Are Organic Farmers Really Better Off Than Conventional Farmers?

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Abstract

We employed the propensity score matching and estimated the causal effect of being certified organic crop producers on farm household income and its various components in the United States. Contrary to the standard assumption in economic analysis, certified organic farmers do not earn significantly higher household income than conventional farmers. Certified organic crop producers earn higher revenue but they incur higher production expenses. In particular, certified organic producers spend significantly more on labor expenses, insurance payments, and marketing charges than conventional farmers. The results suggest that early adopters of organic farmers have done so for non pecuniary reasons and the lack of economic incentives can be an important barrier to conversion to organic farming in the United States.

Keywords: organic farming, propensity score matching, nearest neighbor matching, average treatment effect

JEL codes: Q10, Q13, J43, C21

1. Introduction

United States Department of Agriculture defines organic farming as “a production system that is managed in accordance with the Organic Foods Production Act and regulations to respond to site-specific conditions by integrating cultural, biological and mechanical practices that foster cycling of resources, promote ecological balance, and conserve biodiversity” (USDA, 2011). Organic farming has been one of the most thriving segments in the U.S. farm sector over the last decade (Kuminoff and Wossink, 2010) due to growing demand for healthy food products by consumers. Although acres under organic farming explained only about 1% of the total acres in the United States in 2008 (Greene, et al., 2010), more than 600,000 acres operated by 9,000 farms were undergoing the transition from conventional to organic farming in 2007 (Census of Agriculture, 2007). The retail sales of organic products have increased by 480% from $3.6 billion in 1997 to $21.1 billion in 2008 (Dimitri and Oberholtzer, 2009).

Organic farming can also meet the growing social concern for conservation of environmental resources in rural America. Environmental benefits of organic farming includes but not limited to improved water quality due to reduced pesticide residues, reduced nutrient pollution, better carbon sequestration, enhanced biodiversity (Greene, et al., 2009), improved soil condition, and more healthy food (O'Riordan and Cobb, 2001). The Food, Conservation, and Energy Act of 2008 increased mandatory funding for organic programs by five-fold compared to the previous legislation (USDA, 2009). The Act also provided financial support to farmers converting to organic for the first time at the national scale (Greene, et al., 2009).

Despite the growing trend in demand for organic products, consumers of organic products recently witnessed periodic shortages of organic products, primarily because supply of organic foods failed to catch up with the rapidly increasing demand (Dimitri and Oberholtzer, 2009). A number of factors are documented as barriers for conventional and beginning farmers to be certified organic in the United States. First, uncertainty surrounding the legislative environment has given farmers incentives to wait and see until more information about subsidy payments and technical assistance becomes available (Kuminoff and Wossink, 2010). Second, there are psychological and sociological costs of converting to organic farming from peer farmers and family members (Gardebroek, 2006). Once determined to convert to (or start up) organic farming, farmers must go through a three-year transition period during which they are required to practice organic farming but not allowed to sell products as organic. With the typically lower yields during this transition period, the conversion process poses significant financial risk to the farmers.

Securing marketing channels for organically grown commodities is another challenge for organic farmers (Khaledi, et al., 2010, Lohr and Salomonsson, 2000). Furthermore, the profit margins for organic products has diminished due to the recent increase in overall food prices (Fromartz, 2008) and the recession in the U.S. economy (Greene, et al., 2009). Finally, but not the least, organic farming is subject to a greater degree of yield variability than conventional farming due to limited opportunities to prevent crop failures through fertilizer and/or pesticide applications (Gardebroek, 2006). Organic farmers face a number of input constraints as they are not allowed to use synthetic chemicals, antibiotics, genetically modified organisms, and hormones in crop and livestock production (Mayen, et al., 2010).

Organic grains and soybeans are perhaps the most susceptible to these barriers as they are the two of the slowest growing sector in organic farming in the United States (Dimitri and Oberholtzer, 2009). While acres devoted to organic pasture land increased by 220% between 2002 and 2007, organic crop acres increased by only 76%. Moreover, organic soybean acres decreased by 28% from 174,000 acres in 2000 to 125,000 in 2008 (USDA, 2010). This is of great concern, as organic grains and soybeans are crucial inputs for organic dairy and meat products. Organic grain and soybeans production continues to be a bottleneck for the growth of organic farming in the United States (Greene, et al., 2009).

Amid the debate about the unstable and often deficient supply of organic products and the potential barriers to convert to or start-up organic farming, there is one important question that has gathered much less attention so far in the literature: Are organic farmers really economically better off than conventional farmers? Of course, organic farmers can receive higher prices for their organic products and consumers exhibit higher willingness to pay for organic products (Stevens-Garmon, et al., 2007). Empirical evidence also suggests that organic farmers typically obtain positive profit margin (McBride and Greene, 2007, McBride and Greene, 2008). However, U.S. farmers have shown reluctance to converting to organic farming despite the growing demand for organic products in the United States. Furthermore, there is a dearth of academic studies on barriers that may exist to explain such reluctance in the United States (Dimitri and Oberholtzer, 2009). In particular, no empirical evidence has demonstrated that organic farmers are making positive economic profits after taking account for the potentially large opportunity cost of organic farming such as additional labor expenses and forgone off-farm income due to additional labor requirements for the operator on the farm. Herein lies the objective of this study. We empirically examine if farms producing certified organic crops are associated with higher farm household income than conventional farms in the United States. We do so by estimating the average treatment effect of various components of farm household income using the propensity score matching. Due to the nature of the data, the focus of this study is limited to certified organic crop producers and it does not include certified organic livestock producers.

The rest of the paper is organized as follows. In the next section, we review existing studies on factors influencing adoption of organic farming. The third section introduces theoretical motivation of the average treatment effect and the propensity score matching with an emphasis on practical application. The fourth section describes data used in this study, followed by empirical results in the fifth section. The final section offers concluding remarks.

2. Adoption of Organic Farming

In the United States, organic certification is administered by the Department of Agriculture under the National Organic Program established in 2002. Organic certification is mandatory for all farmers and food handlers with at least $5,000 annual sales in organic products. Certification procedure begins with selecting a certifying agency, out of 50 state and private certification programs currently available in the United States. Applicants must go through a three-year transition period during which they are required to practice organic farming but not allowed to sell products as organic.

Organic farming has a longer history and a wider social recognition in Europe than in the United States as European governments have been more active in subsidizing organic farming to promote environmental benefits (Flaten, et al., 2010). Most empirical studies on factors associated with conversion to organic farming are conducted in Europe using a various form of limited dependent variable models.

Burton et al. (1999) estimated a multivariate logit model to identify a range of sociological factors associated with certified organic, non-certified organic and conventional farming for a sample of 237 horticultural producers in the United Kingdom. They found that female operators, awareness toward environmental issues and membership with environmental organizations are positively associated with being certified organic whereas farmers' age was negatively associated with organic farming. Lohr and Salomonsson (2000) employed a probit model to analyze factors that determine the need for government subsidy to convert to organic farming in Sweden. They found that more diversified farms or farms with many sales outlets for organic products do not require subsidy to convert to organic farming. Flaten et al. (2010) examined the characteristics of farmers who had ceased organic operation in Norway using factor analysis and linear regressions. Regulations regarding organic farming and economics reasons were the primary reasons for discontinuing organic production among Norwegian farmers. In a study using panel data from Finnish farms, Pietola and Lansink (2001) used a switching-type Probit model to estimate factors determining the choice between organic and conventional farming. Factors such as input and output prices and subsidy rates influence the probability of converting to organic from conventional. Specialization in either livestock or crop production reduces the likelihood of the conversion as it allows conventional farmers to exploit economies of scale and increase profitability. Finally, Gardebroek (2006) and Flaten, et al. (2005) confirmed the generally held belief that organic farmers are more risk prone than conventional farmers in Netherland and Norway, respectively.

There exists a dearth of quantitative analyses exploring reasons for and barriers to converting to organic farming in the United States and North America. As a few recent exceptions, Khaledi, et al. (2010) estimated a upper-limit Tobit model to identify factors influencing the share of organic acres in the total operated acres, using data from a survey of organic farmers in Canada. Higher satisfaction with marketer functions, less problem in marketing (both of which are measured on a Likert scale), and use of the Internet for marketing positively influence the intensity at which farmers adopt organic production. On the other hand, older farmers, farms with larger total cultivated acres, and longer distance from the farm to cleaning location are associated with lower adoption intensity of organic production. Kuminoff and Wossink (2010) developed a theoretical model to assess the option value to switch to organic farming and employed a switching regression model to shed light on reasons for the slow growth of organic soybean farming in the United States. Uncertainty surrounding profitability of organic farming and sunk cost associated with the conversion were the crucial barrier for U.S. farmers to convert to organic. Finally, MacInnis (2004), using a Tobit and a logit model, examined the effect of transaction cost on the choice of marketing channels for organic and conventional farmers in the United States. The results suggest that lack of marketing channels for organic products can be a significant barrier to entry to organic farming.

The review of literature above sheds light on an important argument that is absent in the existing literature. Few studies, if any, have directly explored economic implications of converting to or starting up certified organic production not just for farm businesses but also for farm households. The latent variable approach adopted in most of the existing studies is based on the random utility framework. The underlying assumption in the random utility framework is that farm operators are rational economic agents who would convert to organic if the net present value of future income stream from certified organic production exceeds that of conventional farming or any other occupational choices available to them. However, non-economic factors can also play an important role in explaining farmers' decision with respect to the conversion to certified organic production especially for those who value land stewardship and the environmental amenity of the farmland. Padel and Lampkin (1994) argued that non-economic factors could be important reasons for converting to organic, especially for early adopters. According to this argument, non-economic factors may have played an important role in the growth of organic farming industry in the United States so far and, if so, the recent slow-down in organic production, especially organic grain production, could be explained by the lack of economic incentives. The potential lack of economic incentives for organic grain production is even more prominent in the United States, due to the presence of genetically modified crop varieties that have become so popular over the last 15 years because of its convenient features (Smith, 2002).

Therefore, the objective of this study is to examine the fundamental assumption of classical economic framework: Are organic farmers really better off than conventional farmers? Our analysis employs the propensity score matching to estimate the average treatment effect of being certified organic crop producers on farm household income and on various components of revenue and cost of production.

3. Average Treatment Effect and Propensity Score Matching

The objective of this study is to estimate the treatment effect of being certified organic crop producers on various components of farm household income. Estimation of "treatment effect" under non-experimental setting has recently become increasingly popular in social science research. There have been a number of reviews on theoretical background (Heckman, et al., 1998, Imbens, 2004, Imbens and Wooldridge, 2009, Morgan and Harding, 2006, Nichols, 2007, Wooldridge, 2001) and practical applications (Abadie, et al., 2004, Baser, 2006, Becker and Caliendo, 2007, Becker and Ichino, 2002, Nannicini, 2007) on this topic as well as some empirical applications in agricultural economics (Liu and Lynch, 2007, Mayen, et al., 2010, Pufahl and Weiss, 2009)

An ideal situation to estimate the average treatment effect is when we can simply compare two outcomes for the same unit when it is assigned to the treatment and when it is not (Imbens and Wooldridge, 2009), or, in the context of this study, a farm's household income when the farm is producing certified organic crops and when it is not. The quantity of interest, the average treatment effect on the outcome variable in the population of interest can be expressed as:

$$ATE = E[Y_1 - Y_0], \tag{1}$$

where Y_1 is the outcome variable with treatment and Y_0 is the outcome variable without treatment. However, a practical problem that arises given a cross sectional dataset is that we can only observe either Y_1 or Y_0, because the assignment to the treatment is mutually exclusive. Thus, estimating the average treatment effect of being a certified organic crop farm on farm household income centers on estimating the counterfactual or imputing missing data (Wooldridge, 2001). That is, it is necessary to estimate farm household income that a certified organic crop farm would have earned if the farm had not been certified organic or farm household income that a conventional farm could have earned had it been certified organic. In this study, we are interested in the former effect or the average treatment effect for the treated (ATT):

$$ATT = E[Y_1 - Y_0 | T = 1], \tag{2}$$

where T is a binary variable that represents the treatment status. $T = 1$ indicates assignment to the treatment and $T = 0$ otherwise.

The biggest challenge in estimating such a causal effect in observational studies is the fact that assignment to treatment is not random. Unlike in an experimental study in which participants can be randomly selected to control and treatment groups, individuals often "self select" into the treatment in most of social science research with observational data. In the context of this study, farmers are not randomly assigned to produce conventionally or organically. Instead, some farmers are more likely to voluntarily choose to obtain organic certification than others. When assignment to the treatment is not random, simply comparing the outcome variable between the two groups ignores some underlying factors that influence both assignment to the treatment and the outcome variable. For example, if farmers' educational attainment is positively correlated with both acquisition of organic certification and farm household income, then the difference in farm household income that may exist between the two groups of farm households may be attributable to both the treatment status, i.e., organic or conventional, and educational attainment. Estimating the average treatment effect without controlling for this sample selection effects leads to a biased estimate.

One special case in which the treatment effect in observational studies can be estimated is when assignment to treatment can be fully explained by observable variables, as in an experimental setting. In such a case, any bias inherent in comparing outcome variable (e.g., farm household income) between the control group (conventional farms) and the treatment group (certified organic crop farms) can be removed by matching observations in the two groups based on observable variables, or covariates. When observations in the treatment group can be matched against observations in the control group that share similar characteristics based on covariates, any difference in the outcome variable that may exist can be assumed to be independent of treatment status. That is,

$$(Y_1, Y_0) \perp T | X = x, \tag{3}$$

where X is a vector of covariates. The implication of equation (3) is that any remaining difference in the outcome variable can be solely attributed to the treatment status (Imbens, 2004) and assignment to the treatment can be considered purely random among observations with similar observable characteristics (Becker and Ichino, 2002). This assumption is termed in various ways, such as "ignorability" (Wooldridge, 2001), "selection on observables" (Fitzgerald, et al., 1998), and "unconfoundedness" (Imbens, 2004, Rosenbaum and Rubin, 1983).

A practical challenge remains as to how observations in two groups can be matched with each other. Even with a large sample, it becomes extremely unlikely to have multiple observations with identical values of k covariates especially when one or more of k variables are continuous. Rosenbaum and Rubin (1983) proposed the propensity score, which is a conditional probability of being in the treatment:

$$p(X) = Prob(T = 1 | X = x) = E(T = 1 | X = x), \tag{4}$$

where $p(X)$ in equation (4) can be obtained by a standard probit or logit model. An important feature of the propensity score in equation (4) is that it summarizes information contained in k-dimentional vector into a single-index variable (Becker and Ichino, 2002). It is important to note that the unconfoundedness assumption in equation (3) is not a testable hypothesis (Becker and Ichino, 2002). What is testable instead is the balancing property:

$$T \perp X | \, p(X) \tag{5}$$

When equation (5) is satisfied, assignment to treatment is random for observations with the same propensity score (See Becker and Ichino, 2002 for more detail). With the two assumptions in equations (3) and (4), Rosenbaum and Rubin (1983) proved that the unconfoundedness assumption in equation (3) can be rewritten as:

$$(Y_1, Y_0) \perp T | p(X). \tag{6}$$

That is, potential outcomes, Y_1 and Y_0, are independent of treatment status, given the propensity score. When equation (6) holds, we have

$$E[Y_0 | T = 1, X] = E[Y_0 | T = 0, X]. \tag{7}$$

The left hand side of equation (7) is the counterfactual, i.e., the population average of the outcome variable which the treated units *would have obtained* if they had not been in the treatment, conditional on covariates. Equation (7) implies that the counterfactual on the left hand side can be estimated by the population average of the outcome variable for the controlled units, again, conditional on covariates.

Observations in the control and treatment groups can be matched according to the propensity score. Because it is infeasible to find an exact match in terms of $p(X)$ for every treated observation, a number of matching procedure has been proposed in literature, including Nearest-Neighbor Matching, Radius Matching, and Kernel Matching (Becker and Ichino, 2002). It is important to note that propensity score matching does not eliminate the selection bias due to unobservable factors that explain assignment to treatment, but it only reduces it (Becker and Ichino, 2002). Also note that there is no *a priori* superior matching method and different matching estimator could obtain different results. In this study, we present results from Nearest-Neighbor Matching proposed by Abadie et al. (2004) and estimate the average treatment effect for the treated with a varying number of matches because it "provides may options for fine-tuning the estimators" (Abadie, et al., 2004)[1].

The estimator for the average treatment effect for the treated is given as:

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[1] Results from Radius Matching and Kernel Matching suggested in Becker and Ichino (2002) are available upon request.

$$ATT = \frac{1}{N_1} \sum_{i:T_i=1}^{N} \left[Y_i - \widehat{Y_{0\iota}}\right], \tag{8}$$

where N_1 is the number of observations in the treatment and the subscript, i, represents individual observations. While Y_i is the observed outcome variable for □th individual, $\widehat{□_{0□}}$ are not observed and given as follows:

$$\widehat{Y_{0\iota}} = \begin{cases} Y_i & \text{if } T_i = 0 \\ \dfrac{1}{M} \displaystyle\sum_{m \in M_i} Y_m & \text{if } T_i = 1 \end{cases} \tag{9}$$

where $M$is the number of matched observation and M_i is the set of observations in the control group matched to ith observation in the treatment. $\widehat{Y_{0\iota}}$ if $T_i = 1$ is simply a weighted average of the outcome variable for all matched observations in the control group.

The estimation of the average treatment effect using the propensity score matching is considered a nonparametric approach as researchers can avoid assumptions common in regression models. First, we do not have to specify a functional form of the dependent variable. In a standard regression setting, we implicitly assume that the dependent variable can be specified as a linear combination of a set of independent variables, including some quadratic terms and interaction terms. In production economics, researchers often choose a specific functional form (e.g., Cobb-Douglas, trans-log, etc.) that is conforming to the theoretical expectation in a given context. However, the average treatment effect estimator using the propensity score matching does not require such an assumption. Second, it also does not require any distributional assumption (Wooldridge, 2001). For example, in the standard least square model, a very restrictive but almost blindly accepted assumption is that conditional distributions of the dependent variable are identical at any values of the covariates except for the means, which are to be estimated by the least square method[2]. For all conditional distributions of the dependent variable given the covariates, variances, skewness and kurtosis are assumed to be identical. However, the estimators of the average treatment effect are free from any kind of distributional assumptions.

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[2] Of course, least squares method can be extended to Generalized Least Squares method to handle heterogeneous variances in conditional distributions, i.e, heteroskedasticity.

4. Data

This study primarily utilizes data obtained from the 2008 Agricultural Resource Management Survey (ARMS), developed by the Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS). The 2008 ARMS queried farmers on all types of financial, production, and household activities. The ARMS is also used to determine production costs and returns of agricultural commodities and measures net farm income of farm businesses. Another aspect of ARMS's important contribution is the information it provides on the characteristics and financial conditions of farm households, including information on input and risk management strategies and off-farm income.

ARMS uses a multi-phase sampling design and allows each sampled farm to represent a number of farms that are similar in the population, the number of which being the survey expansion factor (Dubman, 2000). The expansion factor, in turn, is defined as the inverse of the probability of the surveyed farm being selected. The survey collects data to measure the financial conditions and operating characteristics of farm businesses, the cost of producing agricultural commodities, and the well-being of farm operator households.

Operators associated with farm businesses representing agricultural production across the United States are the target population in the survey. USDA defines farm as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year. Farms can be organized as sole proprietorships, partnerships, family corporations, nonfamily corporations, or cooperatives. For the purpose of this study, operator households organized as nonfamily corporations or cooperatives were excluded. We also excluded farms whose total value of crop sales is less than $5,000 considering the facts that farms with less than $5,000 of organic sales are not required to be certified organic and that the 2008 ARMS data only collects information about certified organic crop production. We have 2,689 observations in this study after these omissions.

In addition to the 2008 ARMS data, we utilize two more variables obtained from obtained from 2007 Census of Agriculture. We use the sum of average acres under and in transition to certified organic production at the county level. This variable is used to capture the peer effect on converting to certified organic production, mentioned in Gardebroek (2006). We also use the median household income at the county level to approximate regional demand for organically produced commodities.

Table 1 provides the definitions of the variables used in our analysis and the mean values for the entire sample, certified organic crop farms and conventional farms. Of 2,689 observations, only 65 of them (or 2.4% of the entire sample) produced certified organic crops in 2008. The last column shows t-test statistic that compares means of the treated and the control observations. For example, relative to conventional farmers, certified organic crop farmers, on average, tend to engage in farming as a primary occupation, possess a more diverse portfolio of enterprises but less likely to grow genetically modified crops and receive government payments. While there are no statistically significant differences between the two groups in terms of uses of marketing and production contacts, organic farmers are more likely to use roadside stores, farmers markets, Community Supported Agriculture (CSA), regional distributors, state branding programs, and direct sales to local grocery stores, restaurants or other retailers as direct marketing outlets. Note that the t-test statistics simply compares the means of each variable for both organic and conventional farmers without controlling for any underlying factors. The purpose of using the propensity score matching is to overcome this issue and estimate the causal effect of the treatment variable on the outcome variable.

5. Empirical Results

Propensity Score Estimation

Conditional probability of growing certified organic crops is estimated by a probit model. Table 2 reports parameter estimates for the model. The set of independent variables used in the model represents the vector of covariates, □, in equations 3 through 7. The variables are selected based on empirical findings in the literature. To represent the farm operator's characteristics, we include operator's years of formal education, primary occupation, and age. We expect that more educated and younger farmers whose primary occupation is farming have higher probability of being certified organic. Farm characteristics included are the entropy index of enterprise diversification, a dummy variable for growing genetically modified crops, total operated acres, debt to asset ratio, a dummy variable for seeking advice from the Natural Resource Conservation Service (NRCS) and a dummy variable for receiving government payments.

Considering the importance of marketing outlets for organic products in the existing literature, we included dummy variables for using marketing contracts, production contracts, and several direct marketing strategies. Direct marketing strategies include use of roadside stores, farm stores, farmers markets, Community Supported Agriculture (CSA), regional distributors, state branding programs, and direct sales to local grocery stores, restaurants, and other retail stores. Use of any of the above marketing strategies is expected to positively influence the decision to convert to or start-up certified organic crop production. High-value crop farms and farms with an Internet connection are expected to be positively associated with having organic certification. To capture potentially heterogeneous impacts of geographical location of the farm, we included dummy variables for farms located in urban and rural counties as well as for five production regions defined by National Agricultural Statistical Service (USDA, 2010). Finally, we make use of two county-level statistics obtained from the 2007 Census of Agriculture. First, we include the number of acres under or in transition to certified organic production. We expect this variable to have a positive impact on the probability of being certified organic; a larger presence and a wider social acceptance of organic farmers in a county should positively influence the decision to be a certified organic farm. Second, we include the county-level median household income to represent purchasing power and demand for organically produced commodities. This variable is also expected to have a positive sign to the extent that organically produced commodities are sold and consumed locally.

The estimated probit model satisfied the balancing property in equation (5) using the algorithm detailed in Becker and Ichino (2002). The likelihood ratio statistics of 122.23 suggests that the estimated model is statistically significant at the 1 percent level. We briefly review the results here. More educated operators and operators whose primary occupation is farming are more likely to be certified organic crop farmers. As expected, farmers growing genetically modified crop corn, soybeans, wheat or cotton are less likely to produce other types of crops with organic certification. Farms that have production contract or sells their commodities through Community Supported Agriculture or regional distributors are positively associated with certified organic crop production. High-value crops farms are also more likely to be certified organic. Farmers in the Atlantic, South and Plains regions are less likely to be certified organic, relative to the West region, which includes states such as California, where organic farming has been very popular. The county average acres under or in transition to certified organic production have a positive coefficient, supporting our expectation about the peer-effect that farmers surrounded by more organic farmers are more likely to convert to certified organic.

The Average Treatment Effect for the Treated

Predicted probability of producing certified organic crops are obtained from the probit model and used as the propensity score to facilitate matching of observations in the treated group against those in the control group. Nearest-Neighbor matching estimator developed by Abadie, et al. (2004) allows users to specify the number of matches, m, for each treated observation. The choice of an appropriate m requires a trade-off. For instance, when $m = 1$, each treated observation is matched with an observation in the control group with the closest propensity score, however, any unmatched observations in the treatment are discarded. When m is larger, on the other hand, more observations can be utilized, but the quality of match may have to be compromised. We estimate the average treatment effect using $m = 1, \cdots 5$. The results in Table 3 shows that, for all the variables for which the ATT is estimated, the choice of m does not influence statistical significance, indicating robustness of the estimated ATT.

Table 3 lists the estimated average treatment effect of certified organic crop production on total farm household income, total off-farm income, gross cash farm income, total production expenses, and various components of production expenses. The average treatment effect for the treated (ATT) on farm household income is positive for all $m = 1, \cdots 5$, but the estimates are not significant even at 10 per cent level. Contrary to the general assumption of profit maximization in many economic analyses, there is no statistically significant difference in terms of farm household income between certified organic crop farms and conventional farms in the United States. The absence of economic profit from certified organic crop production in terms of farm household income indicates that there are some important non-pecuniary reasons to drive farmers to convert to or establish certified organic crop production. The result here is in accordance with the argument put forth by Padel and Lampkin (1994) that factors such as land stewardship and concerns for environmental conditions of the farmland can be important motivations for early adopters of organic farming.

The ATT on off-farm income is also insignificant for all $m = 1, \cdots 5$, indicating that there is no significant difference in off-farm income that can be attributable to treatment status. Because organic farming is often considered more labor intensive, it may be reasonable to surmise that conventional farmers earn higher off-farm income. However, no such difference is detected at a statistically significant level once we match certified organic crop famers with conventional farmers who are equally committed to farm operation.

Certified organic crop farmers earn significantly higher gross cash farm income than conventional farmers, but they also incur significantly higher production costs. The ATT on gross cash farm income ranges from \$1 to \$1.4 million while the ATT on total production expenses is between $885,000 and $1 million. Even though certified organic crop farmers make significantly higher revenue relative to conventional farmers, a majority of revenue margin is explained by higher production cost, which is consistent with the fact that the ATT on farm household income is not significant. Given the fact that certified organic farmers incur much higher production costs than conventional farmers, we estimate the ATT on various components of production costs to delineate different cost structures that may exist between certified organic and conventional farmers. While the ATT on chemical and fertilizer expenses is not significant for all $m = 1, \cdots 5$, the ATT for labor expenses, insurance expenses and marketing charges are all positive and significant. The point estimates of the ATT indicate that certified organic farmers on average spend $310,000 to $361,000 more on labor, of which $230,000 to $300,000 are explained by cash wages paid to hired farm workers, not including custom works. Certified organic crop farmers also pay $8,000 to $12,000 more for insurance programs, relative to conventional farmers. This confirms the view that organic production poses more risk and uncertainty to farmers (Gardebroek, 2006). Even though organic farmers are more risk prone than conventional farmers (Flaten, et al., 2005, Gardebroek, 2006), certified organic producers are actively hedging risks by spending more on insurance programs. Finally, certified organic crop farmers, on average, pay somewhere between $110,000 and $120,000 more for marketing services than conventional farmers. The existing literature often pronounce the importance of securing sales outlets for organically produced commodities and the lack thereof as a potential barrier to converting to organic (Greene, et al., 2009, Khaledi, et al., 2010, Lohr and Salomonsson, 2000, MacInnis, 2004). Additional financial burden of more than $110,000 that certified organic farmers choose to bear attests to the significant marketing risks certified organic farmers face in the United States.

6. Conclusion

Although organic farming has been one of the most thriving segments in the U.S. farm sector over the last decade (Kuminoff and Wossink, 2010), consumers of organic products recently witnessed periodic shortages of organic products. There is a dearth of academic studies on barriers that may exist to explain barriers to converting to or establishing certified organic production in the United States (Dimitri and Oberholtzer, 2009). The objective of this study was to examine if organic farmers were really better off than conventional farmers, in an effort to explore reasons for the relatively low adoption rate of organic farming in the United States (Kuminoff and Wossink, 2010). Instead of the conventional parametric regression method, we employed a nonparametric approach and used the propensity score matching method to estimate the average treatment effect of being certified organic crop farms on farm household income, off-farm income, farm revenue, and various components of production costs. The propensity score matching method allowed us to estimate the marginal effect of being certified organic crop producers on various components of farm household income without specifying functional forms or making distributional assumptions about the conditional distribution of the dependent variables.

Our findings suggest that organic crop farmers are not significantly better off in terms of farm household income. Even though the average gross cash income for certified organic crop farms is approximately $1 million higher than that for conventional farms, they also incur significantly higher production costs, which explains at least about 60% of the extra revenue they receive relative to conventional farms. Most of the additional cost for organic farming is explained by labor cost, insurance expenses and marketing charges. Organic farms on average pays $310,000 to $361,000 more on labor, of which $230,000 to $300,000 are explained by cash wages paid to hired farm workers, not including custom works. Despite the finding that organic farmers are more risk prone than conventional farms, our findings suggest that they are very active in hedging greater risk and uncertainty inherent in organic farming. Insurance expenses are up to $12,000 per year higher for organic farms than conventional farms. Organic farms pays up to $120,000 more for marketing charges than conventional farms.

Finally, it is important to note that the additional production expenses that certified organic crop producers must bear do not include potentially very large fixed cost of converting to certified organic production. Given the fact that most of the government subsidy for certified organic producers is currently directed toward conversion costs, we suggest that more policy efforts be made to provide support for covering the additional variable cost such as insurance payments and marketing charges to hedge extra risk and uncertainty inherent in organic farming.

References

Abadie, A., D. Drukker, J.L. Herr, and G.W. Imbens. 2004. "Implementing matching estimators for average treatment effects in Stata." *Stata Journal* 4(3):290-311.

Baser, O. 2006. "Too Much Ado about Propensity Score Models? Comparing Methods of Propensity Score Matching." *Value in health : the journal of the International Society for Pharmacoeconomics and Outcomes Research* 9(6):377-385.

Becker, S.O., and M. Caliendo. 2007. "Sensitivity analysis for average treatment effects." *Stata Journal* 7(1):71-83.

Becker, S.O., and A. Ichino. 2002. "Estimation of average treatment effects based on propensity scores." *Stata Journal* 2(4):358-377.

Burton, M., D. Rigby, and T. Young. 1999. "Analysis of the Determinants of Adoption of Organic Horticultural Techniques in the UK." *Journal of Agricultural Economics* 50(1):47-63.

Dimitri, C., and L. Oberholtzer. 2009. "Marketing U.S. Organic Foods: Recent Trends from Farms to Consumers." *United States Department of Agriculture Economic Information Bulletin* 58.

Dubman, R.W. (2000) Variance estimation with USDA's farm costs and returns surveys and Agricultural Resource Management Study surveys., vol. no. AGES 00-01, U.S. Department of Agriculture. Economic Research Service, Resource Economics Division., pp. U.S. Department of Agriculture. Economic Research Service, Resource Economics Division.

Fitzgerald, J., P. Gottschalk, and R. Moffitt. 1998. "An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics." *The Journal of Human Resources* 33(2):251-299.

Flaten, O., G. Lien, M. Koesling, and A.-K. Løes. 2010. "Norwegian farmers ceasing certified organic production: Characteristics and reasons." *Journal of Environmental Management* 91(12):2717-2726.

Flaten, O., G. Lien, M. Koesling, P.S. Valle, and M. Ebbesvik. 2005. "Comparing risk perceptions and risk management in organic and conventional dairy farming: empirical results from Norway." *Livestock Production Science* 95(1-2):11-25.

Fromartz, S. (2008) Rising prices hit the organic supply chain.

Gardebroek, C. 2006. "Comparing risk attitudes of organic and non-organic farmers with a Bayesian random coefficient model." *European Review of Agricultural Economics* 33(4):485-510.

Greene, C., C. Dimitri, B.-H. Lin, D.W. McBride, L. Oberholtzer, and T. Smith (2009) Emerging Issues in the U.S. Organic Industry, vol. No. (EIB-55) 36 pp, USDA Economic Research Service.

Greene, C.R., E. Slattery, and D.W. McBride. 2010. "America's Organic Farmers Face Issues and Opportunities." *Amber Waves* 8(2):34-39.

Heckman, J.J., H. Ichimura, and P. Todd. 1998. "Matching as an Econometric Evaluation Estimator." *The Review of Economic Studies* 65(2):261-294.

Imbens, G.W. 2004. "NONPARAMETRIC ESTIMATION OF AVERAGE TREATMENT EFFECTS UNDER EXOGENEITY: A REVIEW." *Review of Economics & Statistics* 86(1):4-29.

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

Khaledi, M., S. Weseen, E. Sawyer, S. Ferguson, and R. Gray. 2010. "Factors Influencing Partial and Complete Adoption of Organic Farming Practices in Saskatchewan, Canada."

Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 58(1):37-56.
Kuminoff, N.V., and A. Wossink. 2010. "Why Isn't More US Farmland Organic?" *Journal of Agricultural Economics* 61(2):240-258.
Liu, X., and L. Lynch. 2007. "Do Agricultural Preservation Programs Affect Farmland Conversion?" Paper presented at Agricultural and Applied Economics Association, 2007 Annual Meeting, July 29-August1, Portland, OR.
Lohr, L., and L. Salomonsson. 2000. "Conversion subsidies for organic production: results from Sweden and lessons for the United States." *Agricultural Economics* 22(2):133-146.
MacInnis, B. 2004. "Transaction Costs and Organic Marketing: Evidence from U.S. Organic Produce Farmers." Paper presented at American Agricultural Economics Assocation Annual Meeting, August 1-4, Denver, Colorado.
Mayen, C.D., J.V. Balagtas, and C.E. Alexander. 2010. "Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States." *American Journal of Agricultural Economics* 92(1):181-195.
McBride, W.D., and C.R. Greene. 2007. "A Comparison of Conventional and Organic Milk Production Systems in the U.S." Paper presented at American Agricultural Economics Association. 2007 Annual Meeting. July 29-August 1, 2007, Portland, Oregon.
---. 2008. "The Profitability of Organic Soybean Production." Paper presented at American Agricultural Economics Association, 2008 Annual Meeting. July 27-29, 2008, Orlando, Florida.
Morgan, S.L., and D.J. Harding. 2006. "Matching Estimators of Causal Effects." *Sociological Methods & Research* 35(1):3-60.
Nannicini, T. 2007. "Simulation-based sensitivity analysis for matching estimators." *Stata Journal* 7(3):334-350.
Nichols, A. 2007. "Causal inference with observational data." *Stata Journal* 7(4):507-541.
O'Riordan, T., and D. Cobb. 2001. "Assessing the Consequences of Converting to Organic Agriculture." *Journal of Agricultural Economics* 52(1):22-35.
Padel, S., and N.H. Lampkin (1994) Conversion to Organic Farming: An Overview, ed. N.H. Lampkin, and S. Padel. Oxon, UK, CAB International, pp. 295-313.
Pietola, K., and A. Lansink. 2001. "Farmer response to policies promoting organic farming technologies in Finland." *European Review of Agricultural Economics* 28(1):1-15.
Pufahl, A., and C.R. Weiss. 2009. "Evaluating the effects of farm programmes: results from propensity score matching." *European Review of Agricultural Economics*.
Rosenbaum, P.R., and D.B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70(1):41-55.
Smith, K.R. (2002) Does Off-Farm Work Hinder 'Smart' Farming?, U.S. Department of Agriculture Economic Research Service., pp. 28-30. U.S. Department of Agriculture Economic Research Service.
Stevens-Garmon, J., C.L. Huang, and B.-H. Lin (2007) Organic Demand: A Profile of Consumers in the Fresh Produce Market, vol. 22, The American Agricultural Economic Association, pp. 109-116.
U.S. Department of Agriculture. (2007). "2007 Census of Agriculture". National Agricultural Statistics Service. Available at http://www.agcensus.usda.gov Retrieved March20, 2011.
U.S. Department of Agriculture. 2010. "National Organic Program" Available at http://www.ams.usda.gov/AMSv1.0/nop Retrieved March 20, 2011.
U.S. Department of Agriculture. 2010. "ARMS III Farm Production Regions Map." Economic Research Service, U.S. Department of Agriculture, Washington, D.C. Available at

http://www.nass.usda.gov/Charts_and_Maps/Farm_Production_Expenditures/reg_map_c.asp Retrieved January 10, 2011.

Wooldridge, J.M. 2001. *Econometric Analysis of Cross Section and Panel Data*. 1 ed: The MIT Press.

Table 1: Variable Definitions and Summary Statistics

Variable Definitions	Mean: Entire Sample	Mean: Conventional	Mean: Certified Organic	T-score	
Certified Organic (=1 if yes, 0 otherwise)	0.02	0.00	1.00		
Operator's years of formal education	13.62	13.60	14.43	-0.00	
Primary occupation (=1 if farming, 0 otherwise)	0.88	0.87	0.95	1.94	*
Operator's age	55.30	55.30	55.29	-0.00	
Entropy index of diversification (1 is completely diversified, 0 is not diversified at all)	0.01	0.01	0.02	-2.01	**
Genetically Modified Crops (=1 if farm grows GM crops, 0 otherwise)	0.54	0.55	0.18	-5.85	***
Total acres in operation	1,750.26	1,765.50	1,108.26	-1.55	
Debt to asset ratio	0.34	0.34	0.17	-0.14	
NRCS (=1 if farm seeks advice from Natural Resource	0.13	0.13	0.15	0.46	
Government Payment (=1 if farm receives government payments, 0 otherwise)	0.72	0.72	0.55	-2.99	***
Marketing contracts (=1 if used, 0 otherwise)	0.47	0.47	0.43	-0.71	
Production contracts (=1 if used, 0 otherwise)	0.09	0.09	0.12	0.97	
Roadside stores (=1 if used, 0 otherwise)	0.05	0.05	0.14	3.25	***
Farm stores (=1 if used, 0 otherwise)	0.04	0.04	0.08	1.48	
Farmers markets (=1 if used, 0 otherwise)	0.04	0.03	0.12	3.92	***
Community Supported Agriculture (=1 if used, 0 otherwise)	0.00	0.00	0.03	4.20	***
Regional distributors (=1 if used, 0 otherwise)	0.02	0.02	0.12	5.77	***
State Branding Program (=1 if used, 0 otherwise)	0.01	0.01	0.03	2.06	**
Direct sales to local grocery stores, restaurants or other retailers (=1 if used, 0 otherwise)	0.06	0.05	0.15	3.47	***
Urban (=1 if the farm located in urban county, 0 otherwise)	0.47	0.47	0.40	-1.13	
Rural (=1 if the farm located in rural county, 0 otherwise)	0.09	0.09	0.03	-1.67	*
Internet (=1 if farm has an Internet connection, 0 otherwise)	0.79	0.79	0.88	1.78	*
High-value crops farm (=1 if farm is classified as high-value crops farm, 0 otherwise)	0.24	0.23	0.60	6.84	***
Atlantic region (=1 if farm is located in Atlantic region)	0.17	0.17	0.18	0.25	
South region (=1 if farm is located in South region)	0.15	0.15	0.03	-2.66	***
Midwest region (=1 if farm is located in Midwest region)	0.29	0.30	0.17	-2.24	**
Plains region (=1 if farm is located in Plains region)	0.18	0.19	0.05	-2.92	***
West region (=1 if farm is located in West region)	0.20	0.19	0.57	7.51	***
Total acres under organic production in county	18.76	21.46	75.31	8.85	***
Median Household Income in county ($ per year)	45,346	45,651	49,638	2.98	***
Total Household Income ($ per year)	209,565	208,407	258,340	0.62	
Total Off-farm Income ($ per year)	35,470	35,721	24,915	-0.80	
Gross Cash Income ($ per year)	1,261,368	1,228,580	2,643,018	3.92	***
Total Cost of Production ($ per year)	789,310	762,191	1,932,063	4.42	***

Cash wage ($ per year)	155,615	146,302	548,056	4.99	***
Total labor expenses ($ per year)	205,475	192,960	732,825	5.26	***
Contract labor expenses ($ per year)	22,536	20,900	91,447	3.25	***
Insurance expenses ($ per year)	30,997	30,989	31,364	0.05	
Marketing Charges ($ per year)	29,124	26,371	145,117	6.13	***
Number of observations	2,689	2,624	65		

Table 2: Probit Model Parameter Estimates

Variables	coefficient	standard errors	p-value
Operator's years of formal education	0.082	0.036	0.024
Primary occupation	0.508	0.261	0.051
Operator's age	-0.005	0.005	0.332
Entropy index of diversification	2.113	2.072	0.308
Genetically Modified Crops	-0.487	0.186	0.009
Total acres in operation	0.000	0.000	0.263
Debt to asset ratio	0.000	0.016	0.992
NRCS	0.099	0.171	0.560
Government Payment	0.234	0.171	0.171
Marketing contracts	0.105	0.134	0.433
Production contracts	0.377	0.192	0.049
Roadside stores	0.171	0.241	0.477
Farm stores	-0.183	0.258	0.480
Farmers markets	0.361	0.258	0.161
Community Supported Agriculture	0.982	0.571	0.086
Regional distributors	0.596	0.262	0.023
State Branding Program	0.028	0.466	0.952
Direct sales to local grocery stores, restaurants or	0.076	0.229	0.739
Urban	0.188	0.150	0.211
Rural	-0.003	0.320	0.992
Internet	0.029	0.189	0.878
High-value crops farm	0.302	0.168	0.073
Atlantic region	-0.329	0.186	0.078
South region	-0.813	0.303	0.007
Midwest region	-0.325	0.199	0.102
Plains region	-0.566	0.255	0.027
Total acres under organic production in county	0.002	0.001	0.013
Median Household Income in county ($ per year)	0.000	0.000	0.487
Constant	-3.660	0.740	0.000
Number of Observations = 2,689		LR test statistic =122.3	
Log-likelihood=-245.057		P-value (LR=0)<0.00	

Table 3: Estimates of the Average Treatment Effect for the Treated (ATT)

Variable	Number of matches (m)	ATT	standard error	p-value
Total Household Income	1	126,279	129,374	0.33
	2	97,512	91,917	0.29
	3	52,109	99,952	0.60
	4	52,112	89,605	0.56
	5	29,922	86,940	0.73
Off-farm Income	1	374	12,346	0.98
	2	1,196	12,896	0.93
	3	727	12,637	0.95
	4	-1,647	12,386	0.89
	5	-1,004	12,572	0.94
Gross cash farm income	1	1,419,264	732,068	0.05
	2	1,322,389	654,926	0.04
	3	1,174,434	649,759	0.07
	4	1,167,293	608,967	0.06
	5	1,043,621	595,396	0.08
Total production expenses	1	1,028,366	528,706	0.05
	2	1,055,155	515,823	0.04
	3	982,724	522,926	0.06
	4	999,293	504,467	0.05
	5	885,084	500,464	0.08
Fertilizer and chemical expenses	1	173,358	171,044	0.31
	2	191,112	162,386	0.24
	3	155,037	166,241	0.35
	4	169,641	161,788	0.29
	5	156,078	159,847	0.33
Labor expenses	1	361,500	194,146	0.06
	2	381,912	179,552	0.03
	3	375,262	181,661	0.04
	4	356,794	172,416	0.04
	5	305,352	171,709	0.08
Cash wages	1	292,514	149,747	0.051
	2	302,029	143,712	0.036
	3	301,123	143,944	0.036
	4	271,409	135,777	0.046
	5	230,613	138,807	0.097
Insurance expenses	1	10,696	5,811	0.07
	2	12,099	5,750	0.04
	3	12,219	6,007	0.04
	4	12,439	5,989	0.04
	5	8,485	5,750	0.14
Marketing Charges	1	126,983	56,984	0.03
	2	124,390	56,376	0.03
	3	120,260	56,641	0.03
	4	118,601	56,451	0.04
	5	111,907	57,399	0.05