratio of choosing any two alternatives is independent of the attributes of any other alternative in the choice set [47,48].

The process of checking the IIA assumption in the multinomial Logit model consists of estimating a complete model that includes all j categories of the dependent variable and a restricted model wherein one category is eliminated. A statistically significant difference between the estimates of the two models indicates a violation of the IIA assumption [48].

The theoretical foundation of the multinomial Logit model is centered on the random utility theory, which highlights that producer preference is modeled primarily using a discrete choice utility framework [49]. The multinomial Logit model computes a different continuous latent variable for each choice, and these variables are like evaluation scores of each individual for each choice. Let X_i be the vector of explanatory variables, β_j and β_k the parameters to be estimated, and ε_j and ε_k the error terms. We obtain the utilities of equipment j and k, and U_j and U_k, respectively, by the formula

$$U_{ij} = \beta_j X_i + \varepsilon_j \text{ and } U_{ik} = \beta_k X_i + \varepsilon_k \quad (1)$$

The probability that producer i with characteristics X chooses equipment type j over k when the utility from bundle j is greater than utility from bundle k is specified as follows:

$$U_{ij} = \left(\beta_j X_i + \varepsilon_j\right) > U_{ik} = \left(\beta_k X_i + \varepsilon_k\right), k \neq j;\ j,\ k = 0, 1, 2 \tag{2}$$

The probability of a producer choosing a combination of equipment is assumed to be a function of some attributes [50]. The probability of a producer i using bundle j among the set of combinations available is

$$P_{ij} = \frac{\exp\left(\beta X_{ij}\right)}{\sum_{j=0}^{2} \exp\left(\beta X_{ij}\right)} \tag{3}$$

where β represents the parameters to be estimated and X_{ij} represents the set of explanatory variables.

The estimation of the multinomial Logit model is based on the maximum likelihood method. The advantage of this method is that it presents a particularly interesting statistical inference because its estimator has properties of efficiency and asymptotic normality, and the observations are independent and identically distributed [51]. The estimated coefficients are used to provide indications on the nature of the relationship between the dependent variable and the explanatory variables.

In the multinomial model, marginal effects measure the expected change in the probability that a particular choice will be made relative to a unit change in an explanatory variable [50,52]. The marginal effects' signs and the respective coefficients may differ because the former depends on the sign and magnitude of all other coefficients [53]. The marginal effects of the explanatory variables on the probability that a producer uses a type of equipment were calculated by [52]:

$$\frac{\partial P_j}{\partial X_i} = \left[\beta_{ij} - \sum_{k=0}^{2} P_k \beta_k\right] = P_j\left[\beta_j - \overline{\beta}\right]. \tag{4}$$

3. Estimation Procedure

3.1. Empirical Model Test of Hypotheses

The empirical model is as follows:

$$\begin{aligned} Equipment = \ & a_0 + a_1 Gender + a_2 Primary\ level + a_3 Secondary\ level \\ & + a_4 Family\ labor + a_5 Age + a_6 Experience + a_7 Area\ cropped \\ & + a_8 Credit\ access + a_9 Land\ access + a_{10} Northen\ zone \\ & + a_{11} Wertern\ Atacora + \varepsilon_i \end{aligned} \tag{5}$$

where *Equipment* is the dependent variable representing the choice of equipment type from the set of equipment. a_i represents the coefficients of the explanatory variables, and ε_i is the error term.

The variable *Equipment* has three categories: 0 for hand tools, 1 for draught animals and 2 for tractors. The multinomial Logit model makes it possible to estimate the probabilities of two categories with respect to a category taken as a reference. The probabilities of categories 1 and 2 are estimated with reference to category $j = 0$.

The choice of explanatory variables is dictated by theoretical behavioral hypotheses and literature. The model's explanatory variables are defined in Table 1. For polytomous qualitative independent variables (i.e., those with more than two categories), Hardy [54] recommended that each of its categories be transformed into binary variables coded by 0 and 1. The new dummy variables created are included in the model, taking one of them as reference. The no-level category was the reference for the producer's level of education variable, and the cotton zone of central Benin was taken as the reference category for the variable of the producer belonging to a given agroecological zone.

The variance inflation factor (VIF) is calculated to detect multicollinearity between the explanatory variables of a model. Chatterjee et al. [55] underlined that a multicollinearity problem is raised when a VIF has a value greater than or equal to 10, and/or when the mean VIF is greater than or equal to 2. In this research, VIF calculation showed that multicollinearity was not a problem, as all VIFs were less than 10 and the mean VIF was 1.48. The model estimation was carried out in the STATA 14 software. For an in-depth analysis of the collinearity diagnostic, Besley et al. [56] and Besley [57] suggest one considers the condition index and the scaled variance decomposition proportions. As an art form, Besley [57] suggested one determine the condition index and the relative strength of the near dependencies by the scaled condition indexes exceeding a threshold of 30. Taking these indicators into account, our data revealed that the variables involved in a near dependency at the largest variance decomposition proportions associated with the large scaled condition index (24.78) are age (0.90) and experience (0.93). To make a correction of this collinearity, experience has been omitted from the final estimated model. The largest scaled condition index is relatively low (10.28), and is very inferior to the threshold of 30.

3.2. Research Area

The research was carried out in three agroecological zones in Benin: the cotton zone of central Benin, the northern cotton zone and the west Atacora zone. One district was chosen per agroecological zone according to the importance of cotton production: Savalou (central cotton zone), Banikoara (northern cotton zone), and Cobly (western zone of Atacora). With the Communal Union of Village Cooperatives of Cotton Producers officials, four villages were selected per district, taking into account representativeness of cotton production and the use of mechanization by producers.

3.3. Sampling Method and Sample Size

The sampling frame by district was extracted from the cotton producers list identified by the Interprofessional Cotton Association in 2019. The sample size required in each district was calculated by the formula of Kothari [58]:

$$n = \frac{z^2 N p(1-p)}{e^2(N-1) + z^2 p(1-p)} \tag{6}$$

where n is the sample size, z is the critical value at the desired confidence interval (1.96 at 95% confidence level), N represents the size of the target population, e represents margin of error (set at 5%), and p is the population proportion with the characteristics of interest. By replacing the components of the formula with their values, the estimated minimum sample sizes were 136, 130 and 131 producers in Banikoara, Cobly and Savalou, respectively. To increase the reliability of the parameter estimation, the number of producers surveyed was increased to 162 in Banikoara, 160 in Cobly and 160 in Savalou. A total of 482 cotton producers were randomly selected and interviewed for research.

3.4. Data Collection

Data were collected regarding the cotton production cycle for the year 2018 through structured interviews using a questionnaire. The information was collected on the socio-economic and demographic characteristics of producers (gender, education level, experience in cotton production, area cropped for cotton production, family labor size), access to land, access to credit and equipment used to produce cotton.

3.5. Descriptive Statistics of the Variables

Producers who used hand tools had a high size of family labor in their household (Table 2). Those who used motorization were the most knowledgeable. The producers engaged in manual farming cultivated the smallest area on average. Animal traction and motorization were used more on secure land where the producer had direct access to land. Almost a quarter of producers obtained credit during the 2018 cotton production cycle. Users of animal traction and motorization used more credit.

Table 2. Descriptive statistics of variables.

Variables	Hand Tools		Draught Animals		Tractors		Together	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Qualitative variables								
Gender	0.82	0.38	0.75	0.43	0.85	0.36	0.81	0.39
Primary level	0.28	0.45	0.71	0.46	0.44	0.50	0.47	0.50
Secondary level	0.04	0.20	0.11	0.32	0.38	0.49	0.18	0.39
Credit access	0.07	0.25	0.38	0.49	0.31	0.47	0.25	0.43
Land access	0.60	0.49	0.81	0.39	0.91	0.29	0.77	0.42
Northern zone	0.04	0.20	0.87	0.33	0.15	0.36	0.34	0.47
Western Atacora	0.02	0.15	0.11	0.31	0.83	0.38	0.33	0.47
Quantitative variables								
Family labor	5.99	3.00	3.41	0.69	3.22	0.73	4.22	2.26
Age	49.24	7.25	47.68	6.07	47.21	5.90	48.05	6.49
Experience	23.64	3.86	22.56	2.49	22.30	3.42	22.84	3.38
Area cropped	9.32	7.04	11.02	10.62	13.37	3.42	11.25	13.89

4. Results

4.1. Mechanization Status in Cotton Production

Different types of equipment were used by cotton producers across the agroecological zones studied (Figure 1). Overall, 34% of cotton producers used hand tools compared to 31% for draught animals and 35% for tractors. Animal traction was practiced by 80% of cotton producers in the cotton zone of northern Benin, while motorization was practiced by 87% of producers in the western zone of Atacora. Farm mechanization was very little developed in the cotton zone of central Benin, and producers continued to use traditional tools to grow cotton. In this research, 7% and 49% of cotton producers, respectively, owned the tractors and draught animals that they used. The other producers used the farm mechanization rental service (Figure 2).

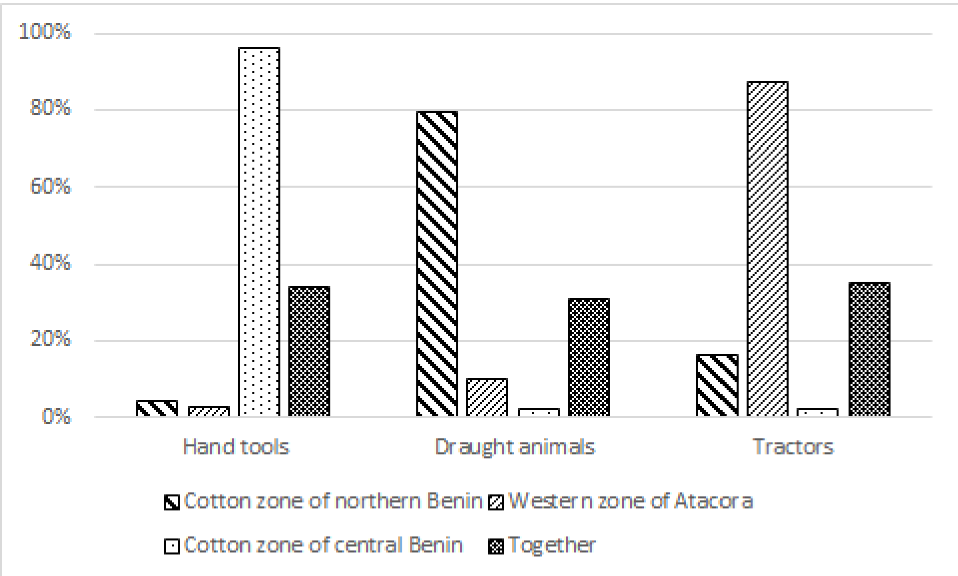

Figure 1. Mechanization status in cotton production.

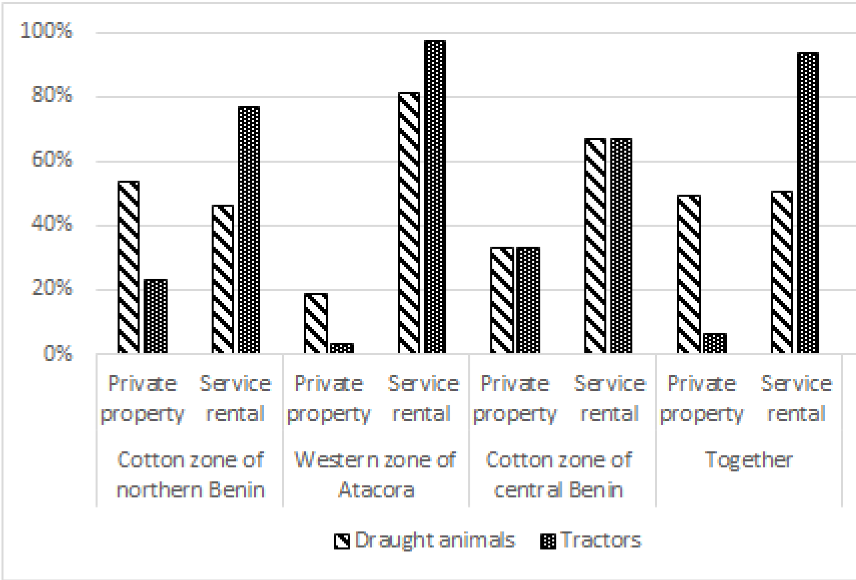

Figure 2. Sources of mechanization in cotton production.

4.2. *Drivers of Farm Mechanization*

In this research, the null assumption of independence of the equipment types used to produce cotton was accepted because the difference between the estimates of the complete and restricted models was not statistically significant ($p > 0.05$). This reflects that the multinomial Logit specification is appropriate for modeling the choice of equipment used by cotton producers in the study area.

The probability that the producer used motorized farm equipment was higher than that of the other categories (Table 3). The likelihood ratio test showed that the model was globally significant at the 1% level (Table 4). The coefficients of variables such as education level, access to credit, size of the area cropped and the producer belonging to a given agroecological zone were positive and influenced the probability of using draught animals and tractors. The family labor size in the producer's household negatively influenced the probability of using a type of agricultural equipment. There was a negative and significant relationship between the age and the probability of using motorization, revealing that young producers were more inclined to use farm motorization than old producers. The chances of using tractors increased when the producer had direct ownership rights over the cotton fields. The results showed a negative relationship between the gender of the producer and the choice of tractors, revealing that women were more likely to use farm motorization than men.

Table 3. Prediction probability of equipment use.

Alternatives	Description	Probability
$j = 0$	Hand tools: the cotton producer used traditional tools (hoe/daba)	$P_{i0} = 0.341$
$j = 1$	Draught animals: the cotton producer used draught animals (ox)	$P_{i1} = 0.310$
$j = 2$	Tractors: the cotton producer used tractors	$P_{i2} = 0.349$

Table 4. Estimation of the multinomial Logit model of the farm mechanization drivers.

Variables	Draught Animals		Tractors	
	Coefficients	**Std. Err.**	**Coefficients**	**Std. Err.**
Constant	−0.870	3.309	1.938	3.394
Gender	−0.457	1.122	−2.310 *	1.196
Primary level	3.476 ***	1.039	2.426 **	1.071
Secondary level	5.715 ***	1.723	7.199 ***	1.726
Family labor	−1.401 ***	0.466	−2.331 ***	0.534
Age	−0.095	0.070	−0.124 *	0.072
Area cropped	0.203 *	0.111	0.284 **	0.112
Credit access	2.794 **	1.340	3.821 ***	1.382
Land access	1.379	1.001	2.605 **	1.089
Northern zone	9.792 ***	1.869	7.994 ***	2.001
Western Atacora	9.284 ***	2.220	13.366 ***	2.346
Base category	Hand tools			
Number of observations	478			
Log likelihood	−114.761			
LR chi2(22)	819.48			
Prob > chi2	0.00001			
Pseudo R2	0.781			

***, **, *, respectively, represent statistical significance at 1%, 5%, 10% levels.

4.3. Marginal Effects of Drivers of Farm Mechanization

The marginal effects of the explanatory variables determining the choice of mechanization by cotton producers were calculated to better understand the impact of these variables (Table 5). The increase in the family labor size per household of one unit led to a 0.038 decrease in the probability of using draught animals and a 0.064 decrease in the probability of using tractors. A one year increase in primary-level education resulted in an increase in the probability of practicing animal traction by 0.089, and an additional year of secondary-level education increased the probability of practicing motorization by 0.121. When the cropped area increased by one hectare, the probability of using tractors increased by 0.006 and the probability of using animal traction increased by 0.003. Access to credit and access to land increased the probability of using tractors by 0.077 and 0.081, respectively. The probability of using tractors increased by 0.114 when the cotton producer was a woman. The fact that a producer belonged to the western zone of Atacora increased their probability of using a tractor by 0.297. The fact that a producer belonged to the cotton zone of northern Benin increased their probability of using draught animals by 0.188.

Table 5. Estimation of the marginal effects of the farm mechanization drivers.

Variables	Draught Animals		Tractors	
	Coefficients	**Std. Err.**	**Coefficients**	**Std. Err.**
Gender	0.096 **	0.039	−0.114 ***	0.039
Primary level	0.089 ***	0.032	−0.043	0.031
Secondary level	−0.028	0.038	0.121 ***	0.035
Family labor	0.038 **	0.016	−0.064 ***	0.017
Age	0.001	0.002	−0.002	0.002
Area cropped	−0.003 *	0.001	0.006 ***	0.001
Credit access	−0.030	0.031	0.077 **	0.031
Land access	−0.054	0.039	0.081 **	0.039
Northern zone	0.188 ***	0.048	−0.052	0.051
Western Atacora	−0.136 ***	0.051	0.297 ***	0.046

***, **, *, respectively, represent statistical significance at 1%, 5%, 10% level.

5. Discussion

This research analyzed the drivers of mechanization in cotton production in Benin. The results showed that women cotton producers were significantly more inclined toward motorization than men. Indeed, because of farm labor scarcity, a household's family labor will first work in the head of the household's fields before helping the head of household's wives. This situation forces women to resort to farm motorization services to respect the cropping schedule. The authors of [59] found that women are constrained in articulating their demand for workload-reducing mechanization solutions. Women in households who use tractors have more time to pursue off-farm work [60].

The larger the area cropped by the producer, the more likely they are to use mechanization. In a context wherein family and casual labor are becoming scarce, large producers have no other choice but to resort to alternatives to farm labor. Yukichi et al. [61] showed that tractors reduce farm labor demand. Farm size is the most important determinant of the use of technologies based on farm mechanization [46,62,63].

Access to credit was an important factor favoring the practice of motorized cultivation. The initial costs of tractors are beyond the reach of producers who generally lack collateral for bank loans. This explains why 7% of producers owned the tractors they used. Most producers depend on their own savings to purchase inputs. Those with access to credit are more likely to have the financial capacity to cover tractor operating expenses or demand tractor rental services than those without credit. Machinery ownership is not necessary for their use, as most producers hire these machine services [22]. In Benin, cotton producers benefit from credits thanks to the support of Decentralized Financial Systems (SFD), the Interprofessional Cotton Association (AIC) and saving groups. The role of credit in the producers' decision to use a technology has been revealed by the literature. Suri [64] proved that if a technology is too costly an investment, the probability of its use will be low despite a favorable benefit/cost ratio, given the financial constraints of producers. Consequently, producers' access to credit strengthens the use of inputs in production [65,66].

The likelihood of using draught animals and tractors increased with the producer's level of education. This result is consistent with this research's expectations, and is explained by the fact that producers with a high education level have more information, allowing them to better understand the gains linked to the use of farm mechanization. Without ignoring the importance of endogenous knowledge, education level could favor the management capacity of the producer. Wanjiku et al. [45] found that formal training positively influences the use of farm mechanization. This is attributed to increased access to resources and information that comes from training. Other authors have also shown that education level is a determining factor in producers' decision to use new technologies [67,68].

Producers who had direct property rights to the land were more likely to use farm mechanization. This result confirms the hypothesis put forward and poses the problem of land tenure security, without which no sustainable investment could be made in the Beninese agricultural sector. Land tenure systems, often characterized by uncertainties in property rights, limit the opportunities for producers to invest in new farm technologies [65].

The increase in the family labor size per household decreased the probability of producers choosing draught animals or tractors. Indeed, the increase in the family labor size per household increases the family labor force, giving producers less incentive to use animal traction or motorization. This is what Alene and Manyong [69] underlined when they reported that the available family labor force could influence the producer's decision to use labor-saving technology.

Belonging to a given agroecological zone positively influenced the probability of using farm mechanization. Producers of the western zone of Atacora had more incentive to practice motorized cultivation, while the chances of moving towards animal traction increased if the producer was from the cotton zone of northern Benin. The specificities linked to the production systems of each agroecological zone can justify the choices of farm equipment used by producers. In addition, the availability of farm mechanization services supply plays an important role. Some producers own the tractors or draught animals they use and offer farm mechanization services to other producers after they finish working in their own fields. In the district of Cobly (western zone of Atacora), private motorization service providers come from neighboring countries (Togo, Ghana) to settle seasonally and provide motorization services to producers. Yebou and Mounirou [70] reported that in the cotton zone of central Benin in particular, key elements of production systems, such as large tubers (yam, cassava), frequency of orchards or presence of many useful trees in the plots, complicate the introduction of animal traction or tractors. In addition, the programs aiming to develop animal traction in the locality face the cost of destumping.

6. Conclusions

The present research analyzed the drivers of mechanization in cotton production in three agroecological zones of Benin. The results showed that several factors must be taken into account to improve the process of farm mechanization in the country. Variables such as education level, area cropped, access to credit, land property rights and agroecological zone had a positive influence on the probability of using mechanization in cotton production. Producers with a high family labor size per household were less likely to practice animal traction or motorization. Moreover, women cotton producers had a greater propensity to use tractors, which indicates the importance that must be given to gender in the development of the farm mechanization policy in Benin. Mechanization policies should adapt agricultural equipment to the specificities of the production systems of each agroecological zone. Animal traction use should be encouraged in the cotton zone of northern Benin, such as in Banikoara, while producers in the western zone of Atacora, such as in Cobly, should be encouraged to use tractors. A policy of promoting mini-tillers could be effective in Savalou in the cotton zone of central Benin, given the production system practiced there. To promote a more inclusive use of farm mechanization, the results underscore the importance of access to credit and land tenure security. It is therefore incumbent on financial institutions to strengthen their interventions in favor of cotton producers by adapting the credits granted to farm activities according to agroecological zones. The land law reforms undertaken to make land a determining element of the agricultural modernization in Benin must be continued and supported by all stakeholders.

Author Contributions: Conceptualization, I.O.S., A.Z., A.K.N.A. and A.N.H.; methodology, I.O.S. and A.Z. software, I.O.S. and A.Z.; validation, I.O.S., A.Z., A.K.N.A. and A.N.H.; formal analysis, I.O.S. and A.Z.; investigation, I.O.S.; resources, I.O.S. and A.Z.; data curation, I.O.S.; writing—original draft preparation, I.O.S. and A.Z.; writing—review and editing, I.O.S., A.Z., A.K.N.A. and A.N.H.; supervision, A.Z., A.K.N.A. and A.N.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors are grateful to cotton producers who provided the collected data.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Sims, B.; Hilmi, M.; Kienzle, J. Agricultural mechanization. A key input for sub-Saharan African smallholders. *Integr. Crop Manag.* **2016**, *23*, 1–42.
2. Wang, X.; Yamauchi, F.; Huang, J. Rising wages, mechanization, and the substitution between capital and labor: Evidence from small scale farm system in China. *Agric. Econ.* **2016**, *47*, 309–317. [CrossRef]
3. Yamauchi, F. Rising real wages, mechanization and growing advantage of large farms: Evidence from Indonesia. *Food Policy* **2016**, *58*, 62–69. [CrossRef]
4. Yang, J.; Huang, Z.; Zhang, X.; Reardon, T. The rapid rise of cross-regional agricultural mechanization services in China. *Am. J. Agric. Econ.* **2013**, *95*, 1245–1251. [CrossRef]
5. Liu, Y.; Hu, W.; Jetté-Nantel, S.; Tian, Z. The influence of labor price change on agricultural machinery usage in Chinese agriculture. *Can. J. Agric. Econ.* **2013**, *62*, 219–243. [CrossRef]
6. Diao, X.; Cossar, F.; Houssou, N.; Kolavalli, S. Mechanization in Ghana: Emerging demand, and the search for alternative supply models. *Food Policy* **2014**, *48*, 168–181. [CrossRef]

7. Takeshima, H.; Nin-Pratt, A.; Diao, X. Mechanization and agricultural technology evolution, agricultural intensification in sub-Saharan Africa: Typology of agricultural mechanization in Nigeria. *Am. J. Agric. Econ.* **2013**, *95*, 1230–1236. [CrossRef]
8. De Janvry, A.; Sadoulet, E.; Kyle, E.; Darr, M. L'adoption des technologies agricoles: Quelles leçons tirer des expérimentations de terrain? *RED* **2015**, *4*, 129–153. [CrossRef]
9. Atidegla, S.C. Agricultural mechanization/motorization in Benin: Different initiatives, challenges and prospective within the period 1930–2016. *Int. J. Curr. Res.* **2019**, *11*, 5121–5126. [CrossRef]
10. Mounirou, I. Agricultural Mechanization as an Expansion Factor of Cropland in Benin: The Case of Tractors. *Sustain. Agric. Res.* **2018**, *7*, 1–10. [CrossRef]
11. Zokpodo, K.L.B.; Dahou, M.N.; Dayou, D.E. Analyse des déterminants liés au fonctionnement des centres d'exploitation des machines agricoles (CEMA) au Bénin. *Ann. Sci. Agron.* **2017**, *21*, 181–202.
12. Kirui, K.O.; von Braun, J. *Mechanization in African Agriculture: A Continental Overview on Patterns and Dynamics*; ZEF Working Paper 169; Center for Development Research (ZEF), University of Bonn: Bonn, Germany, 2018.
13. Bonou-zin, D.C.R.; Allali Khalil, F.A.; Yabi, A.J. Environmental efficiency and economic performance of cotton production in Benin: What relationship? *JAES* **2019**, *8*, 161–175. [CrossRef]
14. INSAE. *Les Echanges Extérieurs du Bénin en 2019, Grands Traits du Commerce Extérieur au Bénin*; INSAE: Cotonou, Bénin, 2020.
15. MAEP. *Plan Stratégique de Développement du Secteur Agricole (PSDSA) 2025 et Plan National D'investissements Agricoles et de Sécurité Alimentaire et Nutritionnelle PNIASAN 2017–2021*; MAEP: Cotonou, Bénin, 2017.
16. Pingali, P.; Bigot, Y.; Binswanger, P.H. *Agricultural Mechanization and the Evolution of Farming System in Sub-Saharan Africa*; The Johns Hopkins University Press: Washington, DC, USA, 1987.
17. Binswanger, P.H. Agricultural mechanization: A comparative historical perspective. *World Bank Res. Obs.* **1986**, *1*, 27–56. [CrossRef]
18. Ruttan, W.V. Induced innovation and agricultural development. *Food Policy* **1977**, *2*, 196–216. [CrossRef]
19. Rijk, G.A. Agricultural mechanization policy and strategy: The case of Thailand. Ph.D. Thesis, Wageningen University, Wageningen, The Netherlands, 1989.
20. Zhang, X.; Yang, J.; Reardon, T. Mechanization Outsourcing Clusters and Division of Labor in Chinese Agriculture. *China Econ. Rev.* **2017**, *43*, 184–195. [CrossRef]
21. Takahashi, K.; Otsuka, K. The increasing importance of nonfarm income and the changing use of labor and capital in rice farming: The case of central luzon, 1979–2003. *Agric. Econ.* **2009**, *40*, 231–242. [CrossRef]
22. Aryal, J.P.; Rahutb, D.B.; Maharjanc, S.; Erenstein, O. Understanding factors associated with agricultural mechanization: A Bangladesh case. *World Dev. Perspect.* **2019**, *13*, 1–19. [CrossRef]
23. Mottaleb, A.K.; Krupnik, J.T.; Erenstein, O. Factors associated with small-scale agricultural machinery adoption in Bangladesh: Census findings. *J. Rural Stud.* **2016**, *46*, 155–168. [CrossRef]
24. Mottaleb, A.K.; Rahut, B.D.; Ali, A.; Gérard, B.; Erenstein, O. Enhancing smallholder access to agricultural machinery services: Lessons from Bangladesh. *J. Dev. Stud.* **2017**, *53*, 1502–1517. [CrossRef]
25. Kirui, K.O. *The Agricultural Mechanization in Africa: Micro-Level Analysis of State Drivers and Effects*; ZEF-Discussion Papers on Development Policy 272; Center for Development Research (ZEF), University of Bonn: Bonn, Germany, 2019.
26. Daum, T.; Birner, R. Agricultural mechanization in Africa: Myths, realities and an emerging and research agenda. *Glob. Food Sec.* **2020**, *26*, 1–10. [CrossRef]
27. Makate, C.; Makate, M. Interceding role of institutional extension services on the livelihood impacts of drought tolerant maize technology adoption in Zimbabwe. *Technol. Soc.* **2019**, *56*, 126–133. [CrossRef]
28. Doss, R.C. Analyzing technology adoption using microstudies: Limitations, challenges, and opportunities for improvement. *Agric. Econ.* **2006**, *34*, 207–219. [CrossRef]
29. Otsuka, K.; Liu, Y.; Yamauchi, F. The future of small farms in Asia. *Dev. Policy Rev.* **2016**, *34*, 441–461. [CrossRef]
30. Grabowski, R. Agriculture, Mechanization and Land Tenure. *J. Dev. Stud.* **1990**, *27*, 43–53. [CrossRef]
31. Asiama, O.K.; Bennett, M.R.; Zevenbergen, A.J. Land consolidation on Ghana's rural customary lands: Drawing from The Dutch, Lithuanian and Rwandan experiences. *J. Rural Stud.* **2017**, *56*, 87–99. [CrossRef]
32. Pingali, P. Agricultural mechanization: Adoption patterns and economic impact. *Handb. Agric. Econ.* **2007**, *3*, 2779–2805. [CrossRef]

33. Gosh, K.B. Determinants of Farm Mechanization in Modern Agriculture: A Case Study of Burdwan Districts of West Bengal. *Int. J. Agric. Res.* **2010**, *5*, 1107–1115. [CrossRef]
34. Rasouli, F.; Sadighi, H.; Minaei, S. Factors Affecting Agricultural Mechanization: A Case Study on Sunflower Seed Farms in Iran. *J. Agric. Sci. Technol.* **2009**, *11*, 39–48.
35. Kuwornu, K.M.J.; Apios, K.E.; Kwadzo, T.-M.G. Access and intensity of mechanization: Empirical evidence of rice farmers in Southern Ghana. *Braz. Arch. Biol. Technol.* **2017**, *60*, 1–17. [CrossRef]
36. Awotide, A.B.; Karimov, A.A.; Diagne, A. Agricultural technology adoption, commercialization and smallholder rice farmers' welfare in rural Nigeria. *Agric. Food Econ.* **2016**, *4*, 1–24. [CrossRef]
37. Paudel, P.G.; Gartaula, H.; Rahut, B.D.; Craufurd, P. Gender differentiated small-scale farm mechanization in Nepal hills: An application of exogenous switching treatment regression. *Technol. Soc.* **2020**, *61*. [CrossRef] [PubMed]
38. Adekunle, A.; Osazuwa, P.; Raghavan, G.S.V. Socio-economic determinants of agricultural mechanisation in Africa: A research note based on cassava cultivation mechanisation. *Technol. Forecast. Soc. Chang.* **2016**, *112*. [CrossRef]
39. Ayodele, O. Economic impact of agricultural mechanization adoption: Evidence from maize farmers in Ondo state, Nigeria. *JABR* **2012**, *1*, 25–32.
40. Paudel, P.G.; Kc, B.D.; Rahut, B.D.; Justice, E.S.; McDonald, J.A. Scale-appropriate mechanization impacts on productivity among smallholders: Evidence from rice systems in the mid-hills of Nepal. *Land Use Policy* **2019**, *85*, 104–113. [CrossRef]
41. Fischer, G.; Wittich, S.; Malima, G.; Sikumba, G.; Lukuyu, B.; Ngunga, D.; Rugalabam, J. Gender and mechanization: Exploring the sustainability of mechanized forage chopping in Tanzania. *J. Rural Stud.* **2018**, *64*, 112–122. [CrossRef]
42. Nepal, R.; Thapa, B.G. Determinants of agricultural commercialization and mechanization in the hinterland of a city in Nepal. *Appl. Geogr.* **2009**, *29*, 377–389. [CrossRef]
43. De Groote, H.; Marangu, C.; Gitonga, M.Z. Trends in Agricultural Mechanization in Kenya' s Maize Production Areas from 1992–2012. *AMA-AGR Mech. Asia. Afr.* **2018**, *49*, 20–32.
44. Nguyen-Van, P.; Poiraud, C.; To-The, N. Modeling farmers's decisions on tea varieties in Vietnam: A multinomial logit analysis. *Agric. Econ.* **2016**, *48*, 1–9. [CrossRef]
45. Wanjiku, J.; Manyengo, U.J.; Oluoch-Kosura, W.; Karugia, J.T. *Gender Differentiation in the Analysis of Alternative Farm Mechanization Choices on Small Farms in Kenya*; Research paper 2007/15; UNU-WIDER: Tokyo, Japan, 2007.
46. Mabuza, L.M.; Sithole, M.M.; Wale, E.; Ortmann, F.G.; Darroch, M. Factors influencing the use of alternative land cultivation technologies in Swaziland: Implications for smallholder farming on customary Swazi Nation Land. *Land Use Policy* **2013**, *33*, 71–80. [CrossRef]
47. Tse, Y.K. A diagnostic test for the multinomial logit model. *J. Bus. Econ. Stat.* **1987**, *5*, 283–286.
48. Hausman, A.J.; McFadden, D. Specification tests for the multinomial logit. *Econometrica* **1984**, *52*, 1219–1240. [CrossRef]
49. Mujeyi, A.; Mudhara, M.; Mutenje, J.M. Adoption determinants of multiple climate smart agricultural technologies in Zimbabwe: Considerations for scaling-up and out. *Afr. J. Sci Technol. Innov. Dev.* **2019**. [CrossRef]
50. Greene, H.W. *Econometric Analysis*, 5th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2003.
51. Nana, T.J.; Thiombiano, T. Adoption of Adaptation Strategies for Climate change: Case of Burkina Faso Farmers. *JAES* **2018**, *7*, 53–65. [CrossRef]
52. Long, J.S. *Regression Models for Categorical and Limited Dependent Variables: Advanced Quantitative Techniques in the Social Science*; Series 7; Sage Publication: Thousand Oaks, CA, USA, 1997.
53. Hassan, R.; Nhemachena, C. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *AfJARE* **2008**, *2*, 83–104.
54. Hardy, A.M. *Regression with Dummy Variables (Quantitative Applications in the Social Sciences)*, 1st ed.; Sage Publication: Newbury Park, CA, USA, 1993.
55. Chatterjee, S.; Hadi, S.A.; Price, B. *Regression Analysis by Examples*, 3rd ed.; Wiley: New York, NY, USA, 2000.
56. Belsley, A.D.; Kuh, E.; Welsch, R.E. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*; John Wiley and Sons: New York, NY, USA, 1980.
57. Belsley, A.D. A guide to using the collinearity diagnostics. *Comput. Sci. Econ. Manag.* **1991**, *4*, 33–50.

58. Kothari, C.R. *Research Methodology: Methods and Techniques*, 2nd ed.; New Age International Publisher: New Delhi, India, 2004.
59. Eerdewijk, A.; Danielsen, K. *Gender Matters in Farm Power*; KIT: Amsterdam, The Netherlands, 2015. [CrossRef]
60. Daum, T.; Capezzone, F.; Birner, R. *Of Trackers and Tractors. Using a Smartphone App and Compositional Data Analysis to Explore the Link between Mechanization and Intra-Household Allocation of Time in Zambia*; ZEF-Discussion Papers on Development Policy 278; Center for Development Research (ZEF), University of Bonn: Bonn, Germany, 2019.
61. Yukichi, Y.M.; Takahashi, K.; Otsuka, K. *Contract Farming, Farm Mechanization, and Agricultural Intensification: The Case of Rice Farming in Cote d'Ivoire*; Working Papers 157; JICA Research Institute: Tokyo, Japan, 2017.
62. Van den Berg, M.; Hengsdijk, H.; Wolf, J.; Van Ittersum, M.; Guanghou, W.; Roetter, R. The impact of increasing farm size and mechanization on rural income and rice production in Zhengjiang province, China. *Agric. Syst.* **2007**, *94*, 841–850. [CrossRef]
63. Paudel, P.G.; Kc, D.B.; Rahut, B.D.; Khanal, P.N.; Justice, E.S.; McDonald, J.A. Smallholder farmers' willingness to pay for scale-appropriate farm mechanization: Evidence from the mid-hills of Nepal. *Technol. Soc.* **2019**, *59*, 1–10. [CrossRef]
64. Suri, T. Selection and comparative advantage in technology adoption. *Econometrica* **2011**, *79*, 159–209. [CrossRef]
65. Hailu, K.B.; Abrha, K.B.; Weldegiorgis, K.A. Adoption and impact of agricultural technologies on farm income: Evidence from Southern Tigray, Northern Ethiopia. *IJFAEC* **2014**, *2*, 91–106.
66. Udry, R.C. The economics of agriculture in Africa: Notes toward a research program. *AfJARE* **2010**, *5*, 284–299. [CrossRef]
67. Croppenstedt, A.; Demeke, M.; Meschi, M.M. Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia. *Rev. Dev. Econ.* **2003**, *7*, 58–70. [CrossRef]
68. Singh, K. Education, technology adoption and agricultural productivity. *Indian J. Agric. Econ.* **2000**, *55*, 473–489.
69. Alene, A.D.; Manyong, V.M. Farmer-to-farmer technology diffusion and yield variation among adopters: The case of improved cowpea in northern Nigeria. *Agric. Econ.* **2006**, *35*, 203–211. [CrossRef]
70. Yebou, J.; Mounirou, I. Innovations techniques et productivités agricoles dans les pays en développement: Cas de la mécanisation agricole en production cotonnière au centre du Benin. *Agron. Afr.* **2018**, *30*, 1–14.