Financial performance of small farm business households: The role of internet

Article *in* China Agricultural Economic Review · November 2016

DOI: 10.1108/CAER-12-2014-0147

2 authors:

Aditya Khanal
Tennessee State University

Ashok K. Mishra
Arizona State University: WP Carey School of…

China Agricultural Economic Review

Financial performance of small farm business households: the role of internet

Aditya R. Khanal Ashok K. Mishra

The current issue and full text archive of this journal is available on Emerald Insight at:
www.emeraldinsight.com/1756-137X.htm

Financial performance of small farm business households: the role of internet

Aditya R. Khanal
Department of Agricultural and Environmental Sciences, Tennessee State University, Nashville, Tennessee, USA, and
Ashok K. Mishra
Morrison School of Agribusiness, WP Carey School of Business, Arizona State University, Tempe, Arizona, USA

Received 28 December 2014
Revised 5 October 2015
27 January 2016
Accepted 7 March 2016

Abstract

Purpose – The purpose of this paper is to investigate the impact of internet usage on financial performance of small farm business households in the USA. In particular, the authors want to assess the impact of internet usage on small farm businesses, where the owner's main occupation is farming. Using a nationwide farm-level data in the USA and a non-parametric matching estimator, the study finds a significant positive impact of internet usage on gross cash income, total household income, off-farm income. The study further suggests that small farm businesses receive benefits from internet usage as it facilitates reduction in income risk through off-farm income sources, as well as a reduction in marketing and storage costs; households' non-farm transportation and vehicle leasing expenses.

Design/methodology/approach – In this study, the authors use the "nearest neighbors" matching method in treatment evaluation, developed by Abadie and Imbens (2002). In this method, a weighting index is applied to all observations and "nearest neighbors" are identified (Abadie *et al.*, 2004). Although matching estimation through the nearest neighbor method does not require probit or logit model estimation *per se*, the authors have estimated a probit model because it allows the authors to check the balancing property and to analyze the association of included variables with the likelihood of internet use.

Findings – The study suggests that small farm business households using 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 farm businesses not using the internet), small farm businesses using the internet earn about $24,000-$26,000 more in total household income and about $27,000-$28,000 more in off-farm income. Also, small farm businesses using the internet earn about $4,100-$4,900 more in gross cash farm income compared to their counterpart. The estimate of ATT for NFI is not different from zero. However, gross cash farm revenue increased significantly.

Practical implications – To this end internet can provide an 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.

Social implications – Farmers will seek assistance in interpreting data and applying information to their farming operations, via the internet. Therefore, it is essential that land grant universities continue to improve the delivery of electronic extension and provide information in a clear and concise manner.

Originality/value – 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

JEL Classification — C14, C13, Q12, Q14

China Agricultural Economic Review
Vol. 8 No. 4, 2016
pp. 553-571

1756-137X
DOI 10.1108/CAER-12-2014-0147

are discussed with references to large scale farm businesses. Thus, the authors know very little about access to the internet when it comes to small farm businesses and small farm households and about how it impacts well-being of small farm households.

Keywords Agricultural technology, Internet, Household analysis, Agribusiness, Agricultural extension services, Treatment effects

Paper type Research paper

1. Introduction

A competitive firm's response to risk is to gather information on output prices, input prices, production functions, firm goals, government farm programs, and cost of acquiring additional information (Robison and Barry, 1987). To this end, the internet can serve as an important tool in information gathering. It is a convenient means to access and exchange information. Information and communication facilitation through the internet has opened up new areas of commerce, social networking, information gathering, and recreational activities beyond geographical bounds. Producers and consumers can take advantage of the internet, in both collaborative and competitive aspects of economic activities, to reduce information asymmetry among economic agents. Internet adoption and usage may be increased, as 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 the internet (Mishra *et al.*, 2009). Internet usage can thus lower the costs of participation in governmental programs and to report to these agencies as needed.

Farm businesses can benefit from the internet by using it for information, as well as from trading and commercializing farm products to a broader set of consumers. Farmers can use the internet to browse for cheaper inputs and build connections and virtual networks with different economic agents – such as contractors and buyers of their product. Particularly small farm businesses who cannot compete with large farms in commodity production, are attempting to differentiate their products – selling as local or organic (such as pasture finished beef, free range poultry, etc.). The internet can be a powerful enabling technology, allowing communication with consumers about their products to coordinating marketing arrangements with the consumers who value these products, and facilitating the transactions[1]. Farmers are using internet applications, to perform tasks such as tracking price, accessing agricultural information, assessing information from government agencies, and online recordkeeping with increasing enthusiasm (Mishra and Park, 2005; Mishra *et al.*, 2009). Internet usage could serve to speed up the diffusion of innovation deemed appropriate for small farm business. Recently, Sila (2013) found that many variables ranging from firm size and firm type to the variables, such as pressure from competitors, network reliability, scalability, top management support, and trust, affecting firms' decision to adopt business-to-business electronic commerce.

Wide arrays of studies have examined household internet usage, access to the internet, and demand for the internet. On the other hand, studies related to internet usage by farm business households have been scarce, studies have mainly investigated factors influencing internet adoption, purchasing patterns through the internet, and internet use and applications. In most cases, impact analyses of communication and information technologies, such as the internet in agricultural businesses, are discussed with references to large scale farm businesses. However, we know very little about the role of internet usage when it comes to small farm business households. Specifically, how internet usage impacts the well-being of small business farming households (where the operator's main occupation is farming), especially total household income, off-farm income, farm financial performance (net farm income and gross cash income), total variable costs (VC), marketing and storage; household living and transportation expenses.

Herein lies the objective of this study. Using nationwide farm-level survey data of farming households and treatment effect models, this study investigates the impact of internet use on household income and farm financial performance of small farming business (defined as those with gross cash farm income $< \$250,000$) households[2] – wherein the owner's main occupation is farming. In particular, the study investigates the impact of internet usage activities (use of internet for at least one of the following activities: farm-related news and information, farm-related e-mail, and conduct farm-related commerce) on gross cash income, total household income, off-farm income, net farm returns, and farm- and household-level expenses.

2. Literature review

There has been a rapid increase in internet use and applications in almost every sector of the economy. Between 1995 and 2008, internet access across the globe increased from 16 million to 1.5 billion including in-home internet access for two-thirds of US adults (Stenberg *et al.*, 2009). With more applications, consumers do not just want access to internet but do care about quality attributes of internet services. While other sectors are heavily using internet services, the rural farm sector is slightly lagging behind as compared with its urban counterpart (Stenberg *et al.*, 2009). A common reason for this inequality is poor access to high-speed internet connections, which reduces the effectiveness of the internet as a tool. Interestingly, farming households possesses the distinct feature of being a consumer as well as a producer of some commodities on its farm. Farm household can use the internet in both consumption and production activities. The internet may provide new supplemental income for some households apart from the farm business. Even if purchases are not made online, farm households can gather information and discover prices that facilitate their decisions. Moreover, through utilization of e-commerce, producers may quickly promote and sell their products as well as seek information to reduce input costs (such as marketing costs, storage costs).

Business models created by internet are also becoming increasingly important in many areas of commerce and finance. The prospect of internet adoption and e-commerce in business is discussed in different context of developed and developing economies. For example, Jennex *et al.* (2004) studies adoption of internet in small companies in developing countries, García-Murillo (2004) (in Mexico), and Dasgupta and Sengupta (2002) (in India). Finally, studies have investigated the use of e-commerce in agribusiness firms (Warren, 2004) and small and rural business entities (Deakins *et al.*, 2004). Most of these studies have discussed the factors influencing adoption of internet, household's purchasing pattern through the internet, and benefits and overall profit potential of the internet, in general.

Broadly, studies analyzing the internet usage have investigated internet from two different perspectives. First, a 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 use by farm business, often concentrated on large farm business, and analyzing the e-commerce activities (Gloy and Akridge, 2000; Henderson *et al.*, 2005). Moreover, farm household studies are focused on the association of socioeconomic factors with adoption of the internet.

Very few studies have analyzed internet use and its impact on the well-being of farm households (such as total household income[3] and off-farm income) and farm business performance and small farm business households in particular.

A study by Mishra and Park (2005) discussed factors influencing the number of internet applications used by farm households. Using the count data model, they found education, farm size, contracts in farming, farm diversification, and farm location are key factors. The authors reported that applications of internet in farm households in the USA 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 were changing. In his study of Ohio farmers, 44 percent of the sample farmers had adopted computers for business in 2005. Of these, about 75 percent were using the internet for communication, transaction processing, and information gathering. Those doing online transactions were only about 25-50 percent of the 44 percent with computers. 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 internet utilization is more likely with larger farm size and relatively more educated and younger operators.

A study that comes close to analyzing the effect of internet on household income is by Chang and Just (2009). However, it should be noted that the authors use access to the internet and not internet usage. Access to the internet does not mean that the households may be using it for information gathering or conducting business through the internet. Chang and Just (2009) used a multi-stage econometric analysis to assess the effect of internet access on farm households' income in Taiwan. Employing a semi-parametric method correcting for selection bias in two separate equations for those with access to the internet and without an access to the internet in the second stage, their results suggested that access to the internet use improves farm household income. Using farm-level data from the USA, Mishra *et al.* (2009) investigated adoption of computers with internet access and purchasing patterns (both farm and non-farm items) and found that education and socioeconomic variables significantly improved farm households decision to adopt computers. They also found that farm businesses and their households are more likely to purchase a greater share of non-durable goods through the internet as distances to markets increase. Briggeman and Whitacre (2010) investigated constraints to wider adoption of the internet among farm households. They point to three main reasons "no computer in the household," "internet security concern," and "inadequate internet service" to explain the lack of internet use by farm households.

There are two noticeable limitations of the aforementioned studies. First, they fail to assess the impact of internet usage on total farm household income and farm financial performance of small farm businesses. Second, data limitation – most studies have used local or regional data from large farms. Although Chang and Just (2009) used farm-level data from Taiwan, it should be pointed out that: they analyzed the impact of access to the internet rather than internet usage, and compared to the USA, the agricultural sector in Taiwan is very small and homogeneous and specializing in rice, sugarcane, fruit, and vegetable production.

3. Conceptual model

Assume a farm household model where the household derives utility from consumption (C_i) and leisure (L_i), U_i (C_i, L_i). This framework is similar to the one proposed by

Blanc *et al.* (2008). The farm household maximizes utility subject to time and income constraints. A distinguished feature of the proposed farm household model is that it derives income from farming activities and off-farm employment. Farm household's utility maximization can be represented as increasing function of household consumption and leisure time subject to budget and time constraints. Total household income (Y_i) can be effectively utilized for consumption such that $Y_i \approx C_i$, assuming no savings (for simplicity). Then substituting C_i by Y_i, a farm household's utility can be represented as: U_i (Y_i, L_i). Farm household i can derive income from farm income (FI_i) and non-farm income (NFI_i). The time allocation between farm and non-farm activities and choice of leisure can simply be represented as $L_i = T_i - (TF_i + TNF_i)$, where farm household's total time, time for farm activities, and time for non-farm activities are represented as T_i, TF_i, and TNF_i, respectively.

Let us represent financial returns (or financial performance) of farm household i by FP_i such that $Y_i(FP_i^j)$ for $j = 1,2, \ldots, k$ financial return measures. Various incomes, such as gross cash income, and net farm income of farm households can be considered as financial returns (performance). These returns/incomes are associated with efficient marketing, information gathering, sales, or operational activities of the farming business and are affected by internet and information technology at various stages. Let total household income (THI) be a representative FP_i, for example. Then:

$$FP_i^{THI} = \left\{NFI_i(I_i, Z_i) + FI_i(I_i, Z_i) - C(FC, VC(IC))\right\},$$

where farm household's income is derived from farm income (FI_i) and non-farm/off-farm income (NFI_i). The third component in the above equation represents the cost of farming, including fixed costs (e.g., long- and short-term loans), VC (like labor, fertilizer, etc.). VC also include cost on information gather (IC, such as time spent on the internet, and access to the internet).

Following Chang and Just's (2009) study, one can show that internet access can improve farm household income. It is plausible that internet usage could play a role in both the revenue and expense components of farm and non-farm income and expenditures. For example, Avlonitis and Karayanni (2000) show that internet usage has a positive impact on product marketing and business performance. Since the internet can be utilized for wide range of activities, such as information gathering, e-commerce, input acquisitions, and online advertisement, it potentially influences on-farm activities and household-level activities – such purchasing household items for consumption.

Note that farm income and off-farm income have two arguments (I_i, Z_i) where I_i represents a dummy variable indicating usage of internet and Z_i represents a vector of all other exogenous variables that influence farm, off-farm and total household income. Farm output is influenced by various farm and farmer attributes (such as farm size, managerial ability, operator age, and educational attainment). We are not only interested in the impact of internet usage on financial performance of small farm businesses but also on total household income, total off-farm income, and farm expenses, including total VC, marketing and storage expenses as well as household living expenses and non-farm transportation and vehicle expenses. Additionally, in the short-run, above incomes indicators represent economic well-being of farm households (Mishra *et al.*, 2002).

Turning our attention to the empirical specification of the above conceptual model, internet usage and its impact on financial performance can be represented by:

$$FP_i^j = a_0 + \sum a_{ij} Z_{ij} + \beta I_i + \in_{0i}; \quad I_i = \theta M_i + \in_{1i}$$

where FP_i^j represents financial performance of farm household i; (j = performance measure – measured by gross cash farm income, total household income, off-farm income, net farm income) and I_i is a dummy variable indicating farmer's use of the internet. The probability of internet usage is influenced by a set of factors, M, and some unobservable factors captured by $\in_1$. Z_{ij} in the above equation represents a vector of variables that represent managerial abilities which influence household incomes and financial performance of farming business.

3.1 Data

This study uses the Agricultural Resource Management Survey (ARMS), a nationwide survey conducted in 2010 across farm households of the USA. The ARMS is conducted annually by the Economic Research Service and the National Agricultural Statistics Service. The survey collects data to measure financial conditions (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 households with a small farm business that has a gross cash farm income of less than $250,000 per year; the owner's main occupation is farming. Hoppe *et al.* (2010) note that small farm businesses in the USA are striving for their survival as most small farm businesses, at least at the lower end of the small farm size spectrum, need to rely on off-farm income. Thus, management of the farm and household income and expenses is crucial for the viability of small farm businesses.

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 full survey is used, generalizations about the entire population of farms are made based on the results, or simple univariate analysis is conducted. Under this scenario, the recommended method for calculating the variance is the delete-a-group jackknife procedure (National Research Council, 2007). However, no clear or unanimous support exists for using the jackknife approach when using subsets of the data or complex, multivariate analyses. Further, Goodwin and Mishra (2006) argue that it is not clear whether stratification alters the likelihood function beyond the simple weights and whether it is appropriate to apply the predefined jackknife replicate weights to subsamples of the ARMS data. Following El-Osta (2011) we employ a bootstrapping technique rather than the jackknife procedure to remedy design problems in this subsample.

Table I defines variables used in our empirical analysis. It also presents mean values for the entire sample of small farm business households (where owner's main occupation is farming), as well as for internet users and non-users. Of the 2,650 small farm business households in the sample, 1,580 (60 percent of the farming occupation small farm business households) had used internet. The last column in Table I shows *t*- or *z*-statistics which compares the means between internet users and non-users group (Column 3 and 4). A significant *t*- or *z*-score for respective variables suggests that internet users were younger and more educated operators and spouses; had elderly household members with ⩾64 years of age, as well as children (household member ⩽17 years of age) living in the household. Mean comparison suggests that both operators and spouses in households with internet use work significantly more off-farm. A significant difference in entropy index[4] suggests that small farming businesses using internet were relatively more specialized than their counterpart.

Variable definition	Entire sample	Mean No internet use	Internet use[a]	t/z score[b]
Internet use		0.40	0.60	
Operator and household characteristics				
Age of operator (years)	59.23	64.44	58.88	11.01***
Education of operator (years)	12.83	12.23	13.48	−18.24***
Age of spouse (years)	58.46	61.48	56.74	8.89***
Education of spouse (years)	11.64	10.43	12.58	−15.75***
Presence of household members ⩾ 64 years of age	0.87	0.42	0.72	−15.36***
Presence of household members ⩽ 17 years of age	0.73	0.11	0.22	−7.43***
Share of off-farm work hours to total work hours, operator	0.12	0.07	0.15	−8.92***
Share of off-farm work hours to total work hours, spouse	0.44	0.33	0.51	−8.09***
Farm characteristics				
Entropy index	0.18	0.16	0.14	3.34**
Distance from nearest market (miles)	25.10	25.52	25.29	0.21
Total acres in operation (in log)	5.13	4.97	5.01	−1.85*
Government payment (= 1 if farm received government payment, 0 otherwise)	0.48	0.37	0.45	−3.75***
Debt-to-asset ratio (= total farm debt/total farm assets)	0.09	0.05	0.10	−7.56***
Farming efficiency (= total value of production/total variable cost)	2.57	2.82	1.99	2.03***
Income variables ($)				
Total household income	54,423.46	39,800.92	61,235.17	−5.25***
Total off-farm income	46,186.30	37,281.28	57,961.93	−5.56***
Gross cash farm income	87,569.14	60,903.46	88,400.00	−9.70***
Net farm income	19,180.91	11,280.87	13,063.84	−0.39
Cost variables ($)				
Total variable expenses	51,613.56	40,523.85	58,856.50	−5.95**
Total household living expenses	31,200.70	29,626.28	37,271.19	−5.15***
Marketing and storage expenses	1,572.35	1,214.42	1,629.03	−2.21***
Non-farm transportation and vehicle leasing expenses transportation leasing expenses	124.00	74.98	158.78	−1.93
Regional dummies (= 1 if farm located in the corresponding region)				
Atlantic region	0.18	0.21	0.22	−0.54
West region	0.14	0.16	0.24	−5.02***
Plains region	0.17	0.21	0.16	2.96***
Midwest region	0.34	0.20	0.19	0.09
South region	0.16	0.24	0.19	2.63***
Farm type dummies				
Crop farm (= 1 if crop farm)	0.43	0.31	0.30	0.57
Livestock farm (= 1 if livestock farm)	0.41	0.53	0.51	0.87
Dairy farm (= 1 if dairy farm)	0.16	0.07	0.04	3.76***
Hog and/or poultry farm (= 1 if hog and/or poultry farm)	0.08	0.07	0.12	−3.65***
Other farm (= 1 if other farm type)	0.06	0.08	0.14	−4.64***
Number of observations	2,650	1,070	1,580	

Notes: [a]Internet use is defined as “Use internet for at least one of the following activities: farm-related news and information, farm-related e-mail, and conduct farm-related commerce.” Farm operators are queried on this. [b]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; for binary variables, test on the equality of proportions is used to compare the differences and *z*-score is reported. ***Statistical significance at 5 percent or higher levels

Table I.
Variable definitions and summary statistics, small farm business households (farming as main occupation), 2010

Internet user farming households had significantly higher household income, off-farm income, and a higher gross cash farm income than non-users. On the expense side internet users had higher total variable expenses as well as higher living expenses as compared to non-users. Additionally, internet user farms had significantly lower marketing and storage expenses and non-farm transportation expenses. A mean comparison of location variables suggests that significant regional differences existed between internet user and non-user small farming business households. For example, in the West region, the share of internet user households was significantly higher than that of non-user households. In the Southern region, on the other hand, the share of non-user households was higher. Figure 1 shows regional classifications used in this study.

Share of internet user farms were significantly higher among poultry and/or hog farms while opposite scenario was true among dairy farms. Note that the *t*- or *z*-scores reported in Table I are based on the mean comparison for each variable between two groups of farms without controlling for any underlying factors. The matching estimator overcomes this issue and provides more appropriate effect of the treatment variable on the outcome variables.

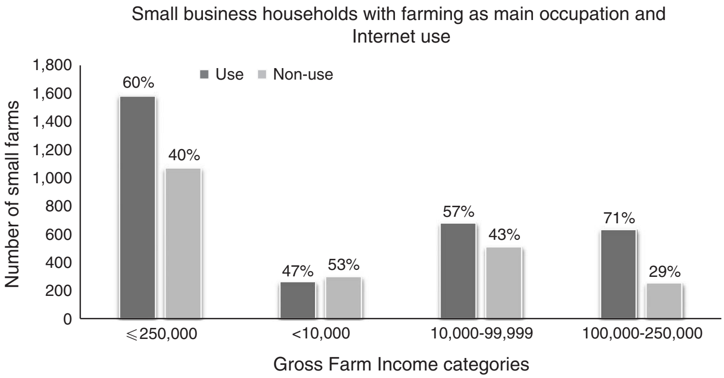
Figure 2 shows internet use among selected gross cash farm income categories within small farm business households. Notice that even for farms generating less than $10,000 in gross cash farm income; about 47 percent of farms in this category were internet users. Figure 3 shows selected categories of internet use patterns among all small farming households. Within 60 percent of internet user households, 77 percent utilized it to assess farm-related news and information (*farm_info*), 42 percent used it for e-commerce activities (*farm_comm*), and 71 percent used it for e-mail communications and social networking (*farm_email*).

3.2 Empirical method

Quantitative impact evaluations can be broadly classified as *ex-ante* and *ex-post* evaluations. *Ex-ante* evaluation is a prediction for a future outcome based on current the situation and a simulation of the assumption about how the economy works. Prediction may involve structural models of the economic environment faced by

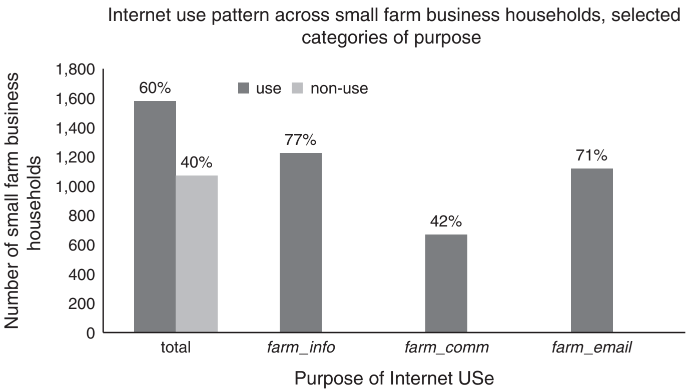
Source: Economic Research Service, US Department of Agriculture, available at: www.ers.usda.gov/data-products/chart-gallery

Figure 1.
US geographic regions



Source: Authors' computation based on United States Department of Agriculture, Economic Research Service (2010)

Figure 2. Internet use, small farm business households, farming as main occupation



Notes: *Fam_info* = small farm businesses using internet for getting farming-related information. *Fam_comm* = small farm businesses using internet to conduct commerce. *Fam_email* = small farm businesses using internet for e-mail communications and social networking
Source: Author's computation based on United States Department of Agriculture, Economic Research Service (2010)

Figure 3. Internet use pattern, small farm business households, farming as main occupation

potential participants (Khandker *et al.*, 2010). The *ex-post* impact evaluation, on the other hand, measures the exact outcome obtained by participants that are attributable to the program or treatment (internet users and non-users in our case). The latter methods are referred to as treatment effect models. Social scientists use parametric and non-parametric approaches of treatment effect model to estimate an impact or change on outcome variables. The objective of this study is to estimate the average treatment effect (ATE) of internet use on various components of farm household income and expenses.

Ideally, ATE can be estimated by simply comparing two outcomes for the same unit: when the unit is assigned to the treatment and when it is not. For instance, ATE of internet use on household and farm income and cost measures[5] of small farm businesses require outcomes with treatment (incomes when a household uses the internet) and those without treatment (incomes of the same household while not using the internet). For individual i, $i = 1, 2, \ldots, N$, with all units exchangeable, let $\{FP_{i0}, FP_{i1}\}$ be two potential outcomes. FP_{i1} is outcome of individual i if exposed to the treatment (in our case, financial performance measures (such as various incomes and costs) if i uses the internet), while FP_{i1} is individual i's outcome when not exposed to the treatment (outcome if i would not use the internet). If both FP_{i1} and FP_{i0} were observable, the effect of treatment on individual i would be: FP_{i1}–FP_{i0}. We can then use this information for population N to compute population ATE as:

$$ATE = E(FP_1 - FP_0) \tag{1}$$

where FP_1 is the outcome variable with treatment and FP_0 is the outcome variable without treatment. However, in cross-sectional data, obtained from household surveys at one in point of time, we do not observe these outcomes together because assignment to the treatment is mutually exclusive. For example, we do not observe the (incomes/costs) status of not using the internet for user household i. For non-user households, on the other hand, we do not observe the incomes (costs) if the household had used the internet. Thus, estimating the ATE of being an internet user on farm household income and expenses centers on estimating the counterfactual or imputing missing data (Wooldridge, 2002). Treatment effect under non-experimental settings is increasingly becoming popular in social science researches (Rosenbaum and Rubin, 1983; Heckman *et al.*, 1998) as well as in empirical applications related to agricultural economics (Uematsu and Mishra, 2012).

Impact can be measured in terms of two estimates under non-experimental settings. We can estimate what would be the income (or expenses) for small farm households not using the internet, had they used it. Alternatively, we can estimate such impact on internet user households, had they not used it. The latter effect is referred to as the ATE for treated (ATT), which we have estimated as:

$$\text{ATT} = E(FP_1 - FP_0 | I = 1) \tag{2}$$

where $I = 1$ indicates assignment to the treatment (internet user); 0 otherwise. Creating a convincing and reasonable comparison is a challenging part of impact evaluation. The accuracy of impact evaluation rests on how well we are able to define the counterfactual. Unlike the experimental studies where we can set up randomness in treatment and control, observational treatment effects are not free from self-selection biases. In our context, we do not randomly assign farmers to become internet users or non-users, but they self-select. Since some farmers are more likely to choose to use the internet than others, we need to account for these self-selection biases. When treatment is not random, simple comparison of the outcome variables between the two groups is not appropriate. Thus, estimation of ATEs without accounting for self-selection leads to biased estimation. Literature suggests some ways to correct for this bias (Cameron and Trivedi, 2005; Khandker *et al.*, 2010). One of the ways currently gaining popularity nowadays is the use of "matching estimators." The basic principle behind matching estimators is to match observations between treatment and control groups on the basis of some key observable factors.

A number of matching estimators have been proposed based on the algorithm to match observations from the two groups. Rosenbaum and Rubin (1983) proposed the propensity score, for which one can use the predicted probability of being in the treatment estimated in either a logit or a probit model. The propensity score summarizes information contained in the multidimensional vector into a single-index variable (Becker and Ichino, 2002).

In this study, we use the "nearest neighbors" matching method in treatment evaluation, developed by Abadie and Imbens (2002)[6]. In this method, a weighting index is applied to all observations and "nearest neighbors" are identified (Abadie *et al.*, 2004). The nearest neighbor matching estimator summarizes information from multiple variables into a single index using the vector norm $\|x\|v = (x'Vx)^{1/2}$, where V is the positive definite variance matrix used to weight variables through normalization by standard deviation, where distance between two observations are defined $\|z-x\|v$, where z and x are the vectors of observable characteristics for the two observations. Applying the weighting index to all observations, the "nearest neighbors" are identified. The ATT estimator in nearest neighbor is given by:

$$\text{ATT} = \frac{1}{N_1}\sum_{i:I_i=1}^{N_1}\left[FP_i - FP'_{0i}\right] \tag{3}$$

where i represents an individual observation and N_1 is the total number of observations in a treatment group. FP_i is observed outcome for individual i, while FP'_{0i} is not observed. FP'_{0i} is found by matching:

$$FP'_{0i} = \left\{\begin{array}{ll} FP_i \quad \text{if} \quad I_i = 0 \\ \frac{1}{M}\sum\limits_{m \in M_i} FP_m \quad \text{if} \quad I_i = 1 \end{array}\right\} \tag{4}$$

where M_i is the set of matched observations in the control group matched with individual i in the treatment group. M is the number of matched observations. The term $(1/M)\sum_{m\in M_i} FP_m$ is simply a weighted average of the outcome variables for all matched observations in the control group. The nearest neighbor matching estimator developed by Abadie and Imbens (2002) allows users to specify the number of matches, m, for each treated observation. There is a tradeoff between the choice of m and quality of match. For example, choosing $M=1$ means that each treated observation is matched with an observation in the control group with the closest distance. When M is larger, on the other hand, more information is utilized in estimating the ATE, but the quality of match may be compromised.

The matching estimator is based on an important assumption, referred to as "ignorability" (Wooldridge, 2002), "selection on observables" (Fitzgerald *et al.*, 1998), or "unconfoundedness" (Rosenbaum and Rubin, 1983). This assumption implies that any remaining difference between outcome variables after matching can be solely attributed to the treatment status, and assignment to the treatment is considered purely random among matched observations (Uematsu and Mishra, 2012). The limitation of the estimator is that we cannot directly test this assumption, but instead test the balancing property. We should be aware that matching estimators do not completely eliminate selection bias due to unobservable factors determining assignment to the treatment, but they reduces it (Becker and Ichino, 2002; Uematsu and Mishra, 2012). As suggested in Becker and Ichino (2002) and applied in several empirical studies, we can test balancing property, which is implemented as follows: first, estimate probit or logit model and get conditional probability of being in the treatment group and then second test for the randomness of the treatment assignment for the observations with same propensity score. Mathematically, balancing property implies $T \perp X|p(X)$, where $p(X)$ is the conditional probability of being in the treatment group. If this condition is satisfied, assignment to the treatment is random for the same propensity score (for a detailed discussion on these assumptions, see Becker and Ichino, 2002; Rosenbaum and Rubin, 1983; Heckman *et al.*, 1998; Imbens, 2004).

Although matching estimation through the "nearest neighbor" method does not require probit or logit model estimation *per se*, we have estimated a probit model because it allows us to check the balancing property and to analyze the association of included variables with the likelihood of internet use. Matching estimators are considered non-parametric types of estimators because we do not need to assume a specific functional form and do not need to impose any distributional assumptions (Cameron and Trivedi, 2005; Wooldridge, 2002).

4. Results and discussion

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 3.2. As mentioned earlier, for many matching estimators, it is required to estimate a binary logit or probit model using the treatment status as the dependent variable. We estimated a probit model using the treatment status (internet use) as a dependent variable. Model estimation provides information on the factors influencing internet usage. We included demographic and socioeconomic factors such as farm and operator characteristics, government farm payments, share of on- and off-farm hours in total work hours, and location, as well as farm type variables. Based on these observable features of a farm, the probit model computes propensity scores and hence allows us to test the balancing property – that is, observations with the same propensity score must have the same distribution of observable characteristics independent of treatment status.

The probit model shown in Table II satisfied the balancing property using the algorithm suggested by Becker and Ichino (2002). The algorithm splits sample into equally spaced interval of propensity scores (blocks) and then tests in each block "whether average propensity score between treated and control units is different." Test continues until average propensity score of treated and control does not differ in each block. If the means of each characteristic between treatment and control for same propensity score do not differ, the balancing test is satisfied. We restricted the algorithm to test in the area of common support (the area belonging to the intersection of the propensity score of treated and control) as this condition enhances the quality of matches in ATT estimation (Becker and Ichino, 2002). The likelihood ratio statistics of 454.29 suggests that the estimated model is statistically significant at the 1 percent level of significance.

4.1 Impact of internet use: ATT estimations

We estimated bias-corrected ATT estimates (Abadie *et al.*, 2004) in order to estimate the impact of internet usage on outcome variables (total income, off-farm income, farm financial performance; costs and other household expenses). In our study, we used the same set of independent variables used in the probit model as a vector of covariates in order to compute the matching distance in the "nearest neighbor" matching estimator. It is important to choose carefully the observable characteristics that compose the matching index to account for potential self-selection bias. Our set of variables represented operator characteristics, farm characteristics, relative share of off- and

Variables	Coefficients	SE	p-values
Age of operator	−0.008**	0.005	0.072
Education of operator	0.164***	0.025	0.000
Age of spouse	−0.005	0.007	0.506
Education of spouse	0.114***	0.025	0.000
Total acres operated (in log)	0.027	0.029	0.350
Government payments	0.323***	0.091	0.000
Entropy index	−0.961***	0.334	0.004
Distance to market	−0.001	0.002	0.720
Presence of family members ⩾64 years old	0.331***	0.101	0.001
Presence of household member ⩽17 years	−0.019	0.108	0.856
Farm efficiency	−0.023	0.018	0.220
Share of off-farm work hours to total work hours operator	0.298**	0.175	0.090
Share of off-farm work hours to total work hours spouse	0.067	0.094	0.474
Crop farms	−0.140	0.157	0.372
Livestock farms	−0.219	0.144	0.129
Dairy farms	−0.757***	0.205	0.000
Hog and/or poultry farms	−0.015	0.341	0.965
Atlantic region	−0.028	0.133	0.835
Plain region	−0.347**	0.126	0.006
Midwest region	−0.169	0.132	0.198
South region	−0.244***	0.127	0.050
Number of observations = 1,545	LR statistics = 332.61		p-value
Log-likelihood = −781.26	$R^2 = 0.18$		(LR = 0) < 0.000

Note: *,**,***Significant at 10, 5 and 1 percent levels, respectively

Table II. Probit model parameter estimates

on-farm work hours vs total work hours, and farm efficiency, as well as farm types and farm location variables.

We specified a number of matches, $M = 1, \ldots, 5$ to compute ATT. Table III presents the ATT of internet use on gross cash farm income, total farm household income, off-farm income, net farm income, total farm VC, total household living expenses, marketing and storage expenses, and non-farm transportation and vehicle leasing expenses. The ATT on total farm household income was positive and highly significant (at the 1 percent significance level) for all $M = 2, \ldots, 5$. This indicates that small business farming households using the internet are better off in terms of total household income than their counterpart. Results in Table III suggest that small business farming households using the internet earned about $12,700-$8,600 per year more in total farm household income[7], compared to small business farming businesses not using the internet.

The ATT on off-farm income was positive and significant for all $M = 1, \ldots, 5$. Results show that the effect of internet use on off-farm income was consistent across all M's, ranging from $11,200 to $13,800 per year. This is consistent with the findings of Mishra *et al.* (2002) who reported that the share of off-farm income in total household income for small farm households could be above 100 percent. We should note two things here. First, off-farm income for farm households, especially for small farm businesses, can be higher than total household income in the cases with negative incomes from farming and small businesses farming households usually report losses from farming (Hoppe *et al.*, 2010). Second, as indicated in the 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

Variable	Number of matches (M)	ATT[a]	SE[a]	p-value
Income variables				
Total household income ($ per year)	1	8,677	7,012	0.191
	2	12,723***	6,513	0.050
	3	10,581***	5,501	0.000
	4	9,163***	4,414	0.001
	5	8,677***	4,268	0.000
Total off-farm income ($ per year)	1	11,918**	6,320	0.051
	2	13,818***	5,701	0.015
	3	11,984***	5,761	0.038
	4	11,177**	5,692	0.050
	5	11,363***	5,528	0.040
Gross farm income ($ per year)	1	9,564***	4,385	0.029
	2	11,859***	4,153	0.004
	3	12,417***	3,996	0.002
	4	11,503***	3,911	0.003
	5	10,859***	3,906	0.005
Net farm income ($ per year)	1	−1,156	4,725	0.807
	2	1,945	4,560	0.670
	3	1,843	4,379	0.421
	4	1,250	4,331	0.773
	5	855	4,311	0.843
Debt-to-asset ratio	1	0.005	0.012	0.652
	2	0.003	0.012	0.820
	3	0.004	0.011	0.753
	4	0.002	0.011	0.865
	5	0.002	0.010	0.872
Cost and expense variables				
Total variable expenses	1	4,737*	2,570	0.065
	2	5,235***	2,443	0.032
	3	5,365***	2,389	0.025
	4	6,132***	2,362	0.009
	5	6,129***	2,361	0.009
Household living expenses	1	4,702*	2,649	0.076
	2	6,283***	2,417	0.009
	3	7,059***	2,332	0.002
	4	7,010***	2,385	0.003
	5	7,333***	2,340	0.002
Marketing and storage expenses	1	−1,656*	1,021	0.100
	2	−2,106**	993	0.034
	3	−1,821**	841	0.030
	4	−2,044***	832	0.014
	5	−2,104***	803	0.009
Non-farm transportation and vehicle leasing expenses	1	−125	95	0.190
	2	−113	88	0.199
	3	−116*	71	0.083
	4	−120*	64	0.071
	5	−126*	68	0.063

Notes: [a]Income and expenses figures are rounded up-to the nearest dollar values. *,**,***Significant at 10, 5 and 1 percent levels, respectively

Table III.
Estimates of the average treatment effect on treated (ATT)

small farm households using the internet earn about \$13,800-\$11,200 per year more in off-farm income compared to their counterparts. Additionally, internet users are likely to have the knowledge of the advantages of the internet and its vital use in daily lives. 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 III indicate that the ATT of internet use on gross cash farm income was positive and significant at the 10 percent level or higher for $M = 2, \ldots, 5$. The ATT on gross cash farm income ranged from \$9,500 to \$12,400 per year, indicating that small farming businesses using the internet can earn on average \$10,000 per year more in gross farm income compared to their counterparts.

Let us turn our attention to the cost side of small farming business households. Table III reports that the ATT for total VC was positive and significant at $M = 1, \ldots, 5$. The positive ATT suggests higher total VC for small farming business households that use the internet. This may be due to higher search costs – time spent on the internet, cost of getting internet services, and having access to the internet. Total household living expenses are also higher for internet users (Table III). This may suggest a change in spending habits for internet users due to the ease of access to goods and services without leaving the confines of their home and/or business; however, in combination with significantly higher total household income and off-farm income, a more plausible explanation is that the small business farming households using the internet are making additional investments in an attempt to generate more revenue for the business and the household.

Finally, our results suggest significantly negative marketing and storage expenses for $M = 1, \ldots, 5$ as well as non-farm transportation and vehicle leasing expenses for $M = 3, \ldots, 5$, indicating that a reduction in these expenses are attributable to internet usage. Small business farming households could potentially reduce marketing and storage expenses between \$1,600 and \$2,100 per year. As noted by Bussolo and Whalley (2002) the internet explosion and related technologies have drastically reduced exchange and search costs in many Organisation for Economic Co-operation and Development countries. The last panel in Table III reports that small farming business households that use the internet can reduce their non-farm transportation and vehicle leasing expenses by \$113-\$126 per year. This might be due to the provision of e-commerce, or online information facilities acquired through the internet. Due to internet use, information on products could be received instantaneously and delivery of the farm product could take place in a matter of two to three days (Mishra *et al.*, 2009).

5. Summary and conclusions

Small farming businesses (defined as small farm business household where operator's main occupation is farming) are a subject of interest in recent agricultural economics and agribusiness literature, particularly how best can they strategically manage the farm business to remain viable in the marketplace. The internet is one of the best options to gather information, search products and sell products; e-commerce and communication and social networking. This study analyzed the impact of internet use on various incomes and expenses of small business farming households using matching estimators and a nationwide ARMS survey of US farmers. The non-parametric "nearest neighbors" matching estimator uniquely allows us to define adequate counterfactual and also account for potential self-selection issue.

Our study suggests that small business farming households using 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 business farming households not using the internet), small business farming household using the internet earn about $12,700-$8,600 per year more in total household income and about $11,200-$13,800 per year more in off-farm income. Also, small business farming households using the internet earn about $9,500-$12,400 per year more in gross cash farm income compared to their counterpart. On the expenses side, we found that households using the internet usage have higher total variable and living expenses, but lower marketing and storage charges, non-farm transportation and vehicle leasing expenses. We explored that small farming businesses, through good management of off-farm and on-farm activities, can get benefit from the internet as it opens up options for quick and wide range of information related to farming and a new marketplace, therefore potentially reducing some costs related to non-farm transportation and vehicle leasing. As indicated by higher total variable and living expenses of internet users, use of internet, perhaps, also enables farmers to invest in new business opportunities and access to consumer goods via shopping on the internet. Subsequent research may explore, but not limited to, internet use pattern for specific farm-related activities and its related effects, such as hours spent on internet for e-commerce, online purchase for inputs, online sales and marketing.

In order for small farm business households to capitalize on the internet, they need to use the internet to their advantage. New low-cost solutions, such as direct marketing of niche products, e-marketing, agritourism, could be strengthened for small farming businesses to establish, manage and raise their presence on the internet – information super highway. The internet could be a key in communicating with and delivering documents to government officials, manufacturers, packers, and retailers. Small farming business household need to increase their revenue source(s) both on and off the farm and reduce their expenditures by seeking information through the internet. Internet provides a platform for businesses to access national and international markets. By providing technical training in processing, packaging and labeling their products, along with internet marketing strategies, small farming businesses and rural businesses in general can help grow rural businesses and maintain rural communities. Additionally, the need for electronic extension is going to continue to rise. Additionally, with budget squeeze in land grant universities, with constraint on personnel hiring, it would make sense and be cheaper to deliver extension services via the internet and/or mobile phones. These results can be useful to both developed countries (like the USA) and developing countries (like China and India), in which the well-being of small farm holders can be improved if the government can provide more support, via subsidies and tax incentives, of internet use.

Notes

1. One such program that has proven to help small farmers is MarketMaker. MarketMaker programs have been implemented in many states, for example, New York, Indiana, Illinois, Arkansas, Louisiana, etc.
2. Small business farming household and small farming business households are used interchangeably in this manuscript. They both represent small farm businesses whose owner/operator reports farming as his/her main occupation.
3. Total household income is composed of off-farm income and farming income. Total off-farm income includes income from wages and salaries, off-farm business income, and income from non-earned sources.

4. The extent of farm diversification among N possible enterprises is measured using the following index and by letting $x_j = $ (% value of production from enterprise j):

$$Entropy_{\mathrm{i}} = \sum_{j=1}^{N} (x_j) \frac{\log\left[\frac{1}{(x_j)}\right]}{\log(N)},$$

where the index ranges from 0 (i.e. a completely specialized farm producing only one commodity) to 100 percent (i.e. a completely diversified farm with equal shares of each commodity).

5. The financial measures used in this study are: income, which includes total household income, total off-farm income, gross cash farm income and net farm income; debt-to-asset ratio of the farm; cost, which includes total variable expenses, total living expenses, marketing and storage costs, and non-farm transportation costs.

6. We used "nnmatch" command in STATA. Further, for robustness check, we also computed treatment effect using "attnd" command, which provided similar mean estimates of ATT. Alternatively we could evaluate the effect using other matching methods, such as stratification matching and radius matching (Khandker *et al.*, 2010). Our ATT results from those alternative-matching techniques were not much different from nearest neighbor matching. Thus, we have only presented our results of nearest neighbor matching estimator in this study. For an application of the nearest matching estimator using STATA, see Abadie *et al.* (2004).

7. Recall total household income is composed of income from both off-farm sources and farm sources.

References

Abadie, A. and Imbens, G.W. (2002), "Simple and bias-corrected matching estimators for average treatment effects", T0283, National Bureau of Economic Research, Inc., Cambridge, MA.

Abadie, A., Drukker, D., Herr, J.L. and Imbens, G.W. (2004), "Implementing matching estimators for average treatment effects in Stata", *Stata Journal*, Vol. 4 No. 3, pp. 290-311.

Avlonitis, G.J. and Karayanni, D.A. (2000), "The impact of internet use on business-to-business marketing: examples from American and European companies", *Industrial Marketing Management*, Vol. 29 No. 5, pp. 441-459.

Batte, M.T. (2005), "Changing computer use in agriculture: evidence from Ohio", *Computers and Electronics in Agriculture*, Vol. 47 No. 1, pp. 1-13.

Becker, S.O. and Ichino, A. (2002), "Estimation of average treatment effects based on propensity scores", *Stata Journal*, Vol. 2 No. 4, pp. 358-377.

Blanc, M., Cahuzac, E. and Elyakime., B. (2008), "Demand for on-farm permanent hired labour on family holdings", *European Review of Agricultural Economics*, Vol. 35 No. 4, pp. 493-518.

Briggeman, B.C. and Whitacre, B.E. (2010), "Farming and the internet: reasons for non-use", *Agricultural and Resource Economics Review*, Vol. 39 No. 3, pp. 571-584.

Bussolo, M. and Whalley, J. (2002), "Globalisation in developing countries: the role of transaction costs in explaining economic performance in India", project paper, UK Department for International Development, London.

Cameron, A.C. and Trivedi, P.K. (2005), *Microeconometrics: Methods and Applications*, Cambridge University Press, New York, NY.

Chang, H. and Just, D.R. (2009), "Internet access and farm household income: empirical evidence using semi-parametric assessment in Taiwan", *Journal of Agricultural Economics*, Vol. 60 No. 2, pp. 348-366.

Dasgupta, P. and Sengupta, K. (2002), "E-commerce in the Indian insurance industry: prospects and future", *Electronic Commerce Research*, Vol. 2 Nos 1-2, pp. 43-60.

Deakins, D., Mochrie, R. and Galloway, L. (2004), "Rural business use of information and communications technologies: a study of the relative impact of collective activity in rural Scotland", *Strategic Change*, Vol. 13 No. 2, pp. 139-150.

El-Osta, H. (2011), "The impact of human capital on farm operator household income", *Agricultural and Resource Economics Review*, Vol. 40 No. 1, pp. 95-115.

Fitzgerald, J., Gottschalk, P. and Moffitt, R.A. (1998), "An analysis of sample attrition in panel data: the Michigan panel study of income dynamics", *The Journal of Human Resources*, Vol. 33 No. 3, pp. 251-299.

García-Murillo, M. (2004), "Institutions and the adoption of electronic commerce in Mexico", *Electronic Commerce Research*, Vol. 4 No. 3, pp. 201-219.

Gloy, B.A. and Akridge, J.T. (2000), "Computer and internet adoption in large US farms", *International Food and Agribusiness Management Review*, Vol. 3 No. 3, pp. 323-338.

Goodwin, B.K. and Mishra, A.K. (2006), "Are 'decoupled' farm program payments really decoupled? An empirical evaluation", *American Journal of Agricultural Economics*, Vol. 88 No. 1, pp. 73-89.

Heckman, J.J., Ichimura, H. and Todd, P. (1998), "Matching as an econometric evaluation estimator", *The Review of Economic Studies*, Vol. 65 No. 2, pp. 261-294.

Henderson, J., Doley, F., Akridge, J. and Carerre, A. (2005), "Adoption of internet strategies by agribusiness firms", *International Food and Agribusiness Management Review*, Vol. 8 No. 4, pp. 42-61.

Hoppe, R.A., McDonald, J.M. and Korb, P. (2010), "Small farms in the United States: persistence under pressure", Economic Information Bulletin Number 63, Economic Research Service, US Department of Agriculture, Washington, DC.

Imbens, G.W. (2004), "Nonparametric estimation of average treatment effects under exogeneity: a review", *The Review of Economics and Statistics*, Vol. 86 No. 1, pp. 4-29.

Jennex, M.E., Amoroso, D. and Adelakun, O. (2004), "E-commerce infrastructure success factors for small companies in developing economies", *Electronic Commerce Research*, Vol. 4 No. 3, pp. 263-286.

Khandker, S.R., Koolwal, G.B. and Samad, H.A. (2010), *Handbook on Impact Evaluation: Quantitative Methods and Practices*, The World Bank, Washington, DC.

Mishra, A.K. and Park, T.A. (2005), "An empirical analysis of internet use by US farmers", *Agricultural and Resource Economics Review*, Vol. 34 No. 2, pp. 253-264.

Mishra, A.K., Williams, R.P. and Detre, J.D. (2009), "Internet access and internet purchasing patterns of farm households", *Agricultural and Resource Economics Review*, Vol. 38 No. 2, pp. 240-257.

Mishra, A.K., El-Osta, H.S., Morehart, M.J., Johnson, J.D. and Hopkins, J.W. (2002), "Farm sector performance and well-being of farm households", Agricultural Economic Report No. 812, US Department of Agriculture, Economic Research Service, Washington, DC.

National Research Council (2007), *Understanding American Agriculture: Challenges for the Agricultural Resource Management Survey*, National Academies Press, Washington, DC.

Robison, L. and Barry, P. (1987), *The Competitive Firm's Response to Risk*, McMillian Publishing Company, New York, NY.

Rosenbaum, P.R. and Rubin, D.B. (1983), "The central role of the propensity score in observational studies for causal effects", *Biometrika*, Vol. 70 No. 1, pp. 41-55.

Sila, I. (2013), "Factors affecting the adoption of B2B e-commerce technologies", *Electronic Commerce Research*, Vol. 13 No. 2, pp. 199-236.

Stenberg, P., Morehart, M., Vogel, S., Cromarti, J., Breneman, V. and Brown, D. (2009), "Broadband internet's value for rural America", Research Report No. 78, Economic Research Service, US Department of Agriculture, Washington, DC.

Uematsu, H. and Mishra, A.K. (2012), "Organic farmers or conventional farmers: where's the money?", *Ecological Economics*, Vol. 78 No. 1, pp. 55-62.

United States Department of Agriculture, Economic Research Service (2010), *Agricultural Resource Management Survey*, Washington, DC.

Warren, M. (2004), "Farmers online: drivers and impediments in adoption of internet in UK agricultural business", *Journal of Small Business and Enterprise Development*, Vol. 11 No. 3, pp. 371-381.

Wooldridge, J.M. (2002), *Econometric Analysis of Cross-Section and Panel Data*, 1st ed., The MIT Press, Cambridge, MA.

Further reading

Goodwin, B.K. and Mishra, A.K. (2004), "Farming efficiency and the determinants of multiple job holding by farm operators", *American Journal of Agricultural Economics*, Vol. 86 No. 4, pp. 722-729.

About the authors

Aditya R. Khanal is an Assistant Professor of Agribusiness at the Tennessee State University, USA. He has a PhD in Agricultural Economics and a MS in Finance from the Louisiana State University, USA. He has also completed a MA in Economics from the Virginia Tech, USA. His research areas in applied economics and finance are focused on small farm business, weather and income risk on farm households, production economics, technology adoption, and economic development.

Ashok K. Mishra is the Kemper and Ethel Marely Foundation Chair in the Morrison School of Agribusiness, W.P. Carey School of Business at the Arizona State University, USA. He has a PhD in Economics from the North Carolina State University, NC, USA and a MS in Agricultural Economics from the University of Aberdeen, UK. He has conducted wide range of research in the area of agribusiness, food systems, food security, and agribusiness finance. Ashok K. Mishra is the corresponding author and can be contacted at: Ashok.k.mishra@asu.edu