Livelihoods Effects of Zero Tillage among Small and Medium Holder Farmers in the Developing World

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Abstract

The biophysical benefits of conservation agriculture (CA) are well documented in the literature. However, the literature on the economic benefits of CA, especially in the context of small and medium-scale farmers is scanty. Using a case study of 621 Syrian wheat farmers and applying the propensity score matching and endogenous switching regression methods, this paper provides empirical evidence on the impacts of conservation tillage (CT) on farm income and wheat consumption. Model results show that after controlling for all confounding factors, adoption of the CT technology leads to US$187/ha (34%) increase in net crop income and 26.4 kg (52%) gain in per capita wheat consumption per year (adult equivalent) which represent a meaningful change in the livelihoods of small and medium-scale farmers in Syria. Besides the biophysical and environmental benefits documented elsewhere, our results suggest that CT can also be justified on economic and food security grounds. Therefore, CT can have sizeable impacts in transforming the agricultural sector in the developing world provided that the technology is well promoted and adopted.

Keywords farm income; consumption; zero tillage; propensity score matching; endogenous switching regression.

JEL code O3, Q1, C2

I. Introduction

Conservation agriculture (CA) involves many different conservation measures and sustainable soil and water management practices including conservation tillage (CT)[1], early sowing, reduced seeding rates, crop rotations, and residue retention. CA is one of the promising technologies that can provide a panacea for the longstanding agricultural problems in the developing world. However, CA is often looked upon with high degree of skepticism mainly due to lack of information and evidence particularly on its economic benefits relative to traditional tillage and other agronomic practices (Belloum, 2007).

Out of the global total cropland, 9% was cultivated using a complete CA package in 2012. Much more extensive land has also been cultivated using only some of the components of the CA package (Friedrich et al., 2012). Particularly, CT has been widely adopted in North America (Fulton, 2010; Horowitz et al., 2010) and Australia (Llewellyn et al., 2012). However, with the exception of few success stories in certain pockets, South Asia and Africa have not yet benefitted from the advances in the CA technology in general and CT in particular (Friedrich et al., 2012; Giller et al., 2009). The same can also be said of the West Asian region.

CT 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. Apart from moisture conservation and cost savings, CT can often lead to higher yields and increased net returns with reduced yield and income variability, which is particularly important in dryland

[1] Different names are used for conservation tillage in different parts of the world. Among the other common names are zero tillage (ZT), no till and minimum tillage (MT)

farming. As in many high income countries, CA can also lead to possible benefits to smallholder farmers, consumers, and rural and national economies in low and middle income countries in Asia and Africa (ICARDA, 2012). With this premise, a number of efforts have been made by the governments of Syria and Iraq to introduce CT and few other components of CA using local resources and funding from international development organizations including the Arab Agency for Agricultural International Development (AAAID), Arab Center for Studies of Arid Zones (ACSAD) and Australian Center for International Agricultural Research (ACIAR) and Australian Agency for International Development (AusAID). Given its fairly recent introduction, adoption and impacts of CT in Iraq are relatively low. However, in Syria, CT has been well received by relatively larger number of farmers in a fairly short time when it was introduced through the ACIAR-AusAID funded project in early 2005. The success of the ACIAR-AusAID project in enhancing the adoption of CT in Syria may be attributed mainly to: greater awareness created by previous project, the ability of the project to facilitate local production of ZT seeders at low cost and its flexibility in letting farmers choose any components of the CA technology package.

The purpose of this study is to verify the economic viability of CT in the developing world context. To this effect, we used a case study from a sample of 621 Syrian wheat farmers and employed the propensity score matching and endogenous switching regression methods to provide empirical evidence that CT is potent in increasing farm income and wheat consumption among small holder farmers. In view of the skepticism about the economic and food security benefits of CA in smallholder agriculture, this paper is expected to fill an important gap in the literature. The results of this study are expected to be useful to policy makers, extension offices, government and nongovernmental development organizations, development agents and researchers working in the developing world.

The remainder of the paper is organized as follows. Section 2 provides an overview of CT in Syria. Sections 3 and 4 present the data and methods. Results and discussions are provided in section 5 and conclusions are drawn and some implications of the findings discussed in section 6.

2. History of Conservation Tillage

Prior to the beginning of the International Center for Agricultural Research in the Dry Areas (ICARDA) project funded by ACIAR, discussion with Syrian farmers revealed that lack of adapted and affordable seeders for CT is one of the major constraints for a wider adoption of the CT technology. The project discussed and demonstrated CT seeding technologies and requirements with local seeder manufacturers in 2007-08. Various prototype CT seeders were developed with modifications to suit local conditions, including ≈ 4 m trailed machines for extensive areas in eastern Syria and ≈2.5 m 3-point linkage machines with spring-loaded tines for rocky areas. These machines have been used effectively at ICARDA research stations in Telhadiya village of Aleppo province. As a result, the total number of seeders has grown from 3 in 2007 to 105 in 2011, 23 of which are privately owned by farmers while the rest are either freely borrowed from the project or rented from private businesses.

The technology was little-known or tested in Syria before the start of the ACIAR-AusAid funded project in 2005. The total area under CT reached at least 15,000 ha in 2010/11 with 320 project participant farmers and many others using the technology. About 70% of this area is estimated to be actual adoption by farmers using their own, rented, or borrowed CT seeders. The rest was sown with local CT seeders freely provided without charge by the project implementers (ICARDA, Aga Khan Foundation and Aleppo Agricultural Machinery Center).

3. Data

Data for this study comes from a farm survey conducted in 2011 by ICARDA scientists. The survey covered 28 villages distributed in 17 districts and 7 wheat growing governorates of Syria. The cluster sampling procedure was used to collect data where the different administrative units were used as clusters. Using power analysis (Cohen 1988), the minimum sample size required under the simple random sampling technique for ensuring 95% confidence and 3% precision levels in capturing up to 10% adoption was determined to be 374. Accounting for the design effect, the minimum sample size under the cluster sampling technique required for ensuring the same levels of confidence, precision and adoption levels was estimated to be 459, with an optimal cluster size of about 17. The primary sampling units (PSUs) were the villages. Accordingly, a decision was made to take a random sample of 500 farmers uniformly distributed across all the 28 sample villages (about 18 farmers in each village).

To avoid the risk of not having adequate representation of CT adopters in the sample, all the 320 farmers who had previously hosted demonstration trials and were participants in the research project were first purposively selected. All 320 of them had tried the CT technology at least once and most were still using it. Then, the random sample of 500 other farmers was taken. Therefore, the total sample was 820 farm households. Details of the sampling design are summarized in Table 1. As this study is concerned on measuring the impact of CT on income and wheat consumption, only the observations relating to 621 wheat farmers in the sample (308 from the random sample and 313 from the purposive sample) are used for analysis in this paper. The rest were barley growers and were excluded from the analysis.

The sample farms were small to medium size (range of 1.4 to 401 ha) with an average size of 1 27.5 ha. Farming seemed to be done by those with little formal education and older people, with the typical farmer having 3.5 years of schooling and 26 years of farming experience. Allowing farmers to test the CT seeders in their fields using their own tractors and inputs and then organizing and holding field days on some of these "demonstration' sites, were approaches used by the project to effectively promote the technologies in a participatory approach. Among the 621 sample wheat producers, 198 (32%) only hosted on-farm demonstrations/tests, 56 (9%) participated in field days only, and 62 (10%) had engaged in both. 249 farmers in the sample were users of the new ZT technology while the remaining 372 were non-users. The average number of years the typical adopter has used the ZT was 2.1 years which is not surprising as the technology was only recently introduced (Table 2).

4- Methodology

4.1 Propensity Score Matching (PSM)

Most previous studies have assessed the impact of technology adoption either by examining the differences in mean outcomes of adopters and non-adopters or by using simple regression procedures which control for adoption status (Nguezet, et al., 2011). Critics have pointed out that such simple procedures are flawed because they fail to appropriately deal with problems associated with selection biases in observational data collected through household surveys (Rubin, 1974; Rosembaum and Rubin, 1983; Rosembaum, 2002; Lee, 2005). Such approaches led to the establishment of causality between adoption and other variables that were subjected to confounding errors.

The propensity score matching method is one of the non-parametric estimation techniques that do not depend on functional form and distributional assumptions. The method is intuitively attractive as it helps in comparing the observed outcomes of technology adopters with the outcomes of counterfactual non-adopters (Heckman et al., 1998). Our main purpose for using the matching method was to find a group of treated individuals (adopters) similar to the control group (non-adopters) in all relevant pre-treatment characteristics, where the only difference was that one group adopted the CT technology and the other did not. The details of the PSM method are well documented in several studies (e.g., Rosenbaum and Rubin 1983; Heckman et al., 1998; Dehejia and Wahba, 2002; Caliendo and Kopeinig, 2008). The semi-parametric matching method which does not require an exclusion restriction or a particular specification of the selection equation is used here to construct the counterfactual and reduce the effects of selection bias on impact estimates.

Let A_{i} denotes a dummy variable such that A_{i} =1 denotes that the i^{th} individual has adopted the CT technology and A_{i}=0 otherwise. Similarly let Y_{1i} and Y_{2i} respectively denote the observed and potential (had the farmer not adopted the technology) income for an adopter farmer i. Then $\Delta = Y_{1i} - Y_{2i}$ is the income impact of CT on the i^{th} individual, usually called treatment effect. In reality, we observe only $Y_i = A_i Y_{1i} + (1 - A_i) Y_{2i}$ rather than actual (Y_{1i}) and the counterfactual outcome (Y_{2i}) at the same time for the same individual, for which we are unable to 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:

$$\tau = E\,(Y_{1i} - Y_{2i} \mid A_i = 1) \tag{1}$$

Supposing that X is the set of covariates that determine the adoption of CT and following Rosenbaum and Rubin (1983), the propensity score can be estimated as:

$$P(X) = P\,(A_i = 1 \mid X) \tag{2}$$

where *E* is the expectations operator and *P* stands for the propensity score.

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

$$E\,(Y_{2i} \mid A = 1, P(X)) = E\big(Y_{2i} \,\big|\, A = 0, P(X)\big). \tag{3}$$

In the above equation, $\perp$ 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:

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

The propensity score is a continuous variable and it is extremely unlikely that there are adopters in the sample with exactly the same score as their non-adopter counterfactuals. Thus, after estimating the propensity score, we need to search for a counterfactual(s) that ‘closely’ match with each adopter depending on their propensity score. This enables us to compute the average treatment effect given by equation (4). In bio-physical science experiments, where assignment to treatments is completely randomized, selection bias is assumed to be automatically minimized (or at best eliminated). However, in non-experimental studies one has to invoke some identifying assumptions to solve the selection problem. According to Caliendo and Kopeinig (2008), there are five steps which need to be followed for implementing PSM. These are estimation of the propensity scores using a binary model, choosing a matching algorism, checking on common support condition, testing the matching quality, and sensitivity analysis.

The propensity score is the probability of an individual adopting the technology given his observed covariates X. It is obtained from the fitted simple logistic regression model by substituting the values of the covariates (Rosenbaum and Rubin 1985).

In our study, the logistic model is estimated to identify the factors influencing adoption of CT technology as follows:

$$Prob\ (Adoption\ = 1)\ =\ 1/(1 + e^{-z}) \tag{5}$$

where $Z = \beta_0\ +\ \sum_{i=1}^{n} \beta_i\ X_i +\ \varepsilon_j$ (6)

Adoption is a dichotomous dependent variable taking a value of 1 if CT technology adoption takes place and 0 otherwise; X_i is the vector of variables included in the model; β_i are parameters to be estimated; ε_j is error term of the model; and e is the base of natural logarithms.

The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the groups of adopters and non-adopters (Lee, 2008). Since we do not condition on all covariates but on the propensity score, it has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment groups. The balancing test is normally required after matching to ascertain whether the differences in the covariates in the two groups in the matched sample have been eliminated, in which case, the matched comparison group can be considered a plausible counterfactual (Ali and Abdulai, 2010). Although several versions of balancing tests exist in the literature, the most widely used is the mean absolute standardized bias (MASB) between adopters and non-adopters suggested by Rosenbaum and Rubin (1985), in which they recommend that a standardized difference of greater than 20 percent should be considered too large and an indicator that the matching process has failed. The standardized bias (SB) is computed as:

$$SB_{before} = 100 \times \frac{X_1 - X_0}{\sqrt{0.5 \cdot (V_1(X) + V_0(X))}} \tag{7}$$

$$SB_{after} = 100 \times \frac{X_{1M} - X_{0M}}{\sqrt{0.5 \cdot (V_{1M}(X) + V_{0M}(X))}} \tag{8}$$

where: X_1 (V_1) is the mean variance in the treatment group before matching and X_0 (V_0) is the corresponding value for the control group. X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values for the matched samples (Caliendo and Kopeining, 2008).

The main problem with using the SB approach is that there is no clear criterion for testing the success of PSM. However, in empirical studies, it is often assumed that an SB below 3% or 5% after matching is acceptable (Caliendo and Kopeinig, 2008). Rosenbaum and Rubin (1985) argue that, after matching, total bias in excess of 20% should be considered as large. The total bias reduction (BR) can be defined as:

$$BR = 100 \times \left(1 - \frac{B(X)_{after}}{B(X)_{before}}\right) \tag{9}$$

where $B(X)_{before}$ and $B(X)_{after}$ are the total bias before and after matching, respectively.

Sianesi (2004) proposed a comparison of the pseudo R^2 and p-values of the likelihood ratio test of the joint significance of all the regressors obtained from the logistic regression before and after matching the samples. After matching, there should be no systematic differences in the distribution of covariates between the two groups. As a result, the pseudo-R^2 should be lower and the joint significance of covariates should be rejected (or the p-values of the likelihood ratio should be insignificant). The Stata software (Stata, 2009) was used for estimation in this study.

4.2 Endogenous switching regression models

To complement the PSM technique and to assess consistency of the results to different assumptions, the endogenous switching regression technique (Maddala and Nelson, 1975) was applied. We specify the selection equation for technology adoption as:

$$y_i = \begin{cases} 1 & if\ y_i^* > 0 \\ 0, & otherwise \end{cases}$$

$$y_i{}^* = x_i \beta + u_i \tag{10}$$

where y_i is the observable variable (in our case the adoption of CT technology), y_i^* is the unobservable or latent variable for technology adoption, x_i are non-stochastic vectors of observed farm and non-farm characteristics determining adoption and u_i is random disturbances associated with the adoption of improved technology.

To account for selection bias, we adopt an endogenous switching regression model of welfare outcomes (i.e., farm income and per capita wheat consumption) which are expected to be influenced by farmers' decision to adopt or not to adopt (regimes 1 and 2 respectively). Following Adamchik and Bedi (2000), the outcomes can be defined as:

$$y_{h1} = x_{h1}\beta_1 + e_{h1} \ if \ d_h = 1 \quad (11)$$

$$y_{h0} = x_{h0}\beta_0 + e_{h0} \ if \ d_h = 0 \quad (12)$$

where y_{h1} and y_{h0} are net farm income or per capita wheat consumption (adult equivalent) in regimes 1 and 2 respectively, x_h represent a vector of exogenous variables thought to influence crop income and wheat consumption.

Finally, the error terms are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix expressed as:

$$cov\ (e_{1i}, e_{2i}, u_i) = \begin{pmatrix} \sigma_{e2}^2 & . & \sigma_{e2u} \\ . & \sigma_{e1}^2 & \sigma_{e1u} \\ . & . & \sigma_u^2 \end{pmatrix} \quad (13)$$

where σ_u^2 is the variance of the error term in the selection equation (10), which can be assumed to be equal to 1 since the coefficients are estimable only up to a scale factor; σ_{e1}^2 and σ_{e2}^2 are the variances of the error terms in the welfare outcome functions (11) and (12), and σ_{e1u} and σ_{e2u} represent the covariance of u_i and e_{1i} and u_i and e_{2i} respectively. Descriptive statistics of the explanatory variables used in the logit model for the propensity score estimation and the endogenous switching regression models are presented in Table 2.

5. Results

5.1 Results from Propensity Score Matching

The main results of the factors explaining the probability of adoption of CT are presented in Table 3. Farmers who have participated in either field days or hosted demonstration trial(s) or participated in both showed high probability of adoption as the coefficient on participation variable is large, positive, and significantly different from zero. This finding underlines the important role of farmers' initial exposure to agricultural technologies in adoption decision, and the effectiveness of linking research to development efforts through participatory methods.

Total area (Ha) positively and significantly influenced the adoption of CT technology. This is intuitive as the large area sizes would justify investment on the expensive CT seers. This result is consistent with other studies which found a positive relationship between total acres farmed and the adoption of soil conservation technology (Feder and Umali, 1993; Westra and Olson, 1997). Adoption is sometimes hampered not only by the inherent characteristics of the technologies themselves but also by lack of awareness of the end users. To adopt the newly introduced technologies, farmers need to be aware of their existence. The positive and significant coefficient on the awareness variable suggests that farmers who have prior knowledge about the CT technology are more likely to adopt. This finding is consistent with Shiferaw et al. (2008), Kristjanson et al. (2005), Kaliba et al. (2000) and Gebreselassie and Sanders (2008).

Higher educational has a positive influence on the adoption of CT technology. Given that the CT is a knowledge intensive technology, the empirical results are consistent with theoretical expectations. Rahm and Huffman (1984) also report that producers with higher levels of education not only have higher propensity to adopt but also to make economically sound decisions. The negative and significant coefficient estimate on distance to the nearest input market suggests that farmers who do not have easy access to productive inputs are less likely to adopt the technology. This is reasonable as CT requires herbicides and other inputs, the availability of which may also influence farmers' decision to adopt the CT technology. However, the negative and significant coefficient on experience is counter intuitive. One possible explanation for this result is that experience is often highly correlated with age and older farmers may be more resistant to adopt new technologies.

5.1.1 Matching adopter and non-adopter households

The estimated mean, minimum and maximum values of the propensity scores for all sample households are 0.40, 0.0021 and 1.00 respectively (Table 4). The corresponding figures for adopter households are 0.8, 0.015 and 1 while that of the non-adopter households are 0.13, 0.0021 and 0.97 – making the common support region to be between 0.015 and 1.00. For sound comparison of effects between adopters and non-adopters, predicted propensity scores should satisfy a common support condition. Thereafter, we discard observations whose predicted propensity scores fall outside the range of the common support region. Consequently, households with estimated propensity scores of less than 0.0150 and greater than 1 are not considered for the matching. Because of this restriction 32 households (all non-adopters) were discarded from the analysis.

5.1.2 Testing the balance of propensity scores

Among three matching algorithms tested namely the Nearest Neighbour, Radius Caliper and Kernel bandwidth, the Radius Caliper (0.01) matching algorithm was found to fit the data best (Table 5). The next step was to check the balancing of propensity scores and the relevant variables in both control and treatment groups. In this study, several procedures were used to do so. These include the reduction in the mean standardized bias between the matched and unmatched households, equality of means using t-test and the chi-square test for joint significance for all the variables included.

The difference between imbalances between the treatment and control groups in terms of the propensity score (the standardized difference) after and before matching is 99.9%. This indicates that sample differences in the unmatched data significantly exceed those in the samples of matched cases indicating the success of the matching procedure as it satisfies the suggestion by Rosenbaum and Rubin (1985). Another approach used was a two-sample t-test to check if there are significant differences in covariate means for both groups. In the unmatched data, several variables exhibit statistically significant differences, while after matching all covariates are balanced (Table 6).

Comparing the pseudo-R^2s before and after matching is another approach applied to check the balancing of propensity score and the relevant variables suggested by Sianesi (2004). The pseudo-R^2 indicates how well the explanatory variables explain the probability of adoption. Test results in this approach indicated that after matching, there are no systematic differences in the distribution of covariates between both groups and the pseudo-R^2 is low (0.05) and not-significant (Table 5).

The above test procedures indicate that the matching procedure is able to balance the characteristics in the adopter and the matched non-adopter (control) groups. Hence, comparison of observed outcomes of adopter and non-adopter groups is now possible as they share a common support.

5.1.3 Impact Estimation: Estimation of Treatment Effects

After controlling for observable confounding factors, we found statistically significant differences in net income and annual per capita wheat consumption between adopter and non-adopter households. The results show that the adoption of CT has raised net farm income on average by 34% (9338 SP/ha or US$187/ha)[2] and per capita wheat consumption on average by 52% (26.4 KG/year adult equivalent) (Table 7).

5.2 Results from the Endogenous Switching Regression

For comparability purposes and to check result robustness of our PSM results, we estimated endogenous switching regression (ESR) that can control for unobservable selection bias. In this paper, the full information maximum likelihood (FIML) estimation method was used to estimate the ESR and model results are presented in Table 8.

With the exception of the outcome equation for net income for non-adopters, the correlation coefficients between the error-terms in the selection and all other outcome equations (*rho_1* and *rho_2*) are statistically significant from zero – implying that the switch is indeed endogenous. For instance, since *rho_1* is positive and significantly different from zero the model suggests that individuals who adopt CT technology have had higher income than an individual randomly drawn from the whole sample, while the insignificant *rho_2* indicates that income of those who did not adopt CT 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 location of farm (zone), education, farmer experience, distance to nearest market and total area have significant influence on net income.

[2] During the study period, the conversion rate was 1 US$ for about 50 Syrian pounds (SP)

The results from the ESR regression indicate that the mean value of income per adult equivalent of CT technology adopters is 10489 SP (US$210) higher than that of non-adopters (Table 9). Likewise, CT technology adoption increases per capita wheat consumption by about 29.1 kg/year (adult equivalent). While there is slight difference in the absolute values, these results are consistent with the results from the propensity score matching method.

6. Conclusions

Achieving agricultural growth and development and thereby improving rural household welfare will require increased efforts to provide yield enhancing and natural resources conserving technologies. Agricultural research and technological improvements are therefore needed for achieving these goals.

This paper used a case study from Syria to evaluate the impacts of conservation tillage (CT) technology on farm household welfare as measured by net crop income and per capita wheat consumption. To measure the impacts of CT, we use the propensity score matching (PSM) method. Moreover, the endogenous switching regression (ESR) method was used to ascertain the robustness of our estimates from the PSM method. Both methods are 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.

Results from both PSM and ESR estimates suggest that the adoption of CT technology leads to significantly higher net crop income (from US$187 to US$210) and per capita wheat consumption (from 26 Kg/year – 29.1Kg/year adult equivalent). These increases in income and wheat consumption represent a meaningful change in the livelihoods of small and medium-scale farmers in Syria. Along with the positive biophysical and environmental benefits of the adoption of CT which are well documented in the literature, our results suggest that CT is one of few technologies which can be justified on economic, food security, biophysical and environmental grounds in production systems involving small and medium farmers. Hence CA in general and CT in particular can have sizeable impacts in transforming the agricultural sector in the developing world. The policy implication of our results is that developing world governments should consider embracing CT as one of the priority technology packages in their national extension programs.

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Tables

Table 1: Survey details

Governorates included in the sample	District Name	Number of villages included in the sample	Total population in the sample villages	Sample size from the district: Whole sample: Total	Whole sample: Wheat producers[3]	Randomly selected: Total	Randomly selected: Wheat producers
Aleppo	Al Bab	1	650	36	25	18	12
	Ein Al Arab	2	700	40	31	36	21
	Sama'an	2	800	26	19	36	22
	Sfiera	1	900	43	33	18	11
Al-haska	Kamshly	4	347	96	75	70	43
	Tel-Hamis	1	66	31	23	18	11
	Malkia	1	190	25	19	18	12
	Amoda	1	270	21	16	18	11
	Hasaka	1	700	62	49	18	12
	Ras-Alain	1	600	22	17	18	11
Edleb	Khan-Shikon	1	400	23	17	18	11
	Almara	4	3270	174	131	70	43
Hamah	Slmiah	3	2400	94	71	54	33
	Sabora	2	1200	50	38	36	22
Homs	Ksier	1	380	26	18	18	12
Deraa	Alshajra	1	410	25	19	18	10
Alswieda	Salked	1	800	26	20	18	11
Total		**28**	**14,083**	**820**	**621**	**500**	**308**

Districts included in the survey

Source: survey data.

[3] Only the 621 wheat producers are included into this analysis out of which 318 are from the purposive sample and the remaining 308 are from the random sample.

Table 2: Explanatory variables included in the models

Variables	Unit	Average values for the entire sample of 621 farmers			Average values only for the random sample of 308 farmers		
		Adopters	Non-Adopters	Total	Adopters	Non-Adopters	Total
Number of farmers	Number	**249.00**	**372.00**	**621.00**	**15.00**	**293.00**	**308.00**
Average farming experience of household head	Years	23.70	27.50	26.00	18.70	26.80	26.50
Average education level of household heads	Years	4.20	3.00	3.50	3.90	2.80	2.90
Proportion of farmers with salinity affected soil	%	5.20	23.70	16.30	0.00	27.30	26.00
Average time since farmer started using CT	Years	2.10	0.00	0.80	2.00	0.00	0.10
Proportion of farmers who are in zone one[4]	%	33.00	36.00	34.80	85.70	72.30	73.40
Proportion of farmers who hosted demonstration trials	%	65.90	8.90	31.70	0.00	0.00	0.00
Proportion of farmers who participated on field days	%	5.20	11.60	9.00	0.00	0.00	0.00
Proportion of farmers who participated in field days and hosted trials	%	22.90	0.80	9.70	0.00	0.00	0.00
Total area cultivated (average)	Hectare	40.00	19.20	27.50	10.70	17.90	17.50
Total wheat area cultivated (average)	Hectare	20.80	8.70	13.60	8.70	7.60	7.70
Proportion of farmers who know the CT technology	%	100.00	59.40	75.50	100.00	50.00	52.60
Average distance to the nearest input market (Km)	km	13.80	15.40	14.70	13.00	18.00	17.70
Average value of total assets(million SP)	SP	1.56	1.59	1.58	1.92	1.59	1.58
What is the total number of plots	Number	2.39	1.90	2.10	2.10	1.80	1.83
Average length of time since the farmer first heard about the CT technology	Year	2.30	1.00	1.60	2.20	1.00	1.10
Area under CT	(Ha)	15.20	0.00	6.10	8.60	0.00	0.00
Average net income	SYP/ha						
Per capita wheat consumption (adult equivalent)	Kg/year	79.6	48.6	61	101	48.1	50.7
Proportion of area under the CT technology	%	73.40	0.00	32.40	95.20	0.00	8.00

Source: survey data.

[4] Syria is divided into five agro-ecological zones where Zone 1 represents the relatively wetter areas with average annual precipitation of about 350mm but with a 33% probability to be less than 350 mm and Zone 2 represents areas with average annual rainfall of about 250mm with more than 33% probability of falling below 250mm.

Table 3: Estimation of Propensity Scores: Logit Model

Adoption of conservation tillage (0,1)	**Coef.**	**Std. Err.**
Zone(0,1)	-0.267	0.326
Participated in Field Days (0,1)	2.095	0.452***
Hosted demonstration trials (0,1)	4.658	0.375***
Both demonstration trials and field days (0,1)	5.939	0.700***
Level of education (Years)	0.118	0.054**
Experience (Year)	-0.049	0.013***
Total area(Ha)	0.004	0.002**
Distance to the nearest input market(Km)	-0.041	0.015***
Do you know the CT technology(0,1)	0.142	0.050***
Value of total assets(SP)	0.000	0.000
Constant	-1.915	0.645***
Log likelihood	1725	

Source: survey data.

Notes: Dependent variable is adoption of conservation tillage (No=0, and Yes=1).

Parameter significance: *** (1%); ** (5%); * (10%)

Table 4. Mean of estimated propensity scores

Group	Obs	Mean	Min	Max
Total households	621	0.400	0.0021	1.000
Non-adopters	372	0.134	0.0021	0.972
Adopters	249	0.797	0.0150	1.000

Source: model results

Table 5. Performance of different matching estimators

Matching estimators	Performance criteria			ATT	
	Balancing test^	Pseudo -R^2	Matched sample size	Net Income	Per capita Consumption (kg/year)
Nearest neighbor (1) ***	7	0.125	621	10362.2	20.40
Nearest neighbor (2) ***	5	0.115	621	10271.3	25.00
Nearest neighbor (3) ***	7	0.113	621	10263.5	25.61
Nearest neighbor (4) ***	6	0.119	621	10608.7	25.67
Nearest neighbor (5) ***	6	0.125	621	10777.6	17.21
Radius caliper(0.01) ***	9	0.053	589	9338.50	26.40
Radius caliper (0.25) ***	6	0.108	589	10445.8	25.77
Radius caliper (0.5) ***	6	0.116	589	10486.3	25.36
Kerner bandwidth (0.1)	6	0.123	621	11534.3	28.97
Kerner bandwidth (0.25)	4	0.164	621	12258.3	29.12
Kerner bandwidth (0.5)	3	0.166	621	12206.4	28.16

Source: Estimation result

^Number of explanatory variables with no statistically significant mean difference between the matched groups of adopter and non-adopter households

***,**,* Significant ATT at 1%, 5% and 10% levels respectively

Table 6. Propensity score and covariate balance test of variables

Variable	Sample	Mean		%bias	%reduction bias	t-test	
		Treated	Control			t	p>t
PSCORE	Unmatched	0.80	0.14	281.90	99.90	34.50	0.00
	Matched	0.75	0.75	0.30		0.02	0.98
Zone	Unmatched	0.33	0.36	-6.50	-60.40	-0.79	0.43
	Matched	0.33	0.37	-10.40		-0.93	0.35
Participated in Field Day	Unmatched	0.05	0.12	-23.00	55.80	-2.71	0.01
	Matched	0.06	0.08	-10.20		-0.98	0.33
Has demonstration	Unmatched	0.66	0.09	145.50	86.00	18.67	0.00
	Matched	0.72	0.64	20.30		1.53	0.13
Both	Unmatched	0.23	0.01	72.60	66.70	9.80	0.00
	Matched	0.13	0.20	-24.10		-1.76	0.11
Education	Unmatched	4.20	2.95	41.00	94.80	5.45	0.00
	Matched	3.89	3.95	-2.10		-0.33	0.74
Experience	Unmatched	23.73	27.54	-31.50	-36.40	-3.82	0.00
	Matched	25.46	30.65	-42.90		-3.95	0.00
Total area	Unmatched	40.00	19.18	38.10	79.60	4.82	0.00
	Matched	41.74	37.49	7.80		0.62	0.54
Distance	Unmatched	17.08	18.90	-17.10	53.20	-2.08	0.04
	Matched	18.29	17.44	8.00		0.69	0.49
Heard	Unmatched	3.09	1.47	87.40	56.20	10.30	0.00
	Matched	3.15	3.86	-38.30		-2.38	0.10
Assets	Unmatched	1.60E+06	1.60E+06	-1.40	-378.30	-0.17	0.86
	Matched	1.50E+06	1.60E+06	-6.80		-0.68	0.50

Source: Estimation result; *, ** and *** significant at the 10%, 5% and 1% levels, respectively

Table 7: ATT for net income and consumption (Using Propensity Score Matching)

Group	Treatment group	Control group	average treatment effect on the treated (ATT)	S.E.	T-stat
			Net income		
Unmatched	37995	27335	10660	967	11.00***
ATT	37103	27764	9338	1713	5.45***
			Consumption		
Unmatched	79. 60	48.60	30.90	2.80	11.30***
ATT	76.90	50.50	26.40	7.60	3.50***

Source: Estimation result; *** indicates significance level at 1%

Table 8**:** Full information maximum likelihood estimates of the endogenous switching regression model

Independent Variables	Net income Equation for Adopter		Net income Equation for Non-Adopter		Adoption of conservation tillage (No=0,Yes=1)		Consumption Equation for Adopter		Consumption Equation for Non-Adopter		Adoption of conservation tillage (No=0,Yes=1)	
	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.	Coef.	Std.Er.
Zone(0,1)	-0.165	0.058***	0.094	0.018***	-0.113	0.173	-0.081	0.053	-0.036	0.066	-0.147	0.182
Participated in Field Day(0,1)	-	-	-	-	1.113	0.251***	-	-	-	-	1.042	0.256
Has demonstration field(0,1)	-	-	-	-	2.660	0.194**	-	-	-	-	2.751	0.204***
Both demonstrations and field days(0,1)	-	-	-	-	3.254	0.334**	-	-	-	-	3.300	0.361***
Level of education (Years)	0.178	0.056***	-0.014	0.018	0.152	0.173	-0.028	0.051	-0.026	0.063	0.013	0.179***
Experience(Year)	0.195	0.048***	-0.018	0.015	-0.599	0.147***	0.107	0.045***	0.011	0.004***	-0.624	0.145***
Total area(Ha)	0.033	0.025	-0.019	0.008**	0.094	0.070	0.023	0.023	0.041	0.022**	0.080	0.076
Do you know the CT technology(0,1)	-	-	-	-	0.088	0.030***	-	-	-	-	0.071	0.032**
Distance to the nearest input market(Km)	-0.292	0.045***	-0.033	0.012***	-0.310	0.120***	-0.030	0.011***	-0.003	0.042	-0.172	0.130
Net income	-	-	-	-	-	-	0.097	0.042**	0.523	0.183***	1.229	0.244***
Value of total assets(sp)	-0.060	0.037	-0.004	0.011	0.140	0.099	0.008	0.033	-0.010	0.038	0.160	0.103
Constant	11.169	0.537***	10.439	0.165	-1.530	0.521***	3.497	0.833***	-1.728	1.010*	-14.519	3.09***
Log likelihood					-134.7						-562.55	
Rho1					0.199	0.1**					0.369	0.203**
Rho2					0.075	0.169					-0.299	0.162*

Source: model results

Note: ***, **, and * represent parameter significance at 1%, 5% and 10% respectively.

Table 9. ATT for net income and for consumption (Endogenous switching regression model)

Group	Treated	Controls	average treatment effect on the treated (ATT)	S.E.	T-stat
			Net income		
ATT	37994	27505	10489	611	17.2***
			Consumption		
ATT	79.5	50. 5	29.1	1.1	26. 6***

Source: Estimation result; *** indicates significance level at the 1%