Assessing the Impact of Internet Access on Household Income and Financial Performance of Small Farms*

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1. Introduction

About ninety-one percent of all U.S. farms are classified as small—gross cash farm income[1] of less than $250,000. These farms generate less than $10,000 in income from farming. Small farm specialize in production of poultry, beef (cow/calf operation), hay, and grain/soybeans. Each of these production operations can be carried out without a full-time commitment of farm labor. Although most of the small do not earn profits from farming, but remain in business in spite of financial losses because their operators have other sources of income (off-farm income) and operate the farm for reasons other than profit. Small farms receive most land-retirement payments because of the sheer number of small farms, because small farms hold a large share of all farmland, and small farms tend to enroll larger shares of their land in retirement programs when they do participate in these programs. Finally, small farms contribute significantly to rural economies as purchases of inputs and suppliers. Small farmers can also make better stewards of natural resources, conserving biodiversity and safe-guarding the future sustainability of agricultural production (Mishra, El-Osta, and Steele, 1999).

Farmers and operators of small farms are concerned with selecting risk management strategies to improve farm production efficiency, risk management and overall returns in order to maintain their farming business. A competitive firm's response to risk is to gather information on output prices, input prices, production functions, firm goals, government programs, and cost of acquiring additional information (Robison and Barry, 1987). To this end Internet can provide an

[1] Gross cash farm income is the sum of the farm's cash and marketing contract revenues from the sale of livestock and crops. It includes all farm-related revenue, not just crop and livestock sales, and is based on annual sales, not the value of annual production.

important role in information gathering. Internet is one of the convenient means to access and exchange information. Information and communication facilitation through Internet have opened up new areas of commerce, social networking, information gathering, and recreational activities beyond a geographical bound. Producers and consumers can take advantages of Internet in both collaborative and competitive aspects in economic activities as it can reduce the information asymmetries among economic agents. Further, in addition to other reasons for Internet adoption, Mishra, Williams and Detre (2009) point out that Farm Service Agency, a major provider of farm program payments to farmers, has about 78 farm program forms available online for farmers to complete and submit electronically via Internet.

Farm households can benefit from Internet by using it for information, as well as trading and commercializing the farm products to a broader set of consumers. Internet users can browse for cheaper inputs and build connections and virtual networks with different economic agents --such as contractors and buyers for their product. Internet based application is one of the most important reasons for computer adoption by farmers in the US (Batte 2005; Mishra et al. 2009). Farmers are increasingly using applications of Internet such as tracking price, accessing agricultural information, assessing information from government agencies, and online record keeping (Mishra and Park, 2005; Mishra et al., 2009), with increasing enthusiasm.

Internet can play a key role in marketing and enterprise performance as it enhances one's ability to manage information quickly and effectively. There are several studies discussing information and communication technologies in rural households and application of Internet in agricultural business (McFarlane et al. 2003; Gloy and Akridge 2000; Henderson et al. 2005; Deakins et al. 2004; Warren 2004; Martin and Matley 2003). Most of these studies have discussed the factors influencing adoption, household's purchasing pattern through Internet, and benefits and overall profit potentials in general. Broadly, studies analyzing the adoption of Internet have investigated adoption from two different perspectives. First set of studies consider household as consumers and analyze the factors influencing Internet adoption, household expenses, and purchasing patterns. The other set of studies consider Internet adoption in farm business, often concentrated on large farm business, and analyzing the e-commerce activities. Moreover, farm household studies are focused on the correlation between socioeconomic factors and the adoption of the Internet. Very few studies have analyzed Internet use in relation to household well-being (such as total household income and off-farm income) and farm business performance.

Interestingly, farming household possess a distinguished feature that it is consumer as well as a producer of some commodities on its farm. Farm household can utilize Internet both in consumption and production activities. Internet may provide new supplemental income for some households apart from farm business. Even if purchases are not done through online, farm households can gather information and discover prices that facilitate their decisions. On the other hand, through utilization of e-commerce, producers may quickly promote and sell their products as well as seeking information to reduce input costs (such as marketing costs, storage costs). The above arguments suggest that the impact of Internet should be analyzed in terms of both household income and farm level economic return.

Herein lies the objective of this study. Using a farm-level survey data of farming households and treatment effect models, this study investigates the impact of Internet access on household income and farm financial performance of small farms (defined as those with sales <$250,000). In particular, the study investigates the impact of Internet access on total household income, off-farm income, value of productions, net farm returns, and farm level expenses.

Rest of the paper is organized as follows. Next section reviews existing literature on factors influencing Internet adoption in farm household and farm business. Third section includes discussion about theoretical background of average treatment effect and matching estimators, methodology used in this paper. Subsequent sections provide discussions on data and results, respectively. Final section provides concluding remarks.

2. Internet use in farm households and small farm businesses

There has been rapid increase in Internet use and applications in almost every sector. Between 1995 and 2008, Internet users across globe increase from 16 million to 1.5 billion including in-home Internet access for two thirds of U.S. adults (Stenberg et al, 2009). With more applications, consumers not just want access to Internet but do care about quality attributes of Internet services. Rosston, Savage, and Waldman (2011) found a substantial marginal willingness to pay for the improvements in reliability and speed in Internet services. They found that the experienced households (those who had adopted Internet from past several years) have higher valuation for Internet quality attributes. This study found that the willingness to pay for high speed increased with education, income and online experience, and decreased with age. However, this assessment may not provide exact picture of farm households because urban consumers with higher income levels may readily pay substantive higher premium for quality (Savage and Waldman, 2009) while rural farmers may not. While other sectors are greatly utilizing facilities through Internet services, rural farm sector is slightly lagging behind as compared to urban counterpart but is increasingly using it for many applications.

A study by Mishra and Park (2005) discussed factors influencing number of Internet applications use in farm households. Using count data model, they found education, farm size, contracts in farming, farm diversification, and farm location as key factors. The authors reported that applications of Internet in farm households in U.S. include price tracking, accessing agricultural information, accessing information from USDA, and data transfer. Batte (2005) highlighted an increase in Internet use in the farm sector as applications of computer in agriculture are changing. In his study of Ohio farmers, 80% of farmers were using Internet for communication, transaction processing, and information gathering. Gloy and Akridge (2000) studied personal computer and Internet adoption in large farms and found a strong correlation between complexity of farm business and Internet use. Large farms with multifaceted business and sophisticated farm management had higher utilization of Internet. Their study suggested that the Internet utilization is more likely with larger farm size and more educated operators while older operators were less likely to utilize Internet.

Chang and Just (2008) used a multi-stage econometric analysis to assess the effect of Internet use on farm household income in Taiwan. Employing a semi-parametric method correcting for selection bias in two separate equations for Internet users and non-users in second stage, their results suggested that access to Internet improves farm household income. In a recent study Briggeman and Whitacre (2010) investigated constraints in wider adoption of Internet among farm households. They point to three main reasons "*no computer in the household*", "*Internet security concern*", and "*inadequate Internet service*" to explain lack of Internet use by farm households.

Two noticeable limitations of the above studies include: 1) the impact of Internet use on farm household income and farm financial performance[2]; 2) data limitation—most studies have used local or regional data from large farms. The impact of Internet access on household income and farm financial performance of small farms have been ignored. Although Chang and Just (2008)

[2] It should be pointed out that most existing studies have explored Internet applications, purchasing patterns, and factors influencing Internet adoption.

used farm-level data from Taiwan, however, it should be pointed out that agricultural sector in Taiwan is very small and homogenous, compared to the US, and farms specialize in rice, sugarcane, fruits and vegetable production.

3. Treatment effect models and matching estimators

Quantitative impact evaluations can be broadly classified as ex-ante and ex-post evaluations. Ex-ante evaluation is the prediction for future outcome based on current situation. This framework is based on simulation of the assumption about how economy works; prediction may involve structural models of economic environment faced by potential participants (Khandker et al. 2010). Ex-post impact evaluation, on the other hand, measure the exact outcome obtained by participants that are attributable to the program or treatment. Later methods are referred as treatment effect models. Impact estimation through treatment effect models are getting popularity in social sciences. However, challenging part in treatment effect models is that it needs outcomes for both participants and non-participants. For instance, this study uses treatment effect model with an aim to assess average treatment effect (ATE) of Internet access on household income and various farm income and costs measures[3] of small farms.

$$ATE = E(Y_1 - Y_0) \quad (1)$$

where Y_1 is outcome variable with treatment and Y_0 is outcome without treatment. However, we do not observe the actual outcome due to Internet use in non-user households or vice versa and thus have to define a counterfactual to compare such differences.

We aim to estimate what would be the income (or profit) for small households not having access to the Internet had they have access to it or such impact on Internet user households had

[3] Financial measures used in this study are: (1) income, which includes total household income, total off-farm income, gross cash farm income, and net farm income; (2) costs which includes, total variable costs, marketing and storage cost, fertilizer and chemical costs, and utilities, household supplies, and other household expenses.

they have not used it. We are interested in later effect referred as average treatment effect on treated (ATT).

$$ATT = E(Y_1 - Y_0 | Y_1 = 1) \qquad (2)$$

where T is the treatment status ($T=1$ indicates assignment to the treatment, 0 otherwise). Creating a convincing and reasonable comparison is a challenging for evaluation. Accuracy of impact evaluation rests on how well we are able to define counterfactual. Unlike the experimental studies where we can set up the randomness in treatment and control, observational treatment effects are not free from self-selection biases which need to be addressed. On our context, we do not randomly assign farmers to become Internet adopters or non-adopters but they self-select. Some farmers are more likely to use Internet than others. When treatment is not random, simple comparison of the outcome variables between the two groups (Internet users and non-users) lacks to account for some underlying influencing factors for both treatment assignment and the outcome. Thus, estimation of average treatment effects without accounting for self-selection leads to biased impact estimation. There are a number of ways developed and suggested to correct for this bias (Cameron and Trivedi 2005; Khandker et al. 2010). One of the ways getting popularity now-a-days is through "matching estimators." Basic principle of 'matching estimator' is to match the observations between treatment and control groups based on some key observable factors.

For this study, we will use nearest neighbor matching method in treatment evaluation, developed by Abadie and Imbens (2002). In this method, weighting index is applied to all observations and "nearest neighbors" are identified (Abadie et al, 2004). ATT estimator in nearest neighbor is given by,

$$ATT = \frac{1}{N_1} \sum_{i:T_i=1}^{N_1} [Y_i - Y'_{0i}] \qquad (3)$$

where *i* represents individual observation and N_1 is the total number of observations in treatment group. Y_i is observed outcome for individual *i* while Y'_{0i} is not observed. Y'_{0i} is found by matching

$$Y'_{0i} = \begin{Bmatrix} Y_i \quad if \quad Y_i = 0 \\ \frac{1}{M}\sum_{m \in M_i} Y_m \; if \quad Y_i = 1 \end{Bmatrix} \qquad (4)$$

where M_i is the set of matched observations in the control group matched with individual *i* in treatment group. *M* is number of matched observations. The term $\frac{1}{M}\sum_{m \in M_i} Y_m$ is simply a weighted average of the outcome variables for all matched observations in the control group. Main principle of matching estimator is that it develops a matching counterfactual (a control group) to estimate the difference due to treatment assuming conditional independence and common support. Conditional independence assumes that the outcomes are independent of treatment, conditional on a set of independent variables (X) as shown in equation (5) (Becker and Ichino, 2002). Further, we need to assume conditional independence between the control group outcome and the treatment group, also referred as "unconfoundedness" (equation 6). However, we cannot directly test this assumption. Therefore, we should be aware of that the matching estimator is not a complete cure for selection bias as unobservables explain assignment to treatment but the estimator reduces the bias (Becker and Ichino, 2002). We can test balancing property, in the case of probit or logit model, balancing condition for matching observations is shown in equation (7).

$$Y_o, Y_1 \perp T|X \qquad (5)$$

$$Y_o \perp T|X \qquad (6)$$

$$T \perp X|P(X) \qquad (7)$$

In equation 7, $P(X)$ represents conditional probability of being in the treatment group. When equation 7 is satisfied, assignment to the treatment is considered random for same propensity score (see Becker and Ichino, 2002, for more detail). Although matching estimation through nearest neighbor method does not require probit or logit model estimation, we have included probit model because it allows us to check balancing property and to analyze the association of included variables with the likelihood of Internet use. Matching estimators are considered non-parametric type of estimators because we do not need to assume specific functional form and do not need to impose any distributional assumptions (Cameron and Trivedi, 2005; Wooldridge, 2001). These methods are being used in different disciplines including agricultural economics. Recently, Uematsu and Mishra (2012) used this approach to investigate farmers' participation in organic farming and the impact of participation on income and expenditures using matching estimator.

4. Data

This study uses Agricultural Resource Management Survey (ARMS), a nation-wide survey conducted in 2010 across the farm households of the United States. The ARMS is conducted annually by the Economic Research Service and the National Agricultural Statistics Service. ARMS uses a multi-phase sampling design. Through an expansion factor, it allows each sampled farm to represent a number of similar farms in the population (Dubman, 2000). The survey collects data to measure the financial condition (farm income, expenses, assets, and debts), operating characteristics of farm businesses, the cost of producing agricultural commodities, and the well-being of farm operator households. Each survey is collected from a single, senior farm operator who undertakes day-to-day management decisions. In this study, we used farm households with small farm business that has gross cash farm income of less than $250,000 (29.59% of entire sample). Hoppe et al. (2010) notes that small farms in U.S. are facing "persistence under pressure" as most of the small farms, at least at the lower end of the small farm size spectrum, need to rely on off-farm incomes. Thus, management of the farm and household incomes and expenses is crucial for the viability of small farms.

Table 1 presents definition of the variables included in the study. The table also presents the mean values for entire small farm sample, farms without Internet access, and farms with Internet access. Of 2,495 small farms in sample, 1,540 (61.7% of the small farm households) had access to the Internet, of which around 44% of the farms were located in the urban counties and 7% in the rural counties. Last column in table 1 shows *t* or *z* statistics to compare the means between treated and control groups. Small farms with Internet access had relatively younger and more educated operators and spouses, had more number of household members with ≥ 64 years of age as well as more number of children (household member ≤ 17 years of age) living in the household, than non-users as suggested by significant *t/z* statistics. A significant difference in entropy index suggests that small farms with Internet access were more specialized than their counterparts.

Internet user households had significantly higher household and off-farm incomes than non-users while they had higher total variable costs, and utility and housekeeping expenses. Mean comparison of location variables suggests that significant regional differences exist between Internet users and non-users. For example, in the West region, the share of small households with Internet access was significantly higher than households without access to the Internet. In Southern region, on the other hand, the share of farm households without Internet access was higher than those with access to the Internet. There were no significant differences in treatment and control groups in net farm income, gross cash farm income, and value of productions under marketing and production contracts. Note that the *t* or *z* scores reported in

Table 1 are based on the mean comparison for each variable between two groups of farms without controlling for any underlying factors. Matching estimator overcomes this issue and provides more appropriate effect of the treatment variable on outcome variables.

The ARMS has a complex stratified, multiframe design where observations in the ARMS represent a number of similar farms when using the provided expansion factors. The expansion factors are most useful and recommended when the goal of the research is making generalizations about the population of farms or the full survey is used. Following El-Osta (2011), we employ a bootstrapping technique rather than the jackknife procedure to remedy the sample design problems associated with the subsample.

5. Results and Discussion

5.1 Probit model estimation

We estimate a probit model using the treatment status (having Internet access) as dependent variable to test the balancing property. Model estimation also provides information on the factors influencing adoption of Internet or in other words access to the Internet. A set of independent variables used in probit model represents the vector of covariates used to compute the matching distance in nearest neighbor matching estimator. Further, to eliminate the potential sample selection effect it is important to carefully choose the observable characteristics which will compose the matching index specified in Section 3. Based on literature, we include variables representing operator characteristics, farm characteristics, and location variables in the model. A cursory look at the result of the Wald chi-squared test shows that the coefficients of the Internet access model, when considered jointly, are all significantly different from zero. Another indicator of the model's overall fit is the estimated value of McFadden pseudo-R^2 of 0.32, which considering the cross-sectional nature of the data points to the model's fair predictive power.

Probit model as shown in table 2 satisfied the balancing property using the algorithm suggested in Becker and Ichino (2002). Estimation result suggests that households with operator and spouse with higher educational attainment are more likely to have an access to the Internet. Increased education corresponds to an increased ability to judge the usefulness of the Internet to gather information for the farm business. Findings here are consistent with Putler and Zilberman (1988), Mishra and Park (2005) and Batte (2004 and 2005). Age of both operator and spouse, on the other hand, is negatively associated with likelihood of Internet adoption. Higher number of older members in the household (age of ≥ 64 years) increases the likelihood of having an access to the Internet, by small farm households. Further, result suggests that small farm households receiving government payments are more likely to have access to the Internet. Finally, compared to West regions, farms located in the Plains, Midwest, and Southern region are less likely to have access to the Internet. These findings are consistent with previous studies (Gloy and Akridge, 2000; Mishra and Park, 2005; Mishra et al, 2009).

5.2 Average treatment effects on treated (ATT) estimations

We included same set of variables as probit model to create distance index in facilitating matching of observations in the treated group with the control group. We specified M=1,2,…5 to compute average treatment effect on treated (ATT). Table 3 presents ATT of access to Internet on total household income, off-farm income, gross cash farm income, net farm income, total variable costs, marketing and storage costs, and fertilizer and chemical expenses and other farm and household expenses. The ATT on total household income is positive and highly significant (at 1% significance level) for all M=1,…5. This indicates that small farm households with Internet access are better off in terms of total household income than their counterpart. Result in table 3 suggest that an ATT range of $24,000 to $27,500, which implies that small farms with access to Internet earn around $24,000 to $27,500 more in household income, compared to small farms without access to Internet.

The ATT on off-farm income is positive and significant for all M=1,….5. Result shows that the effect of access Internet on off-farm income is even higher than that on the total household income. We should note two things here. Firstly, off-farm income for farm households, especially for small farms, can be higher than total household income in the cases with negative incomes from farming (Hoppe, 2009). Secondly, as indicted in literature, small farm households usually rely on off-farm income and thus they continue surviving through better management of off-farm and on-farm resources. Our ATT results indicate that small farm households with access to Internet earn $26,000 to $29,000 more in off-farm income compared to small farms without access to the Internet. A possible reason for this is that operators and spouses of small farms are more likely to work off the farm (Mishra and Park, 2005) access to Internet at work may facilitate quicker access and knowledge of the advantages of the Internet. Hence, as pointed out by Mishra et al., (2009) members of the household may use the Internet to conduct off-farm business and earn higher off-farm income (Mishra et al. 2009).

Results in table 3 indicate that the ATT of Internet access on gross farm income is positive and significant at the 5% level or higher for all M=1,…5. The ATT on gross farm income ranges from around $2,200 to $2,700. This indicates that small farms with access to Internet were earning around $2,200 to $2,700 higher in gross farm income compared to small farms without access to the Internet. The ATT of Internet access on net farm income is negative but non-significant for all M=1,….5. Negative ATT on net farm income (one of the measures of farm profitability) range from $300 to $700 is not surprising for the current sample of small farms.

The ATT for total variable costs is positive but only significant at m=1. Positive ATT may suggest higher total variable costs for Internet users. The ATT of having access to the Internet on fertilizers and chemicals expenses is negative for all M=4 and 5, at the 10% level of significance. This indicates small farm households may potentially reduce fertilizers and chemicals expenses through the use of Internet. Reduction in fertilizers and chemicals expenses due to the Internet makes sense as online information on inputs can be achieved quickly and delivery of the product could take place in a matter of 2-3 days (Mishra et al. 2009).

6. Summary and Conclusions

Wide array of studies have examined household Internet use, access to the Internet, and demand for the Internet. Studies in farm households have mainly investigated factors influencing Internet adoption, purchasing patterns through Internet, Internet use and applications. In most cases, impact analyses of communication and information technologies such as Internet in agricultural businesses are discussed with references to large scale farm businesses. Thus, we know very little about Internet use in relation to small farm business and about how it impacts well-being of small farm households. Small farm businesses are subject of interest in recent agricultural economics and agribusiness literature, particularly how best they strategically manage farm business to remain viable in the market. This study analyzed the impact of access to Internet on various incomes and expenses of small farm households using matching estimator and a nation-wide ARMS survey in the United States. Non-parametric nearest neighbor matching estimator uniquely allows us to define adequate counterfactual and to account for potential self-selection issue.

Our study suggests that small farm households with access to the Internet are better off in terms of total household income and off-farm income. As compared to the control group (which is counterfactual, representation of small farms without access to the Internet) small farms with access to the Internet earn $24,000 to $27,000 more in total household income and $26,000 to $29,000 more in off-farm income. On expenditure side, we explored that small farm business, through well management of off-farm and on-farm activities, can get benefit from Internet service as it opens up options for quick and wide range of information and thus potentially reducing input costs and household expenses. Also, small farms with access to the Internet earning approximately $2,200 to $2,700 more in gross farm income compared to small farms without access to the Internet. Finally, matching coefficient results show a significant reduction in fertilizer and chemical expenses at the 10% significance level.

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Table 1: Variable definitions and summary statistics, small farms (<$250,000 in gross cash farm income)

Variable definitions	Mean			t/z score[¥]
	Entire sample	No internet access	Internet access	
Internet access	0.617			
Operator and Household characteristics				
Age of operator	59.68	63.47	56.76	12.60***
Education (years) of operator	13.34	12.48	13.78	-17.68***
Age of spouse	56.42	60.47	54.31	11.02***
Education of spouse	11.82	10.53	12.56	-13.75***
Number of household members ≥ 64 years of age	1.29	0.75	1.64	-17.64***
Number of household members ≤ 17 years of age	0.27	0.06	0.40	-9.47***
Farm characteristics				
Entropy index	0.101	0.10	0.08	2.44**
Distance from nearest market	22.55	22.87	22.33	0.57
Total acres in operation (in log)	4.039	3.99	3.89	1.65*
Government payment (=1 if farm received government payment, 0 else)	0.25	0.22	0.21	0.74
Contract (=1 if farm has production or marketing contract)	0.003	0.002	0.002	0.07
Debt to asset ratio	0.054	0.03	0.07	-5.87***
Income variables				
Total household income	75059.42	46222.01	92923.81	-7.75***
Total off-farm income	83393.9	51589.3	103096.4	-8.43***
Gross cash farm income	6616.91	6585.66	6636.29	-0.17
Net farm income	-3124.877	787.4199	-5551.01	1.55
Value of production under marketing contract	268.43	205.32	394.36	-1.12
Value of production under production contract	377.151	149.7173	179.6825	-0.12
Cost variables				
Total variable expenses	10121.81	7350.324	11840.49	-1.93**
Marketing and storage charges	156.19	153.23	157.89	-0.20
Maintenance and repair expenses	1679.73	1245.47	1949.02	-3.17***
Fertilizers and chemicals expenses	1401.64	948.33	1682.75	-0.84
Utilities, housekeeping supply expenses	3793.04	2992.33	4307.13	-6.20***
County level variables				
Urban (=1 if farm located in urban county)	0.44	0.43	0.44	-0.45
Rural (=1 if located in rural county)	0.08	0.062	0.07	-0.87
Regional dummies (=1 if farm located in the corresponding region)				
Atlantic region	0.15	0.19	0.21	-1.10
West region	0.17	0.18	0.24	-4.07***
Plain region	0.22	0.22	0.21	0.44
Midwest region	0.27	0.17	0.17	0.14
South region	0.19	0.24	0.16	4.76***
Number of observations	2,495	955	1,540	

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

[¥] The differences in means are obtained by subtracting means for farm households with internet access from those of households with no access. For continuous variables, t-test is used and t-statistics is reported; test on the equality of proportions is used to compare the differences for binary variables and z-score is reported.

Table 2: Probit model parameter estimates

Variables	Coefficients	Standard errors	p-values
Age of operator	-0.011	0.007	0.000
Education of operator	0.157	0.024	0.000
Age of spouse	-0.012	0.007	0.000
Education of spouse	0.101	0.024	0.000
Contract	0.409	0.677	0.545
Total acres operated	0.007	0.029	0.814
Government payments	0.222	0.107	0.039
Entropy index	-0.677	0.359	0.060
Urban	0.038	0.080	0.635
Rural	-0.051	0.170	0.765
Number of family members ≥ 64 years of age	0.101	0.039	0.010
Number of household members ≤ 17 years of age	-0.035	0.046	0.450
Distance to market	-0.001	0.002	0.805
Atlantic region	-0.120	0.125	0.336
Plain region	-0.332	0.122	0.007
Midwest region	-0.263	0.131	0.046
South region	-0.389	0.125	0.002
Number of observations = 1,445 Log-likelihood= -763.36	LR statistics = 279		p-value (LR=0)<0.000

Table 3: Estimates of the average treatment effect on treated (ATT)

Variable	Number of matches (m)	ATT	Standard errors	p-value
Income variables				
Total household income ($ per year)	1	27464.881	8949.577	0.002
	2	27630.660	8725.659	0.002
	3	26058.532	8611.950	0.002
	4	24699.091	8694.806	0.005
	5	23935.422	8733.610	0.006
Total off-farm income ($ per year)	1	29762.000	8992.094	0.001
	2	29729.331	8783.844	0.001
	3	28164.523	8675.245	0.001
	4	26881.170	8756.092	0.002
	5	26025.221	8797.191	0.003
Gross farm income ($ per year)	1	2767.848	1182.436	0.019
	2	2239.880	1147.775	0.050
	3	2291.766	1104.129	0.038
	4	2425.999	1089.196	0.026
	5	2547.781	1073.766	0.018
Net farm income ($ per year)	1	-705.014	1387.100	0.611
	2	-765.003	1342.123	0.569
	3	-527.301	1297.571	0.601
	4	-504.575	1280.629	0.647
	5	-324.911	1271.625	0.689
Production under marketing contract	1	418.979	378.117	0.268
	2	398.100	372.135	0.285
	3	404.498	363.562	0.266
	4	409.276	358.982	0.254
	5	397.757	356.254	0.264
Cost and expenses variables				
Total variable expenses	1	1569.975	842.351	0.062
	2	1284.062	833.466	0.123
	3	1102.538	808.317	0.173
	4	1210.167	788.922	0.125
	5	1131.976	782.377	0.148
Marketing and storage charges	1	-7.410	54.721	0.791
	2	-6.191	50.722	0.892
	3	-5.281	50.052	0.901
	4	-10.132	48.941	0.923
	5	-9.152	48.490	0.850
Fertilizers and chemicals expenses	1	-74.112	211.990	0.526
	2	-307.191	220.051	0.132
	3	-318.473	209.531	0.105
	4	-332.833	201.787	0.090
	5	-355.714	201.607	0.078
Utilities, housekeeping supplies, and other household expenses	1	4.226	432.228	0.992
	2	-221.185	429.587	0.509
	3	-302.7059	439.838	0.491
	4	-270.432	427.010	0.527
	5	-318.991	435.516	0.464