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Does Agritourism Enhance Farm Profitability?

Brian J. Schilling, Witsanu Attavanich, and Yanhong Jin

The 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.

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

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 motives 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 among many forms of agriculture (Nickerson, Black, and McCool, 2001; Schilling, Sullivan, and Komar, 2012). Other motivations for agritourism adoption include family goals, social objectives, and personal entrepreneurial goals (Nickerson, Black, and McCool, 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 have more substantial effects on farm income (Barbieri, 2013; Schilling, Sullivan, and Komar, 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 rely instead 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, Sullivan, and Komar, 2012). The lack of a consistent definition for "agritourism" and similarly variable nomenclature combine to be

Brian J. Schilling is an assistant extension specialist in the Department of Agricultural, Food, and Resource Economics and Rutgers Cooperative Extension at Rutgers University. Witsanu Attavanich is a lecturer in the Department of Economics, Faculty of Economics at Kasetsart University, Bangkok, Thailand. Yanhong Jin is an associate professor in the Department of Agricultural, Food, and Resource Economics and Rutgers Cooperative Extension at Rutgers University.
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impediments 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 the sampling frames necessary to conduct statistically reliable survey research capable of supporting generalizations about this sector of agriculture (Veeck, Che, and Veeck, 2006; Schilling, Sullivan, and Komar, 2012).

In addition, there exist myriad reasons—both financial and nonfinancial—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, Black, and McCool, 2001; Ollenburg and Buckley, 2007) and 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 United States (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, Che, and Veeck, 2006; Barbieri, 2013). Failure to account for the heterogeneity of purposes and motives that individuals have for incorporating agritourism into 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 that needs 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 skills 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.

This study examines 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 "agritourism and recreational services" and a broader measure that 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 (more than $250,000 in sales) size classes.

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% 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 by the accommodation of guests seeking farm-based recreation, entertainment, or education activities. The receptivity of the nonfarm public to such opportunities is similarly evident (Carpio, Wohlgenant, and Boonsaeng, 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) find 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 United States when viewed in the 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 1–3% of U.S. farms report income from farm-based recreation (Brown and Reeder, 2007; U.S. Department of Agriculture, National Agricultural Statistics Service, 2009).

While national data show that only a small percentage of U.S. farms are currently engaged in agritourism, Schilling, Sullivan, and Komar (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 these activities within the heavily urbanized Northeast region of the United States. New Jersey is the most urbanized state in the nation and ranks first and sixth in the proportion of state farm sales derived, respectively, from agritourism and direct marketing (Schilling, Sullivan, and Komar, 2012). 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 nonfarm 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, Black, and McCool, 2001; McGehee, Kim, and Jennings, 2007; Sharpley and Vass, 2006; George et al., 2011; Schilling, Sullivan, and Komar, 2012). However, improving farm financial performance is generally a primary motive behind the development of agritourism enterprises. In a survey of Montana farmers, Nickerson, Black, and McCool (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, Kim, and Jennings, 2007) and Australia (Ollenburg and Buckley, 2007) generate similar conclusions. Among California agritourism operators, George et al. (2011) find that 75% 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 (specifically farm-based accommodations) 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 report 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 agritourism is a supplemental source of income for most farms.[1] George 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% following the addition of agritourism enterprises to their operations.

Survey research clearly highlights the importance of economic goals to operators entering agritourism. Several studies suggest that agritourism impacts farm financial performance 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 (U.S. Department of Agriculture, National Agricultural Statistics Service, 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 40% of small agritourism farms (those earning less than $250,000 from farming annually) generate all of their farm income from agritourism, but do not directly examine the impacts of agritourism on farm profitability. For many conventional (i.e., production-wholesale oriented operations) farms, incorporating 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 of managerial effort. These factors have implications for farm expenses and the net effect on farm profitability therefore remains poorly understood.

Methods

Our study goal is to evaluate the effect of agritourism enterprise development on farm profitability by estimating 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:

$$ATT = E(Y_1|T = 1) - E(Y_0|T = 1), \tag{1}$$

where T represents treatment status (engaging in agritourism). However, the expression $E(Y_0|T = 1)$ is not observable because the treatment assignment is mutually exclusive, 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 nonexperimental studies) assignment to a treatment cannot be assumed to be random. In the current context, it is reasonable to expect that innate differences exist 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, making differences in outcomes observed between matched observations attributable to treatment (Imbens,

[1] Examination of data presented by Veeck, Che, and Veeck (2006) (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.

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, Ichimura, and Todd, 1997).

PSM has been employed in several recent agricultural economic contexts, including evaluating the effects of organic certification on farm income (Uematsu and Mishra, 2012), 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, nonexperimental 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 nonexperimental 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

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

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 rewritten as

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

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.

Data

Data used in this study derive primarily from 7,575 respondent-level records from the 2007 New Jersey Census of Agriculture collected by the National Agricultural Statistics Service. Since a standardized definition of agritourism is still lacking (Phillip, Hunter, and Blackstock, 2010; Arroyo, Barbieri, and Rich, 2013), two treatments were defined. The distinction between the two treatment definitions is the exclusion or inclusion of the sale of "agricultural products directly to individuals for human consumption" (what we label in shorthand as direct-to-consumer marketing, or DCM). The first, *T_ARS*, is a narrowly defined treatment that assumes a value of 1 if a farm reported earned income from "agritourism and recreational services" (ARS) in the 2007 Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2009). *T_ARS* takes a value of 0 if a farm did not earn any income from ARS or DCM.

Nationally, 23,350 farms reported income from agritourism and recreational services in the 2007 Census of Agriculture; 322 were located in New Jersey (U.S. Department of Agriculture, National Agricultural Statistics Service, 2009). More specific information on the types of agritourism activities in which farmers are engaged are not provided; however, examples of relevant activities

[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).

listed on the census questionnaire include "farm or winery tours, hay rides, hunting, fishing, etc." While not directly comparable to the Census of Agriculture, the USDA's 2006 Agriculture and Resource Management Survey (ARMS) offers some insight into the nature of such activities occurring on U.S. farms. Documenting 47,380 agritourism farms in the United States (considerably more than in the Census of Agriculture), ARMS finds that nearly three-quarters of agritourism farms offer outdoor recreation (e.g., hunting, fishing, horseback riding, etc.).[3] Consultation with a Western state director of the National Agricultural Statistics Service (NASS) confirms that hunting leases and other outdoor recreational activities are particularly popular on large ranches in Western states.

A survey conducted by the NASS New Jersey Field Office in 2006 found that on-farm direct marketing was the most common agritourism activity, offered by nine of ten agritourism farms in the state (Schilling, Sullivan, and Komar, 2012). This finding comports with a nearly identical survey conducted in Vermont in 2002 (New England Agricultural Statistics Service, 2004). The New Jersey study further finds that 12% of farms allowed outdoor recreation (e.g., hunting, fishing, bird watching, horseback riding, etc.), 7% offered educational tours, roughly 7% hosted entertainment-oriented events (e.g., corn mazes, hayrides, petting zoos, etc.), and fewer than 4% reported on-farm accommodations (e.g., bed and breakfasts, weddings, event hosting, etc.).

The second treatment, *T_ARS_DCM*, is more broadly defined to be consistent with previous NASS assessments of agritourism in New Jersey and Vermont. *T_ARS_DCM* is assigned a value of 1 if a farm earned income from ARS or DCM. It takes a value of 0 if a farm did not earn any income from ARS or DCM. Recreational and educational activities on the farm are often integrated components of direct-marketing operations. The use of the broader treatment definition is also predicated on the fact that farmers in New Jersey and other Northeast states rely disproportionately more on direct-to-consumer marketing than do their counterparts in other regions. Schilling, Sullivan, and Komar (2012) report that the percentage of total farm sales derived from direct marketing is roughly five times higher in the Northeast region than it is for the United States overall. They further show that the nine Northeast states rank ahead of all other states in terms of the proportion of farm sales linked to direct marketing.[4] Census of Agriculture data reveal that direct-to-consumer marketing sales in the broader Northeast region more than doubled from $101 million in 1997 to $213 million in 2007, outpacing growth at the national level (Diamond and Soto, 2009).

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 predominant share of the treatment group pertaining to *T_ARS_DCM* is DCM-only farms ($n = 1,415$).

The farm-profitability outcome evaluated is net cash income per acre, which is calculated in the Census of Agriculture by subtracting (on a per acre basis) total farm expenses from total sales, government payments, and other farm-related income. Depreciation is not considered in the calculation. It is worth noting that net cash income per acre is a proxy for farm profit, but it does not reflect all cost and income factors that would be needed to derive true economic profit. For example, net cash income per acre does not reflect the opportunity cost of capital or the implicit costs of farm operator and family labor if they do not receive salaries.[5]

[3] The authors are grateful to an anonymous reviewer who conveyed this information. Citing 2006 ARMS data, the reviewer further notes that 13% of U.S. farms engage in hospitality services (farm stays, overnight accommodations), 6% offer entertainment services (e.g., harvest festivals, rodeos, petting zoos), and 2% provide guided farm tours. The disparity between the number of agritourism farms documented in the Census of Agriculture and ARMS is likely attributable to sampling issues and differences in the phrasing of the respective survey questions. For example, ARMS (in 2006) posed questions ascertaining the presence or absence of income from five specific types of agritourism; the Census asked only one general questions about income from "agritourism and recreational services."

[4] The disproportionate reliance on farm direct marketing in New Jersey is evidenced by the fact that the state ranks twelfth in total direct-marketing sales, while ranking only fortieth in total farm sales.

[5] The authors gratefully acknowledge an anonymous reviewer's observation that net cash income also excludes the implicit rental value of the farm operator's dwelling. S/he further notes that net cash income does not account for cash expenses associated with the dwelling (e.g., maintenance, mortgage payments). These omissions may result in decidedly different perspectives of the financial performance of farms based on the financial measure used, particularly for small farms.

Table 1. Description of Variables

Variables	Description
Outcome	
NETCASHINC	Net cash income per acre
Treatments	
T_ARS	The reported income from agritourism and recreational services (1) or not (0)
T_ARS_DCM	The reported income from either "agritourism 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)
Farm Types	
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
NONFAMILY*	Nonfamily 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

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Table 1. – continued from previous page

Variables	Description
Regions in New Jersey	
GATEWAY	Gateway region- Middlesex, Union, Essex, Hudson, Bergen, Passaic
GT_ATLANTIC	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

Notes: A single asterisk "*" captures dummy variables that are omitted in the models.

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 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 1 if the operator resides on the farm), and whether an heir is present.[6] 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 also 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), or maintains internet access. A series of dummy variables also categorize farms based on which commodity generates the highest percentage of farm income and the USDA-Economic Research Service's farm typology, which classifies 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 earn less than $250,000 in annual 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

[6] An heir is assumed to be present if several conditions are met, including whether 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 or her time employed in agriculture (and is not a hired manager).

is a primary occupation and earn, respectively, less than $250,000 in sales and $250,000 or more in sales annually.

Table 2 presents summary statistics for selected variables for farms with and without income from agritourism as 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 treatment definition (*T_ARS_DCM*). We observe that per acre farm profitability (*NETCASH*) is higher under both treatment definitions for farms engaging in agritourism relative to farms that do not engage in agritourism. These relationships are consistent across the full sample and the three subsamples. Nonparametric 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.

Empirical Results

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 **??** and **??** 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 79–96%.

While differences in statistical significance among 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 to engage in agritourism among hobby farms in the model using the treatment variable *T_ARS*, but it does not influence the decision to engage in agritourism among hobby farms in the model using the treatment variable *T_ARS_DCM*.

Estimated Effects of Agritourism on Farm Probability

A propensity score is derived for each farm 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 Appendix A. The use of multiple matching estimators is a useful robustness check, allowing the sensitivity of estimated ATTs to the selected matching estimator to be observed.

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), for which we calculate the analytical standard error suggested by Abadie and Imbens (2006, 2008). We apply both the trimming approach and

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

	Full Sample		Lifestyle		Intermediate		Commercial	
Variables	**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	0.80	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	0.80	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	0.99	0.98	0.98	0.99	0.99	0.99	1.00	0.97
BLACK	0.01	0.01	0.02	0.01	0.00	0.00	0.00	0.00
ASIAN	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.03
OTHER	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00
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	0.10	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	0.80	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	0.20	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	30.70	31.38	31.36	32.36	30.94	29.78	25.90	27.18
POP_DENSITY ($1,000)	1.30	1.30	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	50.70	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	48.20	45.27	45.45	45.93	52.01	44.26	47.43	41.20
N	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

	Full Sample		Lifestyle		Intermediate		Commercial	
Variables	**With**	**Without**	**With**	**Without**	**With**	**Without**	**With**	**Without**
Potential Outcomes								
NETCASHINC ($1,000)	0.86	0.78	0.25	−0.06	0.75	−0.31	7.77	7.67
Operator Characteristics								
GENDER	0.80	0.80	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	19.90	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	0.80	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	0.98	0.98	0.98	0.98	0.97	0.99	1.00	0.97
BLACK	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00
ASIAN	0.01	0.01	0.01	0.01	0.02	0.01	0.00	0.03
OTHER	0.01	0.00	0.00	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	0.10	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	85.60	91.87	91.09	79.50	77.12	59.95	62.10
ANIMAL	0.34	0.20	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	4.40	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
N	1,594	5,405	961	3,085	309	986	92	426

Table 4. Estimated Treatment Effects (ATTs) of Agritourism on Farm Profitability Using the Trimming Approach

	Matching Algorithms					
Samples	**NN1**	**NN5**	**LLR Gauss**	**LLR Epan**	**Radius 0.02**	**Radius 0.05**
			Treatment variable: T_ARS			
Full sample	2,585**	2,406*	2,755**	2,794**	2,837**	2,788**
	(1,195)	(1,292)	(1,201)	(1,337)	(1,331)	(1,297)
Lifestyle farms	1,367*	1,189*	1,393*	1,446**	1,361**	1,314**
	(702)	(642)	(758)	(644)	(674)	(609)
Intermediate farms	3,423**	2,429***	2,587**	2,449**	2,964**	2,388***
	(1,567)	(893)	(1,233)	(1,025)	(1,160)	(908)
Commercial farms	8,214	5,056	7,777	4,702	6,842	5,493
	(5,948)	(4,655)	(83,768)	(11,754)	(7,777)	(7,435)
			Treatment variable: T_ARS_DCM			
Full sample	621***	705***	386	378	443*	429*
	(183)	(184)	(291)	(299)	(262)	(255)
Lifestyle farms	350***	334**	256**	257**	289**	269**
	(132)	(136)	(120)	(122)	(131)	(126)
Intermediate farms	894*	1,029**	1,084***	1,089	1,034**	1,024***
	(542)	(406)	(395)	(700)	(401)	(393)
Commercial farms	2,174	3,049	-879	1,071	2,293	1,406
	(2,784)	(2,806)	(9,528)	(3,940)	(4,874)	(3,984)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. 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), for which we use the analytical standard error suggested by Abadie and Imbens (2006, 2008).

common support. (Results based on the common support are presented in table **??** of Supplementary Information.) The discussion below is based on the trimming approach (thick support) suggested by Crump et al. (2009), which addresses the possibility of limited overlap between agritourism farms and observationally equivalent non-agritourism farms.[7]

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—and the size of agritourism effects on farm profitability measured by net cash income varies 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 the 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 they are considerably smaller in magnitude in all cases 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 $429 to $705. In the lifestyle and intermediate-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.

[7] 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_DCM*, 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. We also find that the results in table 4 are consistent with those from the non-trimming approach (common support) provided in table **??** of Supplementary Information.

These results provide empirical evidence to support 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. 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.

A conclusive explanation for the disparity between net cash income effects attributable to the *T_ARS* and *T_ARS_DCM* treatments is not readily apparent in the current literature, nor is one made immediately evident through our analysis. This is a proverbial "less is more" finding: higher net cash income, on average, is observed for agritourism farms that do not engage in direct-to-consumer marketing. This finding is confirmed when we replicate the analysis and calculate the effect of only direct-to-consumer marketing on farm profitability. Focusing on the thick support estimates, the ATT associated with direct-to-consumer marketing only ranges from only \$271 to \$356 (Supplemental Information table **??**), substantially less than the effects estimated for the *T_ARS* treatment.

The dampening "direct-marketing effect" dominates the ATTs estimated for the *T_ARS_DCM* treatment. Among the 1,594 farms assigned to this treatment, only 268 farms (less than one-fifth) engage only in agritourism and recreational services. Vogel (2012) assesses several types of on-farm diversification strategies in the United States and observes lower revenue generation from direct marketing than agritourism (an average of \$11,185 versus \$15,255 per farm). A considerably more striking revenue disparity is evident in New Jersey; the average farm reporting income from agritourism and recreational services earned \$76,708 from such activities in comparison to an average of only \$15,591 in direct-to-consumer sales among direct-marketing farms (U.S. Department of Agriculture, National Agricultural Statistics Service, 2009). A review of Census of Agriculture data shows that some of this revenue difference may be scale-related. Direct marketing is a popular marketing strategy among very small farms. In fact, 62% of all New Jersey direct-marketing farms earn less than \$10,000 in gross farm sales. In contrast, only 43% of farms reporting income from agritourism and recreational services fall into this sales class.

We also believe that the lower ATTs estimated for the *T_ARS_DCM* treatment is evidence of different levels of investment (e.g., new physical infrastructure, staffing, etc.) required across agritourism operations more focused on recreational and educational activities versus those that encompass direct marketing. For example, we surmise that many of the types of activities that one would observe under the *T_ARS* treatment (e.g., an educational tour for school children, hunting and bird watching, a petting zoo or corn maze, etc.) more often rely on the farm premises in its existing condition, requiring minimal new investments in infrastructure or staffing. In contrast, we anticipate a greater level of infrastructure development is required for many direct-marketing enterprises (e.g., construction of a farm market). Further, some on-farm recreational or educational activities are seasonal and confined to relatively short time periods. For example, many New Jersey corn mazes operate for fewer than eighteen days annually (three days per week for the six weeks leading to Halloween). Similarly, harvest or "wassailing" events occur only periodically, often in the autumn. Validation of these suppositions will require research.

Matching Quality and Robustness Checks

To assess the quality of the estimated treatment effects, we first 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, we report the mean differences for each matching covariate between the treated and untreated groups before and after matching as well as their statistical significance in tables **??** and **??** of the Supplementary Information. A clear lack of balance before matching is observed: 25 (30) of 44 mean differences are statistically significant at the 5% level for the *T_ARS*

Table 5. 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
1.2	0.012	0.000	0.012	0.000	0.019	0.000	0.173	0.000	0.009	0.000	0.014	0.000
1.4	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

Notes: [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.

(*T_ARS_DCM*) treatment. Matching improves the balance significantly. After matching, the mean differences for all covariates are not statistically significant for either the *T_ARS* or *T_ARS_DCM* treatments. We also find similar matching quality among the subsamples.

Second, we employ different matching parameters: ten 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 and the *T_ARS_DCM* treatment (see Supplemental Information tables **??** and **??**, respectively).

Finally, as discussed in the methods section, PSM relies on the conditional independence assumption. That is, estimates of treatment effects based on matching are 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 relevant covariates 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 5, 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 lifestyle-farms and intermediate-farms subgroups remain robust (threshold gamma=1.25).

Conclusions

Agritourism has emerged as an important adaptation strategy among small farms, particularly in Northeast states that have advanced urbanization pressures (Schilling, Sullivan, and Komar, 2012). While economic motives are often cited as important drivers of agritourism development, the literature remains inconclusive as to 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.

Our primary empirical contribution is the validation of qualitative claims that agritourism improves farm financial performance for certain farm types. 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 among intermediate-scale and lifestyle farms but has no discernible impact on the net cash income per acre generated by commercial-scale farms (those earning $250,000 or more in annual sales). This latter finding comports with the finding of Schilling, Sullivan, and Komar (2012) that farms of this scale, while frequently engaged in agritourism, often do so for nonpecuniary reasons (e.g., to educate the public about farm issues, generate support for farm retention policies, etc.).

Recognizing 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 these views ignore 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, lifestyle farms; however, we find that agritourism farms in this farm subgroup generate higher net cash returns per acre from farming than their counterparts that do not engage in agritourism. Census data show that 91% of retirement and residential lifestyle farms earn less than 25% of household income from farming (U.S. Department of Agriculture, National Agricultural Statistics Service, 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 rely on farm-based revenue to differing extents to supplement household income. Agritourism may contribute to making farm household income "whole," covering farm ownership costs, offsetting retirement expenses, or meeting other economic objectives. Similarly, operators of intermediate-scale farms—smaller 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%) of industry revenue, they represent three-quarters of all farms and manage more than 302,000 acres of farmland (42% of the state's land in farms). From a broad perspective, the financial performance of small farms often lags considerably 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. Academically, this is validation that definitions matter. In our study, a more parsimonious definition of agritourism yields significantly different (higher) treatment effects than when agritourism is defined more expansively to include direct marketing. This suggests the need for caution when interpreting and comparing studies on the impacts of agritourism on farm financial performance. While further research is needed to fully understand the implications for farm financial performance of these alternative components of agritourism, this finding emphasizes the importance of standardizing the definition of agritourism in 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 in which observational 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 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. Third, net cash income per acre does not reflect all farm income and expense components and is not a perfect proxy for evaluating farms' economic profits. More nuanced impacts of agritourism on farm profitability may be exposed with the use of refined financial metrics. Fourth, agritourism in New Jersey, as well as in other Northeast states, may be atypical of agritourism in other regions of the United States. Consequently, the impact of agritourism on farm profitability in other regions may differ.

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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Appendix: Propensity Score Matching

This study utilizes 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, given below:

$$C_i^0(M) = \{l = 1, \ldots, N | T_l = 0, \; |P_i - P_l| \leq d_i(M)\}, \tag{A1}$$

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

$$\sum_{l:T_l=0} 1\{|P_i - P_l| < d_i(M)\} < M \tag{A2a}$$

and

$$\sum_{l:T_l=0} 1\{|P_i - P_l| \leq d_i(M)\} \geq M, \tag{A2b}$$

where $1\{\cdot\}$ is the indicator function that equals 1 when the value in brackets is true and 0 otherwise. This study 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 sizable. 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-agritourism engagement farms within the caliper. A benefit of this approach is that it uses only as many non-agritourism 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 is reasonable for the tolerance level. This study uses a 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 as

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

where $G_{ij} = G((P_j - P_i)/h)$ 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 experiment with different values of the bandwidth around the optimal bandwidth and find that the choices 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 a hypothesis (e.g., Black and Smith, 2004; Heckman, Ichimura, and Todd, 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).

Supplemental Information

Table S1. Estimated Coefficients from Logit Models - Farms with/without Income from Agritourism 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	-0.0630*	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	8.E-07	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	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. 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 nonfamily farm.

Table S2. Estimated Coefficients from Logit Models: Farms with/without Income from either "Agritourism 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	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. 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 nonfamily farm.

Table S3. Estimated Treatment Effects (ATTs) of Agritourism on Farm Profitability Using the Non-Trimming Approach (Common Support)

	Matching Algorithms					
Samples	NN1	NN5	LLR Gauss	LLR Epan	Radius 0.02	Radius 0.05
			Treatment variable: T_ARS			
Full sample	2,313**	2,166*	2,501**	2,560**	2,467**	2,496**
	(1,044)	(1,123)	(1,003)	(1,096)	(1,106)	(1,033)
Lifestyle farms	2,027***	1,870**	1,975**	2,031**	1,969**	1,917**
	(788)	(807)	(762)	(831)	(852)	(826)
Intermediate farms	2,683**	1,954**	1,904**	1,887*	2,286**	1,813**
	(1,372)	(789)	(932)	(1,077)	(1,043)	(856)
Commercial farms	10,221	7,695	4,796	4,759	6,910	5,632
	(7,644)	(5,961)	(7,285)	(9,461)	(8,409)	(7,278)
			Treatment variable: T_ARS_DCM			
Full sample	818***	899***	558*	553*	587*	569*
	(204)	(217)	(314)	(319)	(327)	(350)
Lifestyle farms	446***	437***	358**	358***	379***	361***
	(153)	(148)	(144)	(125)	(141)	(130)
Intermediate farms	1,001*	1,061***	995***	998***	976**	977***
	(546)	(381)	(336)	(339)	(378)	(373)
Commercial farms	3,309	3,398	1,381	1,103	2,329	1,694
	(3,576)	(3,780)	(4,330)	(4,349)	(4,578)	(4,147)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. 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), for which we use the analytical standard error suggested by Abadie and Imbens (2006, 2008).

Table S4. Estimated Treatment Effects (ATTs) of Agritourism on Farm Profitability Using the Treatment Variable of Income from Direct-to-Consumer Marketing (DCM)

		Matching Algorithms					
Samples	Types of Support	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	233**	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	1,128**	862**	867**	862**	901**	872**
		(453)	(395)	(391)	(416)	(422)	(425)
Commercial farm	Common support	-3,038	-5,642	-4,056	-3,706	-8,104	-4,673
		(3,393)	(4,928)	(4,758)	(4,922)	(8,412)	(5,524)
	Thick support	-3,808	-5,831	-3,729	-3,296	-10,187	-5,760
		(2,470)	(3,964)	(3,367)	(3,749)	(8,270)	(5,012)

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. 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), for which we use the analytical standard error suggested by Abadie and Imbens (2006, 2008).

Table S5. 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
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***

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Table S5. – continued from previous page

Variable	Sample	Full	Lifestyle	Intermediate	Commercial
	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
GREATATLANTIC	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**	−0.0490***	−0.0560	−0.1528**
	M	−0.0007	0.0057	−0.0013	0.0062

Notes: The radius matching with caliper 0.02 is used for the balancing test and performs relatively well across samples in terms of the matching quality (See table S7). Other matching algorithms also provide very similar conclusion. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. UM and M are abbreviations for unmatched and matched samples. *RESIDENT_RETIRE*, *LIMIT_RESOURCES*, *INTERMEDIATE*, *COMMERCIAL*, *RESIDENT/LIFE*, *HIGHSALES*, and *VERYLARGE* are dummy variables capturing farm types according to the ERS typology. *GATEWAY*, *GREATATLANTIC*, *SHORE*, *SKYLANDS*, and *SOUTHSHORE* are fixed effect dummy variables capturing regions in New Jersey.

Table S6. 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***	0.432***	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
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***

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Table S6. – continued from previous page

Variable	Sample	Full	Lifestyle	Intermediate	Commercial
	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
GREATATLANTIC	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

Notes: The radius matching with caliper 0.02 is used for the balancing test and performs relatively well across samples in terms of the matching quality (see table S8). Other matching algorithms also provide very similar conclusion. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. UM and M are abbreviations for unmatched and matched samples. *RESIDENT_RETIRE*, *LIMIT_RESOURCES*, *INTERMEDIATE*, *COMMERCIAL*, *RESIDENT/LIFE*, *HIGHSALES*, and *VERYLARGE* are dummy variables capturing farm types according to the ERS typology. *GATEWAY*, *GREATATLANTIC*, *SHORE*, *SKYLANDS*, and *SOUTHSHORE* are fixed effect dummy variables capturing regions in New Jersey.

Table S7. 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 (Gauss)	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 (Gauss)	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 (Gauss)	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 (Gauss)	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%

Notes: 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 $SB_{before} = 100 \times \frac{\overline{X}_1 - \overline{X}_0}{\sqrt{0.5 \times (V_1(X) + V_0(X))}}$ and the SB after matching is given by $SB_{after} = 100 \times \frac{\overline{X}_{1M} - \overline{X}_{0M}}{\sqrt{0.5 \times (V_{1M}(X) + V_{0M}(X))}}$, where X_1 (V_1) is the mean (variance) in the treatment group before matching, X_0 (V_0) is the analogue for the control group, and X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values for the matched samples.

Table S8. 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 (Gauss)	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 (Gauss)	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 (Gauss)	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 (Gauss)	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%

Notes: Optimal bandwidth associated with the kernal 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 $SB_{before} = 100 \times \frac{\overline{X}_1 - \overline{X}_0}{\sqrt{0.5 \times (V_1(X) + V_0(X))}}$ and the SB after matching is given by $SB_{after} = 100 \times \frac{\overline{X}_{1M} - \overline{X}_{0M}}{\sqrt{0.5 \times (V_{1M}(X) + V_{0M}(X))}}$, where X_1 (V_1) is the mean (variance) in the treatment group before matching, X_0 (V_0) is the analogue for the control group, and X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values for the matched samples.