Does Agritourism Enhance Farm Profitability?

Brian J. Schilling[a]

Witsanu Attavanich[b]

Yanhong Jin[c]

[a] Assistant Extension Specialist, Department of Agricultural, Food & Resource Economics and Rutgers Cooperative Extension, Rutgers University, 108 Cook Office Building, 55 Dudley Road, New Brunswick, NJ, 08901, USA. E-mail: schilling@njaes.rutgers.edu

[b] Lecturer, Department of Economics, Faculty of Economics, Kasetsart University, 50 Phahonyothin Road, Chatuchak, Bangkok, Thailand, 10900. E-mail: attavanich.witsanu@gmail.com

[c] Associate Professor, Department of Agricultural, Food & Resource Economics and Rutgers Cooperative Extension, Rutgers University, Cook Office Building, 55 Dudley Road, New Brunswick, NJ, 08901, USA. E-mail: yjin@aesop.rutgers.edu

Corresponding Author

Correspondence concerning this article may be addressed to: Dr. Witsanu Attavanich, Lecturer, Department of Economics, Faculty of Economics, Kasetsart University, 50 Phahonyothin Road, Chatuchak, Bangkok, Thailand, 10900. Office phone: (66) 2-561-3474 ext. 211. E-mail: attavanich.witsanu@gmail.com

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Abstract

Impacts of agritourism on farm profitability are poorly understood. Using Census of Agriculture records, we employ propensity score matching to estimate the effects of agritourism on the net cash income per acre of New Jersey farms. We find that agritourism has statistically significant and positive effects on farm profitability. Profit impacts are highest among small farms operated by individuals primarily engaged in farming. Positive but smaller effects are observed for lifestyle farms. Profit effects among larger farms are not statistically significant.

JEL CLASSIFICATIONS: **Q12, Q13**

Key words: agritourism, direct-to-consumer marketing, farm profitability, propensity score matching

Highlights:

- Agritourism is found to generally enhance profitability of New Jersey farms.
- Profitability impacts associated with agritourism are heterogeneous across farm types.
- The effect is highest for intermediate-scale farms, followed by life-style farms.
- No statistically significant profit effects are evident among commercial farms.
- The size of agritourism effect on farm profitability depends on the definition of agritourism.

1. Introduction

Sociological research consistently identifies economic motives as important drivers of agritourism development (Nickerson, Black and McCool, 2001; McGehee and Kim, 2004; Ollenburg and Buckley, 2007; McGehee, Kim and Jennings, 2007; Tew and Barbieri, 2012; Barbieri, 2013). These economic objectives may include increasing income generation from existing farm resources, diversifying farm revenue streams, expanding marketing and farm brand awareness, and smoothing seasonal fluctuations in farm revenue that are customary in many forms of agriculture (Nickerson et al., 2001; Schilling, Sullivan and Komar, 2012). Other motivations behind agritourism adoption often include familial goals, social objectives, and personal entrepreneurial goals (Nickerson et al., 2001; Tew and Barbieri, 2012).

Economic research on U.S. agritourism remains surprisingly thin and the implications of incorporating farm-based recreation and education activities for the profitability of farming remain ambiguous. Some studies conclude that agritourism provides only nominal financial returns to farms (e.g., Busby and Rendle 2000; Oppermann, 1995), while others suggest that these activities are having more substantial farm income effects (Barbieri, 2013; Schilling et al., 2012). These divergent conclusions drive Tew and Barbieri (2012) to find existing research on the economic benefits of agritourism to be inconclusive. However, existing assessments of the income impacts of agritourism are not based on direct empirical observation, but rather rely on qualitative farm operator assessments of how agritourism has affected farm profitability.

Parsing out the effects of agritourism on farm income is challenging for several reasons. First is the limited data on this sector of agriculture. The National Agricultural Statistics Service has collected information on agritourism in only the last two Censuses of Agriculture (2002 and 2007) and employs a rather narrow definition (Schilling et al., 2012). It is well recognized that the lack of a consistent definition of "agritourism" and similarly variable nomenclature combine as an impediment to comprehensive research on the sector because of data variability across studies (Oppermann, 1995; Busby and Rendle, 2000; McGehee and Kim, 2004; Phillip, Hunter, and Blackstock, 2010; Arroyo, Barbieri, and Rich, 2013). Further, limited information on the population characteristics of U.S. agritourism farms hinders the construction of sampling frames necessary to conduct statistically reliable survey research capable of supporting generalizations about this sector of agriculture (Veeck, Che and Veeck, 2006; Schilling et al., 2012).

In addition, there exist myriad reasons, both financial and non-financial, that farmers have for farming generally and developing agritourism enterprises more specifically. These reasons have been found to vary across farm types and scales, operator characteristics, and geography (see, for example, Nickerson et al., 2001 and Ollenburg and Buckley, 2007). These reasons may also change over an operator's life cycle (Ollenburg and Buckley, 2007). For example, the phenomenon of individuals retiring into farming is not uncommon in the U.S. (Kirkpatrick, 2013). These retirement farmers may seek nominal income from relatively less intense farming activities, prioritizing lifestyle benefits over economic rewards. In contrast, other farm operators may seek higher economic returns from agritourism to compensate for low agricultural returns without the need to secure off-farm employment, support multiple generations within the farm family, or facilitate farm succession (Fleischer and Tchetchik, 2005; Veeck et al., 2006; Barbieri, 2013). Failure to account for the heterogeneity of purposes and motives individuals have for incorporating agritourism within farm operations can muddle efforts to document the economic importance of farm-based recreational and educational activities.

Lastly, there exists a strong likelihood of self selection effects that need to be addressed. Comparison of the profitability of farms offering agritourism with the profitability of farms that do not is too simplistic because it fails to consider the real possibility that farms that do participate are systematically different from those that do not. Consider the possibility that only the "best" farm operators (e.g., those possessing high entrepreneurial skill or marketing acumen) decide to engage in agritourism. Is it the innate aptitude of these highly skilled farm operators that drives profitability, or is it the actual engagement in agritourism itself? If not addressed, self-selection will result in biased estimates of the agritourism effect on the economic performance of farms.

The objective of this study is to examine the effect of agritourism on the profitability of New Jersey farms using 2007 Census of Agriculture data. We empirically evaluate the profitability of New Jersey agritourism farms against the financial performance of observationally equivalent non-agritourism farms. Net cash income per acre is used to measure farm profitability. We define two treatments that reflect the Census of Agriculture definition of "agri-tourism and recreational services" and a broader measure which expands this definition to also include direct marketing of farm products. The propensity score matching approach (Rosenbaum and Rubin, 1983) is used to address the issue of self selection and control for inherent differences (e.g., scale of operation, commodities produced, operator characteristics) between farms that offer agritourism and observationally equivalent farms not offering agritourism. Importantly, we stratify farms using a modified Economic Research Service farm typology to evaluate differentials in profitability impacts across lifestyle and retirement farms and those operated by persons for whom farming is a primary occupation. The latter category of farms is further bifurcated into intermediate (less than $250,000 in annual farm sales) and commercial (at least $250,000 in sales) size classes. Implications for agricultural retention and development policy are discussed.

2. Motivations for Agritourism Enterprise Development

Global market factors, rising input costs, unstable prices, domestic policy changes, and urbanization pressures continue to squeeze farm incomes in the United States. As a result, many small farm operators pursue strategies outside of traditional farm production to meet farm household financial objectives. Farmers for whom an exit from farming is undesirable may, for example, allocate more time to off-farm employment or diversify and expand farm-based revenue. Vogel (2012) finds that 13 percent of U.S. farm households are engaged in on-farm diversification activities, within which agritourism may be classified. These same farms produce nearly one-quarter of the total value of national farm production.

Farm business climate factors portend continued farmer interest in the opportunities afforded through the accommodation of guests seeking farm-based recreation, entertainment, or education activities. The receptivity of the non-farm public to such opportunities is similarly evident (Carpio et al., 2008). A survey conducted more than a decade ago by the Travel Industry Association of America revealed that 87 million Americans visited a rural destination, most often for leisure purposes (Brown and Reeder, 2007). More specifically, Barry and Hellerstein (2004) found that 62 million American adults visited a farm at least once between 2000 and 2001.

The promise of agritourism for farm and rural development is a relatively new concept in the U.S. when viewed in context of its longer history in other parts of the world, particularly Europe (Brown and Reeder, 2007; Busby and Rendle, 2000). For example, Bernardo, Valentine and Leatherman (2004) estimate that one-third of farms in the United Kingdom offer agritourism, with higher proportions in France and Italy. Federal statistics are somewhat variable but show that only one to three percent of U.S. farms report income from farm-based recreation (Brown and Reeder, 2007; NASS, 2009).

While national data show only a small percentage of U.S. farms are currently engaged in agritourism, Schilling et al. (2012) suggest that agritourism is an especially important adaptation strategy for small family farms that lack scale efficiencies and face constrained wholesale market access. These challenges are exacerbated in areas with advanced urbanization pressures due to declining farmland resources, high land values, right to farm issues, and diminishing supply and market infrastructure. At the same time, proximity to urban centers presents market opportunities, including direct marketing and agritourism (Berry, 1978; Lopez, Adelaja and Andrews, 1988; Daniels and Bowers, 1997). This latter point is evidenced by the disproportionately high reliance on agritourism within the heavily urbanized Northeast region of the United States. Particularly at the rural-urban interface, agritourism may also provide for social capital formation, which Sharp and Smith (2003) identify as instrumental in alleviating conflicts between farmers and non-farm neighbors.

Past research confirms that agritourism development is often motivated, at least in part, by socially or ideologically-based objectives including fulfillment of personal entrepreneurial goals, education of the public about farming, and social interactions with guests (Weaver and Fennell, 1997; Nickerson et al., 2001; McGehee et al., 2007; Sharpley and Vass, 2006; Rilla, Hardesty, Getz, and George, 2011; Schilling et al., 2012). However, improving farm financial performance is generally a primary motive behind the development of agritourism enterprises. In a survey of Montana farmers, Nickerson et al. (2001) identify economic factors (i.e., additional income, full use of farm resources, mitigation of income fluctuations, family employment) as primary motivators for agritourism development. Replications of the Nickerson survey in Virginia

(McGehee et al., 2007) and Australia (Ollenburg and Buckley, 2007) generate similar conclusions. Among California agritourism operators, Rilla et al. (2011) find that 75 percent entered agritourism to enhance farm profitability. Sharpley and Vass (2006) find that farm diversification and increased income generation were prime factors influencing the adoption of agritourism among farmers in northeastern England.

Fewer studies have examined farmers' perceptions of the economic benefits actually received from agritourism. Oppermann (1995) concludes that agritourism (farm-based accommodations, specifically) is a “minor contributor” to the incomes of farmers in southern Germany, a sentiment echoed by Busby and Rendle (2000). However, Barbieri (2013) finds that agritourism operators are not only more motivated by farm profitability than farmers engaged in other forms of agricultural entrepreneurship (e.g., those engaged in value added processing or farm asset leasing), but that the former reporting significantly higher profit growth following farm diversification. Veeck, Che, and Veeck (2006) observe a range of net returns across different types of agritourism attractions in Michigan, concluding generally that for most farms agritourism is a supplemental source of income.[1] Rilla et al. (2011) find that profitability impacts reported by farmers are variable across regions, farm scales, and types of agritourism activities. Tew and Barbieri (2012) surveyed Missouri farmers and reported an average profit increase of nearly 56 percent following the addition of agritourism enterprises into their operations.

Survey research clearly highlights the importance of economic goals to operators entering agritourism, and several studies suggest that agritourism is impacting farm financial performance

[1] Examination of data presented by Veeck et al. (table 3, pg. 243) also shows a high level of variability in profit margins (i.e., net income as a proportion of gross sales) across agritourism activities.

in positive ways. However, little research has directly measured the economic contributions of agritourism. Census of Agriculture data show that farm income derived from agritourism grew from $202.2 million to $566.8 million between 2002 and 2007 (NASS, 2009).

In a state-level assessment, Schilling, Sullivan and Komar (2012) find that New Jersey farmers earned $57.5 million from agritourism (defined to include farm-based entertainment and educational activities, accommodations, outdoor recreating, and direct marketing). They find that forty percent of small agritourism farms (those earning less than $250,000 from farming) generated all of their farm income from agritourism, but did not directly examine the impacts of agritourism on farm profitability. For many conventional (i.e., production-wholesale oriented operations) farms, the incorporation of agritourism activities may represent an entirely new business model that necessitates investments in the training or expansion of farm staff, farm infrastructure modifications, and a reallocation managerial effort. These factors have implications for farm expenses and the net effect on farm profitability remains poorly understood.

3. Methods

Our study goal is to estimate the effect of agritourism enterprise development on farm profitability through estimation of the average treatment effect on the treated (ATT). Defining Y_1 as the profitability outcome associated with farms engaged in agritourism (e.g., farms receiving treatment) and Y_0 as the profitability outcome for farms without agritourism activities, then the ATT is expressed as:

(1) $$ATT = E(Y_1 | T = 1) - E(Y_0 | T = 1)$$

where T represents treatment status. However, the expression $E(Y_0 | T = 1)$ is not observable because the treatment assignment is mutually exclusive, thus necessitating the imputation of missing data through construction of a counterfactual. Estimating the *ATT* by calculating the mean difference between $E(Y_1 | T = 1)$ and $E(Y_0 | T = 0)$ is inappropriate due to the problem of self selection into a treatment. That is, $E(Y_0 | T = 0)$, while observable, is not a suitable proxy for $E(Y_0 | T = 1)$ because, as is common in non-experimental studies, assignment to a treatment cannot be assumed as random. In our current context, it is reasonable to expect that there are innate differences between farms that engage in agritourism and those that do not. Failure to control for sample selection effects will result in potentially biased estimates of treatment effects.

To address selection bias, we estimate the effects of agritourism on farm profitability by employing the propensity score matching (PSM) technique, which matches agritourism farms with observationally equivalent control farms (i.e., those without agritourism) (Rosenbaum and Rubin, 1983). An attractive aspect of PSM is that the predicted probability of being in the treatment, estimated with a logit or probit model, ameliorates the difficulty of matching farms based on a large number of variables (Becker and Ichino, 2002). The validity of PSM is integrally linked to the assumption that treatment status is randomly assigned among matched observations, thereby making differences in outcomes observed between matched observations attributable to treatment (Imbens, 2004; Becker and Ichino, 2002).[2] PSM also assumes that the overlap in the characteristics of farms with and without agritourism is sufficient to enable good matching of treatment and control observations. Failure to satisfy the overlap condition can lead to biased estimation results (e.g., Heckman et al., 1997).

[2] PSM cannot definitively eliminate all selection bias due to the possibility that unobservable factors also influence whether an observation is subject to treatment (see Becker and Ichino, 2002).

PSM has been employed in several recent agricultural economic contexts, including the evaluation of organic certification on farm income (Uematsu and Mishra, 2012), effects of farmland preservation on land values (Lynch, Gray, and Geoghegan, 2007), and zoning impacts on farmland values (Liu and Lynch, 2011). When lacking exogenous changes matching techniques have several advantages over other non-experimental evaluation techniques. First, matching does not impose any specific functional form between the dependent variable and independent variables, thus avoiding possible model misspecification errors (Rosenbaum and Rubin, 1983). The so-called LaLonde's (1986) critiques suggest that non-experimental estimates are sensitive to model specification and differ greatly from the experimental estimates. Second, matching can impose a common support requirement. The poor overlap on support between the treated and untreated groups raises questions about the robustness of parametric methods relying on the functional form to extrapolate outside the common support (Dehejia and Wahba, 1999; Smith and Todd, 2005). Third, matching allows endogenous covariates (Caliendo and Kopeinig, 2008).

Based on the conditional independence and common support assumptions, the estimated counterfactual outcome of treated individual *i* is:

(2) $$\hat{Y}_{0i} = \sum_{j \in C_i^0} \left(w_{ij} Y_j \middle| T_j = 0 \right)$$

where C_i^0 is the set of matches of individual *i*, $w_{ij} \in [0,1]$, and $\sum_i w_{ij} = 1$. Equation (2) can be re-written as:

(3) $$ATT = \frac{1}{N_1} \sum_{i|T_i=1} \left(Y_{1i} - \hat{Y}_{0i} \right)$$

where $N_1 = \sum_i T_i$ and $\hat{Y}_{0i}$ is the estimated potential outcome if not treated in equation (2).

To account for the sensitivity of the matching technique, we examine matching quality, employ different matching algorithms, and conduct a series of robustness checks.

4. Data

Data used in this study derive primarily from 7,575 respondent-level 2007 New Jersey Census of Agriculture records collected by the National Agricultural Statistics Service. Since a standardized definition of agritourism remains lacking (Phillip et al., 2010; Arroyo, Barbieri & Rich, 2013), two treatments were defined. The first, *T_ARS*, is a narrowly defined treatment that assumes a value of one is a farm reported earned income from "agri-tourism and recreational services" in the 2007 Census of Agriculture, and zero otherwise (NASS, 2009). The second treatment, *T_ARS_DCM*, is more broadly defined and is assigned a value of one if a farm earned income from “agri-tourism and recreational services” or income from the sale of "agricultural products directly to individuals for human consumption", and zero otherwise (see Schilling et al., 2012). After omitting cases with missing data, the full sample modeled under the *T_ARS* treatment contained 4,716 farms (268 with agritourism). The sample used for the more broadly defined *T_ARS_DCM* treatment contained 6,999 farms (1,594 with agritourism). The profitability outcome evaluated is net cash income per acre, which is calculated by subtracting, on a per-acre basis, total farm expenses from total sales, government payments, and other farm-related income.[3]

The PSM technique is based on the assumption that selection is exclusively based on observable characteristics. Operationally, this requires the estimation of a logit (or probit) model

[3] Ideally, a measure of the return to managerial effort would be a preferred metric for comparing the profitability impacts of alternative agricultural enterprises; however, such measures are not available from the Census of Agriculture.

that explains the decision to participate in agritourism. Using guidelines from economic theory and previous research, we compile data on three categories of covariates and provide descriptions of variables in Table 1. A detailed set of *operator characteristics* and *farm attributes* were derived from the respondent-level Census of Agriculture records. A series of *location/spatial variables* were developed from data compiled from the New Jersey Department of Environmental Protection's Bureau of Geographic Information Systems, the Office of the New Jersey State Climatologist, the U.S. Bureau of Labor Statistics, the U.S. Census Bureau, and the New Jersey State Agriculture Development Committee.

As shown in Table 1, farm operator characteristics include age, years in farming, and the number of individuals living in the operator's household. Binary variables are constructed to reflect operator gender, primary occupation, race, and place of residence (equal to one if the operator resides on the farm), and whether an heir is present.[4] Farm attributes include total acreage, a product diversification measure (e.g., number of commodity types sold), percentage of acreage classified as prime soil, and percentage of farm acreage owned by the operator. Binary variables were constructed to reflect whether the farm is preserved under a conservation easement, engages in organic production, employs conservation practices, earns most of its income from rent sources (e.g., leasing land to others), and maintains internet access. A series of dummy variables also categorize farms based which commodity generates the highest percentage of farm income and the USDA-Economic Research Service's farm typology, which classifies

[4] An heir is assumed to be present if several conditions are met. These include: the farm is a family farm or family held corporation, has at least two operators, and at least one of the secondary operators spends the majority of his/her time employed in agriculture (and is not a hired manager).

farms based on economic scale and operator occupation (see Hoppe, Banker and MacDonald, 2010).

Farm location characteristics are intended to capture spatial effects related to natural amenities, urbanization pressure, and market opportunities. Municipality-level measures of the percentage of land classified as agricultural and forested, as well as population density, are indicators of the area's location along the urban-rural continuum. Municipal median household income, Euclidean distance measures to major urban centers (e.g., New York City and Philadelphia), and a series of binary variables designating tourism promotion regions reflect a farm's market environment. A measure of local competition for agricultural products is constructed (*SAMEPRODUCTS*) as the percentage of farms within a municipality that sell the primary product (based on sales) sold by a subject farm. Temperature and precipitation variables capture regional variability in microclimates across the state.

To account for possible unobserved heterogeneity, such as motivations for farming, we segment our sample into three subgroups: lifestyle and retirement farms (herein referred to as lifestyle farms), intermediate-scale farms, and commercial-scale farms. Lifestyle farms are those earning less than $250,000 sales and are operated by individuals for whom farming is not a primary occupation (including retirees). Intermediate and commercials farms are operated by a person for whom farming is a primary occupation and earn, respectively, less than $250,000 in sales and $250,000 or more in sales.

Table 2 presents summary statistics for selected variables of farms with and without income from agritourism defined using the narrower treatment definition (*D_ARS*). Data are presented for the full sample and each of the three farm subgroups. Table 3 presents the same information, using the broader (*T_ARS_DCM*) treatment definition. We observe that per-acre farm profitability (*NETCASH*) is higher for farms engaging in agritourism, under both treatment definitions, relative to farms that do not engage in agritourism. These relationships are consistent across the full sample of farms and the three subsamples. Non-parametric student t tests show that the mean differences in *NETCASH* between farms with and without agritourism are generally statistically significant, except for in the full sample corresponding to the *T_ARS_DCM* treatment variable and the commercial farm subgroups corresponding to both treatment definitions. However, no conclusions may be drawn from these simple comparisons without addressing potential selection bias.

5. Empirical Results

5.1 Propensity Score Estimation

As the first stage of the PSM technique, we estimate logit models for the full sample and each of the three subsamples by regressing each binary treatment variable on the multi-dimensional vector of covariates previously described. [Tables S1 and S2 in Supplementary Information provide the parameter estimates obtained from models corresponding to the treatment variables *T_ARS* and *T_ARS_DCM*, respectively.] All eight models perform well according to the percentage of correct predictions, which range from 79 to 96 percent.

While differences in statistical significance of variables are observed across models, results generally converge with profit theory and the existing literature on agritourism. Across both treatment variable models, farms in the full sample were more likely to engage in agritourism if they were operated by individuals primarily engaged in farming as an occupation, produced organic products, raised fruits or vegetables, installed conservation practices, had internet access, and were diversified (produced multiple farm products). Local competition (measured by *SAMEPRODUCTS*) tended to reduce the likelihood of a farm engaging in agritourism. The presence of an heir increased the probability of a farm having agritourism activities in several models. Variability in the statistical significance of covariates is observed across models. For example, having an heir interested in farming statistically affects the decision of agritourism engagement of hobby farms in the model using the treatment variable *T_ARS*, while it does not influence the decision to engage in agritourism of hobby farms in the model using the treatment variable *T_ARS_DCM*.

5.2 Estimated Effects of Agritourism on Farm Probability

For each farm, a propensity score is derived as the predicted probability of engaging in agritourism. Farms are then matched based on the propensity scores using nearest neighbor matching (using 1 and 5 neighbors, with replacement), radius matching (with caliper settings of 0.02 and 0.05), and local linear regression matching (using Gaussian and Epanechnikov kernel functions). Details on each matching algorithm are provided in the Appendix. The use of multiple matching estimators is a useful robustness check, allowing observation of the sensitivity of estimated ATTs to the selected matching estimator.

Table 4 summarizes the ATTs of participation in agritourism on the net cash income (per acre) of farms in the full sample and each farm subgroup. Standard errors are reported in parentheses under each estimated treatment effect using bootstrapping with 1,000 replications, except for the nearest neighbor (NN1) and oversampling (NN5) in which we calculate the analytical standard error suggested by Abadie and Imbens (2006; 2008). To address the possibility of limited overlap between agritourism farms and observationally equivalent non-agritourism farms, we apply the trimming approach (thick support) suggested by Crump et al. (2009) in all cases.[5]

Examining first the treatment effects associated with *T_ARS*, there is strong evidence that agritourism has a positive effect on New Jersey farm profitability and that such effects are heterogeneous across farm types. The estimated ATTs for the full sample are statistically significant across matching estimators, ranging from $2,406 to $2,837 based on the thick support. The effects of agritourism on farm profitability vary across farm types. The largest effects ($2,388 to $3,423) are estimated within the intermediate farm group. Agritourism effects are smaller for lifestyle farms, but remain significant and in the range of $1,189 to $1,446. While positive, the effects of agritourism on the profitability of commercial farm group are statistically insignificant across all matching estimators.

Under the expanded definition of agritourism (e.g., inclusive of direct farm marketing) that corresponds to the *T_ARS_DCM* treatment assignment, similar patterns of profitability effects are observed, although in all cases they are considerably smaller in magnitude than those observed under the narrowly defined *T_ARS* treatment. In the full sample, the estimated agritourism effect based on the *T_ARS_DCM* treatment ranges from only $409 to $705. In the intermediate and commercial farm groups, treatment effects range from $256 to $350 and $894 to $1,084, respectively. Again, no statistically significant effects of agritourism on profitability are observed in the commercial farm group.

[5] We trim any observations with a propensity score below 0.029 in the full sample, 0.021 in the lifestyle farm subsample, 0.047 in the intermediate farm, and 0.010 in the commercial farm subsample for the model using the treatment variable *T_ARS*. For the model using the treatment variable *T_ARS_D*CM, We trim any observations with a propensity score below 0.076 in the full sample, 0.093 in the lifestyle farm subsample, 0.070 in the intermediate farm, and 0.011 in the commercial farm subsample.

These results evidence the supposition of Busby and Rendle (2000) that the lack of a standardized definition of "agritourism" stands as a hindrance to generalizations within the growing body of agritourism research. In this study, the inclusion of direct-to-consumer marketing within the definition of agritourism results in significantly lower estimated treatment effects. This suggests that there are substantial differences between the economics of the agritourism enterprises defined narrowly on the basis of offering only recreational or educational activities, and those defined more expansively to also include direct marketing. This is confirmed when we replicate the analysis and calculate the effect of direct-to-consumer marketing only on farm profitability. Focusing on the thick support estimates, the ATT associated with direct-to-consumer marketing ranges from only \$271 to \$356 [Supplemental Information Table S3], substantially less than the effects estimated for the T_ARS treatment. The "direct marketing" effect dominates the ATT associated with the *T_ARS_DCM* treatment because among 1594 farms assigned to this treatment, who less than 1/5 (268 farms) engage in only in "agri-tourism and recreational services".

5.3 *Matching Quality and Robustness Checks*

To assess the quality of the estimated treatment effects, we perform the following tasks. First, we test for balance of covariates between the treated and untreated groups before and after matching for each treatment variable. Overall, we find that the balancing property is satisfied for the full sample and all three subsamples. Taking the full sample as an example, for each matching covariate, we report the mean differences between the treated and untreated groups before and after matching as well as their statistical significance in Table 5. For the *T_ARS* treatment, the results show a clear lack of balance before matching: 25 of 44 mean differences are statistically significant at the 5% level. Matching improves the balance significantly. After matching, the mean differences for all covariates are not statistically significant. Similarly, table 5 also suggests good matching quality for the treatment *T_ARS_DCM*. We find similar matching quality for the subsamples [Supplemental Information Tables S4 and S5].

Second, we employ different matching parameters: 10 neighbors in the comparison group to match every treated individual for NNM, a series of fixed bandwidths for LLM, and radius matching with caliper 0.01– with and without trimming. The treatment effects based on each of the new specifications are very similar to reported results.

Third, the quality of matching outcomes for each matching estimator is validated on the basis of sharp reductions of mean standardized bias, pseudo R^2 and Chi-Square after matching for the case of the *T_ARS* treatment, as shown in Table 6. [See Supplemental Information Table S6 for the *T_ARS_DCM* treatment].

Finally, as discussed in the methods section, PSM relies on the conditional independence assumption. That is, estimates of treatment effects based on matching is unbiased if all relevant covariates are included in the model and no unobservable confounding factors exist, which is a rather restrictive assumption. Therefore, a common concern of matching models is that they may fail to account for a relevant covariate(s) that are not observable to researchers. Rosenbaum (2002) developed a method of sensitivity analysis to examine whether matching estimates are robust to the possible presence of an unobservable confounding factor. We implement the Rosenbaum bounds approach with one-by-one matched pairs. As shown in Table 7, our results are robust with the threshold gamma (measuring the strength of unobserved variables on treatment assignment) equal to 1.30 (with 95% confidence interval) corresponding to the treatment variable *T_ARS*. This means that the statistical significance of the ATTs is less likely to be questionable if the odds ratio of engaging in agritourism between agritourism and non-agritourism farms differs by less than 1.30. Under the *T_ARS_DCM* treatment, we find that the results are less robust in the full sample (threshold gamma=1.15), while results from the subgroups of lifestyle farms and intermediate farms remain robust (threshold gamma=1.25).

6. Conclusions

Agritourism has emerged as an important adaptation strategy among small farms, particularly in Northeast states where urbanization pressures are advanced. While economic motives are often cited as important drivers of agritourism development, the literature remains inclusive on the extent and distribution of such benefits. We make several contributions to this line of inquiry. To our knowledge, this is the first study to empirically estimate the effects of agritourism on farm profitability. We demonstrate the application of propensity score matching, together with quality and robustness checks, as a means to address self selection issues that may confound analysis of farm differences attributable to agritourism development. By comparing agritourism farms to observationally equivalent control farms through PSM, we reduce the impact of selection bias on our estimates of farm profitability differentials.

Validation of qualitative claims that agritourism improves farm financial performance - for certain farm types - is our primary empirical contribution. Our research demonstrates that estimating the economic benefits of agritourism across the general population of farms obfuscates considerable variability in such impacts across more homogeneously defined farm types. We find that agritourism development significantly enhances profits of intermediate-scale and lifestyle farms, but has no discernible impact on the net case income per acre generated by commercial-scale farms (those earning more than $250,000 in annual sales). This latter finding comports with the finding of Schilling et al. (2012) that farms of this scale, while frequently engaged in agritourism, often do so for non-pecuniary reasons (e.g., to educate the public about farm issues, generate support for farm retention policies, etc.).

Recognition of farmers’ goals is important to policies and programming aimed at farm retention and development. Particularly among small farms, conventional economic views of income maximization as a motivational driver for farming are overly myopic as it ignores other objectives that may be equally or more important to the farm household (Harper and Eastman, 1980; Blank, 2002). By definition, farming is not the primary occupational pursuit for operators of small, so-called lifestyle farms; however, we find that agritourism farms in this farm subgroup are generating higher net cash returns per acre from farming than their non-agritourism counterparts. Census data show that ninety-one percent of retirement and residential lifestyle farms earn less than 25 percent of household income from farming (NASS, 2009). However, this does not mean that farm income is altogether unimportant in these households. While some operators in this segment of agriculture are purely hobbyists, others will rely to differing extents on farm-based revenue to supplement household income. Agritourism may contribute to making farm household income "whole," covering farm ownership costs, offsetting retirement expenses, or meeting whatever other economic objectives exist. Similarly, operators of intermediate-scale farms, small farms operated by individuals with stronger occupational ties to farming, also appear to be finding success in agritourism. Important industry and landscape implications are evidenced by the fact that while collectively New Jersey's small farms - lifestyle and retirement farms and intermediate farms - generate only a small portion (9 percent) of industry revenue, they represent three-quarters of all farms and manage more than 302,000 acres of farmland (42 percent of the state's land in farms). From a broad perspective, the financial performance of small farms often lags considerable behind that of their larger counterparts, among whom most farm production is concentrated (Hoppe, MacDonald and Korb, 2010). This study suggests that agritourism is an important strategy for overcoming this economic disparity and enhancing the viability of small farms.

This study also finds that profit impacts differ markedly based on the definition of agritourism employed. Specifically, the more parsimonious definition of agritourism yields substantially higher profit impact estimates than when agritourism is defined more broadly to include direct marketing. Although further research is needed to more fully understand the implications for farm financial performance of these alternative components of agritourism, this fining emphasizes the importance of standardizing the definition of agritourism when conducting evaluative research.

A few caveats to our research are warranted. First, the use of PSM ameliorates but does not eliminate the challenge of producing reliable treatment effects in instances where observational study participants self select into a treatment. While robustness checks give us confidence in our study results, the potential remains that unobserved heterogeneity linked to the decision to engage in agritourism remains may also be affecting farm profitability. Second, longitudinal data on agritourism are limited. Monitoring of the profitability impacts of agritourism as the sector matures (and more data become available) is needed to evaluate the long-term viability of agritourism as an economic development strategy for farms.

In conclusion, we find strong support that the attention on agritourism as an agricultural economic development strategy is well placed. Policy makers with interest in supporting farm retention and viability may be well-advised to consider strategies to stimulate and sustain agritourism, including deeper integration of agritourism into travel and tourism promotions. Expanded Cooperative Extension programming is also needed to support current and prospective agritourism operators in areas such as hospitality and retail management and staff training, farm safety, risk and liability management, marketing, and enterprise budgeting.

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Table 1. Description of variables

Variables	Description
Outcome	
NETCASHINC	Net cash income per acre
Treatments	
T_ARS	The reported income from agri-tourism and recreational services (1) or not (0)
T_ARS_DCM	The reported income from either “agri-tourism and recreational services” or “direct-to-consumer marketing” (1) or not (0)
Operator characteristics	
Gender	Gender of the principle operator (1 for male and 0 for female)
AGE	Age of the principle operator
TENURE	Number of years the principal operator operated on the farm
FARMING	The principal operator spends majority of the work time on farming (1) or not (0)
LIVEONFARM	Whether the principal operator lives on farm (1) or not (0)
HEIR	Whether the principal operator has an heir to continue farming (1) or not (0)
HHSIZE	Number of household members in the operator's household
Race of the principal operator	
*WHITE**	Whether the principal operator is white
BLACK	Whether the principal operator is black or African American
ASIAN	Whether the principal operator is Asian
OTHER	Whether the principal operator has other races
Farm characteristics	
ACRES	Total acres of farmland operated
ORGANIC	Whether the farm produces organic products for sale (equal to 1 if yes)
CONSERVE_MED	Whether the farm has any conservation methods (equal to 1 if yes)
PRESERVED	Whether any portion of the farm was preserved (equal to 1 if preserved)
NUM_PRODUCTS	The number of commodity types sold in the farm
RENTAL_INC	Whether the largest source of farm income was rental income (equal to 1 if yes)
PRIME_SOIL	Percent of farm acreage with soils classified as “prime”
INTERNET	Whether the farm has the internet access
FARMOWN	Percent of farmland owned by the principal operator
Commodity type: Binary variable indicating the largest portion of total gross sales was from	
ANIMAL	animals (1) or not (0)
EQUINE	equine (1) or not (0)
FRUIT	fruits and berries (1) or not (0)
VEGETABLE	vegetable (1) or not (0)
NURSERY	nursery and greenhouse products (1) or not (0)
*GRAINHAY**	grain, hay and other crops (1) or not (0)

Table 1 (Continued)

Variables	Description
<u>*Farm types*</u>	
LIFESTYLE	Residential/lifestyle and retirement farm according to the ERS typology
LIMITED_RES	Small family farm with limited resource according to the ERS typology
INTERMEDIATE	Small family farm with high and low sales according to the ERS typology
COMMERCIAL	Large and very large family farm according to the ERS typology
NON-FAMILY[*]	Non-family farm according to the ERS typology
Location characteristics	
AGLAND	Percent of municipal area that is in agriculture in 2007
FORESTLAND	Percent of municipal area that is forested in 2007
POP_DENSITY	Population density (square mile) for municipality in which farm is located
MED_HH_INC	Median household income for municipality in which farm is located
TEMPERATURE	Average growing seasonal temperature (°F) from April to September
PRECIPITATION	Total annual precipitation (inches)
SAMEPRODUCTS	Percent of the number of farms that have engaged at least one same commodity type to the total number of farms in the municipality
DIST_NYC	Euclidian distance, in miles, of the farm to New York City
DIST_PHILA	Euclidian distance, in miles, of the farm to Philadelphia
<u>*Regions in New Jersey*</u>	
GATEWAY	Gateway region- Middlesex, Union, Essex, Hudson, Bergen, Passaic
GT_ALTANTIC	Greater Atlantic City region- Atlantic
SHORE	Shore region- Monmouth, Ocean
SKYLANDS	Skylands region- Sussex, Morris, Warren, Hunterdon, Somerset
SOUTHSHORE	Southern Shore region- Cumberland, Cape May
DEL_RIVER[*]	Delaware River region- Mercer, Burlington, Camden, Gloucester, Salem

Note: "*" captures dummy variables that are omitted in the models.

Table 2. Mean values of selected variables for farms with/without income from agritourism and recreational services (*T_ARS* treatment) for full sample and by farm type

Variables	Full sample		Lifestyle		Intermediate		Commercial	
	With	Without	With	Without	With	Without	With	Without
Outcome								
NETCASHINC ($1,000)	3.41	0.91	1.86	-0.04	1.14	-0.40	12.55	9.38
Operator characteristics								
GENDER	0.81	0.8	0.84	0.83	0.75	0.75	0.95	0.94
AGE	56.62	57.56	60.94	58.82	53.32	54.49	55.47	55.84
OPYEARS	22.77	20.74	22.55	20.34	22.11	20.86	29.02	26.03
FARM_OCCUP	0.66	0.46	0.30	0.21	1.00	1.00	1.00	0.89
LIVEONFARM	0.78	0.8	0.82	0.82	0.80	0.84	0.72	0.64
HEIR	0.12	0.06	0.14	0.05	0.08	0.06	0.19	0.18
HH_MEMBERS	2.87	2.78	2.73	2.79	2.92	2.85	3.12	2.92
WHITE	0.993	0.985	0.991	0.989	1.000	0.993	1.000	0.965
BLACK	0.011	0.006	0.018	0.005	0.000	0.004	0.000	0.000
ASIAN	0	0.009	0.000	0.005	0.000	0.006	0.000	0.035
OTHER	0.011	0.004	0.009	0.005	0.013	0.001	0.000	0.000
Farm characteristics								
ACRES	138.15	87.68	67.05	42.05	130.68	105.52	369.86	419.42
ORGANIC	0.05	0.01	0.05	0.01	0.04	0.01	0.05	0.00
CONSERVE_MED	0.39	0.19	0.35	0.15	0.42	0.26	0.51	0.38
PRESERVED	0.19	0.1	0.11	0.07	0.18	0.15	0.42	0.34
NUM_PRODUCTS	2.01	1.44	1.88	1.42	2.04	1.53	2.42	1.45
RENTAL_INC	0.01	0.01	0.02	0.01	0.00	0.01	0.00	0.00
PRIME_SOIL	25.51	28.04	26.77	27.31	25.69	29.69	24.31	30.66
INTERNET	0.8	0.61	0.75	0.60	0.82	0.62	0.86	0.79
FARMOWN	77.79	85.46	84.64	91.00	76.91	75.76	58.40	62.34
ANIMAL	0.19	0.2	0.21	0.22	0.13	0.20	0.14	0.08
EQUINE	0.15	0.13	0.13	0.11	0.22	0.18	0.02	0.03
FRUIT	0.12	0.05	0.14	0.05	0.11	0.04	0.14	0.10
VEGETABLE	0.16	0.06	0.12	0.04	0.20	0.06	0.26	0.23
NURSERY	0.16	0.18	0.15	0.14	0.12	0.19	0.35	0.43
GRAINHAY	0.22	0.38	0.25	0.44	0.22	0.33	0.09	0.13
Location characteristics								
AGLAND	17.94	20.33	18.29	20.02	20.17	21.54	15.81	21.80
FORESTLAND	30.7	31.38	31.36	32.36	30.94	29.78	25.90	27.18
POP_DENSITY ($1,000)	1.3	1.3	1.75	1.30	1.08	1.31	0.97	0.84
MED_HH_INC ($1,000)	70.99	66.65	67.76	67.54	70.56	66.33	73.62	59.40
TEMPERATURE	65.37	65.56	65.49	65.46	65.19	65.68	65.35	66.23
PRECIPITATION	4.55	4.39	4.44	4.42	4.59	4.37	4.70	4.07
SAMEPRODUCTS	56.61	50.7	55.29	51.11	56.92	51.78	60.76	46.56
DIST_NYC	59.44	66.94	63.52	65.72	58.21	67.44	55.00	77.33
DIST_PHILA	48.2	45.27	45.45	45.93	52.01	44.26	47.43	41.20
No. observations	268	4,448	110	2,577	77	817	43	318

Table 3. Mean values of selected variables for farms with/without income from either agritourism and recreational services or direct-to-consumer marketing (*T_ARS_DCM* treatment) for full sample and by farm type

Variables	Full sample		Lifestyle		Intermediate		Commercial	
	With	Without	With	Without	With	Without	With	Without
Potential outcomes								
NETCASH ($1,000)	0.86	0.78	0.25	-0.06	0.75	-0.31	7.77	7.67
Operator characteristics								
GENDER	0.8	0.8	0.82	0.83	0.76	0.74	0.93	0.95
AGE	57.09	57.58	58.23	58.87	54.68	54.53	57.24	55.75
OPYEARS	19.9	20.72	19.36	20.26	20.17	20.48	29.76	26.48
FARM_OCCUP	0.48	0.46	0.22	0.21	1.00	1.00	0.98	0.90
LIVEONFARM	0.84	0.8	0.87	0.82	0.84	0.84	0.72	0.65
HEIR	0.08	0.07	0.06	0.05	0.08	0.06	0.20	0.17
HH_MEMBERS	2.86	2.79	2.85	2.79	2.89	2.84	3.05	2.94
WHITE	0.977	0.984	0.98	0.99	0.97	0.99	1.00	0.97
BLACK	0.009	0.006	0.01	0.01	0.01	0.00	0.00	0.00
ASIAN	0.013	0.008	0.01	0.01	0.02	0.01	0.00	0.03
OTHER	0.008	0.004	0.01	0.00	0.01	0.00	0.00	0.00
Farm characteristics								
ACRES	65.84	90.25	34.79	41.05	79.45	103.54	320.90	424.35
ORGANIC	0.07	0.01	0.06	0.01	0.11	0.01	0.05	0.00
CONSERVE_MED	0.27	0.19	0.24	0.15	0.34	0.25	0.47	0.41
PRESERVED	0.1	0.11	0.05	0.06	0.14	0.15	0.39	0.35
NUM_PRODUCTS	1.92	1.45	1.86	1.43	2.04	1.52	2.35	1.47
RENTAL_INC	0.01	0.01	0.01	0.02	0.00	0.01	0.00	0.00
PRIME_SOIL	25.36	28.22	25.41	27.49	25.55	29.94	25.06	30.92
INTERNET	0.68	0.61	0.66	0.60	0.72	0.65	0.82	0.78
FARMOWN	86.85	85.6	91.87	91.09	79.50	77.12	59.95	62.10
ANIMAL	0.34	0.2	0.39	0.22	0.24	0.19	0.13	0.10
EQUINE	0.04	0.14	0.03	0.12	0.07	0.21	0.01	0.03
FRUIT	0.15	0.05	0.17	0.05	0.11	0.04	0.18	0.11
VEGETABLE	0.25	0.06	0.21	0.04	0.33	0.06	0.32	0.24
NURSERY	0.08	0.18	0.06	0.14	0.09	0.18	0.28	0.41
GRAINHAY	0.14	0.37	0.14	0.43	0.16	0.32	0.08	0.11
Location characteristics								
AGLAND	18.01	20.31	18.14	19.91	18.35	21.88	17.09	21.78
FORESTLAND	33.16	31.23	34.49	32.33	32.27	29.45	25.31	27.22
POP_DENSITY ($1,000)	1.13	1.28	1.23	1.33	0.95	1.27	1.12	0.79
MED_HH_INC ($1,000)	69.21	67.01	69.78	68.08	69.07	66.82	66.34	59.00
TEMPERATURE	65.27	65.58	65.15	65.46	65.31	65.70	65.99	66.23
PRECIPITATION	4.53	4.4	4.57	4.44	4.53	4.38	4.40	4.05
SAMEPRODUCTS	53.55	50.54	53.57	50.87	53.45	51.33	56.07	47.69
DIST_NYC	61.47	66.76	60.69	65.19	61.04	67.36	65.27	78.16
DIST_PHILA	47.99	45.06	48.42	45.90	48.56	43.70	43.72	40.69
No. observations	1,594	5,405	961	3,085	309	986	92	426

Table 4. Estimated treatment effects (ATTs) of agritourism on farm profitability

Samples	Types of support	Matching algorithms					
		NN1	NN5	LLR Gauss	LLR Epan	Radius 0.02	Radius 0.05
		Treatment variable: T_ARS					
Full sample	common support	2313**	2166*	2501**	2560**	2467**	2496**
		(1044)	(1123)	(1003)	(1096)	(1106)	(1033)
	thick support	2585**	2406*	2755**	2794**	2837**	2788**
		(1195)	(1292)	(1201)	(1337)	(1331)	(1297)
Lifestyle farms	common support	2027***	1870**	1975**	2031**	1969**	1917**
		(788)	(807)	(762)	(831)	(852)	(826)
	thick support	1367*	1189*	1393*	1446**	1361**	1314**
		(702)	(642)	(758)	(644)	(674)	(609)
Intermediate farms	common support	2683**	1954**	1904**	1887*	2286**	1813**
		(1372)	(789)	(932)	(1077)	(1043)	(856)
	thick support	3423**	2429**	2587**	2449**	2964**	2388**
		(1567)	(893)	(1233)	(1025)	(1160)	(908)
Commercial farms	common support	10221	7695	4796	4759	6910	5632
		(7644)	(5961)	(7285)	(9461)	(8409)	(7278)
	thick support	8214	5056	7777	4702	6842	5493
		(5948)	(4655)	(83768)	(11754)	(7777)	(7435)
		Treatment variable: T_ARS_DCM					
Full sample	common support	818***	899***	558*	553*	587*	569*
		(204)	(217)	(314)	(319)	(327)	(350)
	thick support	621***	705***	386	378	443*	429*
		(183)	(184)	(291)	(299)	(262)	(255)
Lifestyle farms	common support	446***	437***	358**	358***	379***	361***
		(153)	(148)	(144)	(125)	(141)	(130)
	thick support	350***	334**	256**	257**	289**	269**
		(132)	(136)	(120)	(122)	(131)	(126)
Intermediate farms	common support	1001*	1061**	995***	998***	976**	977***
		(546)	(381)	(336)	(339)	(378)	(373)
	thick support	894*	1029**	1084***	1089	1034**	1024**
		(542)	(406)	(395)	(700)	(401)	(393)
Commercial farms	common support	3309	3398	1381	1103	2329	1694
		(3576)	(3780)	(4330)	(4349)	(4578)	(4147)
	thick support	2174	3049	-879	1071	2293	1406
		(2784)	(2806)	(9528)	(3940)	(4874)	(3984)

Note: ***, **, * are significant at the 1, 5, and 10 percent level, respectively. Standard errors are reported in parentheses. The standard errors for all matching algorithms are estimated using bootstrapping with 1,000 replications, except for the nearest neighbor (NN1) and oversampling (NN5) in which we use the analytical standard error suggested by Abadie and Imbens (2006; 2008).

Table 5. Balancing test for the mean difference in the full sample – before and after matching corresponding to each treatment variable

Covariates	Sample	With *ARS*	With *ARS_DCM*	Covariates	Sample	With ARS	With ARS_DCM
GENDER	UM	0.0057	-0.0029	*FRUIT*	UM	0.0699***	0.1025***
	M	0.0123	0.0004		M	-0.0213	-0.0089
AGE	UM	-0.9414	-0.4920	*VEGETABLE*	UM	0.0977***	0.1819***
	M	-0.7454	0.0890		M	0.0169	0.0202
OPYEARS	UM	2.0260**	-0.8200**	*NURSERY*	UM	-0.0140	-0.0950***
	M	-0.3970	0.0700		M	0.0094	0.0095
FARM_OCCUP	UM	0.2060***	0.0166	*AGLAND*	UM	-2.3850**	-2.3010***
	M	0.0372	0.0079		M	-0.1590	-0.2870
LIVEONFARM	UM	-0.0118	0.0478***	*FORESTLAND*	UM	-0.6760	1.9220***
	M	0.0010	-0.0031		M	-0.1020	0.2190
HEIR	UM	0.0586***	0.0125*	*POP_DENSITY*	UM	6.5000	-150.90
	M	-0.0044	0.0038		M	23.1000	29.0000
HH_MEMBERS	UM	0.0858	0.0727*	*MED_HH_INC*	UM	4,336.00***	2,202.00***
	M	0.0256	-0.0157		M	275.0000	570.0000
BLACK	UM	0.0051	0.0029	*TEMPERATURE*	UM	-0.1980*	-0.3060***
	M	-0.0002	0.0010		M	0.0190	-0.0190
ASIAN	UM	-	0.0048*	*PRECIPITATION*	UM	0.1555***	0.1388***
	M	-	0.0024		M	-0.0084	0.0141
OTHER	UM	0.0074*	0.0036*	*SAMEPRODUCTS*	UM	5.9070***	3.0090***
	M	0.0016	0.0024		M	-0.1620	-1.0860
ACRES	UM	50.4670***	-24.4090***	*DIST_NYC*	UM	-7.4940***	-5.2890***
	M	5.1800	-3.9450		M	-0.0210	-0.4800
ORGANIC	UM	0.0404***	0.0578***	*DIST_PHILA*	UM	2.9350**	2.9320***
	M	0.0042	0.0189		M	-0.5040	0.0860
CONSERVE_MED	UM	0.1990***	0.0796***	*RESIDENT_RETIRE*	UM	-0.1689***	0.0321**
	M	0.0063	0.0131		M	-0.0102	0.0026
PRESERVED	UM	0.0897***	-0.0114	*LIMIT_RESOURCES*	UM	-0.0529***	-0.0058
	M	0.0120	0.0049		M	-0.0045	-0.0017
NUM_PRODUCTS	UM	0.5639***	0.4710***	*INTERMEDIATE*	UM	0.0999***	0.0114
	M	-0.0001	-0.0095		M	0.0199	0.0059
RENTAL_INC	UM	0.0011	-0.0075**	*COMMERCIAL*	UM	0.0890***	-0.0211***
	M	-0.0012	0.0007		M	0.0068	-0.0043
PRIME_SOIL	UM	-2.5330**	-2.8540***	*GATEWAY*	UM	0.0605***	0.0171***
	M	0.2980	-0.0550		M	0.0130	0.0053
INTERNET	UM	0.1911***	0.0674***	*GREATALTANTIC*	UM	-0.0214	-0.0098
	M	0.0127	-0.0012		M	-0.0010	-0.0036
FARMOWN	UM	-7.6760***	1.2500	*SHORE*	UM	-2E-05	-0.0071
	M	-1.8530	-0.0110		M	0.0049	0.0018
ANIMAL	UM	-0.0129	0.1363***	*SKYLANDS*	UM	0.0136	0.0763***
	M	0.0092	-0.0476		M	-0.0202	0.0008
EQUINE	UM	0.0248	-0.0954***	*SOUTHSHORE*	UM	-0.0395**	-0.0288***
	M	0.0010	0.0051		M	-0.0007	-0.0004

Note: The radius matching with caliper 0.02 is used for the balancing test. It performs relatively well across samples in terms of the matching quality (See Tables S5 & S6). Other matching algorithms also provide very similar conclusion. ***, **, * are significant at the 1, 5, and 10 percent level, respectively. UM and M are abbreviation of unmatched and matched samples, respectively. *RESIDENT_RETIRE, LIMIT_RESOURCES, INTERMEDIATE, COMERCIAL, RESIDENT/LIFE, HIGHSALES, and VERYLARGE* are dummy variables capturing farm types according to the ERS typology. *GATEWAY, GREATALTANTIC, SHORE, SKYLANDS,* and *SOUTHSHORE* are fixed effect dummy variables capturing regions in New Jersey.

Table 6. Matching quality indicators with imposition of common support corresponding to the treatment variable *T_ARS*

	Before Matching			After Matching		
	Mean Bias	Pseudo R^2	Chi^2	%Mean Bias Reduction	$\%Chi^2$ Reduction	% Pseudo R^2 Reduction
			Full Sample			
NN1	18.02	0.15	310.02	-65.47%	-77.48%	-92.08%
NN5	18.02	0.15	310.02	-78.69%	-90.07%	-96.52%
Local Linear (Guass)	18.02	0.15	310.02	-77.04%	-89.40%	-96.32%
Local Linear (Epan)	18.02	0.15	310.02	-76.27%	-82.58%	-70.46%
Radius 0.02	18.02	0.15	310.02	-87.14%	-96.69%	-98.78%
Radius 0.05	18.02	0.15	310.02	-73.14%	-88.74%	-96.10%
			Residential/Lifestyle and Retirement Subsample			
NN1	13.52	0.14	126.21	-43.57%	-50.36%	-83.70%
NN5	13.52	0.14	126.21	-66.39%	-88.32%	-96.27%
Local Linear (Guass)	13.52	0.14	126.21	-79.94%	-94.29%	-98.11%
Local Linear (Epan)	13.52	0.14	126.21	-78.82%	-92.05%	-93.61%
Radius 0.02	13.52	0.14	126.21	-81.27%	-94.89%	-98.40%
Radius 0.05	13.52	0.14	126.21	-74.11%	-89.78%	-96.68%
			Intermediate Subsample			
NN1	19.92	0.18	92.82	-43.39%	-47.37%	-72.38%
NN5	19.92	0.18	92.82	-63.97%	-73.74%	-89.37%
Local Linear (Guass)	19.92	0.18	92.82	-74.44%	-86.59%	-94.54%
Local Linear (Epan)	19.92	0.18	92.82	-68.62%	-79.89%	-91.96%
Radius 0.02	19.92	0.18	92.82	-77.19%	-89.94%	-96.34%
Radius 0.05	19.92	0.18	92.82	-74.54%	-88.27%	-95.26%
			Commercial Farm Subsample			
NN1	29.45	0.36	95.12	-38.43%	-36.93%	-69.69%
NN5	29.45	0.36	95.12	-74.05%	-81.16%	-93.43%
Local Linear (Guass)	29.45	0.36	95.12	-79.92%	-91.41%	-97.06%
Local Linear (Epan)	29.45	0.36	95.12	-79.62%	-91.14%	-96.94%
Radius 0.02	29.45	0.36	95.12	-67.70%	-84.76%	-95.21%
Radius 0.05	29.45	0.36	95.12	-80.64%	-92.24%	-97.46%

Note: Optimal bandwidth associated with the kernel function in each sample is obtained using the rule of thumb suggested by Silverman (1986). Results with thick support are very similar. The mean standardized bias (SB) before matching is given by $SB_{before} = 100 \cdot \frac{\overline{X}_1 - \overline{X}_0}{\sqrt{0.5 \cdot (V_1(X) + V_0(X))}}$ and the SB after matching is given by $SB_{after} = 100 \cdot \frac{\overline{X}_{1M} - \overline{X}_{0M}}{\sqrt{0.5 \cdot (V_{1M}(X) + V_{0M}(X))}}$ where X_1 (V_1) is the mean (variance) in the treatment group before matching and X_0 (V_0) the analogue for the control group. X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values for the matched samples.

Table 7. Sensitivity Analysis with Rosenbaum Bounds

	Critical *p*-Value for Gammas[a]											
	Treatment variable: *T_ARS*						Treatment variable: *T_ARS_DCM*					
	Full		Lifestyle		Intermediate		Full		Lifestyle		Intermediate	
Gamma	sig+	sig-	sig+	sig-	sig+	sig-	sig+	sig-	sig+	sig-	sig+	sig-
1	0.000	0.000	0.001	0.001	0.003	0.003	0.000	0.000	0.000	0.000	0.000	0.000
1.05	0.001	0.000	0.002	0.000	0.005	0.002	0.001	0.000	0.000	0.000	0.001	0.000
1.1	0.002	0.000	0.004	0.000	0.008	0.001	0.007	0.000	0.000	0.000	0.002	0.000
1.15	0.006	0.000	0.007	0.000	0.013	0.001	$\boxed{0.047}$	0.000	0.002	0.000	0.006	0.000
1.2	0.012	0.000	0.012	0.000	0.019	0.000	0.173	0.000	0.009	0.000	0.014	0.000
1.25	0.025	0.000	0.019	0.000	0.027	0.000	0.403	0.000	$\boxed{0.035}$	0.000	$\boxed{0.029}$	0.000
1.3	$\boxed{0.045}$	0.000	0.028	0.000	0.037	0.000	0.665	0.000	0.097	0.000	0.055	0.000
1.35	0.075	0.000	$\boxed{0.040}$	0.000	$\boxed{0.049}$	0.000	0.858	0.000	0.211	0.000	0.094	0.000
1.4	0.117	0.000	0.056	0.000	0.064	0.000	0.955	0.000	0.373	0.000	0.147	0.000
1.45	0.171	0.000	0.075	0.000	0.081	0.000	0.989	0.000	0.555	0.000	0.214	0.000
1.5	0.236	0.000	0.098	0.000	0.101	0.000	0.998	0.000	0.721	0.000	0.294	0.000

[a] Gamma, log odds of differential assignment due to unobserved factors; sig+, upper bound significance level; sig-, lower bound significance level. The boxed numbers indicate the critical level of the strength of the effect, Gamma for each of the dependent variables.

APPENDIX: PROPENSITY SCORE MATCHING

This study utilize several PSM algorithms including: nearest neighbor matching (NNM); radius matching (RM); and local linear regression matching (LLR). The NNM estimator compares every treated unit with one or more units from the comparison group that are most similar in terms of the propensity score. It defines the set of matches with replacement is given below:

(A1)
$$C_i^0(M) = \left\{ l = 1, \ldots, N \,\middle|\, T_l = 0, \left| P_i - P_l \right| \le d_i(M) \right\}$$

where M indicates the number of matches (neighbors) and $d_i(M)$ is the distance from individual i to the M^{th} nearest match in the comparison group. We implicitly define $d_i(M)$:

(A2-a)
$$\sum_{l:T_l=0} 1\left\{ \left| P_i - P_l \right| < d_i(M) \right\} < M$$

and

(A2-b)
$$\sum_{l:T_l=0} 1\left\{ \left| P_i - P_l \right| \le d_i(M) \right\} \ge M$$

where $1\{\cdot\}$ is the indicator function that equals to 1 when the value in brackets is true, and zero otherwise. This article implements NNM method using one and five nearest neighbors and with replacement. Replacement means that untreated units can be used more than once as the matches for the treated units. Nevertheless, the NNM estimator could be biased if the distances between "best" matches are sizeable. Therefore, we also use the radius matching with caliper recommended by Dehejia and Wahba (2002) to increase matching quality. The basic idea of the radius matching is to use not only the nearest neighbor within each caliper, but all of the non-agritoursim engagement farms within the caliper. A benefit of this approach is that it uses only as many non-agritoursim engagement farms as are available within the caliper and therefore allows for usage of extra (fewer) units when good matches are (not) available (Caliendo and

Kopeinig, 2008). However, as discussed in Smith and Todd (2005), it is difficult to know a priori what choice for the tolerance level is reasonable. This study uses the caliper of 0.02 and 0.05.

The last PSM algorithm implemented in this study is the LLR. It uses a kernel-weighted average over multiple persons in the comparison group as the counterfactual outcome of the treated observation. Fan (1992) shows that LLR converges faster and that it is more robust to different densities of data than kernel matching. The weight of LLR is given below:

(A3) $$w_{ij} = \frac{G_{ij} \sum_{l \in C_i^0} G_{il} \left(P_l - P_i\right)^2 - \left[G_{il}\left(P_l - P_i\right)\right]\left[\sum_{l \in C_i^0} G_{il}\left(P_l - P_i\right)\right]}{\sum_{j \in C_i^0}\left[G_{ij}\sum_{l \in C_i^0} G_{il}\left(P_l - P_i\right)^2\right] - \left[\sum_{l \in C_i^0} G_{il}\left(P_l - P_i\right)\right]^2}$$

where $G_{ij} = G\left(\left(P_j - P_i\right)/h\right)$ and h is the bandwidth. We use the distributions of Gaussian and Epanechnikov as the kernel functions. The optimal bandwidth for each type of kernel function is selected using the rule of thumb suggested by Silverman (1986). We also experimented with different values of the bandwidth around the optimal bandwidth. We find that the choice of kernel function and bandwidth have very little effect on the performance of the LLR estimator.

Bootstrapping is often used to obtain standard errors for matching estimators to test the hypothesis (e.g. Black and Smith, 2004, Heckman, et al., 1997, Sianesi, 2004). Each bootstrap sample is a random sampling with replacement from the original data set. We draw 1,000 bootstrap samples and estimate 1,000 average treatment effects for the treated. The distribution of these means approximates the sampling distribution (and thus the standard error) of the population mean. However, Abadie and Imbens (2008) show that bootstrap standard errors are not valid as the basis for inference with NNM estimators with replacement and a fixed number of neighbors. Therefore, for NNM, we use the analytical standard error suggested by Abadie and Imbens (2006).

Table S1. Estimated coefficients from logit models - Farms with/without income from agri-toursim and recreational services for full sample and by farm type

	Full		Lifestyle		Intermediate		Commercial	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
				Operator characteristics				
GENDER	0.0404	0.1883	0.2302	0.2766	-0.0052	0.3796	0.0715	1.1279
AGE	-0.0053	0.0079	0.0231*	0.0132	-0.0118	0.0183	0.0004	0.0268
OPYEARS	0.0129*	0.0066	0.0066	0.0097	0.0222*	0.0133	0.0241	0.0243
FARM_OCCUP	0.5720***	0.1919	0.8380**	0.4091	-	-	-	-
LIVEONFARM	-0.1435	0.1783	-0.1783	0.2959	-0.3034	0.3811	0.2044	0.5640
HEIR	0.4308*	0.2204	0.9223***	0.3176	0.0787	0.4342	-0.4446	0.6150
HH_MEMBERS	0.0039	0.0497	-0.0562	0.0722	0.0380	0.1283	0.0214	0.1661
BLACK	1.1547*	0.6671	1.5072**	0.6954	-	-	-	-
ASIAN	-	-	-	-	-	-	-	-
OTHER	0.8173	0.5781	-0.063*	0.7303	-	-	-	-
				Farm characteristics				
ACRES	-0.0004	0.0003	0.0014***	0.0008	0.0007	0.0010	-0.0006	0.0008
ORGANIC	1.1780***	0.3742	1.4240***	0.5300	0.3008	0.7279	-	-
CONSERVE_MED	0.4769***	0.1606	0.8193	0.2250	0.5321	0.3274	0.0154	0.4721
PRESERVED	0.3113	0.1953	0.0133***	0.3590	0.0842	0.3630	0.1408	0.5151
NUM_PRODUCTS	0.7753***	0.1056	0.6182	0.1591	0.8050***	0.2256	1.4577***	0.3612
RENTAL_INC	0.3692	0.6070	0.3807	0.7614	-	-	-	-
PRIME_SOIL	-0.0100	0.0063	0.0025**	0.0097	-0.0083	0.0118	-0.0302	0.0197
INTERNET	0.6792***	0.1687	0.5904*	0.2440	0.7846**	0.3535	0.4922	0.5502
FARMOWN	-0.0022	0.0021	-0.0063	0.0036	0.0044	0.0040	-0.0031	0.0068
ANIMAL	0.2704	0.2047	0.3414	0.2938	0.0157	0.4651	1.1495	1.1383
EQUINE	0.4138*	0.2482	0.5258***	0.3927	0.6614	0.5030	-0.2492	1.7388
FRUIT	0.9732***	0.2767	1.2864***	0.3912	0.7859	0.6318	1.8157*	1.0934
VEGETABLE	0.7916***	0.2582	1.3557**	0.3883	1.3031**	0.5261	-0.3030	0.9177
NURSERY	0.0944	0.2381	0.7193	0.3418	-0.2734	0.5971	0.1602	0.9824
				Location characteristics				
AGLAND	-0.0057	0.0074	-0.0099	0.0115	0.0045	0.0150	-0.0367	0.0312
FORESTLAND	-0.0041	0.0062	-0.0008	0.0097	-0.0143	0.0139	-0.0555**	0.0278
POP_DENSITY	0.0000	8.E-06	-1.E-06	6.E-06	2.E-05	2.E-05	-5.E-05	9.E-05
MED_HH_INC	1.E-05**	4.E-06	-1.E-06	7.E-06	1.E-05	8.E-06	2.E-05	1.E-05
TEMPERATURE	0.1230	0.1066	-0.0296	0.2354	0.1159	0.1785	-0.1554	0.3087
PRECIPITATION	-0.1072	0.2344	0.1370	0.4235	-0.4183	0.4097	1.0736	0.8076
SAMEPRODUCTS	-0.0101**	0.0042	-0.0035	0.0065	-0.0156*	0.0080	-0.0236	0.0188
DIST_NYC	-0.0066	0.0076	-0.0052	0.0121	-0.0034	0.0152	0.0054	0.0293
DIST_PHILA	0.0120*	0.0069	-0.0071**	0.0134	0.0353***	0.0128	-0.0209	0.0297
Constant	-12.1131*	7.0299	-4.5003***	15.7531	-11.6683	11.6112	2.7046	20.7953
Pseudo R^2	0.1555		0.1404		0.1803		0.3568	
% Correct Predict	94.72		95.98		91.94		91.69	
No. observations	4,716		2,687		893		361	

Note: ***, **, * are significant at the 1, 5, and 10 percent level, respectively. Models also include fixed effect dummy of six regions in New Jersey including Delaware River, Gateway, Great Atlantic, Shore, Skylands and South Shore. Moreover, the model using the full sample includes dummy variables of farm types defined by ERS typology including lifestyle farm, intermediate farm, commercial farm, and non-family farm.

Table S2. Estimated coefficients from logit models - Farms with/without income from either "agritoursim and recreational services" or "direct-to-consumer marketing" for full sample and by farm type

	Full		Lifestyle		Intermediate		Commercial	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
			Operator characteristics					
GENDER	0.0288	0.0886	0.0392	0.1161	0.0559	0.2097	-0.5829	0.6476
AGE	-0.0041	0.0038	-0.0036	0.0054	0.0036	0.0099	0.0075	0.0188
OPYEARS	0.0025	0.0032	0.0018	0.0042	0.0077	0.0079	0.0138	0.0159
FARM_OCCUP	0.2214**	0.0906	0.0381	0.1481	-	-	1.2601	1.0863
LIVEONFARM	0.0707	0.0931	0.1644	0.1292	-0.0311	0.2312	0.0733	0.3471
HEIR	0.2204*	0.1239	0.2481	0.1745	0.0737	0.2540	-0.0608	0.3853
HH_MEMBERS	-0.0145	0.0261	-0.0435	0.0345	0.0516	0.0680	0.0608	0.1053
BLACK	0.2852	0.3653	0.3386	0.4732	-0.1618	1.4320	-	-
ASIAN	-0.1727	0.2992	0.1332	0.4291	0.9063	0.8650	-	-
OTHER	0.3149	0.3609	0.1754	0.4993	0.9136	0.8566	-	-
			Farm characteristics					
ACRES	-0.0009***	0.0003	-0.0011	0.0008	-0.0004	0.0008	-0.0007	0.0007
ORGANIC	1.3615***	0.2071	1.5597***	0.3095	1.1958***	0.3922	2.5298***	0.9135
CONSERVE_MED	0.2750***	0.0867	0.4471***	0.1148	0.2121	0.1985	0.1017	0.3642
PRESERVED	-0.0732	0.1288	-0.3079	0.2123	-0.2853	0.2551	0.0567	0.3632
NUM_PRODUCTS	0.8639***	0.0616	0.8106***	0.0821	0.9258***	0.1391	1.6134***	0.2588
RENTAL_INC	-0.6778*	0.3537	-0.8334**	0.4053	-0.8390	1.0538	-	-
PRIME_SOIL	-0.0037	0.0032	-0.0003	0.0042	0.0014	0.0075	-0.0352**	0.0148
INTERNET	0.2303***	0.0754	0.0530	0.0977	0.4803**	0.1865	0.1593	0.3542
FARMOWN	0.0004	0.0013	-0.0009	0.0020	0.0011	0.0025	-0.0039	0.0049
ANIMAL	1.3873***	0.0912	1.5833***	0.1129	0.7936***	0.2380	0.8633	0.7548
EQUINE	-0.4815***	0.1547	-0.4678**	0.2147	-0.6692**	0.3153	-1.4352	1.7233
FRUIT	1.9126***	0.1336	2.1641***	0.1679	1.1855***	0.3603	1.9535**	0.8260
VEGETABLE	2.1710***	0.1215	2.4673***	0.1661	2.1873***	0.2875	0.0543	0.6954
NURSERY	0.1119	0.1246	0.0202	0.1753	-0.1718	0.3155	-0.2142	0.7572
			Location characteristics					
AGLAND	-0.0076**	0.0038	-0.0072	0.0049	-0.0086	0.0089	-0.0053	0.0210
FORESTLAND	-0.0038	0.0033	-0.0029	0.0043	0.0040	0.0077	-0.0375**	0.0182
POP_DENSITY	0.0000	6.E-06	-2.E-06	6.E-06	-1.E-05	2.E-05	0.0001	0.0001
MED_HH_INC	0.0000	2.E-06	-4.E-07	3.E-06	4.E-06	5.E-06	7.E-06	1.E-05
TEMPERATURE	0.0825	0.0608	-0.0739	0.0805	0.2450*	0.1272	0.4458**	0.2213
PRECIPITATION	-0.0733	0.1113	-0.0128	0.1527	-0.3547	0.2388	0.3947	0.5395
SAMEPRODUCTS	-0.0096***	0.0022	-0.0068**	0.0030	-0.0141***	0.0051	-0.0324***	0.0111
DIST_NYC	-0.0064	0.0040	-0.0020	0.0053	-0.0089	0.0092	-0.0021	0.0187
DIST_PHILA	0.0051	0.0037	-0.0045	0.0050	0.0176**	0.0083	0.0220	0.0153
Constant	-8.3333**	3.9751	2.3339	5.2971	-18.8025**	8.3061	-35.0514**	14.6982
Pseudo R^2	0.2157		0.2265		0.2472		0.3280	
% Correct Predict	80.30		78.99		81.54		87.45	
No. observations	6,999		4,046		1,295		518	

Note: ***, **, * are significant at the 1, 5, and 10 percent level, respectively. Models also include fixed effect dummy of six regions in New Jersey including Delaware River, Gateway, Great Atlantic, Shore, Skylands and South Shore. Moreover, the model using the full sample includes dummy variables of farm types defined by ERS typology including lifestyle farm, intermediate farm, commercial farm, and non-family farm.

Table S3. Estimated treatment effects (ATTs) of agritourism on farm profitability using the treatment variable of income from direct-to-consumer marketing (DCM)

Samples	Types of support	Matching algorithms					
		NN1	NN5	LLR Gauss	LLR Epan	Radius 0.02	Radius 0.05
Full sample	common support	338**	239	236	227	254	255
		(151)	(244)	(224)	(218)	(220)	(206)
	thick support	305**	127	166	163	183	146
		(140)	(253)	(217)	(211)	(221)	(254)
Lifestyle farms	common support	134	163	232.51**	231**	246**	233**
		(131)	(115)	(99)	(101)	(107)	(107)
	thick support	147	169	237**	232**	257**	245**
		(140)	(123)	(111)	(115)	(109)	(114)
Intermediate farm	common support	989**	780**	822**	820**	822**	813**
		(424)	(367)	(357)	(370)	(372)	(368)
	thick support	1128**	862**	867**	862**	901**	872**
		(453)	(395)	(391)	(416)	(422)	(425)
Commercial farm	common support	-3038	-5642	-4056	-3706	-8104	-4673
		(3393)	(4928)	(4758)	(4922)	(8412)	(5524)
	thick support	-3808	-5831	-3729	-3296	-10187	-5760
		(2470)	(3964)	(3367)	(3749)	(8270)	(5012)

Note: ***, **, * are significant at the 1, 5, and 10 percent level, respectively. Standard errors are reported in parentheses. The standard errors for all matching algorithms are estimated using bootstrapping with 1,000 replications, except for the nearest neighbor (NN1) and oversampling (NN5) in which we use the analytical standard error suggested by Abadie and Imbens (2006; 2008).

Table S4. Balancing test for the mean difference – before and after matching corresponding to the treatment variable *T_ARS*

Variable	Sample	Full	Lifestyle	Intermediate	Commercial
GENDER	UM	0.0057	0.0090	-0.0003	0.0101
	M	0.0123	-0.0106	0.0115	0.0624
AGE	UM	-0.9414	2.1120*	-1.1780	-0.3780
	M	-0.7454	-0.1200	0.7680	0.8070
OPYEARS	UM	2.0260**	2.2080	1.2410	2.9920
	M	-0.3970	-0.3250	0.9500	-0.4940
FARM_OCCUP	UM	0.2060***	0.09433**	-	-
	M	0.0372	0.0221	-	-
LIVEONFARM	UM	-0.0118	0.0013	-0.0334	0.0763
	M	0.0010	-0.0097	0.0442	-0.0461
HEIR	UM	0.0586***	0.0840***	0.0153	0.0037
	M	-0.0044	0.0074	0.0088	-0.0275
HH_MEMBERS	UM	0.0858	-0.0647	0.0741	0.1949
	M	0.0256	-0.0077	0.0215	0.1350
BLACK	UM	0.0051	0.0131*	-	-
	M	-0.0002	0.0035	-	-
OTHER	UM	0.0074*	0.0044	-	-
	M	0.0016	0.0046	-	-
ACRES	UM	50.4670***	24.9960***	25.1600	-49.5600
	M	5.1800	-2.8930	-2.1800	-62.9300
ORGANIC	UM	0.0404***	0.0476***	0.0260*	-
	M	0.0042	0.0072	0.0020	-
CONSERVE_MED	UM	0.1990***	0.2024***	0.1652***	0.1311*
	M	0.0063	0.0285	0.0330	-0.0860
PRESERVED	UM	0.0897***	0.0420*	0.0361	0.0821
	M	0.0120	0.0073	0.0244	0.0087
NUM_PRODUCTS	UM	0.5639***	0.4639***	0.5120***	0.9721***
	M	-0.0001	-0.0095	-0.0020	-0.0329
RENTAL_INC	UM	0.0011	0.0054	-	-
	M	-0.0012	0.0034	-	-
PRIME_SOIL	UM	-2.5330**	-0.5440	-4.0100**	-6.3500**
	M	0.2980	0.1080	-0.0160	-0.4930
INTERNET	UM	0.1911***	0.1455***	0.1916***	0.0743
	M	0.0127	0.0101	0.0246	-0.0062
FARMOWN	UM	-7.6760***	-6.3610**	1.1540	-3.9380
	M	-1.8530	-1.5020	0.2140	6.3580
ANIMAL	UM	-0.0129	-0.0086	-0.0679	0.0609
	M	0.0092	0.0203	0.0091	-0.0245
EQUINE	UM	0.0248	0.0159	0.0401	-0.0082
	M	0.0010	0.0032	0.0176	-0.0048
FRUIT	UM	0.0699***	0.0894***	0.0636**	0.0358
	M	-0.0213	-0.0053	-0.0282	-0.0501
VEGETABLE	UM	0.0977***	0.0751***	0.1337***	0.0294

	M	0.0169	0.0085	-0.0139	0.0309
NURSERY	UM	-0.0140	0.0152	-0.0676	-0.0788
	M	0.0094	0.0095	0.0071	0.0909

Table S4. (Continue)

Variable	Sample	Full	Lifestyle	Intermediate	Commercial
AGLAND	UM	-2.3850**	-1.7300	-1.3700	-5.9850**
	M	-0.1590	-0.0120	-0.8320	-1.8860
FORESTLAND	UM	-0.6760	-0.9940	1.1540	-1.2860
	M	-0.1020	-0.5060	-1.2550	-1.2480
POP_DENSITY	UM	6.5000	449.3000	-228.0000	124.2500
	M	23.1000	62.3000	139.1500	84.3300
MED_HH_INC	UM	4,336.0000***	216.0000	4,231.0000*	14,221.0000***
	M	275.0000	878.0000	1,240.0000	270.0000
TEMPERATURE	UM	-0.1980*	0.0330	-0.4920**	-0.8860***
	M	0.0190	-0.0160	0.1640	-0.1030
PRECIPITATION	UM	0.1555***	0.0132	0.2197**	0.6290***
	M	-0.0084	0.0283	0.0519	0.0800
SAMEPRODUCTS	UM	5.9070***	4.1740**	5.1470*	14.2000***
	M	-0.1620	-0.2090	-0.7030	0.7510
DIST_NYC	UM	-7.4940***	-2.2060	-9.2350***	-22.3330***
	M	-0.0210	-0.7200	-0.7820	-3.5950
DIST_PHILA	UM	2.9350**	-0.4790	7.7460***	6.2340**
	M	-0.5040	-0.0190	-1.2700	3.6210
RESIDENT_RETIRE	UM	-0.1689***	-	-	-
	M	-0.0102	-	-	-
LIMIT_RESOURCES	UM	-0.0529***	-	-	-
	M	-0.0045	-	-	-
INTERMEDIATE	UM	0.0999***	-	-	-
	M	0.0199	-	-	-
COMMERCIAL	UM	0.0890***	-	-	-
	M	0.0068	-	-	-
RESIDENT/LIFE	UM	-	-0.0190	-	-
	M	-	-0.0044	-	-
HIGHSALES	UM	-	-	0.0970**	-
	M	-	-	0.0120	-
VERYLARGE	UM	-	-	-	0.0292
	M	-	-	-	0.1056
GATEWAY	UM	0.0605***	-0.0028	0.0829***	0.1389***
	M	0.0130	0.0006	0.0330	0.0561
GREATALTANTIC	UM	-0.0214	-0.0087***	-0.0129	-
	M	-0.0010	-0.0032	-0.0058	-
SHORE	UM	-2E-05	0.0608***	-0.0747*	-0.0824
	M	0.0049	-0.0100	0.0017	0.0203
SKYLANDS	UM	0.0136	-0.0466***	0.1108*	0.2268***
	M	-0.0202	0.0174	-0.0312	-0.0240

SOUTHSHORE	UM	-0.0395**	-0.049***	-0.0560	-0.1528**
	M	-0.0007	0.0057	-0.0013	0.0062

Note: The radius matching with caliper 0.02 is used for the balancing test. It performs relatively well across samples in terms of the matching quality (See Tables 6 in the main text & S6). Other matching algorithms also provide very similar conclusion. ***, **, * are significant at the 1, 5, and 10 percent level, respectively. UM and M are abbreviation of unmatched and matched samples, respectively. *RESIDENT_RETIRE, LIMIT_RESOURCES, INTERMEDIATE, COMERCIAL, RESIDENT/LIFE, HIGHSALES, and VERYLARGE* are dummy variables capturing farm types according to the ERS typology. *GATEWAY, GREATALTANTIC, SHORE, SKYLANDS,* and *SOUTHSHORE* are fixed effect dummy variables capturing regions in New Jersey.

Table S5. Balancing test for the mean difference – before and after matching corresponding to the treatment variable *T_ARS_DCM*

Variable	Sample	Full	Lifestyle	Intermediate	Commercial
GENDER	UM	-0.0029	-0.0031	0.0179	-0.0112
	M	0.0004	-0.0088	-0.0041	-0.0051
AGE	UM	-0.4920	-0.6380	0.1460	1.4850
	M	0.0890	0.0790	-0.0160	0.3700
OPYEARS	UM	-0.8200**	-0.8920*	-0.3090	3.2840**
	M	0.0700	-0.0510	0.2870	-0.0770
FARM_OCCUP	UM	0.0166	0.0121	-	0.0792**
	M	0.0079	0.0039	-	0.0090
LIVEONFARM	UM	0.0478***	0.0452***	0.0005	0.0625
	M	-0.0031	-0.0007	0.0155	-0.0059
HEIR	UM	0.0125*	0.0076	0.0192	0.0219
	M	0.0038	0.0073	0.0214	-0.0335
HH_MEMBERS	UM	0.0727*	0.0590	0.0510	0.1106
	M	-0.0157	-0.0199	0.0398	0.1129
BLACK	UM	0.0029	0.0042	0.0024	-
	M	0.0010	0.0026	0.0006	-
ASIAN	UM	0.0048*	0.0049	0.0176***	-
	M	0.0024	0.0058	-0.0101	-
OTHER	UM	0.0036*	0.0024	0.0044	-
	M	0.0024	-6E-05	0.0052	-
ACRES	UM	-24.4090***	-6.2650**	-24.0900**	-103.4500*
	M	-3.9450	-1.0070	1.6580	-50.4000
ORGANIC	UM	0.0578***	0.0494***	0.0926***	0.0497***
	M	0.0189	0.0203	0.0070	-0.0068
CONSERVE_MED	UM	0.0796***	0.0881***	0.0851***	0.0542
	M	0.0131	0.0114	0.0074	0.0019
PRESERVED	UM	-0.0114	-0.0156*	-0.0172	0.0415
	M	0.0049	0.0010	0.0024	-0.0234
NUM_PRODUCTS	UM	0.4710***	0.4328***	0.5198***	0.8736***
	M	-0.0095	0.0167	-0.0177	0.0335
RENTAL_INC	UM	-0.0075**	-0.0096**	-0.0089	-
	M	0.0007	0.0019	0.0002	-
PRIME_SOIL	UM	-2.8540***	-2.0830***	-4.3900***	-5.8590***
	M	-0.0550	0.2440	-0.7960	-0.6880
INTERNET	UM	0.0674***	0.0571***	0.0724**	0.0359

	M	-0.0012	-0.0109	0.0409	-0.0391
FARMOWN	UM	1.2500	0.7840	2.3730	-2.1560
	M	-0.0110	0.8980	0.2500	0.7670
ANIMAL	UM	0.1363***	0.1692***	0.0531**	0.0295
	M	-0.0476	-0.0567	-0.0252	-0.0106
EQUINE	UM	-0.0954***	-0.0879***	-0.1389***	-0.0197
	M	0.0051	0.0046	0.0014	-0.0040
FRUIT	UM	0.1025***	0.1278***	0.0654***	0.0768**
	M	-0.0089	0.0099	-0.0137	-0.0215

Table S5. (Continue)

Variable	Sample	Full	Lifestyle	Intermediate	Commercial
VEGETABLE	UM	0.1819***	0.1629***	0.2725***	0.0781
	M	0.0202	0.0084	0.0074	0.0617
NURSERY	UM	-0.0950***	-0.0850***	-0.0909***	-0.1282**
	M	0.0095	0.0056	0.0109	-0.0186
AGLAND	UM	-2.3010***	-1.7700***	-3.5300***	-4.6880***
	M	-0.2870	-0.0300	-0.8500	0.4180
FORESTLAND	UM	1.9220***	2.1580***	2.8230***	-1.9160
	M	0.2190	0.1560	1.3400	1.1380
POP_DENSITY	UM	-150.9000	-97.5000	-312.3000	325.5700
	M	29.0000	132.5000	98.1000	-18.8500
MED_HH_INC	UM	2,202.0000***	1,705.0000**	2,254.0000*	7,333.0000***
	M	570.0000	-26.0000	775.0000	1,060.0000
TEMPERATURE	UM	-0.3060***	-0.3130***	-0.3930***	-0.2400
	M	-0.0190	-0.0070	-0.1170	-0.1310
PRECIPITATION	UM	0.1388***	0.1286***	0.1538***	0.3447***
	M	0.0141	0.0037	0.0447	0.0376
SAMEPRODUCTS	UM	3.0090***	2.7020***	2.1210	8.3850***
	M	-1.0860	-0.4830	-1.2180	0.7830
DIST_NYC	UM	-5.2890***	-4.4990***	-6.3200***	-12.8970***
	M	-0.4800	0.0300	-0.8250	-1.0470
DIST_PHILA	UM	2.9320***	2.5240***	4.8640***	3.0340
	M	0.0860	-0.0440	1.0530	-0.1570
RESIDENT _RETIRE	UM	0.0321**	-	-	-
	M	0.0026	-	-	-
LIMIT_RESOURCES	UM	-0.0058	-	-	-
	M	-0.0017	-	-	-
INTERMEDIATE	UM	0.0114	-	-	-
	M	0.0059	-	-	-
COMMERCIAL	UM	-0.0211***	-	-	-
	M	-0.0043	-	-	-
RESIDENT/LIFE	UM	-	0.0135	-	-
	M	-	-0.0028	-	-
HIGHSALES	UM	-	-	-0.0198	-
	M	-	-	0.0126	-
VERYLARGE	UM	-	-	-	-0.0490
	M	-	-	-	0.0014
GATEWAY	UM	0.0171***	0.0072	0.0325**	0.0905***
	M	0.0053	0.0053	0.0012	0.0228
GREATALTANTIC	UM	-0.0098	-0.0066	0.0078	-0.0780**
	M	-0.0036	-0.0052	0.0056	0.0138
SHORE	UM	-0.0071	0.0023	-0.0327	-0.0281
	M	0.0018	0.0024	0.0157	-0.0212
SKYLANDS	UM	0.0763***	0.0763***	0.0968***	0.0878*
	M	0.0008	-0.0082	0.0144	0.0101
SOUTHSHORE	UM	-0.0288***	-0.0190**	-0.0373**	-0.0953**
	M	-0.0004	0.0025	-0.0021	-0.0482

Note: The radius matching with caliper 0.02 is used for the balancing test. It performs relatively well across samples in terms of the matching quality (See Tables 6 in the main text & S6). Other matching algorithms also provide very similar conclusion. ***, **, * are significant at the 1, 5, and 10 percent level, respectively. UM and M are abbreviation of unmatched and matched samples, respectively. *RESIDENT_RETIRE, LIMIT_RESOURCES, INTERMEDIATE, COMERCIAL, RESIDENT/LIFE, HIGHSALES, and VERYLARGE* are dummy variables capturing farm types according to the ERS typology. *GATEWAY, GREATALTANTIC, SHORE, SKYLANDS,* and *SOUTHSHORE* are fixed effect dummy variables capturing regions in New Jersey.

Table S6. Matching quality indicators with imposition of common support corresponding to the treatment variable *T_ARS_DCM*

	Before Matching			After Matching		
	Mean Bias	Pseudo R^2	Chi^2	%Mean Bias Reduction	$\%Chi^2$ Reduction	% Pseudo R^2 Reduction
			Full Sample			
NN1	13.86	0.22	1,632.69	-76.07%	-94.47%	-96.86%
NN5	13.86	0.22	1,632.69	-84.50%	-97.24%	-98.41%
Local Linear (Guass)	13.86	0.22	1,632.69	-85.37%	-97.70%	-98.70%
Local Linear (Epan)	13.86	0.22	1,632.69	-85.02%	-97.70%	-98.68%
Radius 0.02	13.86	0.22	1,632.69	-85.87%	-97.70%	-98.58%
Radius 0.05	13.86	0.22	1,632.69	-86.25%	-97.70%	-98.71%
			Residential/Lifestyle and Retirement Subsample			
NN1	14.03	0.23	1,016.49	-76.03%	-92.58%	-95.61%
NN5	14.03	0.23	1,016.49	-83.56%	-95.20%	-97.19%
Local Linear (Guass)	14.03	0.23	1,016.49	-82.82%	-96.94%	-98.29%
Local Linear (Epan)	14.03	0.23	1,016.49	-82.26%	-96.94%	-98.27%
Radius 0.02	14.03	0.23	1,016.49	-84.56%	-96.94%	-98.06%
Radius 0.05	14.03	0.23	1,016.49	-82.98%	-96.94%	-98.19%
			Intermediate Subsample			
NN1	17.11	0.25	352.60	-61.59%	-83.06%	-89.83%
NN5	17.11	0.25	352.60	-76.15%	-92.34%	-95.50%
Local Linear (Guass)	17.11	0.25	352.60	-81.24%	-99.63%	-97.12%
Local Linear (Epan)	17.11	0.25	352.60	-81.18%	-95.16%	-97.12%
Radius 0.02	17.11	0.25	352.60	-78.83%	-95.16%	-97.37%
Radius 0.05	17.11	0.25	352.60	-81.14%	-94.76%	-96.79%
			Commercial Farm Subsample			
NN1	22.09	0.33	157.78	-64.41%	-52.76%	-82.33%
NN5	22.09	0.33	157.78	-76.29%	-87.42%	-95.28%
Local Linear (Guass)	22.09	0.33	157.78	-76.67%	-92.94%	-97.34%
Local Linear (Epan)	22.09	0.33	157.78	-75.85%	-92.64%	-97.22%
Radius 0.02	22.09	0.33	157.78	-77.98%	-90.80%	-96.74%
Radius 0.05	22.09	0.33	157.78	-76.49%	-92.94%	-97.38%

Note: Optimal bandwidth associated with the kernel function in each sample is obtained using the rule of thumb suggested by Silverman (1986). Results with thick support are very similar. The mean standardized bias (SB) before matching is given by $SB_{before} = 100 \cdot \frac{\overline{X}_1 - \overline{X}_0}{\sqrt{0.5 \cdot (V_1(X) + V_0(X))}}$ and the SB after matching is given by $SB_{after} = 100 \cdot \frac{\overline{X}_{1M} - \overline{X}_{0M}}{\sqrt{0.5 \cdot (V_{1M}(X) + V_{0M}(X))}}$ where X_1 (V_1) is the mean (variance) in the treatment group before matching and X_0 (V_0) the analogue for the control group. X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values for the matched samples.