ISSN No:-2456-2165

How Can Innovation Platforms Enhance Crop Technology Adoption and Yield: An Empirical Evidence from Wheat Sector in Sudan

Elrashid A. Fageer
Agricultural Research Corporation.
Dongola, Sudan.

Abstract:- This study aims to evaluate the impacts of innovation platforms as a technology transfer approach on adoption a recommended package and yield of wheat in the Sudan using a purposive random sample of 532 wheat farmers in season 2016/2017. The determinants of adoption were analyzed using logistic regression, multivariate probit and double hurdle models while the impact on yield was estimated using instrumental variables regression. Empirical results proved that farmers participation in innovation platforms significantly enhanced adoption, the determinants of area allocation under the package were mostly farm-related such as the farm area and access to services while both technology-related and marketing factors determined yield. The average increase in yield was 0.99 ton/ha with 1.12, 1.03, 0.69, 1.02 ton/ha estimated for the River Nile, Northern, Gezira and Kassala states, respectively. Policy implication urges using innovation platforms as a new technology transfer approach for enhanced wheat production in the Sudan.

Keywords:- *Adoption, innovation platforms, Sudan, technology transfer, wheat.*

I. INTRODUCTION

Despite its importance for food security in the Sudan, the trend for wheat self-sufficiency was declining since 1980 (OECD-FAO, 2014).Local wheat production decreased steadily, while its demand was in the rise driven by population growth, changes in consumption preferences and rapid urbanization (CBS, 2015). This was reflected in an annual increase of wheat consumption by 14% during the period from 1961-1995 which was mostly covered by imports from other countries (Table1). As a result, Sudan has turned to be net wheat importer with low self-sufficiency ratio that ranged between 20%-39% during 2001-2011 (CBOS, 2013).

Period	Area (000'ha)	Yield (ton/ha)	Production (000' t)	Imports (000' ton)	Total wheat supply ('000t)	Self-sufficiency (%)
1982-1986	114.6	1.39	150	570	720	21%
1987-1991	229.7	1.43	426	649	1075	40%
1992-1996	328.2	1.66	560	451	1011	55%
1997-2001	187.7	2.06	381	753	1134	34%
2002-2006	161.6	2.56	416	1272	1688	25%
2007-2011	278.6	1.95	552	1723	2275	24%

Table 1: Five- year averages for wheat area, yield, production, imports, and self-sufficiency (%) during 1982–2011 in the Sudan.

Source: MoFEP, (2012)

Only 33% of the demand for wheat was locally produced during 1982-2011 (Table 1) and the amount imported during 2007-2011 was 1.72 million tons /year (CBS 2012). Sudan faced severe deficit in its local wheat supply while the average imports increased by 15% per year since mid-1990s worsening its negative balance of trade (Osman 1989; Hassan &Faki, 1993). Most literature on the Sudanese wheat production suggest that low yield levels at the farmers' fields significantly impedes realizing acceptable self-sufficiency ratios with its negative impacts on food security (Babiker&Faki, 1994). As a country which is entirely located outside the global wheat zone, yield improvement in the Sudan was possible after the development of heat tolerant varieties along with a set of recommended cultural practices suitable for different agro environments. Wheat is mainly produced in the Gezira scheme, Northern and River Nile states which contributed to 57%, 13% and 14% of the total wheat area, respectively and provided together 88% of the Sudan's total wheat production in 2016 (Table 2).

State/Scheme	Area (1000 ha)	Yield (ton/ha)	Production (1000 ton)	% of area	% of production
Gezira scheme	142	3.57	507	57%	65%
Northern state	33.18	4.05	131	13%	17%
River Nile state	33.6	2.86	47	14%	6%
White Nile state	18.98	2.14	35	8%	4%
New Halfa scheme	18.3	3.09	57	7%	7%
Rahad scheme	0.59	2.38	1.40	0.6%	0.7%
Kahrtoum state	0.42	1.67	0.70	0.4%	0.3%
Total	247 (226)	3.33	778.6		

Table 2: Wheat area, yield and production in the Sudan by geographical location, 2016

Source: Calculated from the National Wheat Project Report- Ministry of Agriculture and Forestry (2016).

While investigating the determinants of yield, most studies focused on technical efficiency analysis so to prove how misallocation of inputs and services adversely affects yield at the farmers' fields. For example, (Al-Feel & Abdul Razig, 2012) while investigating the causes of low wheat yield in Gezira scheme, identified poor timing agricultural operations, inadequate irrigation water and land ownership problems as the main sources of inefficiency and estimated the technical efficiency at 0.63. Also, (FadlAllah, 2010) and (Albashir, 2010) estimated the range of technical efficiency between 0.63 and 0.73 for the same scheme in 2010 while (Adil&Hanan, 2015) estimated efficiency for the River Nile State wheat farms at 0.66 and (Fageer *et al*. 2013) estimated it at 0.67 for the Northern State farms. They found that factors such as effective extension, farmers training, farmers' age, availability of credit, and the use of improved varieties were significant determinants of the technical efficiency. Hassan (2008) found that technical efficiency was higher for middle-age farmers (35-45 years) relative to other age groups in Rahad scheme. These findings were consistent with (Trueblood& Coggins, 2001) who estimated in the Sudan wheat production sector efficiency at 0.67 and identified gender, marital status, education and land tenure as main sources of inefficiency.

There are many reasons for why technologies are not always adopted by farmers; however, one common argument is a concern over the efficacy of linear technology development and dissemination approaches used during the past decades. The above review that indicates a minimum level of 23% lower levels than the potential yield due to technical inefficiency implicitly suggests that enhancing wheat production requires the involvement of different stakeholders along the wheat value chain. Historically, yield improvements evolved with the implementation of different agricultural technology transfer and extension approaches starting from a linear commodity-based extension model in the 1960s. Later, the commodity based extension model was criticized as being strictly top-down, with technology recommendations developed by researchers and transferred to farmers without their participation in technology generation to meet their specific or other stakeholders needs (Seevers*etal.*, 1997). The Training and Visit model was alternatively introduced by the World Bank in 1980s to overcome the drawbacks of commodity approach. However, the T&V system was considered a rigid and costly approach in a way that did not lead to the desired transformation of Sudanese agriculture (Axinn, 1988). The need for a pluralistic extension system that lead to effective information and service provision was suggested by (Schwartz &Kampen, 1992) and (Contado, 1997). Since then, the focus of the desired technology transfer approach moved to more broad-based innovation systems which integrate farmers, service providers, end users, researchers and extension agents to coordinate their efforts in planning by knowledge sharing for enhanced production that benefits all stakeholders along the wheat value chain for improved livelihood. As defined by (World Bank 2012), the agricultural innovation system is a network of organizations, enterprises and individuals who bring new products, processes, and forms of organization into economic use. An innovation platform represents a group of individuals (who often represent organizations) with different backgrounds and interests who come together to diagnose problems, identify opportunities and find ways to achieve their goals.

Season	Description	Northern State	River Nile State	Gezira State	Kassala State	Total/ Av.
2012/2013	Number of wheat farmers	700	1000	9424	7860	18984
	Wheat Area (ha)	229	417	3460	4451	8557
	Wheat area/ total area (%)	5%	2%	15%	83%	10%
2014/2015	Number of wheat farmers	300	300	2186	2136	4922
	Wheat Area (ha)	500	2100	8907	6976	18483
	Wheat area/ total area (%)	12%	12%	35%	65%	21%
2015/2016	Number of wheat farmers	300	1000	5403	2136	8839
	Wheat Area (ha)	550	2100	9080	6976	18706
	Wheat area/ total area (%)	13%	12%	36%	65%	21%

Table 3: Total cultivated area, wheat area and number of farmers in SARD-SC intervention areas during 2012-2016.

Source: WRP, 2016

The innovation platforms approach was first introduced as a method of technology transfer in the year 2012 within the project: Strengthening Agricultural Research for Development of Strategic Crops (SARD-SC) funded by the African Development Bank and jointly implemented by the International Centre for Agricultural Research in the Dry Areas (ICARDA), and the Agricultural Research Corporation of Sudan. The project covered 88,000 ha in four main wheat production areas in the Sudan namely; the Gezira and New Halfa schemes, Northern and River Nile states (Table 3).

The total area under wheat production in these states varied across seasons where it represented 21% of the total crop area in 2016 compared to 10% only in 2012. Yet, area variation across successive seasons was mainly attributed to government area allocation policies in the irrigated schemes. The use of innovation platforms approach targeted 8839 farmers directly while other 50,000 farmers benefited indirectly through spillover of knowledge and seed multiplication. Most of the selected sites were located in the Gezira scheme as it represented 57% of total wheat area and produced 65% of the wheat quantity in season 2015/2016.

The objective of this study is to evaluate the effectiveness of innovation platforms as a new technology transfer approach. However, before entering into the next sections, it is useful to review some methodologies used in behavioral and impact evaluation research. Most studies of agricultural technology adoption have used either binary outcome logistic or probit regression equations (Ashford & Snowden, 1970) or (Amemiya, 1974). Thestandard Tobit model has been used to deal with censored dependent variables as it specifically incorporates all observations,including those censored at zero. As an improvement of the two stage regression models (Cragg, 1971) suggested the double-hurdle model to overcome thepresence of zero outcomes in the survey data, by assuming two hurdles, which must be crossed before positive values of the outcome can be observed. In contrast to Heckman's model (Heckman 1979), the double hurdle model assumes that both adopters and non-adopters can report zero land area under the improved package for different reasons. The double hurdle model has been widely used since its first introduction by Cragg in 1971. For example (Dong *et al.*, 2004) used it to study milk purchasing from panel data whereas (Newman *et al.*, 2003) applied the model to study household expenditures on prepared meals for home consumption in Ireland while (Yen & Jones, 1997) used the model to study U.S. household consumption of cheese while (Jensen & Yen 1996) used it to examine food expenditures away from home while (Yen & Huang, 1996) applied the model to study the household demand for finfish in the U.S.

The zero values reported in the first stage estimation (participation decision) arise from non- adoption, and in the second stage (land allocation under the recommended package) come due to the respondents' deliberate decisions or random circumstances. In this regard, Wooldridge (2002) conclude that the double hurdle model can be considered as an improvement over both the standard Tobit and Heckman models. The use of two latent variables allows for modeling each of the two decision processes separately, with a probit (or logistic) model determining selection and a censored model determining the area under the technology (Blundell & Meghir 1987). Assuming that the error terms in the selection and outcome equations are independent, the log-likelihood function of the double-hurdle model is equivalent to the sum of the log-likelihoods of a truncated model plus a probit regression (Aristei&Pieroni, 2008) and (McDowell, 2003). Hence, the log-likelihood functions of the double-hurdle model allow for maximizing two separate components i.e. the probit equation for all observations, followed by a truncated equation on the positive observations only (Shrestha *et al.* 2006) which results in more rigorous estimation of the two equations in the model compared with the two-stages estimation of Heckman model.

II. METHODOLOGY

A. Sampling

A field survey using a purposive random sample 532 wheat farmers from 2015/2016 season was used to collect data and draw results. For comparison purposes, farmers were divided into two groups based on their participation in demonstration plots, fields days. The analysis in our study was carried out for innovation platforms participants versus non-participants based on this distinction. The sample was designed to include both participant and non-participant households and six regional sites were identified as the intervention sites, where innovation platforms were established, namely, Khor Argo from the Northern State, Abu Seleim from the River Nile State, Demiat and Debeira in New Halfa Agricultural Corporation and Wad Elbur and Bassatna in the Gezira Scheme. A random sample of 544 households was purposively drawn from wheat farmers to collect primary data. However, due to data inadequacy problems only 532 households were used in the analysis. For the purposes of this study, a participant farmer is defined as any wheat farmer in the study domain who have either hosted demonstration plots, attended technology transfer activities or both in any of the six innovation platforms.

B. Empirical Models and Specification

As discussed by Ashford and Snowden (1970) and Amemiya (1974), the dependent variable in a binary probit model can assume two outcomes, the presence or absence of an event. The probit model assumes the linearity for the continuous independent variables but there is no Gaussian assumption on the residuals.

Mathematically, the expected value of an outcome y is the probability that the event will occur.

$$E(y) = p1 = (1\text{-}p)\ 0 = p \qquad (1)$$

If this probability is a function of a vector of explanatory variables $\boldsymbol{X}$ and a vector of unknown parameters β then the general binary choice model is written as:

$$\text{Prob.}\ (y = 1) \,\big|\, \boldsymbol{X} = \mathrm{F}(\beta' \boldsymbol{X}) \qquad (2)$$

And the probit model is written as:

$$F(\beta' \boldsymbol{X}) = \Phi\ (\beta' \boldsymbol{X}) = \int_{-\infty}^{\beta X} \frac{1}{\sqrt{2\pi}} e^{\frac{-u^2}{2}} du \qquad (3)$$

Further, we use the double hurdle model as an alternative of the probit regression equation. This model allows decisions to pass through two hurdles before adoption is observed as a positive outcome in two equations of a combined probit and Tobit estimators as follows:

$$d_i^* = z_i^{'}\alpha + \varepsilon_{1,i} \qquad (4)$$

$$y_i^{**} = X_i^{'}\beta + \varepsilon_{2,i} \qquad (5)$$

$$\binom{\varepsilon_{1,i}}{\varepsilon_{2,i}} \sim N\left[\binom{0}{0}\begin{pmatrix}1 & 0\\ 0 & \sigma^2\end{pmatrix}\right] \qquad (6)$$

The error term variance of $\varepsilon_{1,i}$is normalized to 1, as required for identification, because the outcome of the first hurdle is binary and the two error terms are assumed to be independently distributed. The first hurdle is represented by:

$$d_i = 1 \text{ if } d_i^* > 0 \qquad (7)$$

$$d_i = 0 \text{ if } d_i^* \leq 0 \qquad (8)$$

The first hurdle is thus assumed to be defined by the latent variabled_i^*. The second hurdle closely resembles the Tobit model:

$$y_i^* = \max\ (y_i^{**}, 0) \qquad (9)$$

And the observed variable is determined as:

$$y_i = d_i y_i^* \qquad (10)$$

Farmer decisions have to cross two hurdles before recording non-zero allocation of land under the recommended wheat package. The first hurdle relates to whether or not the farmer has adopted the package, while the second hurdle models allocation of land under recommended package through adoption. Here, only farmers who have recorded positive adoption will cross the first hurdle before deciding on how much land will they allocated under the recommended package.

In order to the estimate determinants of farmers selection to participate in the innovation platforms, logistic regression was estimated using participation as a binary dependent variable which is regressed to a subset of explanatory variables. The multivariate probit (MVP) model is a generalization of the binary probit model introduced by Ashford and Snowden (1970) and Amemiya (1972) which jointly estimates a set of equations assuming that their error terms are correlated.

For the detailed MVP model, Let y_{ij}denote a binary 0/1 response on the $i\ th$ observation unit and jth variable, and let Y_i= $(Y_{i1},\ldots,Y_{ij})'$ ($1 \leq i \leq n$) denote the collection of responses on all j variables. According to the multivariate probit model, the probability that Y_j=Y_i conditioned on parameters $\beta\sum$ and a set of covariates X_{i1} is given by
[

$$\text{pr}\ (Y_i = y_i \mid \beta\textstyle\sum = \int_{Aij} \ldots \int_{Aij} \emptyset, (t \mid 0, \sum)\ dt, \qquad (11)$$

Where $\emptyset, (t \mid 0, \sum)$ is the density function of J -variable normal distribution with mean vector 0 and correlation matrix $\sum = \{\sigma_{ij}\}$ is the interval.

$$A_{ij} = \begin{cases}(-\infty, x'_{ij}\beta_j\ ) \text{ if} y_{ij} = 1\\ [x'_{ij}\beta_j, \infty) \quad \text{if} y_{ij} = 0\end{cases} \qquad (12)$$

$\beta_j \epsilon R^k$is an unknown parameter vector and $\beta' = (\beta'_1,\ldots,\beta'_j)\ \epsilon\ R^k$, $k = k_i$.

In order to estimate the impact of participation on wheat yield, we used the instrumental variables regression which involves finding a variable (or instrument) that is highly correlated with an outcome variable (i.eadoption in our case) but that is not correlated with unobserved characteristics affecting the outcome (Spirtes and Cooper, 1999) and (Spirtes*et al*.,(2000). The instrumental variable regression allows for endogeneity in individual participation. In addition, Khandker (2006) provided an example of how exogeneity and bias can be addressed. The instrumental variables estimation is shown using econometric models (Bowden and Turkington, 1984; Morgan and Winship, 2007; Wooldridge, 2002). The requirements of this model are violated when the independent variables are systematically related to unobserved causes of the outcome. This commonly occurs when factors related to the independent variable that predict outcomes are omitted from the regression model or when independent variables are measured with an error (Wooldridge, 2002). One major advantage of the IV approach is that its estimates are less sensitive to model misspecifications. The disadvantages are the possibility to use weak instruments and correlation with the unobserved characteristics leading to biased estimates of the program effect besides difficulties in finding a good instrument as shown by Rothenberg (1984) and Cerulli (2015). Well-reasoned IV specifications may involve modeling uncertainty and this modeling should be reflected in the standard errors associated with IV estimates. However, it is difficult to quantify this uncertainty, which is often ignored (Gerber *et al*., 2004). The problem with the selected instrument is to ensure that it is exogenous to the IV model and no remaining effect is embedded in the error term making it endogenous to the model and therefore violates the IV model assumptions (Cerulli, 2015). In order to overcome this problem, Cerulli (2015) proposed an empirical IV model that accounts for the dependent variable in the selection equation to be more flexible with embedded tests for endogeneity to ensure that the instrument is truly uncorrelated with the error term.

Recently, many studies used IV regression in impact assessment studies. Duflo and Pande (2004) used land gradient as an instrument for dam construction in explaining poverty in India whereas Acemoglu*et al*. (2001) used the mortality of colonial settlers to estimate the effect of current institutional arrangements on economic performance. Kern &Hainmueller (2009) used the IV approach to study the

ISSN No:-2456-2165

effect of television programs on political attitudes in Germany.

Mathematically, the IV model follows Murray (2006), Gelman&Hill (2006), and Angrist &Pischke, (2008) and it can be written as follows:

$$Y_i = \beta_0 + \beta_1 X_i + \sum_i \lambda_i Q_i + u_i \quad (13)$$

$$X_i = \alpha_0 + \alpha_1 Z_i + \sum_i \gamma_i V_i + e_i \quad (14)$$

Where;

i is a subscript denoting observations 1 through N.

Y_i is the dependent variable. X_i is the endogenous regressor Q_i, is a vector of exogenous covariates explaining the outcome variable.

Z_i is the instrument for the endogenous regressor (X_i)

V_i, is a vector of exogenous covariates explaining the endogenous variable. Some of the variables in Q_i may also be in V. β_i, λ_i, α_i and γ_i are parameters to be estimated.

u_i, and e_i error terms each indexed with the subscript i.

The IV method involves the estimation of equation 14 first, generating the predicted values $\widehat{X_i}$ of X_i and lastly replacing X_i in Equation 13 with $\widehat{X_i}$ and estimation of Equation 13.

We used participation in the innovation platform activities as an instrument because it is highly correlated with the endogenous variable (adoption) while not expected to correlate with important omitted variables such as skills that affect the yield. In the first stage, the endogenous variable (adoption) is regressed against a subset of explanatory variables and the predicted values of explanatory variables were used to estimate the impact in the second stage.

III. RESULTS AND DISCUSSION

First, this section will present the results of determinants for farmers' participation in innovation platforms. Second, the effect of participation on adoption decision and area allocation under the recommended package will be presented and lastly, the impact of adoption on wheat yield as an indirect indicator of participation. The logistic regression parameter estimates showing the determinants participation in innovation platforms are presented in Table 4.

[

One important factor that significantly encouraged farmers to participate in innovation platforms was their membership in agricultural societies or farmer associations in the project sites as indicated by the significant coefficient of this variable in Table 4. This result indicates that cooperatives and agricultural associations were effective means to enhance farmers' participation in the innovation platforms. Another interesting result from this analysis from the Gezira scheme is that higher participation of small size families/low male families indicate that family-related factors were more important as determinants of participation relative to other factors.

Variable	**Sudan**	**Gezira Scheme**	**Kassala state**	**River Nile state**	**Northern state**
Family size (persons)	-0.102	-0.58**	-0.019	0.342	0.250
Distance to output market (km)	0.055**	0.115	-0.073	-0.071	0.120
Have their own seed (yes/no)	-1.49***	-1.694	-2.850**		-0.075
Farming experience (dummy)	-0.295	0.696	-0.945**		-1.938
Number of males in the household	0.130	1.290**	-0.114	-0.517	-0.970
Percent of males in the household	-0.076	-7.316*	0.527	5.049	4.529
Member in agric. society (yes/no)	2.48***	4.95***	1.970**	2.052*	2.58**
Practice rotation (yes/no)	-0.033	0.652	-0.316	0.059	2.09**
Age of the household head (years)	0.022**	0.007	0.042**	-0.009	0.049
Distance to microfinance (km)	-0.041*	-0.16***	0.107	-0.017	-0.134
Constant	-14.39	-11.668	-15.93	-3.01	-2.55
Pseudo R2 and sig.	0.25***	0.55***	0.25***	0.180	0.36***

Table 4: Factors affecting farmers' participation in the innovation platforms in Sudan, 2016.

Source: Field survey, 2016.

NB: Statistical significance at 0.01 (***), 0.05 (**), 0.1 (*)

On the other hand, farm-related factors were more important in Kassala where lower farming experience and non-self-seed production families more were likely to participate in the platforms. Similarly, market-related factors such as market-oriented wheat production significantly increased participation relative to subsistence wheat farming in the Northern state as well.

Factor	Platform Participation	Access to credit	Receive training	Seek counseling	Seed production
Access to credit and inputs	-0.303***				
Received training	0.032	-0.228***			
Seek counseling	0.263***	-0.238	0.492***		
Seed production	0.325***	-0.287	0.250	1.119***	
Improved practices	- 0.043	-0.158***	1.564***	0.275***	0.013

Table 5: The estimated MVP parameters for wheat farms in the Sudan, 2016

Source: Field survey, 2016

NB: Statistical significance at 0.01 (***), 0.05 (**), 0.1 (*)

The correlation between error terms in the multivariate probit model presented in Table 5 reflect the inter-relationships between different factors related to participation. Farmers with limited access to credit or who need agricultural counseling had higher tendency of participation while farmers who produced their own seeds in the preceding season were less likely to participate in the platforms compared to other farmers.

In order to arrive better in-depth analysis, weights were assigned to the adoption rate and degree. Generally, the results presented in Table 6 show that the distribution of adoption is consistent in the study area where 56% of wheat farmers allocated 54% of their cultivated wheat area under the recommended package.

State / IP site	Weighed adoption rate (% of adopter farmers)	Weighed adoption degree (% of wheat area under the technology)
Gezira scheme	88%	92%
Kassala state	72%	51%
River Nile state	20%	58%
Northern state	15%	14%
Sudan	56%	54%

Table 6: Weighed adoption rate and degree of recommended wheat package in Sudan, 2016.

Source: Field survey, 2016

There is variation in adoption at the state-level as for example, while the adoption rate in Kassala was high (72%), the percentage area under the package was much less than that of the percentage number of adopter farmers (51%) implying that the innovation platforms approach favored small scale farmers with numerous farms with limited land areas. This is contrary to what existed in the River Nile state where the technology transfer approach favored large scale farmers as expressed by the low adoption rate (20%) relative to a higher adoption degree (58%) implying that only few farmers had adopted the recommended package with large land areas. The variation in addressing different farming scales might be affected by the size of land holdings, or by the used project team approach to involve small or large scale farmers in each state.

In order to attribute the variation in adoption to its causal factors, we estimated the double hurdle model which eliminated the effect of non-observable factors on both participation and land allocation (Table 7). The double hurdle estimates show that adoption of the recommended package was significantly enhanced by participation in the innovation platforms, but its effect on land allocation was not significant. This indicates that while participation convinced farmers to adopt the recommended package, but it failed to convince them to allocate more land under the recommended package. One possible explanation to this result is that the platforms activities were primarily designed to focus on certain components of the recommended package such as distribution of improved variety seeds, organizing field days and farmer field schools more than solving area expansion problems such as availing more irrigation water, improving farmers access to inputs and services and solving marketing problems. Results also show that participation was not the only cause of enhanced adoption. Rather, many other factors were significant determinants of adoption such as the farmers' financial capability beside household characteristics such as the percentage of males. Results in Table 7 show that factors which determine participation are different from those which determine land allocation. More land allocation under the recommended package was enhanced by market-oriented production, more farming experience land available for wheat expansion.

Variable	Tier1		Tier2	
	Coefficient	SE±	Coefficient	SE±
Constant	0.639	0.679	-18.250	14.88
Participation in SARD-SC project (yes/no)	0.747***	0.255	-3.510	2.913
Family size (persons)	0.011	0.021	0.393	0.300
Farming experience (years)	- 0.057***	0.012	0.364**	0.166
Received training in agriculture (yes/no)	0.736***	0.179	- 0.227	2.531
Membership in agricultural society	- 0.033	0.254	2.663	2.888
Percent of males in the household	- 1.233***	0.465	8.879	5.666
Use diesel as a source of power (yes/no)	- 0.772***	0.231		
Access to credit for wheat production (yes/no)	0.604***	0.215	4.130	2.538
Total farm area (ha)			0.503***	0.163
Number of irrigations			0.320	1.194
Distance to inputs market (km)			0.067	0.095
Distance to output market (km)			0.045	0.040
Age of the household head (years)			-0.057	0.092
Market oriented wheat production (yes/no)			11.48***	3.936
Sigma	6.824***	1.083		

Table 7: The estimated double hurdle model for wheat farms in Sudan, 2016

Source: Field survey, 2016

NB: Statistical significance at 0.01 (***), 0.05 (**), 0.1 (*)

A significant increase in land allocation under the package is unlikely to take place unless higher yield is guaranteed through enhanced adoption of the recommended package.

The impact of participation and hence increased adoption on wheat yield proves the effectiveness of innovation platforms as a technology transfer approach. As explained in the methodology part of this paper, the impact on yield was estimated using instrumental variables regression, the parameter estimates of which are presented in Table 8. The IV model was used because it accounts for both observable and hidden factors which affect the impacts on yield.

Factor	Coefficient	SE±
Constant	1.764***	0.374
Participation in SARD-SC project activities (yes/no)	0.904***	0.265
Number of irrigations applied in the previous season	0.067*	0.039
Farm with fertile soil (yes/no)	0.168*	0.087
Percent of males to total household family members	-0.579**	0.289
Number of males in the household	0.035*	0.021
Total farm area (ha)	0.015***	0.006
Used the recommended seed rate (yes/no)	-0.297***	0.114
Used the recommended urea dose (yes/no)	0.465***	0.097
Used the recommended varieties (yes/no)	0.474***	0.178
Farming experience (years)	-0.017**	0.007
Estimation statistics:		
Durbin (score) chi^2	5.005 ***	
Sorgan (score) chi^2	20.13 ***	
Minimum eigenvalue statistic for weak instruments	13.27	
R^2	0.25	
Wald Chi^2	20.33 ***	
N	521	

Table 8: Estimated instrumental variable regression parameters for wheat farms in Sudan, 2016.

Source: Field survey, 2016

NB: Statistical significance at 0.01 (***), 0.05 (**), 0.1 (*)

Due to significant correlation between participation and adoption, farmers' participation in the innovation platforms was used as an instrument in the model after testing it for endogeneity, weak instruments and overidentification as indicated by estimation statistics in Table 8. The results for model fitting show that participation is endogenous to the IV model and the model was correctly specified without an overidentification problem. Participation was treated as a binary outcome variable in the IV model and was regressed against a subset of explanatory variables in the first stage estimation. Then, the predicted values from the first stage estimation were used as an independent variable in the outcome equation to estimate the impacts on yield. Results of the model estimates show that adoption which was enhanced by participation, has lead to significant increase in yield as expressed by the positive and significant coefficient of the participation variable in the estimated model presented in Table 8.

Beside the most important package-related factors such as growing improved varieties, sowing at the recommended dates and applying the recommended fertilizer and seed rates, a number of non-package factors significantly determined yield levels.

State	Participation	IV model estimation	Conventional estimation	Difference
Gezira Scheme	Participants	3.67	3.66	0.01
	Control	2.98	3.28	-0.30
	Difference	0.69***	0.38 ***	0.31
Kassala State	Participants	3.41	3.04	0.37
	Control	2.39	2.37	0.02
	Difference	1.02***	0.67 ***	0.35
River Nile state	Participants	3.46	3.13	0.33
	Control	2.34	2.28	0.06
	Difference	1.12***	0.85***	0.32
Northern state	Participants	3.20	2.99	0.21
	Control	2.17	2.14	0.03
	Difference	1.03***	0.85 ***	0.18
Sudan	Participants	3.50	3.18	0.32
	Control	2.51	2.60	-0.09
	Difference	0.99***	0.58***	0.41

Table 9: Impact of IP participation on wheat yield (ton/ha) in Sudan, 2016.

Source: Field survey, 2016

NB: Statistical significance at 0.01 (***), 0.05 (**), 0.1 (*)

Among the non-package yield determinants, more available land within the farm, more experience in wheat farming and higher percentage of males in the household lead to significant increase in yield.

The average increase was of 0.99 ton/ha for platform participants compared to non-participant farmers. However, there was variation in yield gain across the states with 1.12, 1.03, 1.02 and 0.69 ton/ha for the River Nile state, Northern state, Kassala state and Gezira scheme, respectively. The highest impact on yield was estimated for the River Nile and Northern states because they are located in the most favorable environment for wheat production in the Sudan which is privileged with an extended winter season of favorable temperature compared to other regions in the country. However, the yield levels presented in Table 9 does not fully reflect yield potentials of the Northern and River Nile states. In order to explain the possible causes of low yield estimates for these potentially high producing regions, we compared yield levels of the IV model with the conventional comparison between participant and on-participant farmers without applying the instrumental variable model so as to trace the effect of how do unobservable farmers characteristics (such as skills and motivations) influence yield gain for the participant farmers. The conventional method yield estimates are presented in Table 9 along with yield differences between the IV model and conventional method estimates.

Yield differences between the IV and conventional methods presented in Table 9 are indicative of the non-observable factors effect on yield. The yield difference was 0.31, 0.35, 0.32 and 0.18 ton/ha for the Gezira scheme, Kassala state, River Nile state and Northern state, respectively. The possible cause of the relatively lower yield levels for the platform participants in the Northern State compared to other regions might be that less motivated farmers with lower skills were chosen to participate in the innovation platforms for the Northern state compared to other regions. This is shown by the lowest yield difference between estimated by these two methods suggesting that even with participation, yield gain was not as high as expected for more motivated and skilled farmers and therefore the non-observable factors were more influential in determining yield in the Northern state compared to other locations.

IV. CONCLUSION AND POLICY IMPLICATIONS

The objective of this study is to evaluate impacts of innovation platforms as a technology dissemination approach used in a pilot project to improve wheat production in Sudan. A sample of 532 wheat producing households was randomly selected in four major wheat producing areas of the Sudan, i.e. Gezira scheme, New Halfa scheme, Northern state and River Nile state. Logistic regression, multivariate probit and double hurdle models were used to analyze adoption while the instrumental variables regression was used to estimate the impacts. Results showed that the need for training, credit and effective marketing were important determinants of participation which in turn significantly enhanced adoption of wheat recommended package and yield. The study concluded that while participation enhanced adoption of the package, it did not significantly increase land allocation under the package. Also, the determinants of adoption were mostly related to the technology package, farm and household characteristics whereas land allocation and yield were mostly related to farm and market determinants. An average increase of 0.99 ton/ha in yield was achieved due to enhanced adoption resulting from farmers' participation in the platforms.

Policy implication should aim at realizing higher wheat production in Sudan through a multi- stakeholder technology transfer approach using the innovation platforms approach that better facilitates access to information about the technology package, better opportunities to have inputs and services at the mean time, and ultimately achieving higher yields of wheat for enhanced food security in the Sudan.

ACKNOWLDGMENT

Funding by the African Development Bank and technical support by the International Centre of Agricultural Research in the Dry Areas (ICARDA) and Agricultural Research Corporation, Sudan are acknowledged.

REFERENCES

[1.] Adil, A.A., &Sulieman. H.M. (2015). Technical efficiency of wheat farms in the River Nile State, Sudan. http://economia.unipv.it/naf/Working_paper/WorkingPaper/Adhn/adhn.pdf

[2.] AEPRC, (2006). Economics of wheat production in Sudan. Agricultural Economics and Policy Research Centre. Annual Report, 2006. Agricultural Research Corporation, Sudan.

[3.] Albashir U.A. (2010). Technical Efficiency of Wheat Production in the Central Gezira Scheme. Unpublished M. Sc. Thesis. Faculty of Agriculture. University of Khartoum (2010).

[4.] Al-Feel M.A., & Abdul Razig A.A. (2012). Economic efficiency of wheat production in Gezira scheme. Journal of the Saudi Society of Agricultural Sciences (11): 1–5

[5.] Amemiya T. (1974). Multivariate regression and simultaneous equation models when the dependent variables are truncated normal. Econometrica J. 42(6): 999–1012.

[6.] ARC-WRP. (2013). Wheat Production in Sudan. Annual report of the project: Enhancing Food Security in the Arab Countries 2013. Agricultural Research Corporation, Sudan, 2013.

[7.] Aristei D., &Pieroni L. (2008). A double-hurdle approach to modeling tobacco consumption in Italy. Journal of Applied Economics (40): 2463–2476.

[8.] Ashenfelter O. (1978). Estimating the effect of training programs on earnings. Review of Economics and Statistics 6: 47–57.

[9.] Ashford J. & Snowden, R. (1970). Multivariate probit analysis. Biometrics Journal 26 (3):535–546.

[10.] Axinn G.H. (1988). Guide on alternative extension approaches. Agricultural Education and Extension Service, Human Resources Institution and Agrarian Reform Division. Rome, FAO, M/8971E//1/12.88/1000.

[11.] Babiker E.A. &Faki, H.H. (1994). Evaluation of farmers' attitudes and their effect on wheat productivity and input use in Rahad Scheme. ICARDA/ARC. Wad Medani, Sudan.

[12.] http://pdf.usaid.gov/pdf_docs/PNACB251.pdf (Accessed 12 January, 2020.).

[13.] Blundell R.W. & Meghir, C. (1987). Bivariate alternatives to the univariate Tobit model. Journal of Econometrics, (33): 179–200.

[14.] CBOS. (2013). Central Bank of Sudan's Annual Report (No. 53). Central Bank of Sudan, Khartoum, Sudan.

[15.] CBS. (2012). Indicators drawn from the population census of 2008. Central Bureau of Statistics, Sudan. http://cbs.gov.sd/fullstory.php? Id=77 (Accessed 10 May, 2019.).

[16.] Contado, T.E. (1997). Formulating Extension Policy. In Improving Agricultural Extension: A reference manual. Swanson et al. Eds) Rome. FAO.

[17.] Cragg, J.G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica (39): 829–844.

[18.] Dong D., Chung C. & Kaiser, H.M. (2004). Modeling milk purchasing behavior with a panel data double-hurdle model. Applied Economics, 36(8), 769–779.

[19.] FadlAllah M.M. (2010). Socio economic factors affecting wheat efficiency in north of Gezeira. Unpublished M.Sc. Thesis. Department of Agricultural Economics, Faculty of Agriculture, University of Khartoum, Sudan.

[20.] Fageer E.A., Dhehibi, B., Mazid, A., Abdalla. A.H. & Aden Aw, H. (2013). The impacts of an improved technology package on production efficiency: the case of wheat farms in the Northern State of Sudan. American-Eurasian Journal of Agricultural and Environmental Sciences. 13 (8): 1114-1123.

[21.] Hassan, H.I.H (2008). Technical efficiency of wheat production in Rahad scheme, unpublished PhD thesis. Faculty of Agriculture. University of Gezira.

[22.] Hassan, R.M. &Faki, H.H.M. (1993). Economic Policy and Technology Determinants of the

Comparative Advantage of Wheat Production in Sudan. CIMMYT Economic. Paper No. 6, Bangkok, Thailand, CIMMYT.

[23.] Heckman, J. (1979). Sample selection bias as a specification error. Econometrica, 47, 153–161.

[24.] Heckman, J.J. & Robb, R. (1985). Alternative methods for evaluating the impact of interventions. In J. Heckman & B. Singer (Eds.), Longitudinal Analysis of Labor Market Data (pp. 156-245). New York: Cambridge University Press.

[25.] Jensen, H. & Yen, S. (1996). Food expenditures away from home by type of meal. Canadian Journal of Agricultural Economics, 44(1): 67–80.

[26.] McDowell, A. (2003). From the help desk: Hurdle models. The Stata Journal, (3): 178–184.

[27.] MoFEP (2012). Economic indicators in the Northern State. Report of Ministry of finance and Economic Planning MoFEP (2012), Northern State, Sudan.

[28.] Newman, C., Henchion, M. & Matthews, A. (2003). A double hurdle model of Irish household expenditure on prepared meals. Applied Economics, 35(9), 1053–1061.

[29.] OECD-FAO (2014). OECD-FAO Agricultural Outlook 2014-2013 OECD Library. Available at http://www.keepeek.com/Digital-Asset-Management/oecd/agriculture-and-food/oecd-fao-agricultural-outlook2014_agr_outlook-2014-en (Accessed: 25Aug. 2019).

[30.] Osman, B. (1989). Study of the potential for inter-regional trade in cereals. Inter-Governmental Authority on Drought and Development (IGADD), Country Report. Sudan, 173-221.

[31.] Schwartz, L.A. &Kampen, J. (1992). Agricultural extension in east Africa. World Bank technical paper No. 164: 4-22.

[32.] Seevers, B., Graham, D., Gamon, J. & Conklin, N. (1997). Educating through Cooperative Extension. Albany, NY: Delmar Publishing.

[33.] Shrestha, R.K., Alavalapati, J.R.R., Seidl, A.F., Weber, K.E. &Suselo, T.B. (2006). Estimating the local cost of protecting KoshiTappu Wildlife Reserve, Nepal: A contingent valuation approach. Journal Environment, Development and Sustainability (9): 1573–2975.

[34.] Wooldridge, J. (2002). Econometric analysis of cross section and panel data. Cambridge, MA: MITPress. https://jrvargas.files.wordpress.com/2011/01/wooldridge_j2002_econometric_analysis_of_cross_section_and_panel_data.pdf (Accessed 7 June, 2020).

[35.] World Bank (2012). Agricultural Innovation Systems: An Investment Sourcebook. Agricultural and Rural Development, World Bank. Available at https://openknowledge.worldbank.org/handle/10968/2247/License:CCBY3.0IGO

[36.] WRP (2016). Wheat Research Program: Report on: Performance of project: Strengthening Agricultural Research for Development of Strategic Crops, Sudan program, Agricultural Research Corporation, Sudan.

[37.] Yen, S.T. & Huang, C.L. (1996). Household demand for finfish: A generalized double hurdle approach. Journal of Agricultural and Resource Economics, 21(2): 202–234.