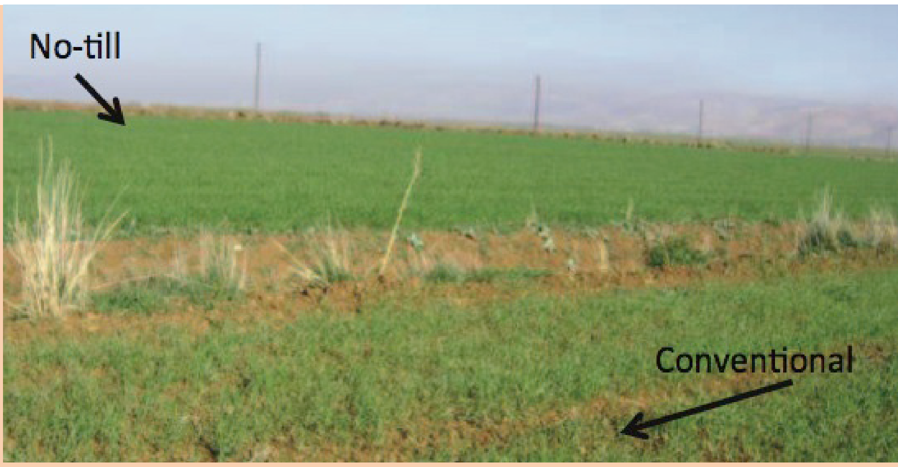
ICARDA
Science for Better Livelihoods in Dry Areas

Working Paper 29



Profitability Analysis of Zero Tillage among Smallholder Farm Households in the Karak Region of Jordan

Samia Akroush, Yigezu A. Yigezu, and Omar Abed Hadi

IFAD
INTERNATIONAL FUND FOR AGRICULTURAL DEVELPMENT

Acknowledgements

Authors: Samia Akroush, Yigezu A. Yigezu, and Omar Abed Hadi

The authors would like to express thanks and appreciation to those who contributed to this paper: National Center for Agricultural Research and Extension (NCARE) and to Rabbah Regional Center in south Jordan. Thanks are extended to ICARDA programs for their support. Thanks and appreciations are due to the International Fund for Agriculture Development (IFAD) for their financial contribution and their keen interest in the results of this project. Special thanks are extended to all farmers and their community for their support and friendliness.

This working paper is an output of the project on “Improving food security and climate change adaptability of livestock producers using the rainfed barley-based system in Iraq and Jordan” (IFAD

Grant 1240-ICARDA)

ICARDA Working Papers document the progress of the ICARDA research program and its support to country partners in more than 40 drylands countries. Working Papers are one of ICARDA’s global public goods; they capture and share knowledge and learning from projects and research partnerships. Each paper is internally reviewed as part of the center’s publishing process.

ISBN: 92-9127 4755

Key words: Zero tillage, Adoption, livelihood, endogenous switching regression, PSM, Jordan

Feedback

ICARDA welcomes comments and feedback on this publication. Please write to us at icarda@cgiar.org

www.icarda.org

International Center for Agricultural Research in the Dry Areas (ICARDA), PO Box 114/5055, Beirut, Lebanon
2015

Table of Contents

Executive Summary

There is rich literature on the biophysical benefits of zero tillage (ZT) while that on its economic benefits, especially in the context of small and medium-scale farmers, is scanty. Using a combination of Propensity Score Matching (PSM) and Endogenous Switching Regression (ESR) models and a case study from a large project which promoted a number of technologies including zero tillage in the Karak region of Jordan, this study attempts to provide evidence on the profitability of ZT. Model results show that adoption of the zero tillage leads to a gain in net margins of about US$357/ha for the typical adopters. Moreover, if the typical non-adopter farmers were to adopt the ZT technology, they would earn about US$240/ha more than their current net margins. Along with the positive biophysical and environmental benefits of the adoption of ZT, which are well documented in the literature, our results suggest that ZT is a robust technology which can be justified on economic, food security, biophysical and environmental grounds. Therefore, wider adoption of ZT has great potential for transforming the agricultural sector in general and the livelihoods of small and medium mixed crop-livestock producers in the Karak governorate of Jordan and similar areas in the West Asian region. The policy implication of our results is that governments in the developing world should consider embracing ZT as one of the priority cropping technology packages in their national extension programs, and develop policies which overcome limitations for wider adoption.

1. Introduction

Severe land degradation and the ever-increasing scarcity of water raise concerns about the future of agriculture, especially crop production, in dryland areas of the Arab region. Conservation agriculture (CA), defined as cropping with minimal soil disturbance, stubble retention and wide rotations (Friedrich et al., 2012), is believed to be a promising technology that can provide some solutions for these longstanding agricultural challenges in the region. However, CA is often looked upon with a high degree of skepticism mainly due to lack of information and evidence, particularly on its effectiveness and profitability relative to traditional tillage and other agronomic practices (Belloum, 2014).

Globally, 9% of total cropland was estimated to be under CA in 2012 but not necessarily the entire CA 'package' (Friedrich et al., 2012). ZT, an important cropping technology in its own right, as well as a defined component of CA, has been widely adopted in North and South America and Australia (Fulton 2010; Horowitz et al., 2010; Llewellyn et al., 2012). However, with the exception of few success stories in certain pockets, South Asia and Africa (Friedrich et al., 2012; Giller et al., 2009) and West Asia (Piggin et al., 2011) have not yet benefitted from the advances of CA technology in general and ZT in particular.

ZT is an agricultural practice or technology whereby planting takes place without any prior tillage. It is also known by various other names including no till (NT), direct seeding (DS) and minimum tillage (MT), and is sometimes confused with the much broader concept of CA. Adoption of ZT conserves soil moisture and reduces fuel, labor and machinery costs (Ribera et al., 2004). In addition, a reduction in wind and water erosion provides significant environmental benefits. ZT can often lead to higher yields, increased net returns and reduced cost, and income variability, which is particularly important in dryland areas. As with many high-income countries, CA can lead to possible benefits to resource-poor farmers and consumers, and improve rural and national economies in low and middle income countries in the Middle East, Asia and Africa, especially those in the dryland regions (ICARDA 2012). ZT is thought to be the most important component of CA for the Middle East providing immediate benefits to farmers (Loss et al., 2015).

The aim of this study is to quantify the livelihood benefits of ZT on rural household barley production in Jordan. In particular, the paper investigates the impacts of adoption of ZT on farm net income. In view of the tremendous skepticism about the economic benefits of CA, especially in the context of mixed crop–livestock production systems, this paper provides the much needed empirical evidence on the profitability of the adoption of ZT. The results will be useful for policy makers, extension offices, government and non-governmental development organizations, development agents and researchers working in Jordan and other areas with similar agro-climatic and production systems.

2. Description of the project and the study area

A three-year project funded by the International Fund for Agricultural Development (IFAD) of the United Nations was launched in 2011 with an objective of increasing productivity and climate change resilience of poor rural households in the rainfed areas of Jordan and Iraq who are dependent on barley and livestock production.

The project targeted areas where annual rainfall ranges between 200 to 350 mm, and barley is the main source of feed for small ruminants (mainly sheep and some goats) in a mixed crop-livestock production systems. In this system, barley and rarely wheat stubble grazing is used as a source of feed for most of the year. Households relying on barley production are highly vulnerable, as the barley-based livestock system is practiced in fragile marginal ecosystems subject to frequent drought, water scarcity, increasingly erratic rainfall, resource over-use, degradation, soil erosion, loss of biodiversity, and very low levels of soil organic matter.

The main target groups of the project were resource-poor farmers and livestock producers in the rainfed barley-based system whose livelihoods are dependent on agriculture. These farmers have limited off farm income or skills for diversification of economic activities. They also have limited access to pertinent information and technological developments.

Specific sites for project implementation were selected in the first growing season (2011/2012) by a multidisciplinary team from the project staff. Site selection was guided by the criteria set in the project document. The team met with farmers, officials and institutions working in the area and based on the results of these meetings and the characteristics of the candidate sites visited, the project implementation sites were selected.

Two wider areas were selected in Jordan. The first area is located to the north east of the Karak Governorate and consists of a cluster of 5 villages namely: Rabbah, Ader, Smakiyeh, Judeydah and H'mud. The second area is located to the south of the governorate from which one village called Sul was selected for inclusion into the project. The selected villages are located within the area covered by the Agricultural Resource Management Project Phase II (ARMP II) - another development project supported by IFAD. The selected villages are located in the dry areas of Jordan where barley and small ruminants are the major agricultural activities.

3. Methodology

There are three potential sources of bias in impact studies. The first one is that participant households may significantly differ from nonparticipants in a community due to observable characteristics (such as household head's education level, farming experience, and age) that may have a direct effect on outcome of interest. Secondly, differences among households can arise due to unobservable household and farmer characteristics. For instance, some households may have certain advantages such as good entrepreneurial spirit or special skills and other sources of income that may significantly influence their adoption behavior and even the outcome variable. Third, there exist externalities (spillover effects) which are exerted by the project on nonparticipants (Davis et al., 2010). Because of the above confounding errors, differences between participants and non-participants may, either totally or partially, reflect initial differences between the two groups rather than the effects of participating in the intervention (which in this particular case is ZT).

The choice of the appropriate model to use for impact evaluation on improved agricultural technologies depends on how the treatment was disseminated to or received by the intended beneficiaries (Spencer et al, 2006). In many cases, participants are not randomly assigned but either chosen by project personnel (or development agents) or included on voluntary basis where participants may decide on whether to participate or not based on their subjective assessment of benefits and costs arising from the technology or intervention of the project, which creates selectivity bias. Unless the bias so introduced is acknowledged and the necessary corrections made, the treatment effect can be misstated (Wei-Ling Song, 2005; Becker and Ichino, 2002). Barley producing farmers exposed to the ZT technology in Jordan had full control over their decision on whether to participate or not (the receipt of the treatment is endogenous). Hence, the most plausible assumption in this case is that of selection bias on unobservable factors (Imbens and Wooldridge, 2009; Diagne, et al., 2009). While a number of methods for program evaluation exist, the most common in the literature are the differences in differences approach (DID), propensity score matching (PSM), endogenous switching regression (ESR) and the instrumental variables approach (IV). If pre and post-project panel data generated through well designed experimental approaches are available, DID has clear advantage over all the others as it is potent in removing biases introduced through both observable and unobservable factors. However, such data are often beyond the reach of researchers and hence the non-experimental approaches are used for statistically tackling the "evaluation problem" (Ravallion, 2001). Among such approaches, the instrumental variables approach is hailed for its strength in minimizing biases due to both observable and unobservable factors, but finding an appropriate instrument always remains to be a great challenge. As the data available for this study is only a one shot survey at the end of the project, the PSM and ESR methods are used in this paper.

Propensity score matching.

The propensity score matching method (Becker and Ichino, 2002) provides a more refined way of comparing the performance of participant and non-participant farmers by accounting for their inherent differences. The basic concept is to compare non-participant farmers who are similar to participant farmers in all relevant characteristics except for the treatment (in this case the adoption of the ZT technology). The differences in the outcomes of participant farmers and the selected non-participant farmers can then be attributed to the adoption of the technology.

The use of PSM to minimize selectivity bias thus suggests that these differences are the result of the adoption of ZT rather than the intrinsic characteristics of the sampled households. However, like the simple mean comparison, PSM may misinterpret the treatment effect, because it only controls for observed variables, and hidden self-selectivity bias may remain. PSM is chosen for this study because it does not require baseline data, the treatment assignment in the IFAD project is not random and is considered as second-best alternative to experimental design in minimizing selection biases mentioned above (Baker, 2000). Moreover, assuming that technology adoption is a function of a wide range of observable characteristics at household level, removing the assumption of "constant technology effect" allows us to follow the PSM method (Mendola, 2007). The PSM approach can be described as follows:

Suppose A_i denotes a dummy variable, such that A_i =1 denotes that the i^{th} individual has adopted ZT and A_i= 0 otherwise. Similarly let Y_{1i} denote the observed outcome (in this case net margins) for an adopter household i and Y_{2i} the potential net margins had they not adopted the technology. Then D= $Y_{1i} - Y_{2i}$ is the impact of ZT adoption on the i^{th} individual adopter, usually called the treatment effect. In reality, we observe only $Y_i = A_i Y_{1i} + (1 - A_i) Y_{2i}$ rather than Y_{1i} and Y_{2i} (counterfactual outcome) for the same individual for which we are unable to directly compute the treatment effect for every unit. The primary treatment effect of interest that can be estimated is therefore the Average Impact of Treatment on the Treated (ATT) given by

$$\tau = E(Y_{1i} - Y_{2i} / Ai = 1) \qquad (1)$$

Suppose that X is the set of covariates that determine the adoption of ZT. Then, using a logit model and following Rosenbaum and Rubin (1983), the propensity score is estimated as:

$$P(X) = P(A_i = 1 / X) \qquad (2)$$

With the assumptions that the potential outcomes are independent of the realized technology adoption decision given X (i.e., $Y_{1i}, Y_{2i} \perp A / X$),

$$E(Y_{2i} / A=1, P(X)) = Y_{2i} / A=0, P(X)) \qquad (3)$$

Where $\perp$ denotes independence, and $0 < P(X) < 1$, i.e., for all X there is a positive probability of either adopting (A=1) or not adopting (A=0). This guarantees every adopter has counterpart in the non-adopter population.

The ATT can then be estimated as:

$$\begin{aligned}\tau &= E(Y_{1i} - Y_{2i} / A_i = 1)\\ &= E[(E(Y_{1i} - Y_{2i} / A_i = 1, P(X))]\\ &= E[(E(Y_{1i} / A_i = 1, P(X)) - E(Y_{2i} / A_i = 0, P(X))] \qquad (4)\end{aligned}$$

The propensity score is a continuous variable and there is no way to always get an adopter with the same score as its counterfactual(s). Thus, estimation of the propensity score is not sufficient to compute the average treatment effect given by equation (4) but instead there is a need for searching for counterfactual(s) that match with each adopter depending on its propensity score. In social experiments where assignments to treatments are random, this concern is eliminated. However, in non-experimental studies, one has to invoke some identifying assumptions to solve the selection problem. The following were the steps followed in this paper to estimate the impact of ZT adoption on net margins: 1) Estimating propensity score using a logit model; 2) Choosing the best matching algorism; 3) Checking overlap and common support and 4) Estimation of the impact. After the estimation of the logit model to generate the propensity scores, the *psmatch2* command in Stata due to Leuven and Sianesi (2003) is used to generate the ATT, the average treatment effect on the untreated (ATU) which measures the expected change in net margins if a typical non-adopter household were to adopt ZT and the average treatment effect (ATE) which is a measure of the expected change in net income for a randomly selected farmer in the project area regardless of adoption status.

Endogenous switching regression

In this study, endogenous switching regression is used to complement the PSM techniques as it is potent in correcting for bias originating from both observable and unobservable factors. Hence, in order to determine the counterfactual impact on net margins for adopters, an endogenous switching regression (ESR) approach is employed. The approach uses a probit model at the first stage to determine the relationship between the decision of adoption and possible determinants of net margins. The second stage regression estimates the determinants of net margins conditional on specific criterion function. The ESR can be briefly described as follows:

Suppose S_i* be a latent variable capturing the expected net margins from ZT adoption. Then, the probit model of the adoption decision can be specified as:

$$S_i = \beta X_i + u_i \quad \text{with} \quad G_i = \begin{Bmatrix} 1 \; if \; S_i^* > \mathbf{1} \\ 0 \; otherwise \end{Bmatrix} \quad (5)$$

Where: S_i* is the unobservable or latent variable for technology adoption, G_i is its observable counterpart (the dependent variable adoption of ZT equals one, if the farmer has adopted ZT, and zero otherwise), X_i are non-stochastic vectors of observed farm and non-farm characteristics believed to determine adoption and u_i is random disturbances associated with the adoption of ZT. In reality, farmers face two regimes, namely: to adopt, and to not adopt defined as follows:

$$\text{Regime 1: } Y_{\mathbf{1}i} = \partial J_{\mathbf{1}i} + e_{\mathbf{1}i} \text{ if } S_{\mathbf{1}i} = 1 \quad (6)$$

$$\text{Regime 2: } Y_{\mathbf{2}i} = \partial J_{\mathbf{2}i} + e_{\mathbf{2}i} \text{ if } S_{\mathbf{2}i} = \mathbf{0} \quad (7)$$

Where Y_i is net margins in regime *i*, J_i represents a vector of exogenous variables that influence net margins and the error terms are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix. Then, the use of the full information maximum likelihood (FIML) enables the simultaneous estimation of the probit model (also called the selection equation) and the outcome equation and generate efficient estimates with consistent standard errors (Lokshin and Sajaia, 2004). The *movestay* command in STATA (Lokshin and Sajaia, 2004).

The aforementioned endogenous switching regression model can be used to compare the expected net margins of the farm households that adopted (a) with respect to the farm households that did not adopt (b), and to investigate the expected net margins in the counterfactual hypothetical cases (c) that the adopted farm households did not adopt, and (d) that the non-adopters farm households did adopt.

$$\text{E}\,(Y_{\mathbf{1}i}\, Y_{\mathbf{1}i} \,/\, S_i = \mathbf{1}\;\; S_i = \mathbf{1}\;) = \partial_1 J_{\mathbf{1}i} + \sigma_{e\mathbf{1}u}\lambda_{\mathbf{1}i}\, \partial_1 J_{\mathbf{1}i} + \sigma_{e\mathbf{1}u}\lambda_{\mathbf{1}i} \quad (a)$$
$$\text{E}\,(Y_{\mathbf{2}i}\, Y_{\mathbf{2}i} \,/\, S_i = \mathbf{0}\;\; S_i = \mathbf{0}\;) = \partial_2 J_{\mathbf{1}i} + \sigma_{e\mathbf{2}u}\lambda_{\mathbf{2}i}\, \partial_2 J_{\mathbf{1}i} + \sigma_{e\mathbf{2}u}\lambda_{\mathbf{2}i} \quad (c)$$
$$\text{E}\,(Y_{\mathbf{2}i}\, Y_{\mathbf{2}i} \,/\, S_i = \mathbf{1}\;\; S_i = \mathbf{1}\;) = \partial_2 J_{\mathbf{1}i} + \sigma_{e\mathbf{2}u}\lambda_{\mathbf{2}i}\, \partial_2 J_{\mathbf{1}i} + \sigma_{e\mathbf{2}u}\lambda_{\mathbf{2}i} \quad (b)$$
$$\text{E}\,(Y_{\mathbf{1}i}\, Y_{\mathbf{1}i} \,/\, S_{\mathbf{1}} = \mathbf{0}\;\; S_{\mathbf{1}} = \mathbf{0}\;) = \partial_1 J_{\mathbf{1}i} + \sigma_{e\mathbf{1}u}\lambda_{\mathbf{1}i}\, \partial_1 J_{\mathbf{1}i} + \sigma_{e\mathbf{1}u}\lambda_{\mathbf{1}i} \quad (d)$$

Where:
Si = 1 if the farmer adopted ZT and 0 otherwise
y1i = net margins if adoption has actually taken place;
y2i = net margins if adoption did not happen

Equations (8) and (10) represent the actual expectations observed in the sample while (9) and (11) represent the counterfactual expected outcomes. In addition, following Heckman et al., (2001), and Di Falco et al., (2011) the following effects are calculated: the effect of the treatment on the treated (TT) as the difference between (a) and (c) (equation 8).

$$\text{TT}= \text{E} (Y_{1i} / G_i = 1) - \text{E} (Y_{2i} / G_i = 1) = - \qquad (8)$$

This represents the effect of ZT adoption on net margins by farmers that actually adopted the technology. Similarly, the effect of the treatment of the untreated (TU) for the farm households that actually did not adopt the technology is calculated as the deference between (d) and (b),

$$\text{TU}= \text{E} (Y_{1i} / G_i = 0) - \text{E} (Y_{2i} / G_i = 0) = - \qquad (9)$$

The expected outcomes described in (4a)-(4d) can be used to calculate the heterogeneity effects. Following Carter and Milon (2005), we define "the effect of base heterogeneity" for the group of farm households that decided to adopt as the difference between (a) and (d):

$$BH_1 = E (Y_{1i} / G_i = 1) - \text{E} (Y_{2i} / G_i = 0) = - \ [\![\lambda_1 2i]\!]_1 (\ )) \qquad (10)$$

Similarly, for the group of farm households that decided not to adopt, "the effect of base heterogeneity" is calculated as the difference between (c) and (b).

$$\text{BH}_2 = \text{E} (Y_{1i} / G_i = 0) - \text{E} (Y_{2i} / G_i = 0 \ G_i = 0) = - \ [\![\lambda_1 2i]\!]_1 (\ )) \qquad (11)$$

4. Data

The stratified sampling approach was used to draw a total of 60 farm households for the survey because the zero tillage (ZT) technology has only recently been introduced into the study communities by the IFAD-funded project with only project participants testing the technology. As a result, all 26 farmers who hosted demonstration trials on their own farms were purposively selected and included into the sample so as to avoid the risk of not having enough adopters in the sample while 4 other farmers who took part only in field days were also included into the sample. Thirty farmers who did not have any relationship with the project were randomly selected for inclusion in the sample. Consequently, adopter farmers represented 43% of the total sample size while the remaining 57% were non-adopters of ZT. The survey took place during the last year of the project (2014). A survey questionnaire was developed and used to collect quantitative and qualitative data on such variables as farm and farmer characteristics, quantities and costs of production inputs and yields under different tillage options. The survey was deemed an important tool to provide the basis and needed data for assessing the impact of the project and the effectiveness with which the impacts were delivered.

By design, the survey covered the same six villages in the Karak governorate namely: Rabbah, Ader, Smakiyeh, Judeydah, Sul, and H'mud where the IFAD project was implemented. The distribution of sample farmers was as follows: 31.7% from Ader, 25% from Sul, 11.7% from Rabba, 16.7% from Smakiyyah, 11.7% from Judayyedah and 3.3% from Hmoud. Version 18 of the Statistical Package for Social Scientists (SPSS) program (SPSS Inc., 2008) was used for data organization.

All respondents were men, 96.7% of whom were household heads with age range of 23 - 56 years. Education-wise, 35% were preparatory school level, 38% were secondary school level and only less than 7% of them had higher education. Farming seems to be a profession which is mainly performed by old farmers who have been in the system for long time. In the sample, farming experience was in the range of 7 and 70 years, with an average of 33 years.

Half (30) of the sample farmers were participants in the project activities through either hosting demonstration trials for testing the technologies on their own farm lands (26), or participating only in field days without applying the ZT technology on their farms (4). All the farmers who hosted demo trials also participated in the field days. The other half (30) however did not have any relationship with the project and hence neither participated in field days nor hosted demonstration trials.

Among the crops cultivated by the sample farmers, barley stands first in terms of number of farmers cultivating it (53), followed by wheat (40) and legumes (20). While animal fodder, olives and vegetables are cultivated by only 5 farmers, 4 farmers, and 1 farmer respectively. Most of the total area surveyed (21369 du[1]) is devoted to barley crop followed by wheat crop (9495 du), and legumes (1650 du).

Out of the 60 sample farm households, 41 (67%) produce sheep while 27 (45%) produce goats. The average number of sheep per flock is 243 while the average number of goats per flock is 61. The maximum flock size is also larger for sheep (at 800 heads) as compared to 300 heads for goats. Likewise, the average number of milking sheep (150) is more than the average number of milking goats (33).

Generally, rangeland and cereal stubble grazing are the major feed sources for small ruminants in Jordan. Farmers also use green barley grazing and barley and wheat straw as sources of feed

1 One Jordanian dunum (du) is equivalent to 0.1ha

for their livestock. However, as these feed sources are not sufficient and cost of purchased feed is very high, farmers also often provide their sheep with limited amounts of barley grain, and wheat and barley bran as supplemental feed. Table 1 presents the average quantities of the different feed types used and their corresponding prices. It also provides the quantities of feed obtained from the different sources (government distribution centers, local markets, and own production). Cereal straw is an important source for winter feeding. There is substantial variation in feed prices depending on the source; feed obtained from government distribution centers are much less in price than the feed obtained from the market. This is because the government subsidizes some components (such as barley) in the fodder. For instance, the price of barley in the distribution centers is 175 JD/ton, while the market price is 320 JD/ton.

Table (1): Feed types, quantities, prices and sources

Fodder	No. of farms	Quantities used (ton)			Prices paid (JD/ton)		
		Min	Max	Mean	Min	Max	Mean
Barley grain	41	0.6	200	25	175	320	184
Green barley	8	100	1000	391.8	17.5	17.5	17.5
Barley Bran	36	0.50	80	5.7	75	200	98.3
Barley straw	8	0.21	5	2.1	250	500	308.3
Barley residues	8	6	500	247	8	15	12.7
Wheat bran	3	0.2	160	57.4	150	167	158.5
Wheat Tiben	4	2	100	48	500	500	500
Barley planted in rangelands (du)	7	100	1000	407.1			

5. Results and Discussion

5.1 Stated Impacts of the Zero Tillage Technology

In the survey, farmers who tested the ZT technology on their own barley fields were asked to provide their own evaluation of the effects of the ZT technology on their livelihood. The results showed that a sizeable number of farmers have a generally favorable evaluation of the ZT technology with 50% of them mentioning that the ZT technology is beneficial with positive effect on their livelihoods. Only 13% of the farmers believed that the ZT technology is harmful with negative effects on their livelihoods and 37% see neither positive nor negative effects of ZT (Figure1).

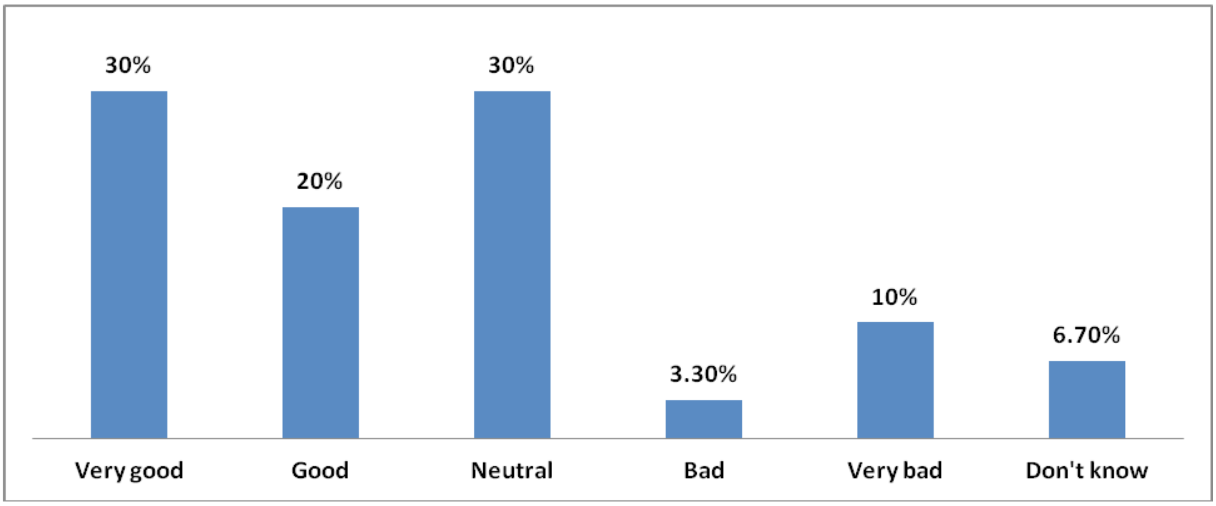


Figure (1): Farmers' evaluation about the effects of the ZT technology on their livelihood

A five scale (increased very much, increased moderately, remained the same, decreased moderately, decreased very much) indicator was used to assess farmers' opinion on how the time spent on the different agricultural activities changed with the adoption of zero tillage. Results showed that 88% of the farmers believed that the time spent for land tillage decreased at varying levels while only 3% believed that time spent on tillage increased (Figure 2).

Farmers were also asked about their opinion on how the amount of time spent on sowing changed with the adoption of ZT. A vast majority of farmers (77%) believed that it remained the same while 23% believed that the time spent on sowing decreased at varying levels (Figure 3).

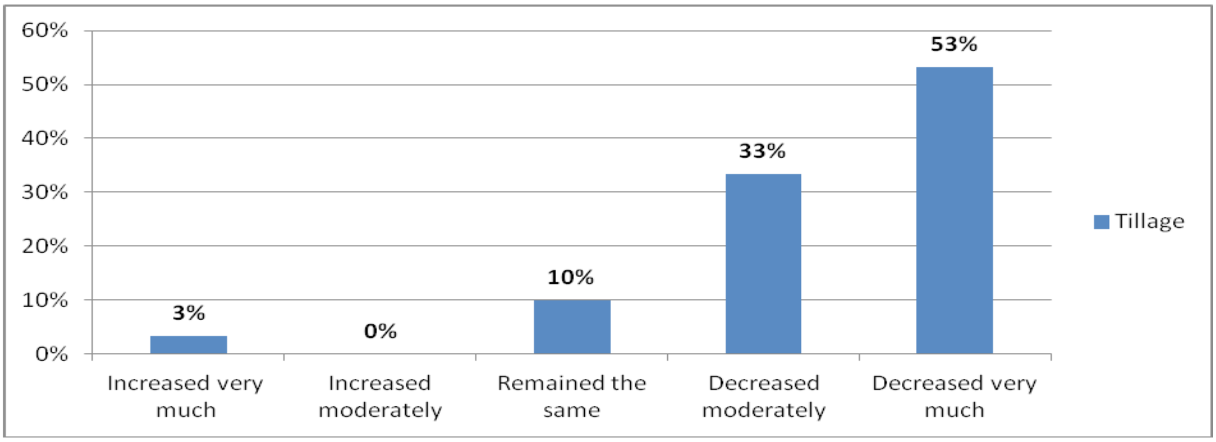


Figure (2): Changes in time spent on tillage with the adoption of Zero tillage

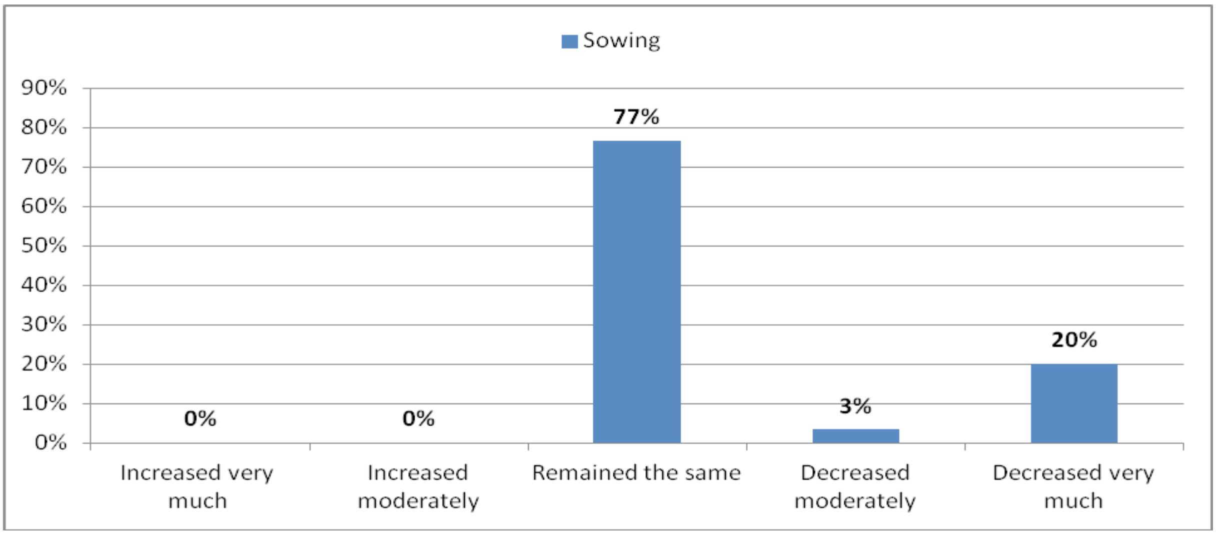


Figure (3): Changes in time spent on sowing with the use of zero tillage

With regards to the amount of time spent on fertilizer and insecticide application, 93% of farmers mentioned that the adoption of ZT does not have any effect. Only 6% and 3% believed that time spent on fertilizer and insecticide applications respectively have increased. Likewise, 50% of the farmers believed that the time spent on herbicide application remained the same as before while 33% believed that it has increased at varying levels (Figure 4).

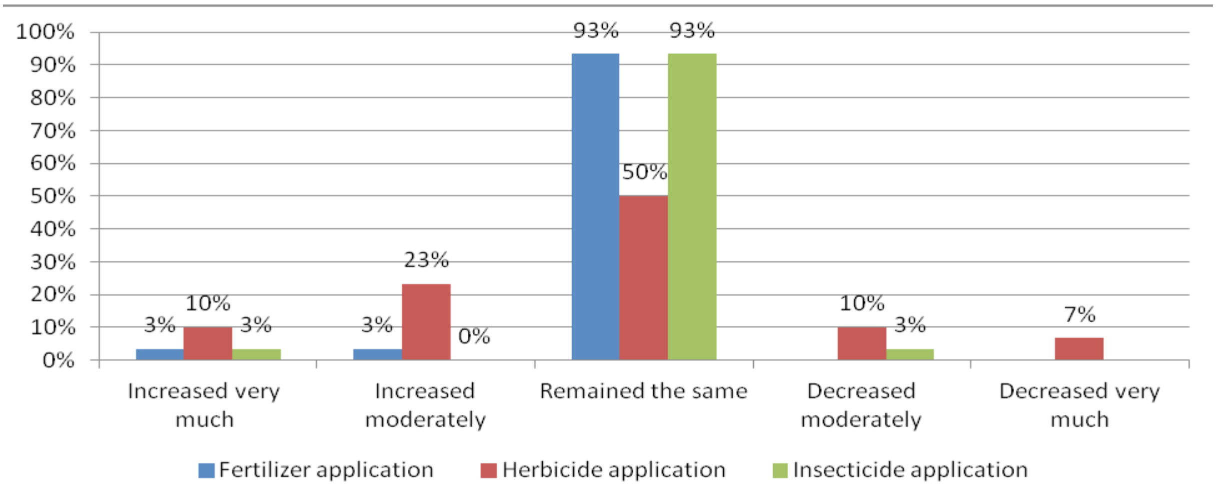


Figure (4): Changes in time spent on Fertilizing, herbicides and insecticides application with the use of Zero tillage

A vast majority (83%, 67% and 77%) of farmers believed that the time spent on weeding, harvesting and threshing respectively have not changed. The remaining farmers had divergent opinions with 10% believing that it has increased. With regard to other farm activities, 6%, 23% and 13% believed that the time spent on weeding, harvesting and threshing respectively have increased (Figure 5).

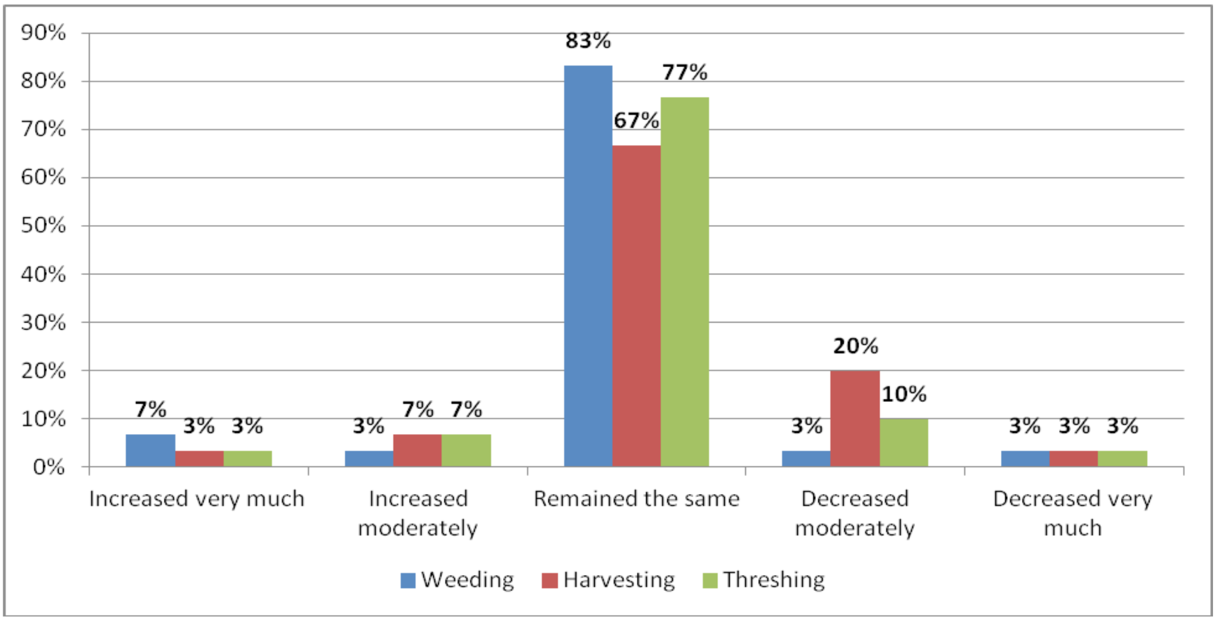


Figure (5): Changes in time spent on weeding, harvesting and threshing with the use of Zero tillage

Farmers were also asked how the cost of different agricultural activities changed with the use of zero tillage. Results show that 87% believed that the cost of tillage decreased at varying levels, with 57% believing that it decreased very much. Only 3% believed that the cost of tillage increased (Figure 6).

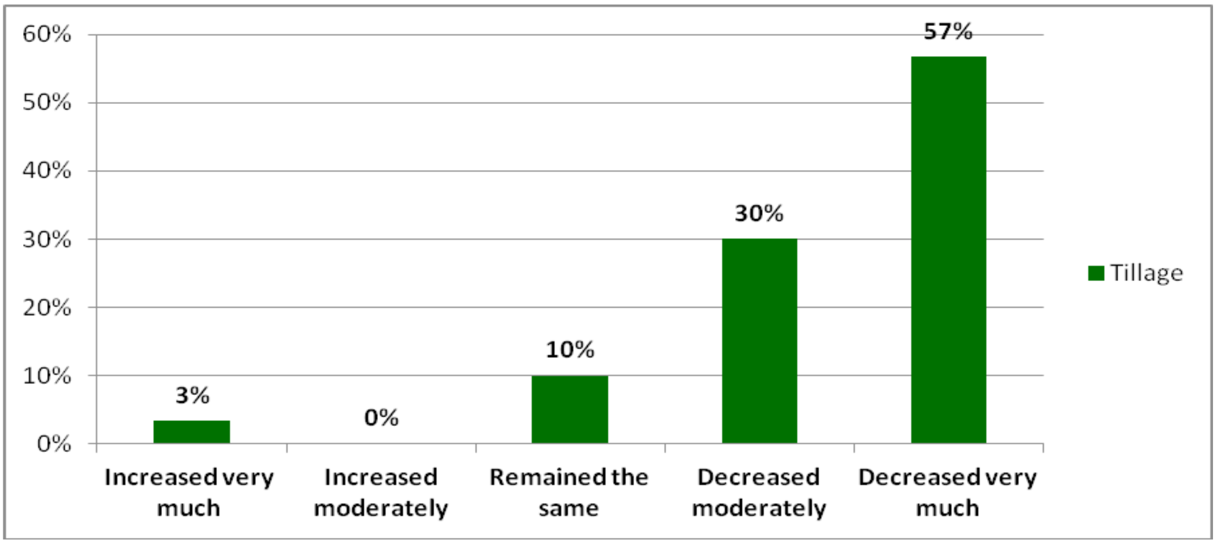


Figure (6): Changes in the cost of tillage with the adoption of Zero tillage

With regard to the cost of sowing, the majority (67%) believed that the adoption of ZT does not have any effect while the remaining 33% believed that it decreased very much. Regarding changes in the costs of application of fertilizers, herbicides and insecticides, 93%, 50% and 90% respectively believed that the adoption of ZT did not affect those costs at all while 3%, 30% and 3% respectively believed that these costs have increased. The remaining 3%, 20% and 6% respectively believed that the costs of application of fertilizers, herbicides and insecticides have increased (Figure 7).

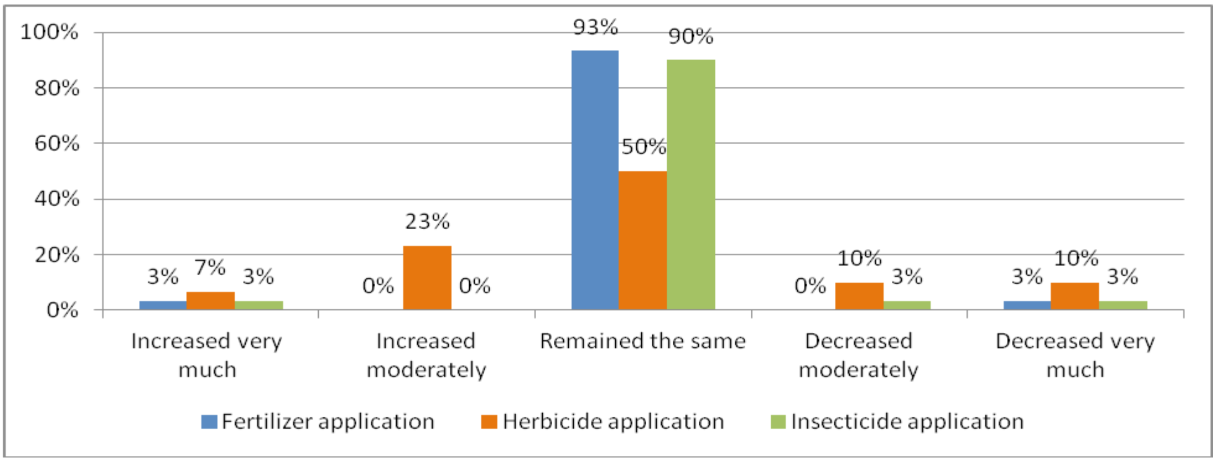


Figure (7): Changes in the costs of application of fertilizers, herbicides, and insecticides with the adoption of Zero tillage

The majority of farmers (80%, 73%, and 80%) believed that the adoption of ZT did not affect the costs of weeding, harvesting and threshing respectively, while 13%, 20% and 13% respectively believed that those costs have decreased.

5.2 Measured impacts of the adoption of zero tillage

5.2.1 Results from propensity score matching

Coefficient estimates of the factors explaining the probability of adoption of ZT from a logit model are presented in Table 2. Model results show that age of the farmer does not have a significant effect on farmers' decision whether to adopt ZT or not. This could possibly be because of the high correlation (0.86) between age and experience. The negative sign on the coefficient estimate however is consistent with theoretical expectation as younger farmers are likely to be more open to new technologies than older farmers.

Table 2: Results of the Logit model

Explanatory Variable	Coef.	Std. Err.	P>z
Age	-0.039	0.038	0.303
Farmer experience	0.063	0.032	0.047**
Education level	0.674	0.221	0.002***
Number of sheep owned	0.006	0.002	0.001***
Number of goats owned	0.011	0.006	0.064*
Total size of barley farm (du)	-0.001	0.001	0.094*
_cons	-1.892	1.531	0.217
Number of observations =	102		
LR chi2 (6) =	39.11		
Prob > chi^2 =	0		
Pseudo R^2 =	0.28		
Log likelihood =	-50.83		

With large and positive coefficient estimates, educational level and experience of farmers are among the most important explanatory variables for adoption where more educated and/or experienced farmers are expected to have a higher propensity to adopt the technology than less educated and/or less experienced farmers. These results are intuitive because the ZT technology is knowledge intensive requiring a good understanding of crop growth, soil fertility and machinery which educated and experienced farmers are expected to have and hence, become eager to reap the potential benefits of the technology. Rahm and Huffman (1984) also reported that producers who are more educated not only have higher propensity to adopt but also to make economically sound decisions in general.

The number of sheep and goats owned also positively and significantly affect farmers' propensity to adopt ZT. A possible explanation is that farmers might be convinced that ZT would lead to higher grain and biomass yields. Given that some farmers in the region do use barley at its early stage for livestock grazing and still are able to produce good amount of grain and biomass, measuring the changes in both grain and biomass production due to the adoption of ZT on farmers' fields was difficult and hence we are unable to substantiate this hypothesis. Total barley area owned negatively influenced the adoption of ZT technology (but only at 10% significance level), showing that larger farmers are not likely to adopt. This is counterintuitive as the large area sizes would justify investment in the purchase of a ZT seeder but free or rented access to ZT seeders may encourage the smaller farmers to use ZT as the opportunity cost of their time on their barley farms, under off farm employment scenario, could be higher.

The estimated mean, minimum and maximum values of the propensity scores for all sample households are 0.54, 0.036 and 0.98 respectively. The corresponding figures for adopter households are 0.69, 0.057 and 0.97 while that of the non-adopter households are 0.35, 0.036 and 0.96 – making the common support region to be between 0.036 and 0.97. For sound comparison of effects between adopters and non-adopters, predicted propensity scores should satisfy a common support condition. Therefore we discarded observations whose predicted propensity scores fell outside the range of the common support region, so households with estimated propensity scores of less than 0.057 and greater than 0.97 were not considered for the matching. Because of this restriction seven observations (three for non-adopters and four for adopters) were discarded from the analysis.

Among three matching algorithms tested namely the Nearest Neighbor, Radius Caliper and Kernel bandwidth, the Kernel bandwidth (0.25) matching algorithm was found to fit the data best (Table 3).

Table 3: Balancing test results

Matching estimators	Balancing test^	Pseudo-R^2	Matched sample size
First nearest Neighbour (NN) - NN(1)	5	0.056	102
Second NN - NN(2)	6	0.030	102
Third NN - NN(3)	6	0.029	102
Fourth NN – NN(4)	5	0.038	102
Radius calliper (0.01)	6	1.000	58
Radius calliper (0.25)	6	0.093	98
Radius calliper (0.4)	5	0.097	98
Kernel bandwidth (0.1)	6	0.042	99
Kernel bandwidth (0.25)	6	0.019	102
Kernel bandwidth (0.5)	5	0.089	102

After controlling for observable confounding factors, we found statistically significant differences in net margins between adopter and non-adopter households. The results show that the adoption of ZT raised net farm income on an average by 29.37JD/du or US$415/ha (34%)[2] . The average treatment effect on the treated is 35.1JD/du and the average treatment effect on the untreated is 22.6JD/ha (Table 4). The difference between ATT and ATU shows that there is endogenous heterogeneity i.e., the adoption of ZT has different effects on the adopter and non-adopter groups which is a sign of inherent differences between the two groups.

Table 4: Treatment effects from the propensity score matching model (JD/du)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net margins (JD/du)	Unmatched	38.26	5.39	32.87	6.39	5.15***
	ATT	38.26	3.08	35.18	8.54	4.12***
	ATU	5.39	27.98	22.59		
	ATE			29.38		

Source: Model results

*** indicates significance at 1% level

5.2.2 Results from the Endogenous Switching Regression

For comparability purposes and to check the robustness of our results from PSM, we estimated endogenous switching regression (ESR) that can control for selection bias from both observable and unobservable factors. In this paper, the full information maximum likelihood (FIML) estimation method was used to estimate the ESR and model results are presented in Table 5.

The correlation coefficients between the error-terms in the selection and the outcome equations (*rho_1* and *rho_2*) are not statistically different from zero – implying that the switch is not endogenous. For instance, since *rho_1* is not different from zero the model suggests that individuals who adopt ZT technology did not have higher income than an individual randomly drawn from the whole sample. Likewise, the insignificant *rho_2* indicates that income of those who did not adopt ZT are not any different from an individual randomly drawn from the whole sample. Results from the endogenous switching regression model estimated by full information maximum likelihood (FIML) indicate that only education has significant effect on net margins for the group of adopters while only the total barley area owned has significant effect on net margins for the group of non-adopters.

The results from the ESR regression indicate that the average gain in net margins due to the adoption of ZT among farmers who actually adopted the technology is 25.29JD/ha (US$357.2/ha). A typical non-adopter would reap a gain of 16.97JD/du (US$240/ha) in net margins if they were to adopt the ZT technology (Table 6). The positive and significant heterogeneity effect estimates (H1 and H2) show that there are inherent differences between adopters and non-adopters regardless of their adoption decisions.

2 During the study period, the conversion rate was 1 US$ for about 0.708 Jordanian Dinars (JD)

Table 5: Estimates of the Endogenous Switching Regression

	Coef.	Std. Err.	P>z	[95% Conf.	Interval]
Net margins (JD/du)_1					
Age	-1.097	0.806	0.173	-2.675	0.482
Exp	0.908	0.751	0.227	-0.564	2.380
Educ	10.429	5.053	0.039	0.524	20.334
Nosheep	0.019	0.033	0.562	-0.046	0.084
Barfrmszdu	-0.017	0.013	0.202	-0.042	0.009
_cons	46.023	37.881	0.224	-28.222	120.269
Net margins (JD/du)_0					
Age	-0.050	0.450	0.911	-0.932	0.832
Exp	0.247	0.373	0.508	-0.485	0.979
Educ	-1.799	3.596	0.617	-8.847	5.248
Nosheep	0.029	0.025	0.238	-0.019	0.078
Barfrmszdu	-0.013	0.008	0.089	-0.028	0.002
_cons	12.104	18.722	0.518	-24.591	48.799
ZT (1=Yes, 0=No)					
Age	-0.027	0.022	0.223	-0.070	0.016
Exp	0.038	0.019	0.043	0.001	0.075
Educ	0.388	0.127	0.002	0.138	0.638
Nosheep	0.003	0.001	0	0.002	0.005
Barfrmszdu	-0.001	0.000	0.131	-0.001	0.000
Nogoats	0.007	0.003	0.044	0.000	0.013
_cons	-0.937	0.887	0.291	-2.677	0.802
/lns1	3.576	0.096	0	3.388	3.765
/lns2	2.979	0.115	0	2.753	3.205
/r1	0.077	0.404	0.849	-0.715	0.869
/r2		0.4286841	0.605	-0.61862	
sigma_1		3.443259			
sigma_2		2.265689			
rho_1		0.4017688		-0.61389	
rho_2		0.4083059		-0.55017	
Number of obs =	102				
Wald chi2(5) =	8.92				
Prob > chi2 =	0.1123				
chi2(1) =	0.24				
Prob > chi2 =	0.6218				

Table 6. Average impact of treatment from the endogenous switching regression (JD/du)

	Decision Stage		
Subsamples/Effects	To Adopt	Not to Adopt	Treatment effect
Farm households that adopted	38.26	12.97	25.29***
Farm households that did not adopt	22.36	5.39	16.97***
Heterogeneity effects	15.9	7.58	8.32***

Source: Model results

*** indicates significance at 1% level

The relatively higher treatment effect estimates from PSM relative to ESR as well as the positive and significant heterogeneity effects from the ESR estimates indicate that there are important selection biases emanating from unobserved factors which, if not corrected, would lead to overestimation of the impacts. Therefore, in the face of these biases, the results of the ESR are better estimates of the true treatment effects.

6. Conclusions

Achieving agricultural growth and development and thereby improving rural household welfare will require increased efforts to provide technologies that enhance yield and conserve natural resources. This paper used a case study from Jordan to evaluate the impacts of adopting the ZT technology on farm income as measured by net margins. The propensity score matching (PSM) method was used to measure impacts. As a check, the endogenous switching regression (ESR) method was also used to ascertain the robustness of estimates from the PSM method. Both the methods were potent in providing estimates of the true welfare effects of technology adoption by controlling for different types of selection biases on production and adoption decisions.

Estimates from the propensity matching (PSM) approach show relatively higher impacts than those from the endogenous switching regression (ESR). Moreover, the estimates of heterogeneity effects from ESR are positive and significant showing that there are inherent differences between adopters and non-adopters regardless of their adoption decisions. These results suggest that given its potency to correct for selection due to unobservable factors, ESR would provide more reliable estimates of impact than PMS. Accordingly, the adoption of ZT leads to a gain in net margins of 25.29JD/du (US$357.2/ha) for the typical adopter and 16.97JD/du (US$240/ha) if the typical non-adopter were to adopt the ZT technology.

Other benefits of the other components of the conservation agriculture technology package (e.g., early planting and retention of some stubble) documented in the literature include: enhancing sustainable management of land resources and increased yields, household income, consumption and food security.

Along with the positive biophysical and environmental benefits of the adoption of ZT, which are well documented in the literature, our results suggest that ZT is a robust technology which can be justified on economic, food security, biophysical and environmental grounds in production systems. Therefore, wider adoption of ZT has great potential for transforming the agricultural sector in general and the livelihoods of small and medium mixed crop-livestock producers in the Karak governorate of Jordan and similar areas in the West Asian region. The policy implication of our results is that governments in the developing world should consider embracing ZT as one of the priority cropping technology packages in their national extension programs, and develop policies which overcome limitations for wider adoption.

References

Baker, J. L. 2000. Evaluating the impact of development projects on poverty: A handbook for Practitioners', World Bank, Washington D.C.

Becker, S. O., and Ichino, A. 2002. Estimation of average treatment effect based on propensity score, *Stata Journal*, Vol. 4:358-77.

Belloum A. 2014. Conservation agriculture in the Arab World between concept and application. In: Stewart BI, Asfary AF, Belloum A, Steiner K, Friedrich T, editors. Conservation Agriculture for Sustainable Land Management to Improve the Livelihood of People in Dry Areas. URL http://www.fao.org/ag/ca/doc/CA%20Workshop%20procedding%2008-08-08.pdf [Accessed March 26, 2015].

Carter, D. W. and Milon, J.W. 2005. Price knowledge in household demand for utility services, *Land Economic,* Vol. 81(2):265-283.

Diagne, A., Adekambi, S. A., Simtowe, F. P. and Biaou, G. 2009. The Impact of Agricultural Technology Adoption on Poverty: The Case of Nerica Rice Varieties in Benin'. A shorter version of the paper is being presented as contributed paper at the 27th Conference of the International Association of Agricultural Economists. August 16-22, Beijing, China, 2009.

Friedrich, T., Derpsch, R., Kassam, A. 2012. Overview of the global spread of conservation agriculture. The Journal of Field Actions. Field Actions Science Reports Special. 2012; 6, URL http://factsreports.revues.org/1941 [Accessed March 26, 2015].

Fulton M. 2010. Foreword. In: Lindwall C, Sonntag B. (editors). Landscapes Transformed: The History of Conservation Tillage and Direct Seeding. Knowledge Impact in Society. Saskatoon, Saskatchewan.2010; 9-14. URL http://www.kis.usask.ca/ZeroTill/LandscapesTransformed_HistoryofCT_Book.pdf [Accessed November 13, 2014].

Giller, K.E., Witter E., Corbeels,M., Tittonell, P. 2009. Conservation agriculture and smallholder farming in Africa: the heretics' view. *Field Crops Research*, vol 114 (1): 23-34.

Horowitz J., Ebel R., Ueda K. 2010. No-till farming is a growing practice. Economic Information Bulletin, No.70. Economic Research Service, USDA, Washington. http://www.ers.usda.gov/publications/eib-economic-information-bulletin/eib70.aspx [accessed December 13, 2014].

Imbens, G., and Wooldridge, J. M. 2009. Recent Developments in the Econometrics of Program Evaluation, *Journal of Economic Literature*, vol. 47(1): 5–86.

International Center for Agricultural Research in the Dry Areas (ICARDA). 2012. Conservation agriculture: opportunities for intensified farming and environmental conservation in dry areas. ICARDA Research to Action 2. http://www.icarda.org/sites/default/files/conv-agree.pdf. [Accessed 17 January, 2015].

Leuven, E., and B. Sianesi. 2003. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Boston College Department of Economics, Statistical Software Components. http://ideas.repec.org/c/boc/bocode/s432001.html. [Accessed on March 25, 2015].

Llewellyn, R.S., D'Emden, F.H., Kuehne, G. 2012. Extensive use of no-tillage in grain growing regions of Australia. *Field Crops Research,* vol 132:204-212.

Lokshin, M. and Sajaia, Z. 2004. Maximum Likelihood Estimation of Endogenous Switching Regression Models, *Stata Journal*. Vol. 4(3):282-289.

Loss, S., Haddad, A. Khalil, Y. Alrijabo, A. Feindel, D. and Piggin, C. 2015. Evolution and adoption of conservation agriculture in the Middle East. In:Farooq M., and Siddique, K.H.M. Eds Conservation Agriculture. Springer.

Mendola, M. 2007. Agricultural technology adoption and poverty reduction: A propensity–score matching analysis for rural Bangladesh', *Food policy*, vol. 32:372-393.

Piggin, C., Haddad, A., and Khalil, Y. 2011. Development and promotion of zero tillage in Iraq and Syria. In: Proc. 5th World Congress on Conservation Agriculture, Brisbane, Australia, 26 –29 September 2011: 304–305.

Ravallion, M. 2001. The Mystery of Vanishing Benefits: An introduction to Impact evaluation, *The World Bank Economic Review,* vol. (15):115-140.

Sianesi, B. 2004. An evaluation of the active labor market programs in Sweden. *The Review of Economics and Statistics*, 186(1):133-155.

Spencer, D., Dorward, A., Abalu, G., Dayo, P. and Ogungbile, D. 2006. Evaluation of Adoption of Nerica and Other Improved Upland Rice Varieties Following Varietal Promotion Activities In Nigeria, The Gatsby And Rockefeller Foundations, Final Report, 2006.

Wei-Ling, S. 2006. Exogenous Switching or Endogenous Selection: Using the Bond Issuers Choice of Underwriters as an Example. Department of Finance E. J. Ourso College of Business Louisiana State University and Wharton Financial Institutions Center, USA.

About ICARDA and the CGIAR

Established in 1977, ICARDA is one of the 15 centers supported by the CGIAR. ICARDA's mission is to improve the livelihoods of the resource- poor in dry areas through research and partnerships dedicated to achieving sustainable increases in agricultural productivity and income, while ensuring efficient and more equitable use and conservation of natural resources.

ICARDA has a global mandate for the improvement of barley, lentil and faba bean, and serves the non-tropical dry areas for the improvement of on- farm water use efficiency, rangeland and small ruminant production. In Central Asia, West Asia, South Asia, and North Africa regions, ICARDA contributes to the improvement of bread and durum wheats, kabuli chickpea, pasture and forage legumes, and associated farming systems. It also works on improved land management, diversification of production systems, and value-added crop and livestock products. Social, economic and policy research is an integral component of ICARDA's research to better target poverty and to enhance the uptake and maximize impact of research outputs.

CGIAR is a global agriculture research partnership dedicated to reducing rural poverty, increasing food security, improving human health and nutrition, and ensuring more sustainable management of natural resources. It is carried out by the 15 centers who are members of the CGIAR Consortium in close collaboration with hundreds of partner organizations and the private sector. www.cgiar.org