Agritourism and Direct Sales Clusters in the United States

Claudia Schmidt
Department of Agricultural Economics, Rural Sociology and Extension Education
Pennsylvania State University
112-A Armsby, University Park, PA 16802, USA
cschmidt@psu.edu

Zheng Tian
Department of Agricultural Economics, Rural Sociology and Extension Education
Pennsylvania State University
007-B Armsby, University Park, PA 16802, USA
zzt36@psu.edu

Stephan J. Goetz
Northeast Regional Center for Rural Development, Pennsylvania State University
Department of Agricultural Economics, Rural Sociology and Extension Education
Pennsylvania State University
207-C Armsby, University Park, PA 16802, USA
sgoetz@psu.edu

Lisa Chase
University of Vermont Extension
University of Vermont,
Brattleboro, VT 05301, USA
Lisa.Chase@uvm.edu

Chadley Hollas
Kadupul Tourism Research Consulting
Austin, TX 78653, USA
crhollas@gmail.com

Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA, July 31-August 2, 2022

Working Paper – Please Do not Cite

Abstract

Agritourism and direct-to-consumer sales are farm diversification strategies that are adopted by all types of agricultural producers to provide additional revenue streams, contribute to rural economic growth, and leverage the tourism industry in rural areas. We use univariate and bivariate local Moran's I to determine hotspots of agritourism and direct sales to consumers in the United States and a SUR Spatial Durbin Model to examine the association between agritourism and direct sales to consumers. Our results show that agritourism and direct sales reinforce each other, which has important implications for census data collection and agritourism research and extension.

1 Introduction

In the conceptual framework developed by Chase et al. (2018), agritourism activities can be classified into five overlapping categories: education, hospitality, outdoor recreation, entertainment, and direct sales of agricultural products. While these categories are consistent with agritourism literature and past research (e.g., Schilling 2012), agritourism and direct-to-consumer sales are captured separately in the USDA National Agricultural Statistics Service (NASS) Census of Agriculture. Both are important diversification strategies and income sources for American farmers, and their impact has been evaluated on farm families, rural economic growth, and the rural tourism industry (Gale, 1997; Thilmany et al, 2019; Barbieri, 2013; Ammirato, et al., 2020), sometimes with mixed results (Stickel et al., 2020).

Agritourism research has been expanding dramatically for the last decade. Its multidisciplinary nature accommodates research that spans from community development (Naidoo and Sharpley, 2016) to the social capital of agritourism entrepreneurs (Khazami, et al., 2020) and its potential to make rural communities more sustainable (Ciolac, 2020) to its relevance to food systems (Brune, et al., 2021) and beyond. Many studies have explored the factors that make an agritourism destination attractive to visitors (Pesonen, 2011). This attraction is beneficial to visitors and farmers alike. Generally, research has indicated that agritourism is used successfully as a diversification strategy by farmers (Barbieri, 2013; Khanal and Mishra, 2014; Hochuli, 2021) and can potentially enhance the perceived profitability of farm businesses (Hollas, et al, 2021). By promoting food heritage, a more lasting meaning is given to farming communities (LaPan and Barbieri, 2014). Agritourism has also provided opportunities for rural entrepreneurs (McGehee, 2004; Dickes, et al., 2020) and supported the viability of rural communities more broadly. However, with this more precise understanding of agritourism, research and the data employed are based on inconsistent definitions.

Early studies on agritourism tackled the definitions and typologies (Arroyo et al., 2013; Flanigan et al., 2014; Phillip et al., 2010), but discrepancies still exist in what is included in 'agritourism' data. Using narrow definitions of agritourism inhibits a complete understanding of how agritourism experiences impact communities, farm owners, and the food systems more broadly. While the USDA NASS Census of Agriculture analyzes direct-to-consumer sales and agritourism separately, looking at both better reflects consumers' views and their experiences with agritourism, as noted in previous research (Nemes, et al., 2019; Sgroi, 2014). Agritourism consumers are strongly motivated by local foods. Even though this type of tourism's impact on local food systems has been questioned (Haven-Tang, et al., 2022), the agritourism experience has been found to impact food purchasing habits after the visitors return home (see Brune, et al. 2021). Through agritourism, farmers can market not only their products but a certain 'way of life' (Tew and Barbieri, 2012) that is embedded in the rural place; as a result, travelers embrace the intra- and inter-regional identities that make each experience special.

'Place-based' and spatial considerations are integral to agritourism. The experiences' proximity to natural amenities (Gartner, 2005; Hill et al., 2014), proximity to urban areas (Che, 2007), and the geographic region (Bagi and Reeder, 2012) all affect the existence and the viability of agritourism enterprises (Van Sandt et al., 2018). Through this research, clusters, or 'hot spots,' of agritourism have been designated, the development of which has been of recent interest to researchers. Drivers of agritourism clusters (not including direct sales) have been explored by Van Sandt et al. (2018) using 2012 census data. Their paper was the first study utilizing regional science methods looking at the connection of agritourism development with place-based factors, using a spatial analysis to determine the location of agritourism clusters in the United States at the county level. They found that "travel infrastructure, region and rurality, characteristics of the local economy, and proximity to outdoor attractions are all significantly associated with the probability of a county being an agritourism hot spot" (p. 592). Khanal and Lucha (2020) utilized spatial regression models, zip-code and county level data to investigate determinants of the location of agritourism operations, finding that higher median household income, higher level of education, and even wood product manufacturing positively impacted the establishment of agritourism farms. Similarly, but looking at organic agriculture, Marasteanu and Jaenicke (2016) identified hot and cold spots in the United States and found that many organic hot spots did not match with general agricultural hot spots. In addition, they tested for spatial autocorrelation using shares of certified organic operations and found spatial spillovers. Agritourism clusters continue to be explored by researchers (see Joshi et al., 2020; Roman, et al., 2020; Rauniyar, et al., 2021 among others). Clearly, clustering agritourism regions is beneficial to understanding how to supporting these place based innovations. Prior studies, however, do not consider direct sales to tourists when analyzing these clusters.

As defined by Chase et al. (2018), direct sales are an integral part of the agritourism experience. Food products, and other direct purchases made on the farm, are, in essence, souvenirs of the agritourism experience. As with other tourism sectors, local purchases such as souvenirs help form the visitor experience (Cohen, 2000; Masset and Decrop, 2021), especially in agritourism. Even though tourists do not always return home with these 'souvenirs' (Bradshaw, 2016), the origin products available directly from the farm are an integral part of the success of agritourism ventures (Domi and Belletti, 2022). This demand for locale-specific agricultural products through direct sales in agritourism showcases consumer desires for short food supply chains (Nemes, et al., 2019). Additionally, this direct sales revenue has been shown to be a crucial part of the viability of the agritourism enterprise (Barbieri and Tew, 2010).

Yet to date, no research has been conducted which considers direct sales in agritourism cluster analysis in the United States. We test two hypotheses: 1) the share of agritourism in a county affects the share of direct-to-consumer sales in this county and vice versa, and 2) any impact crosses county lines. We thus add to Van Sandt's et al. (2018) analysis of placed-based factors an analysis of the interdependence with direct sales operations.

Our results show that agritourism and direct sales reinforce each other. Counties that have higher shares of farms with direct sales five years earlier tend to have higher shares of farms with agritourism, and vice versa, while such mutual impacts are statistically significant within counties not across neighboring counties. In addition, not only do the previous shares of farms with agritourism and direct sales adversely affect their own current values in a county, but they also adversely affect those values in the neighboring counties. Compared with Marasteanu and Jaenicke (2016) and Van Sandt et al. (2018), who used single-year data from the 2007 and 2012 Census of Agriculture, respectively, and analyzed univariate local Moran's I and spatial regression models, we use panel data for three recent census years, 2007, 2012, and 2017, and estimate bivariate local Moran's I and seemingly-unrelated-regression spatial Durbin models (SUR-SDM) to explore the relatedness of agritourism and direct sales.. The paper is organized as follows: we first describe the results of a descriptive analysis of the farms involved in direct sales and agritourism and their geographical focus across the United States. This is followed by an exploratory study of the spatial correlation between agritourism and direct sales. Next, we refine our analysis with the SUR-SDM to examine the association of farms with these different types of sales and conclude with observations on the impact of the results on census data collection and agritourism research and extension.

2 Capturing Data on Agritourism and Direct-to-Consumer Sales in the United States

The USDA NASS Census of Agriculture takes place every five years, mostly recently in 2017. The census asks questions about direct-to-consumer sales, which consist of "edible agricultural products for human consumption." There is a separate question about agritourism income. The "agritourism" question excludes direct sales and has a limiting way of explaining agritourism,[1]which does not capture the entirety of agritourism activities. For example, visitors to a vineyard may be able to tour the winery free of charge, and thus no money will be considered "agritourism," according to the Census of Agriculture. Those same visitors may buy a case of wine, which would be regarded as direct sales. Popular agritourism activities such as cutting Christmas trees are not included in either category of agritourism or direct sales.

[1] The two questions that pertain to agritourism in the USDA NASS Census of Agriculture in 2017 are worded in the questionnaire for farms and ranches as follows:
1) “Report the gross dollar amount received before taxes and expenses in 2017 for income from agri-tourism and recreational services, such as farm tours, hay rides, hunting, fishing, etc.”
2) “How much was received in 2017 for the food produced and sold directly to consumers: farmers markets, on-farm stores or farm stands, roadside stands or stores, u-pick, CSA (Community Supported Agriculture), online marketplaces, etc.”? Include edible agricultural products for human consumption. Exclude non-edible products such as hay, cut flowers, Christmas trees, nursery products, etc.; commodities produced under production contracts; products purchased and resold.

In addition, researchers cannot distinguish between on-farm and off-farm direct sales. The census question about direct sales confounds data collection on agritourism, as it may overcount direct sales of food because off-farm sales are included, while at the same time undercounting direct sales of non-edible products that are considered part of agritourism. The agritourism variable includes farms with agritourism income and farms with agritourism and direct to consumer sales income.

Despite these limitations, the USDA NASS Census of Agriculture currently is the best source of national data from the producer side. U.S. agritourism sales nearly doubled from 2007 to 2017, from $567 to $949 million in nominal dollars. Only 28,575 farms reported such activity in 2017, and although this was a 22% increase from 2007, they represent less than 1.5% of all farms. While the number of farms engaged in direct sales fell (144,530 in 2012 and 130,056 in 2017, a 10% decrease), the total value of direct sales rose from $1,309.8 million in 2012 to $2,805.3 million in 2017 in nominal dollars, a 114% increase, which is due in part to a change in the survey question to include value-added products[2] (USDA NASS Census of Agriculture). The following tables show the type of farms that offer agritourism and direct-to-consumer sales and their geographical distribution[3]. Table 1 shows the number of farms with agritourism and/or direct sales in the U.S. and four census regions. The Northeast region has the highest share of farms engaging in agritourism or direct sales, with 18.8% of all farms in the region, followed by the Western region with 10.8%, and the Midwest region has the least. As expected, the number

[2] According to the Census: "Value of food sold directly to consumers. Data represent the value of edible products, including value added products, produced and sold for human consumption directly to consumers at farmers markets, on-farm stores or farm stands, roadside stands or stores, u-pick, CSA (Community Supported Agriculture), online marketplaces, etc. In 2012 this item was labeled Value of food sold directly to individuals for human consumption. Data are not directly comparable to 2012. In 2012 Value of food sold directly to individuals for human consumption excluded value added sales"

[3] Data in this section are drawn from a special Census data request. These are not available for recall on the Quickstat Database.

of farms with direct sales but no agritourism activity is far greater than that of farms with agritourism but no direct sales, and that of having both businesses. The Northeast also has the highest share of farms that offer agritourism (6.3%).

Table 1: Farms with agritourism and direct sales: U.S. and regions

State	Direct sales or agritourism		Direct sales, No agritourism		Agritourism, No direct sales		Agritourism and direct sales	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
US	153,961	7.54%	125,386	6.14%	23,905	1.17%	4,670	0.23%
Midwest	41,450	5.67%	35,045	4.79%	5,260	0.72%	1,145	0.16%
Northeast	24,235	18.81%	21,309	16.54%	1,916	1.49%	1,010	0.78%
South	53,502	6.21%	40,085	4.65%	11,986	1.39%	1,431	0.17%
West	34,774	10.83%	28,947	9.02%	4,743	1.48%	1,084	0.34%

[1]Percentages are computed with respect to the total number of farms, including farms without agritourism or direct sales, in each row. The same for all tables that follow.

Texas, California, and Pennsylvania are the top three states with producers with direct sales or agritourism income (Table 2). However, the share of farms with direct sales or agritourism is much higher in New York (18.6%) and Oregon (16.3%).

Table 2: Farms with agritourism and/or direct sales: U.S. and top 10 states, rank by number of farms

State	Direct sales or agritourism		Direct sales, No agritourism		Agritourism, No direct sales		Agritourism and direct sales	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Texas	13,181	5.31%	7,458	3.00%	5,514	2.22%	209	0.08%
California	8,423	11.94%	7,293	10.34%	800	1.13%	330	0.47%
Pennsylvania	6,936	13.05%	6,225	11.71%	533	1.00%	178	0.33%
Ohio	6,642	8.54%	5,939	7.63%	512	0.66%	191	0.25%
Michigan	6,231	13.08%	5,477	11.50%	562	1.18%	192	0.40%
New York	6,222	18.61%	5,396	16.14%	525	1.57%	301	0.90%
Oregon	6,069	16.13%	5,588	14.86%	349	0.93%	132	0.35%
Wisconsin	5,579	8.61%	4,949	7.64%	491	0.76%	139	0.21%
North Carolina	4,859	10.47%	3,864	8.32%	801	1.73%	194	0.42%
Washington	4,845	13.54%	4,360	12.18%	342	0.96%	143	0.40%

Source: USDA, NASS special data request and authors' calculation.

Table 3 lists the type of farming for each direct sales category and agritourism. In general, agritourism visitors are drawn to farms that offer various agricultural products and unique experiences that lend themselves to human interactions, such as horses, petting areas, and pick-your-own fruit and vegetable farms (Van Sandt et al., 2018). The percentages in each category are computed with respect to the total number of farms in each NAICS. Notably, 42% of all vegetable and melon-producing farms are involved in direct sales. This is also the biggest agritourism and direct sales category (2.23%). Most farms that received agritourism income are beef, cattle and ranching farms (29%), followed by sugarcane, hay, and other crops (18%) and aquaculture and other animals (18%). The latter two categories point to the diversified nature of agritourism farms. The state with the most farms claiming agritourism income is Texas, where 60% of these farms are cattle farms and ranches, probably offering hunting. However, this is only based on anecdotal data as the census does not collect information on what type of activities agritourism farms received their income from.

Table 3: Farms with agritourism and/or direct sales by NAICS: U.S.

	Direct sales or agritourism		Direct sales, No agritourism		Agritourism, No direct sales		Agritourism and direct sales		Share of Total sales AT+DS
	#	%[1]	#	%[1]	#	%[1]	#	%[1]	%
Oilseed and grain farming (1111)	7,234	2.23%	5,001	1.54%	2,091	0.64%	142	0.04%	8%
Vegetable and melon farming (1112)	20,702	45.84%	19,004	42.08%	689	1.53%	1,009	2.23%	6%
Fruit and tree nut farming (1113)	20,742	21.73%	18,772	19.67%	1,018	1.07%	952	1.00%	7%
Greenhouse, nursery, and floriculture production (1114)	7,332	16.12%	5,753	12.65%	1,227	2.70%	352	0.77%	6%
Tobacco farming (11191)	184	4.90%	134	3.57%	45	1.20%	5	0.13%	0%
Cotton farming (11192)	120	1.36%	42	0.48%	77	0.87%	1	0.01%	0%
Sugarcane, hay, and all other crop (11193, 11194, 11199)	17,931	4.04%	12,898	2.91%	4,508	1.02%	525	0.12%	18%
Beef cattle ranching and farming (112111)	35,887	5.59%	27,629	4.31%	7,731	1.21%	527	0.08%	29%
Cattle feedlots (112112)	1,092	8.16%	967	7.23%	93	0.70%	32	0.24%	0%
Dairy cattle and milk production (11212)	2,520	6.68%	2,171	5.75%	256	0.68%	93	0.25%	1%
Hog and pig farming (1122)	3,808	16.52%	3,494	15.16%	256	1.11%	58	0.25%	1%
Poultry and egg production (1123)	8,481	19.16%	7,902	17.85%	374	0.85%	205	0.46%	2%
Sheep and goat farming (1124)	10,498	11.29%	9,297	10.00%	960	1.03%	241	0.26%	4%
Aquaculture and other animal (1125,1129)	17,430	7.84%	12,322	5.54%	4,580	2.06%	528	0.24%	18%

[1]Percentages are computed with respect to the total number of farms in each NAICS. Source: USDA NASS, special data request.

3 Local spatial correlation of Agritourism and Direct Sales

In an exploratory analysis, we use the local Moran's I to identify the hotspots of agritourism and direct sales to consumers. Further, we use the bivariate local Moran's I to detect the spatial association of agritourism and direct sales. The expression for the local Moran's I for variable *x*, which has a mean of zero and a standard deviation of one, in county *i* can be written as

$$I_i = \frac{\sum_j w_{ij} x_i x_j}{\sum_i x_i^2} = c x_i \sum_j w_{ij} x_j, \text{ where } c = 1/\sum_i x_i^2 \tag{1}$$

w_{ij} is the (i, j) element in a queen-type contiguity spatial weight matrix for all counties in 48 continental states. We use permutation tests (999 permutations) to compute the p-value of the significance of a local Moran's I in a county and then identify High-High, High-Low, Low-High, and Low-Low clusters based on the classification process in Anselin (2020). A High-High cluster means that *x* in county *i* and the weighted average of *x* in neighboring counties are higher than the overall average and such a gap is significant at the 95% level. To assess the spatial association of two variables, agritourism (*x*) and direct sales (*y*), both of which are standard normalized, we compute the bivariate local Moran's I as follows

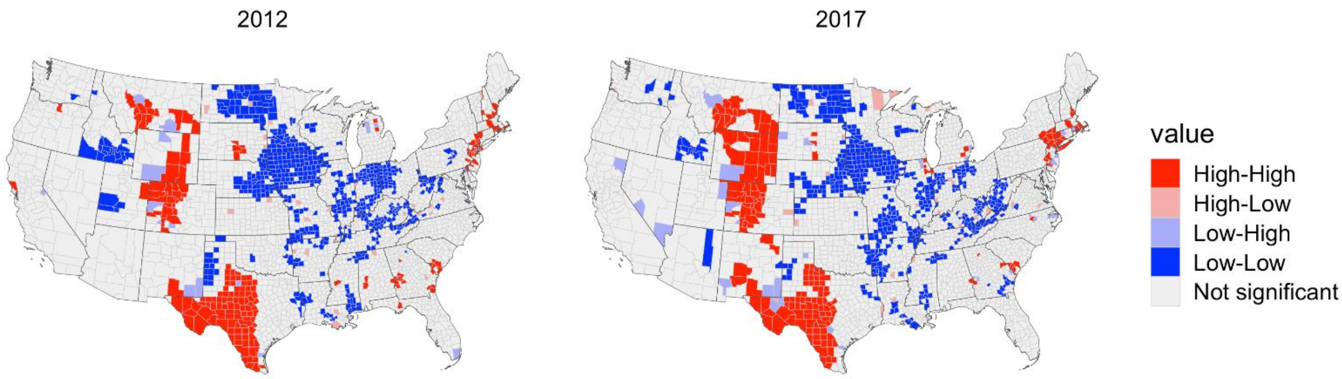
$$I_i^B = c x_i \sum_j w_{ij} y_j \tag{2}$$

where w_{ij} and *c* are similarly defined as in equation (1). We again use permutation tests to identify clusters of agritourism and direct sales, whereby a High-High cluster indicates that x_i in county *i* and the average of *y* in neighboring counties are higher than the overall average and significant at the 95% level. But the bivariate local Moran's I does not control for the correlation between the two variables at each location (i.e., the correlation between x_i and y_i) (Anselin, 2020, Chapter 3), which we can measure with Pearson correlation coefficients or partial correlation coefficients in a linear regression model.

Local univariate Moran's I

Figure 1 shows the maps of clusters of agritourism and direct sales in 2012 and 2017, based on their local Moran's I, respectively. The two largest High-High clusters (in red) stretch across the Midwest region, from Montana to Texas, and another relatively large one is in the Northeast region close to New York City. A similar 2012 map is published in Van Sandt et al. (2018). They found that the probability of a county being a hot spot is influenced by outdoor attractions, travel infrastructure, and rurality. In comparison, the 2017 map shows some expansion of the High-High clusters near New York City and in Wyoming and Colorado.

Figure 1. Local Moran's I for agritourism



There is a strong regional variation for direct-to-consumer sales in the United States, mainly caused by the type of agricultural production in the region (fruits and vegetables) and history of outlet development for farmer to growers and farm to school channels, and farmers' markets. The highest direct to consumer sales can be found on the west coast and Northeast (Low and Vogel, 2011). Previous research found a "neighborhood effect" with direct-to-consumer sales, meaning that farms with these types of sales are surrounded by similar farms (Low and Vogel, 2011). This is also evident in the hot and cold spots for this category.

As mentioned above, direct-to-consumer sales census data are not comparable between 2012 and 2017. Figure 2 shows hot and cold spots for direct sales for 2017. As expected, the hot spots are clustered in the Northeast region, coastal areas in the West, and counties around the Great Lakes.

Figure 2 Local Moran's I for Direct-to-Consumer Sales 2017

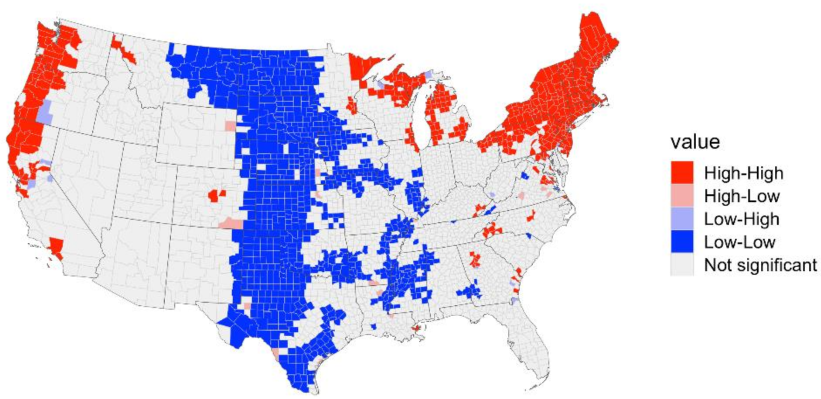
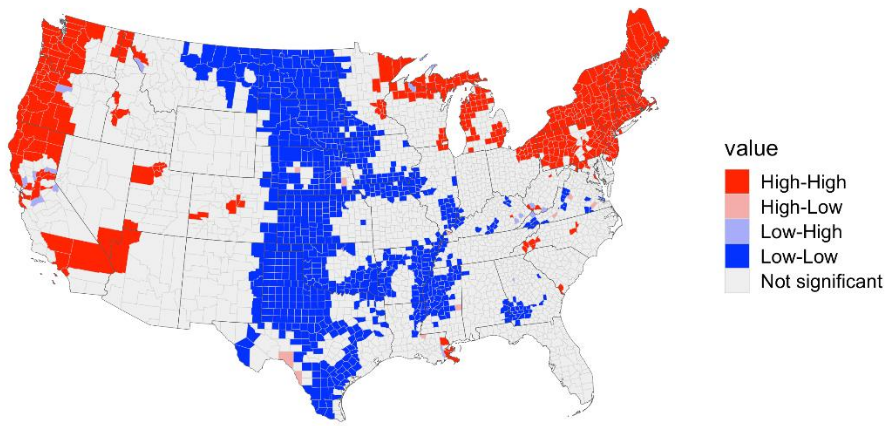


Figure 3 shows the local Moran's I for direct-to-consumer sales in 2012. Even though sales were higher in 2017, because of the addition of the value-added category, in 2017, in comparison with

2012, high clusters on the west coast appear to wane, while those in the Northeast and Great Lakes regions are relatively intact.

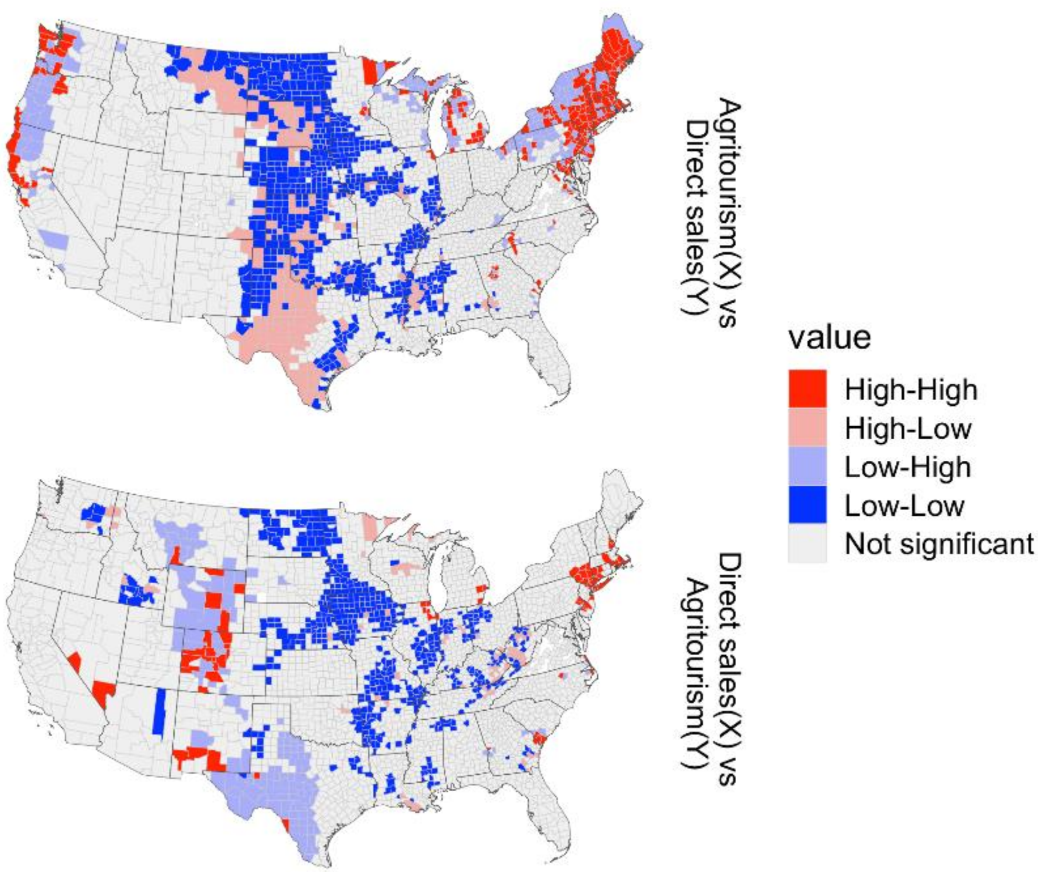
Figure 3 Local Moran's I for Direct to Consumer Sales 2012



Local bivariate Moran's I

Figure 4 shows the agritourism and direct sales clusters, based on the bivariate local Moran's I, using the 2017 Census of Agriculture data. When we consider agritourism as *x*, i.e., local variable, and direct sales as *y*, i.e., neighboring variable (first map), the location of the High-High clusters are determined mainly by the hot spots of direct sales as indicated in Figure 1. The bivariate High-High clusters are still concentrated in the Northeast region, some west coastal counties, and some counties around the Great Lakes, although the number of counties in these clusters is much smaller than in that of direct-sales-alone clusters. Other counties in these regions that are within the direct-sale-alone clusters are classified into the Low-High clusters where local agritourism businesses are not significant, but direct sales in neighboring counties are. On the contrary, the High-Low clusters are determined mainly by the agritourism-alone High-High clusters, as indicated in Figure 1. When flipping the role of agritourism and direct sales as local and neighboring variables, we observe far fewer counties identified as the High-High clusters as shown in the second row in Figure 4 than in the first row. The greater influence of direct sales compared to agritourism in determining the High-High clusters echoes the fact that there are many more farms with direct sales than with agritourism as shown in Tables 1-3. Since the local bivariate Moran's I cannot assess the correlation of agritourism and direct sales in the same county, we compute the simple correlation coefficients between agritourism and direct sales, which is 16.7% and statistically significant at the 1% level.

Figure 4 Bivariate Moran's I (2017)



The exploratory analyses with univariate and bivariate local Moran's I show that many counties are in either the High-High or Low-Low clusters, implying to some degree a positive association of the two activities. However, we also observe many counties in the Low-High or High-Low clusters, where we cannot tell whether the set two activities are positively associated. Further confirmation requires regression analysis.

4 Spatial Seemingly Unrelated (SUR) Models

We use a Seemingly-Unrelated-Regression Spatial Durbin Model (SUR-SDM) to examine the association of farms with agritourism and farms with direct sales to consumers. Based on Lopez et al. (2020), a SUR-SDM model can be expressed as follows.

$$\begin{aligned} AgTour_t = {} & \rho_1 \boldsymbol{W} AgTour_t + \alpha_{10} + \alpha_{11} AgTour_{t-1} + \alpha_{12} DiSale_{t-1} + \boldsymbol{X}_{t-1}\boldsymbol{\beta}_1 \\ & + \boldsymbol{W}(\theta_{11} AgTour_{t-1} + \theta_{12} DiSale_{t-1} + \boldsymbol{X}_{t-1}\boldsymbol{\gamma}_1) + \mu_1 \\ & + \delta_{11} Year2012 + \delta_{12} Year2017 + e_{1t} \end{aligned} \tag{3}$$

$$\begin{aligned} DiSale_t = {} & \rho_2 \boldsymbol{W} DiSale_t + \alpha_{20} + \alpha_{21} AgTour_{t-1} + \alpha_{22} DiSale_{t-1} + \boldsymbol{X}_{t-1}\boldsymbol{\beta}_2 \\ & + \boldsymbol{W}(\theta_{21} AgTour_{t-1} + \theta_{22} DiSale_{t-1} + \boldsymbol{X}_{t-1}\boldsymbol{\gamma}_2) + \mu_2 \\ & + \delta_{21} Year2012 + \delta_{22} Year2017 + e_{2t} \end{aligned} \tag{4}$$

The dependent variables are $AgTour_t$ and $DiSale_t$, two $n \times 1$ vectors of n counties at time t, for agritourism and direct sales. $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix based on the queen-typed contiguity with sharing either borders or shared vertices. The association of agritourism and direct sales is modeled with the terms $DiSale_{t-1}$, $\boldsymbol{W}\ DiSale_{t-1}$ in equation (3) for agritourism and $AgTour_{t-1}$, $\boldsymbol{W}\ AgTour_{t-1}$ in equation (4) for direct sales. For the residuals in the two equations, e_{1t} and e_{2t}, we assume $E(e_{1,it}) = E(e_{2,it}) = 0, Var(e_{1,it}) = \sigma_1^2, Var(e_{2,it}) = \sigma_2^2$, and

$Cov(e_{1,it}, e_{2,it}) = \sigma_{12}, i = 1, \ldots n$. The correlation in residuals captures any unaccounted association of agritourism and direct sales in the model.

Other terms in the SUR-SDM model include spatial autoregressive terms, $\rho_1 \boldsymbol{W} AgTour_t$ and $\rho_2 \boldsymbol{W} DiSale_t$, determinant factors for agritourism and direct sales, $\boldsymbol{X}_{t-1}$**,** and its neighboring values, $\boldsymbol{W}\boldsymbol{X}_{t-1}$, county fixed effects, μ_1 and μ_2, and time fixed effects, *Year2012 and Year2017*. County fixed effects account for the influence of time-invariant factors, such as natural conditions and distance to big cities. All the right-hand-side variables except for the spatial autoregressive terms in the model take the value lagged by five years to alleviate the concern of endogeneity.

We choose the SUR-SDM model with three considerations. First, the exploratory analysis with local Moran's I suggests a strong spatial autocorrelation of agritourism and direct sales, which necessitates the inclusion of spatial autoregressive terms. Second, we hypothesize that the determinant factors from one county's neighboring counties, such as population density and personal income, also influence local agritourism and direct sales on a county, i.e., spatial spillover effects, which are accounted for with the Durbin terms, $\boldsymbol{W}\boldsymbol{X}_{t-1}$. Third, following the LM tests for model selection proposed by López, Mur, and Angulo (2014), although a spatial autoregressive model with spatially autoregressive errors (SARAR) has the highest LM statistic, the difference of the LM statistic between an SARAR model and a spatial error model (SEM), the second most preferred model, is small. Moreover, according to LeSage and Pace (2009), who show that an SDM model embeds spatial autoregressive errors, we believe an SDM is the most appropriate model for this study. (Tests for model selection are shown in Tables S2-S4 in supplemental materials.)

Variable Selection and Data Sources

Variables used for the analysis are listed in table 5. First, we calculate the two dependent variables, shares of farms with agritourism and farms with direct sales to consumers, from the 2007-2017 Census of Agriculture. Next, we calculate the regressors, including the lagged dependent variables, farms in various size categories, farms with various commodity specializations, female farm operators, principal operators' experiences, and others., from the 2002-2012 Census of Agriculture. In the panel data regression model, we use the regressors that are five years lagged the dependent variables to alleviate endogeneity concerns. We also include variables from the American Community Survey, Regional Economic Accounts of the Bureau of Economic Analysis, and other data sources, such as the election variable from MIT Election Data and Science Lab. Van Sandt et al. (2018) suggested that counties with more agritourism businesses may have high rates of innovation and entrepreneurship and measured this with the rate of patents. We use the social capital variable from the Northeast Regional Center for Rural Development, Pennsylvania State University (Rupasingha, Goetz, and Freshwater 2006). Marastenu and Jaenicke (2016) posited a positive impact of liberal political orientation as they might be more interested to learn about different agricultural production practices, we include the percentage of democrat candidates won in presidential elections. Compared with Marasteanu and Jaenicke (2016) and Sandt, Low, and Thilmany (2018) studies who used single-year data from the 2007 and 2012 Census of Agriculture, we use panel data for three recent census years, 2007, 2012, and 2017. These two papers also use GIS data for distance and transportation variables, but such variables are time-invariant, which cannot be used in our fixed effects panel data models.

We grouped the variables as follows: 1) farm characteristics (average operated area per farm value of average prime farmland (in log), total sale ($2012, and also in log), share of farms with 50 acres or less, share of farms with sales of $10,000 or less, share of farms with more than 2,000 acres, and share of farms with sales of more than $500,000) 2) operator characteristics: (average farm proprietor income, excluding subsidies, share of farms with female principal operators, average age of principal operators, share of farms with principal operators on present farms for more than 10 years, average number of years where principal operators have worked on the present farms); 3) socioeconomic characteristics (population density (in log), personal income per capita, average nonfarm wage, poverty rate, female labor participation rate, share of female with at least a bachelor's degree, daycare per 10,000 individuals, social capital index (standardized), percentage that democrat candidates won in the presidential elections) and 4) farm production type (share of farms specialized in poultry and eggs, sheep and goat, oilseed and grain, vegetable and melon, aquaculture, and other animal productions).

Table 4: Descriptive statistics

Variables	2002	2007	2012	2017
Farms with agritourism	1.82 (3.34)	1.38 (2.14)	1.89 (2.59)	1.69 (2.32)
Farms with direct sales to consumers	5.36 (4.49)	6.02 (5.01)	6.75 (6.05)	6.30 (5.88)
Farm Characteristics				
Log(average operated area per farm)	1.19 (1.01)	1.13 (1.01)	1.16 (1.00)	–
Log (value of prime farmland)	7.53 (0.83)	7.85 (0.75)	7.96 (0.72)	–
Log (total sale), deflated to 2012	17.54 (1.26)	17.77 (1.35)	17.93 (1.40)	–
Farms with land <= 50 acres	31.58 (17.33)	34.97 (18.03)	34.73 (17.53)	–
Farms with sales <= $10,000	58.67 (17.51)	59.11 (16.24)	55.91 (15.89)	–
Farms with acres > 2000 acres	5.72 (10.16)	5.54 (9.54)	5.78 (9.62)	–
Farms with sales > $500,000	3.59 (4.31)	5.89 (6.20)	8.28 (8.40)	–
Operator Characteristics				
Average farm proprietor income, excluding subsidies	4.86 (37.86)	18.32 (43.29)	32.31 (68.03)	–
farms with female principal operators	11.22 (5.32)	13.85 (5.86)	13.42 (6.11)	–
Average age of principal operators	55.43 (2.03)	57.21 (1.98)	58.47 (2.22)	–
Principal operators on present farms for 10+ years	72.63 (6.33)	73.94 (6.10)	77.94 (5.01)	–
Socioeconomic Characteristics				
Female labor participation rate	55.06 (6.34)	55.69 (6.45)	55.70 (6.68)	–
Female with at least Bachelor’s degree	16.38 (6.85)	17.88 (7.31)	19.56 (7.92)	–
Log (population density)	3.70 (1.57)	3.72 (1.59)	3.73 (1.61)	–
Log(personal income per capita, deflated to 2012)	10.32 (0.20)	10.42 (0.22)	10.50 (0.24)	–
Social capital, standardized	0.02 (1.38)	0.01 (1.33)	0.01 (1.26)	–
Percentage of Democrat candidates won in presidential elections	39.40 (11.46)	40.92 (13.35)	37.73 (14.13)	–
Poverty rate	14.43 (6.30)	15.16 (6.28)	16.31 (6.37)	–
Daycare per 10,000 persons	2.50 (1.64)	2.55 (1.69)	2.37 (1.68)	–
Log (average nonfarm wage, deflated to 2012)	10.38 (0.18)	10.45 (0.18)	10.48 (0.18)	–
Farm production type				
Farms specialized in poultry and eggs	2.14 (4.54)	2.99 (4.00)	2.70 (4.11)	–
Farms specialized in sheep and goat	2.09 (3.05)	2.87 (3.21)	3.17 (3.30)	–
Farms specialized in oilseed and grain	17.07 (19.88)	16.25 (19.69)	18.22 (20.23)	–
Farms specialized in vegetable and melon	1.76 (2.65)	1.88 (2.51)	2.08 (2.72)	–
Farms specialized in aquaculture and other animal production	11.01 (7.78)	11.61 (7.89)	11.06 (7.51)	–

5 Estimation Results

We estimate several model specifications, each containing a different set of regressors. This section explains the model that uses all explanatory variables in Table 4, which yield the smallest Akaike Information Criterion (AIC) even with the largest number of parameters to be estimated. Since the SUR-SDM model contains the spatially lagged dependent variables ($\rho_1 \boldsymbol{W} AgTour_t$ and) at the right-hand side of the equation, according to LeSage and Pace (2009), we cannot straightforwardly explain the effect of each explanatory variable from its estimated coefficient. Instead, we need to compute the direct, indirect, and total impacts of each explanatory variable. The direct impact measures the marginal effect of an explanatory variable in a county i on the dependent variable in the same county, the indirect impact measures the effect of the explanatory variable from neighboring counties on the dependent variable in county i, and the total impact is the sum of the direct and indirect impacts that we can think of as the global effect of an explanatory variable. We show the estimated impacts in Table 5 and estimated coefficients in all model specifications in Table S1 in supplemental materials.

Table 5: Impacts in fully specified SDM models

Variable	**Agritourism**			**Direct sales**		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Lag of farms with agritourism	-0.233***	-0.245***	-0.478***	0.119***	0.054	0.174***
	(0.010)	(0.020)	(0.024)	(0.016)	(0.048)	(0.054)
Lag of farms with direct sales to consumers	0.014**	-0.003	0.011	-0.235***	-0.210***	-0.445***
	(0.007)	(0.016)	(0.019)	(0.011)	(0.032)	(0.037)
Farm Characteristics						
Lag of log(average operated area per farm)	-0.164	0.191	0.028	0.040	0.046	0.087
	(0.137)	(0.259)	(0.310)	(0.232)	(0.705)	(0.803)
Lag of log (total sale), deflated to 2012	-0.358***	0.088	-0.271*	-0.939***	-0.574*	-1.513***
	(0.060)	(0.124)	(0.145)	(0.106)	(0.320)	(0.356)
Lag of farms with land <= 50 acres	-0.006	0.002	-0.004	-0.010	-0.028*	-0.038**
	(0.004)	(0.008)	(0.010)	(0.007)	(0.016)	(0.018)
Lag of farms with sales <= $10,000	-0.005	0.003	-0.002	-0.020***	-0.014	-0.034*
	(0.004)	(0.006)	(0.008)	(0.006)	(0.017)	(0.019)

Variable	Agritourism			Direct sales		
	Direct	Indirect	Total	Direct	Indirect	Total
Lag of farms with acres > 2000 acres	-0.009	-0.037*	-0.046**	0.016	0.036	0.052
	(0.009)	(0.020)	(0.023)	(0.017)	(0.046)	(0.052)
Lag of farms with sales > $500,000	-0.009	-0.000	-0.009	0.006	0.037	0.043
	(0.006)	(0.009)	(0.011)	(0.010)	(0.031)	(0.034)
Lag of log (value of prime farmland)	-0.440***	0.032	-0.408**	-0.396***	0.751***	0.355
	(0.074)	(0.135)	(0.160)	(0.125)	(0.228)	(0.278)
Operator Characteristics						
Lag of average farm proprietor income, excluding subsidies	0.001**	-0.001*	-0.000	0.001*	-0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Lag of farms with female principal operators	0.014***	-0.011	0.003	-0.027***	0.020	-0.007
	(0.004)	(0.009)	(0.010)	(0.007)	(0.016)	(0.018)
Lag of average age of principal operators	-0.002	0.010	0.008	0.012	-0.090	-0.078
	(0.013)	(0.029)	(0.034)	(0.022)	(0.069)	(0.077)
Lag of principal operators on present farms for 10+ years	-0.007**	-0.004	-0.011	-0.037***	0.009	-0.028
	(0.004)	(0.008)	(0.009)	(0.006)	(0.017)	(0.019)
Socioeconomic Characteristics						
Lag of female labor participation rate	0.016***	0.026	0.042**	-0.012	0.009	-0.003
	(0.006)	(0.018)	(0.019)	(0.011)	(0.035)	(0.039)
Lag of female with at least bachelor's degree	0.038***	-0.032	0.006	0.030**	-0.092**	-0.063
	(0.008)	(0.022)	(0.024)	(0.014)	(0.044)	(0.048)
Lag of principal operators on present farms for 10+ years	-0.007**	-0.004	-0.011	-0.037***	0.009	-0.028
	(0.004)	(0.008)	(0.009)	(0.006)	(0.017)	(0.019)
Lag of log (population density)	0.439*	0.141	0.580	0.959**	-0.470	0.489
	(0.235)	(0.316)	(0.401)	(0.406)	(1.811)	(1.903)
Lag of log(personal income per capita, deflated to 2012)	0.376**	0.021	0.397	-0.180	0.136	-0.044
	(0.181)	(0.404)	(0.462)	(0.299)	(0.920)	(1.030)
Lag of social capital, standardized	0.026	0.057	0.083	0.122*	0.207	0.329
	(0.041)	(0.066)	(0.083)	(0.071)	(0.191)	(0.211)
Lag of percentage of democrat candidates won in presidential elections	0.003	0.002	0.005	0.036***	0.011	0.047***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.011)	(0.013)
Lag of poverty rate	0.019***	-0.003	0.016	0.022*	-0.082**	-0.060
	(0.007)	(0.018)	(0.020)	(0.012)	(0.039)	(0.043)
Lag of daycare per 10,000 persons	-0.018	-0.043	-0.061*	0.018	-0.075	-0.056
	(0.011)	(0.029)	(0.033)	(0.020)	(0.056)	(0.064)
Lag of log(average nonfarm wage, deflated to 2012)	-1.284***	-0.163	-1.447**	-0.728*	1.791	1.063
	(0.259)	(0.519)	(0.619)	(0.424)	(1.423)	(1.592)
Farm production type						
Lag of farms specialized in poultry and eggs	0.013	-0.005	0.008	0.019	0.106**	0.125**
	(0.009)	(0.017)	(0.020)	(0.016)	(0.044)	(0.051)
Lag of farms specialized in sheep and goat	0.007	-0.035**	-0.028	0.050***	0.025	0.075*
	(0.009)	(0.018)	(0.021)	(0.014)	(0.036)	(0.042)
Lag of farms specialized in oilseed and grain	-0.000	0.002	0.001	-0.025***	-0.040**	-0.066***

Variable	Agritourism			Direct sales		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
	(0.004)	(0.007)	(0.008)	(0.007)	(0.017)	(0.020)
Lag of farms specialized in vegetable and melon	0.021**	0.011	0.032	0.069***	-0.038	0.030
	(0.010)	(0.022)	(0.025)	(0.018)	(0.053)	(0.059)
Lag of farms specialized in aquaculture and other animal production	0.021***	0.000	0.021**	0.018**	-0.022	-0.003
	(0.004)	(0.009)	(0.010)	(0.007)	(0.018)	(0.020)

Notes: (1) The spatial autoregressive coefficient for agritourism is 0.343 (0.016), and that for direct sales is 0.288 (0.015). (2) The correlation coefficient for the residuals of the two equations in the SUR-SDM is 0.128. (3) The number of observations is 2892, the log-likelihood is -28,410, and the AIC is 57,058. (4) Significance levels: *** 1%, ** 5%, and * 1%.

Mutual impacts of agritourism and direct sales to consumers. We confirm the mutual benefits of the two types of farm businesses with the positive and statistically significant *direct* impact of the 5-year-lagged share of farms with direct sales on agritourism and the positive and significant *direct and total* impacts of the lagged share of farms with agritourism on direct sales. In other words, the *direct* effect of a variable means from within the same county; *indirect* effects are the spillover effects of that variable from adjacent counties. Although the indirect impact of the lagged direct sales on agritourism is negative, it is statistically insignificant. The direct, indirect, and total impacts of the lagged agritourism and direct sales on their own current value are all negative, implying that farms adjust their businesses in the next five years, resulting in a trend reversal.

Variables that represent farm characteristics: While average operated farmland is not a significant factor in either agritourism or direct sales, the prime farmland value negatively affects agritourism given the significantly negative direct *and* total impact. But the impact of the prime farmland value on direct sales is ambiguous. A higher prime farmland value in a county reduces the share of farms with direct sales, but higher values in neighboring counties increase the share, resulting in an insignificant total impact. Higher total farm sales also adversely affect agritourism and direct sales, but this does not mean more profitable farms would have less agritourism or direct sales because we also find significant negative direct impacts on direct sales in counties that have a higher share of farms with farm-related sales only less than $10,000, and the impact from counties having more farms with sales greater than $500,000 is not significant. Regarding farm size in acreage, we find both significantly negative indirect impacts from neighboring counties with more small farms that have less than 50 acres and counties with more large farms that have more than 2,000 acres.

Variables that represent farmers' characteristics. The impacts of average farm proprietor income on agritourism and direct sales are canceled out by the positive direct impacts from a county and the negative indirect impacts from its neighboring counties. For example, a higher share of principal female operators in a county will contribute to more farms with agritourism but lead to fewer farms with direct sales. However, the presence of principal female operators in the neighboring counties does not significantly affect agritourism or direct sales. The share of principal operators on the present farm for more than ten years has significantly negative direct impacts on both agritourism and direct sales, but the impacts of farmers' age are not significant.

Variables that represent socioeconomic characteristics: The share of farms with agritourism in a county is positively associated with population density, income per capita, female labor participation rate, the share of females with at least a bachelor's degree in the same county, and are negatively associated with the average nonfarm wage and daycare per 10,000 individuals. In addition, the shares of farms with agritourism are adversely affected by the share of females with at least a bachelor's degree and daycare per 10,000 individuals in neighboring counties. On the other hand, the share of farms with direct sales is positively associated with population density, poverty rate, the share of females with at least a bachelor's degree, social capital, and the percentage of voters who voted for Democratic presidential candidates. In addition, the shares of farms with direct sales are adversely affected by the poverty rate and the share of females with at least a bachelor's degree in the neighboring county.

Variables that represent the nature of farming. Positive direct impacts on agritourism come from counties with a higher share of farms specializing in vegetable and melon as well as aquaculture and other animal production. In addition, more farms specializing in sheep and goats in neighboring counties will adversely affect agritourism. On the other hand, the share of farms with direct sales in a county is positively affected by the share of farms specialized in sheep and goats, vegetable and melon, aquaculture, and other animal production in the same county and the share of poultry and eggs in neighboring counties. However, direct sales are negatively affected by the share of farms specializing in oilseed and grain in local and neighboring counties.

6 Conclusion

Our results show that agritourism and direct sales reinforce each other. Counties with higher shares of farms offering agritourism five years earlier also have a higher share of direct-to-consumer sales, both through the direct (own-county) and total effects. The share of farms with direct-to-consumer sales five years earlier has a positive impact on the share of farms providing agritourism services within a county. Neighboring counties have no spillover effects in terms of these two variables, indicating that they are neither enhancing (as in a cluster) nor cannibalizing sales. Furthermore, shares of farms with agritourism and direct-to-consumer sales five years earlier adversely affect their own current values in a county both directly and indirectly (through spillovers), suggesting potential cannibalization over time, which is worth further investigation. Like Van Sandt et al. (2018), as well as Schmidt et al. (2021), we also find that counties with more female farmers and farms with more disposable income offer more agritourism, and counties with large farms have less agritourism.

Our results show empirically the intrinsically linked nature of agritourism and direct-to-consumer sales. We argue that data collection for agritourism and direct sales should be refined to capture these growing farm diversification activities better, especially now as the popularity of agritourism and direct sales, partly due to the COVID-19 pandemic, appears to have increased in the past years. This has not been captured yet in federal data, as the next census will be conducted in 2022. For now, we have only anecdotal evidence and regional survey data available; but according to USDA NASS, census data is "the only source of uniform, comprehensive, and impartial agriculture data for every county in the nation."[4] Census agritourism data impacts the sector in different ways, from resource allocation and promotion in extension service and tourism to rural revitalization strategies and lawyers arguing the importance of agritourism in zoning cases. By undercounting agritourism and not providing breakdowns of types of agritourism and direct sales, research is hindered, and resources are not allocated where needed. We recommend that data collection be expanded and refined. The census does not distinguish between on-farm (i.e., on-farm stores) and off-farm sales (i.e., farmers' markets). We propose that both agritourism activities and on-farm-direct sales should be included in agritourism as they involve welcoming visitors to their farms and, as mentioned above, these activities are intrinsically linked. It also is essential to include agritourism activities such as direct sales that involve non-edible products, such as Christmas trees and fiber. More detailed information about types of agritourism activities would be helpful for research and extension programming. For example, while we know that a significant percentage of beef farms and ranches in Texas offer agritourism, we cannot determine the specific activities and can only speculate that most revolve around hunting, which is very different from the Northeast activities,

[4] https://www.nass.usda.gov/AgCensus/

for example farm dinners and tours. Understanding the types of agritourism activities is critical because different agritourism options need distinct sets of support (Quella et al., 2021; Hollas et al., 2022). This detailed data would help direct resources where they are needed most, significantly improving the effectiveness of research and extension to support agricultural producers.

References

Ammirato, S., Felicetti, A. M., Raso, C., Pansera, B. A., and Violi, A. (2020). Agritourism and Sustainability: What We Can Learn from a Systematic Literature Review. *Sustainability, 12*(22), 9575.

Anselin, L. (2020). Geoda Workbook. Available online: https://geodacenter.github.io/workbook/

Arroyo, C. G., Barbieri, C., & Rich, S. R. (2013). Defining agritourism: A comparative study of stakeholders' perceptions in Missouri and North Carolina. *Tourism Management*, *37*, 39-47.

Bagi, F. S., & Reeder, R. J. (2012). Factors affecting farmer participation in agritourism. *Agricultural and Resource Economics Review*, *41*(1203-2016-95369), 189-199.

Barbieri, C. (2013). Assessing the sustainability of agritourism in the US: A comparison between agritourism and other farm entrepreneurial ventures. *Journal of Sustainable Tourism*, 21(2), 252-270.

Barbieri, C. and Tew, C. (2010). Perceived impact of agritourism on farm economic standing, sales and profits San Antonio, TX Proceedings for the 2010 Travel and Tourism Research Association Conference, June 20–22

Bradshaw, Miranda. (2016). The market potential for food and agricultural tourism in Utah. All Graduate Theses and Dissertations. 4754.

Brune, S., Knollenberg, W., Stevenson, K. T., Barbieri, C., Schroeder-Moreno, M. (2021). The Influence of Agritourism Experiences on Consumer Behavior toward Local Food. *Journal of Travel Research. Volume*, 60(6): 1318-1332.

Chase, L. C., Stewart, M., Schilling, B., Smith, B., & Walk, M. (2018). Agritourism: Toward a conceptual framework for industry analysis. *Journal of Agriculture, Food Systems, and Community Development*, *8*(1), 13-19.

Ciolac, R., Iancu, T., Brad, I., Popescu, G., Marin, D., & Adamov, T. (2020). Agritourism activity—a "smart chance" for mountain rural environment's sustainability. *Sustainability*, 12(15): 6237.

Dickes, L., Arogundade, T., & Lamie, D. (2020). Rural innovation and entrepreneurial motivation: The case of agritourism with new and beginning farmers in a southern us state. *International Journal of Entrepreneurship*, *24*(3), 1-12.

Domi, S., & Belletti, G. (2022). The role of origin products and networking on agritourism performance: The case of Tuscany. *Journal of Rural Studies*, *90*, 113-123.

Haven-Tang, C., Thomas, A., & Fisher, R. (2022). To What Extent Does the Food Tourism' Label'Enhance Local Food Supply Chains? Experiences from Southeast Wales. *Tourism and Hospitalit*y, 3(1), 153-160.

Hochuli, A., Hochuli, J., & Schmid, D. (2021). Competitiveness of diversification strategies in agricultural dairy farms: Empirical findings for rural regions in Switzerland. *Journal of Rural Studies*, 82, 98-106.

Hollas, C. R., Chase, L., Conner, D., Dickes, L., Lamie, R. D., Schmidt, C., ... & Quella, L. (2021). Factors Related to Profitability of Agritourism in the United States: Results from a National Survey of Operators. *Sustainability*, *13*(23), 13334.

Joshi S, Sharma M, Singh RK. (2020). Performance Evaluation of Agro-tourism Clusters using AHP–TOPSIS. *Journal of Operations and Strategic Planning*, 3(1):7-30.

Khanal, A. R., & Mishra, A. K. (2014). Agritourism and off-farm work: survival strategies for small farms. *Agricultural economics*, *45*(S1), 65-76.

Khanal, A. R., Honey, U., & Omobitan, O. (2020). Diversification through 'fun in the farm': analyzing structural factors affecting agritourism in Tennessee. *International Food and Agribusiness Management Review*, *23*(1030-2020-240), 105-120.

Khazami, N., Nefzi, A., & Jaouadi, M. (2020). The effect of social capital on the development of the social identity of agritourist entrepreneur: A qualitative approach. *Cogent Social Sciences*, 6(1), 1787680.

López, Fernando A., Jesús Mur, and Ana Angulo. (2014). "Spatial Model Selection Strategies in a SUR Framework. The Case of Regional Productivity in EU." *The Annals of Regional Science* 53 (1): 197–220. https://doi.org/10/gk6d4c.

López, Fernando A., Román Mínguez, and Jesús Mur. (2020). "ML versus IV Estimates of Spatial SUR Models: Evidence from the Case of Airbnb in Madrid Urban Area." *The Annals of Regional Science* 64 (2): 313–47. https://doi.org/10.1007/s00168-019-00914-1.

Lucha, C., Ferreira, G., Walker, M., & Groover, G. (2016). Profitability of Virginia's Agritourism Industry: A Regression Analysis. *Agricultural and Resource Economics Review*, *45*(1), 173-207.

McGehee, N. G., & Kim, K. (2004). Motivation for agritourism entrepreneurship. *Journal of Travel Research*, 43(2), 161-170.

Montefrio, M. J. F. & Sin, H. L. (2019). Elite governance of agritourism in the Philippines, *Journal of Sustainable Tourism*, *27*(9), 1338-1354.

Naidoo, P & Sharpley, R. (2016). Local perceptions of the relative contributions of enclave tourism and agritourism to community well-being: The case of Mauritius, *Journal of Destination Marketing & Management*, 5(1): 16-25.

Nemes, G., Csizmadiáné Czuppon, V., Kujáni, K. O., Orbán, É., Szegediné Fritz, Á., & Lajos, V. (2019). The local food system in the 'genius loci'–the role of food, local products and short food chains in rural tourism. *Studies in Agricultural Economics*, 121(2), 111-118.

Pesonen, J., Komppula, R., Kronenberg, C., & Peters, M. (2011). Understanding the relationship between push and pull motivations in rural tourism. *Tourism Review*, 66(3), pp. 32–49.

Quella, L., Chase, L., Conner, D., Reynolds, T., Wang, W., & Singh-Knights, D. (2021). Visitors and values: A qualitative analysis of agritourism operator motivations across the US. *Journal of Agriculture, Food Systems, and Community Development*, *10*(3), 1-15.

Rauniyar, S., Awasthi, M. K., Kapoor, S., & Mishra, A. K. (2021). Agritourism: Structured literature review and bibliometric analysis. *Tourism Recreation Research*, 46(1), 52-70.

Roman, M., Roman, M., & Prus, P. (2020). Innovations in agritourism: Evidence from a region in Poland. *Sustainability*, 12(12), 4858.

Schilling, B.J., Attavanich, W. and Jin, Y. (2014). Does agritourism enhance farm profitability?. *Journal of Agricultural and Resource Economics*, pp.69-87.

Sgroi, F., Di Trapani, A. M., Testa, R., & Tudisca, S. (2014). The rural tourism as development opportunity or farms. The case of direct sales in Sicily. *American Journal of Agricultural and Biological Sciences*, 9(3), 407-419.

Van Sandt, A., Low, S.A. and Thilmany, D. (2018). Exploring Regional Patterns of Agritourism in the US: What's Driving Clusters of Enterprises?. *Agricultural and Resource Economics Review*, *47*(3), pp.592-609.

Appendix

Appendix Table A.1: Variable description and data sources

Variables	Units	Groups	Source
Farms with agritourism	%	Dependent variables	Census of Agriculture
Farms with direct sales to consumers	%	Dependent variables	Census of Agriculture
Log(average operated area per farm)	log(100 acres)	Farm characteristics	Census of Agriculture
Average farm proprietor income, excluding subsidies	$1,000	Farm characteristics	BEA
Log (total sale), deflated to 2012	Log ($1)	Farm characteristics	Census of Agriculture
Farms with land <= 50 acres	%	Farm characteristics	Census of Agriculture
Farms with sales <= $10,000	%	Farm characteristics	Census of Agriculture
Farms with acres > 2000 acres	%	Farm characteristics	Census of Agriculture
Farms with sales > $500,000	%	Farm characteristics	Census of Agriculture
Farm related incomes, deflated to 2012	$1,000	Farm characteristics	Census of Agriculture
Log (value of prime farmland)	Log ($/acre)	Farm characteristics	Census of Agriculture
farms with female principal operators	%	Farmer characteristic	Census of Agriculture
Female labor participation rate	%	Farmer characteristic	Census of Agriculture
Female with at least Bachelor's degree	%	Farmer characteristic	Census of Agriculture
Average age of principal operators	Years	Farmer characteristic	Census of Agriculture
Principal operators on present farms for 10+ years	–	Farmer characteristic	Census of Agriculture
Average years when principal oprators worked on the present farms	Years	Farmer characteristic	Census of Agriculture
Log (population density)	–	Local context	Census Bureau
Log(personal income per capita, deflated to 2012)	log($1)	Local context	BEA
Social capital, standardized	Index	Local context	NERCRD
Percentage of Democrat candidates won in presidential elections	%	Local context	MIT Datalab
Poverty rate	%	Local context	ACS
Daycare per 10,000 persons	Number	Local context	CBP
Average nonfarm wage	$1,000	Local context	BEA
Log(average nonfarm wage, deflated to 2012)	log($1000)	Local context	BEA
Farms specialized in poultry and eggs	%	Type of farming	Census of Agriculture
Farms specialized in sheep and goat	%	Type of farming	Census of Agriculture
Farms specialized in oilseed and grain	%	Type of farming	Census of Agriculture
Farms specialized in vegetable and melon	%	Type of farming	Census of Agriculture
Farms specialized in aquaculture and other animal production	%	Type of farming	Census of Agriculture

Supplemental Material

Table S1: Estimated coefficients in SDM models

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	AG	DS	AG	DS	AG	DS	AG	DS	AG	DS
Lag of farms with agritourism	-0.214***	0.122***	-0.244***	0.131***	-0.281***	0.091***	-0.271***	0.118***	-0.224***	0.117***
	(0.010)	(0.018)	(0.010)	(0.018)	(0.010)	(0.017)	(0.010)	(0.017)	(0.011)	(0.018)
Lag of farms with direct sales to consumers	0.023***	-0.191***	0.023***	-0.207***	0.083***	-0.253***	0.086***	-0.227***	0.014*	-0.225***
	(0.007)	(0.012)	(0.007)	(0.012)	(0.006)	(0.011)	(0.007)	(0.011)	(0.007)	(0.013)
Lag of log(average operated area per farm)	-0.235*	-0.135							-0.171	0.038
	(0.141)	(0.238)							(0.143)	(0.242)
Lag of average farm proprietor income, excluding subsidies	0.001***	0.002***							0.001**	0.001*
	(0.000)	(0.001)							(0.000)	(0.001)
Lag of log (total sale), deflated to 2012	-0.345***	-0.888***							-0.362***	-0.914***
	(0.068)	(0.115)							(0.068)	(0.115)
Lag of farms with land <= 50 acres	0.002	0.005							-0.006	-0.009
	(0.004)	(0.007)							(0.004)	(0.007)
Lag of farms with sales <= $10,000	-0.003	-0.010							-0.005	-0.019***
	(0.004)	(0.006)							(0.004)	(0.007)
Lag of farms with acres > 2000 acres	-0.014	0.005							-0.008	0.014
	(0.011)	(0.018)							(0.011)	(0.018)
Lag of farms with sales > $500,000	-0.011*	0.001							-0.009	0.004
	(0.006)	(0.010)							(0.006)	(0.010)
Lag of log (value of prime farmland)	-0.507***	-0.608***							-0.441***	-0.429***
	(0.076)	(0.129)							(0.081)	(0.136)
Lag of farms with female principal operators			0.018***	-0.006					0.014***	-0.028***
			(0.005)	(0.008)					(0.005)	(0.008)
Lag of female labor participation rate			-0.014*	-0.017					0.015**	-0.012
			(0.008)	(0.013)					(0.007)	(0.011)
Lag of female with at least bachelor's degree			0.064***	0.067***					0.039***	0.034**
			(0.010)	(0.017)					(0.009)	(0.015)
Lag of average age of principal operators			0.031**	0.021					-0.002	0.016
			(0.014)	(0.025)					(0.014)	(0.024)

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	AG	DS	AG	DS	AG	DS	AG	DS	AG	DS
Lag of principal operators on present farms for 10+ years			-0.001	-0.009					-0.007*	-0.037***
			(0.004)	(0.007)					(0.004)	(0.006)
Lag of log (population density)					0.720**	1.265**			0.434*	0.979**
					(0.307)	(0.517)			(0.263)	(0.441)
Lag of log(personal income per capita, deflated to 2012)					-0.488**	-0.868**			0.376*	-0.186
					(0.233)	(0.398)			(0.202)	(0.340)
Lag of social capital, standardized					0.048	0.102			0.024	0.112
					(0.052)	(0.090)			(0.045)	(0.076)
Lag of percentage of democrat candidates won in presidential elections					-0.000	0.034***			0.003	0.036***
					(0.004)	(0.006)			(0.003)	(0.005)
Lag of poverty rate					0.016*	0.015			0.020**	0.026**
					(0.009)	(0.016)			(0.008)	(0.013)
Lag of daycare per 10,000 persons					-0.018	-0.003			-0.016	0.022
					(0.015)	(0.026)			(0.012)	(0.021)
Lag of log(average nonfarm wage, deflated to 2012)					-0.721**	-1.189**			-1.278***	-0.807*
					(0.342)	(0.585)			(0.279)	(0.472)
Lag of farms specialized in poultry and eggs							0.031***	0.039**	0.013	0.014
							(0.010)	(0.018)	(0.010)	(0.017)
Lag of farms specialized in sheep and goat							0.001	0.009	0.009	0.049***
							(0.010)	(0.018)	(0.010)	(0.016)
Lag of farms specialized in oilseed and grain							-0.009*	-0.034***	-0.001	-0.024***
							(0.005)	(0.009)	(0.004)	(0.007)
Lag of farms specialized in vegetable and melon							-0.013	-0.086***	0.021*	0.070***
							(0.010)	(0.017)	(0.012)	(0.020)
Lag of farms specialized in aquaculture and other animal production							0.007	0.013	0.021***	0.019**
							(0.005)	(0.008)	(0.005)	(0.008)
W * lag of farms with agritourism	-0.149***	0.030	-0.185***	-0.006	-0.203***	-0.005	-0.210***	-0.004	-0.146***	0.007
	(0.014)	(0.038)	(0.015)	(0.041)	(0.016)	(0.039)	(0.015)	(0.041)	(0.016)	(0.039)
W * lag of farms with direct sales to consumers	-0.007	-0.090***	-0.012	-0.101***	-0.027**	0.041*	-0.020	0.037*	-0.006	-0.091***
	(0.012)	(0.024)	(0.013)	(0.024)	(0.012)	(0.021)	(0.012)	(0.021)	(0.014)	(0.026)
W * lag of log(average operated area per farm)	0.259	0.016							0.192	0.023

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	AG	DS	AG	DS	AG	DS	AG	DS	AG	DS
	(0.207)	(0.550)							(0.227)	(0.559)
W * lag of average farm proprietor income, excluding subsidies	-0.001	-0.000							-0.001**	-0.001
	(0.001)	(0.001)							(0.001)	(0.001)
W * lag of log (total sale), deflated to 2012	0.129	-0.202							0.152	-0.163
	(0.103)	(0.258)							(0.107)	(0.263)
W * lag of farms with land <= 50 acres	-0.002	-0.014							0.003	-0.019
	(0.007)	(0.011)							(0.007)	(0.013)
W * lag of farms with sales <= $10,000	0.003	0.005							0.003	-0.005
	(0.005)	(0.012)							(0.005)	(0.014)
W * lag of farms with acres > 2000 acres	-0.025	0.069**							-0.028	0.023
	(0.016)	(0.035)							(0.017)	(0.038)
W * lag of farms with sales > $500,000	0.003	0.028							0.002	0.026
	(0.008)	(0.024)							(0.008)	(0.025)
W * lag of log (value of prime farmland)	0.205**	0.646***							0.126	0.682***
	(0.094)	(0.175)							(0.119)	(0.192)
W * lag of farms with female principal operators			-0.014*	-0.019					-0.012	0.023*
			(0.008)	(0.014)					(0.008)	(0.014)
W * lag of female labor participation rate			0.010	0.022					0.017	0.010
			(0.014)	(0.034)					(0.015)	(0.028)
W * lag of female with at least bachelor's degree			-0.026	-0.099**					-0.034*	-0.078**
			(0.020)	(0.041)					(0.019)	(0.035)
W * lag of average age of principal operators			0.010	-0.101*					0.008	-0.071
			(0.025)	(0.057)					(0.025)	(0.054)
W * lag of principal operators on present farms for 10+ years			-0.001	0.024					-0.002	0.017
			(0.007)	(0.015)					(0.007)	(0.014)
W * lag of log (population density)					-0.256	-2.657*			0.014	-0.631
					(0.309)	(1.539)			(0.295)	(1.500)
W * lag of log(personal income per capita, deflated to 2012)					-0.194	0.141			-0.069	0.155
					(0.408)	(0.917)			(0.360)	(0.764)
W * lag of social capital, standardized					-0.009	0.041			0.040	0.121
					(0.058)	(0.191)			(0.057)	(0.161)
W * lag of percentage of democrat candidates won in presidential elections					0.003	0.006			0.001	-0.002

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	AG	DS	AG	DS	AG	DS	AG	DS	AG	DS
					(0.003)	(0.011)			(0.003)	(0.009)
W * lag of poverty rate					-0.024	-0.086**			-0.007	-0.069**
					(0.017)	(0.038)			(0.016)	(0.031)
W * lag of daycare per 10,000 persons					-0.030	-0.100*			-0.031	-0.062
					(0.031)	(0.056)			(0.025)	(0.045)
W * lag of log(average nonfarm wage, deflated to 2012)					-0.079	3.703***			0.159	1.564
					(0.540)	(1.396)			(0.462)	(1.164)
W * lag of farms specialized in poultry and eggs							-0.021	0.126***	-0.007	0.075**
							(0.017)	(0.037)	(0.015)	(0.035)
W * lag of farms specialized in sheep and goat							-0.010	0.044	-0.030**	0.005
							(0.015)	(0.037)	(0.015)	(0.029)
W * lag of farms specialized in oilseed and grain							0.000	-0.012	0.002	-0.023*
							(0.006)	(0.014)	(0.006)	(0.014)
W * lag of farms specialized in vegetable and melon							-0.002	-0.217***	0.004	-0.049
							(0.019)	(0.033)	(0.019)	(0.041)
W * lag of farms specialized in aquaculture and other animal production							0.001	-0.019	-0.005	-0.022
							(0.007)	(0.014)	(0.007)	(0.015)
Year 2012	0.499***	1.016***	0.164***	0.653***	0.425***	0.823***	0.312***	0.680***	0.419***	1.008***
	(0.038)	(0.064)	(0.045)	(0.080)	(0.047)	(0.080)	(0.038)	(0.065)	(0.055)	(0.092)
Year 2017	0.561***	0.944***	-0.058	0.345***	0.324***	0.866***	0.205***	0.602***	0.443***	1.109***
	(0.048)	(0.081)	(0.062)	(0.109)	(0.065)	(0.111)	(0.039)	(0.066)	(0.083)	(0.141)
Intercept	-0.349***	-0.518***	-0.012	-0.351***	-0.356***	-0.496***	-0.208***	-0.352***	-0.382***	-0.756***
	(0.046)	(0.061)	(0.091)	(0.118)	(0.078)	(0.090)	(0.032)	(0.053)	(0.122)	(0.135)
Rho	0.239***	0.315***	0.204***	0.331***	0.122***	0.354***	0.128***	0.343***	0.227***	0.288***
	(0.016)	(0.015)	(0.017)	(0.015)	(0.017)	(0.015)	(0.017)	(0.015)	(0.016)	(0.015)
N	2892	2892	3029	3029	3037	3037	3037	3037	2892	2892
T	3	3	3	3	3	3	3	3	3	3
LogLik	-28584	-28584	-33881	-33881	-34691	-34691	-34684	-34684	-28410	-28410
AIC	57271	57271	67839	67839	69476	69476	69447	69447	57058	57058
Resid.Corr	0.135	0.135	0.103	0.103	0.067	0.067	0.068	0.068	0.128	0.128

Table S2: LM tests for alternative spatial SUR models

Tests	**Statistics**	**P-values**
LM-SUR-SLM	1289.20	0.000
LM-SUR-SEM	1334.96	0.000
LM*-SUR-SLM	6.05	0.049
LM*-SUR-SEM	51.82	0.000
LM-SUR-SARAR	1341.01	0.000

Table S3: LR tests for SLM versus SDM models

Models	**Log Likelihood**	**DF**	**AIC**	**BIC**	**LR statistic**	**P-value**
SLM	-28,621	65	57,372	57,287		NA
SDM	-28,410	119	57,058	56,902	421.839	0.000

Table S4: VIF of group-demeaned regressors

Variable	**VIF**
Lag of farms with agritourism	1.17
Lag of farms with direct sales to consumers	1.34
Lag of log(average operated area per farm)	1.85
Lag of average farm proprietor income, excluding subsidies	1.56
Lag of log (total sale), deflated to 2012	2.40
Lag of farms with land <= 50 acres	1.75
Lag of farms with sales <= $10,000	1.65
Lag of farms with acres > 2000 acres	1.39
Lag of farms with sales > $500,000	3.05
Lag of log (value of prime farmland)	2.79
Lag of farms with female principal operators	1.27
Lag of female labor participation rate	1.13
Lag of female with at least bachelor's degree	1.82
Lag of average age of principal operators	2.81
Lag of principal operators on present farms for 10+ years	1.84
Lag of log (population density)	1.30
Lag of log(personal income per capita, deflated to 2012)	3.33
Lag of social capital, standardized	1.10
Lag of percentage of democrat candidates won in presidential elections	1.15
Lag of poverty rate	1.34
Lag of daycare per 10,000 persons	1.01
Lag of log(average nonfarm wage, deflated to 2012)	2.53
Lag of farms specialized in poultry and eggs	1.14
Lag of farms specialized in sheep and goat	1.25
Lag of farms specialized in oilseed and grain	1.27
Lag of farms specialized in vegetable and melon	1.19
Lag of farms specialized in aquaculture and other animal production	1.18