FARMERS' MARKETS AND SMALL FARMS: DETERMINING A RELATIONSHIP

By

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A THESIS PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE

UNIVERSITY OF FLORIDA

2014

To my family

ACKNOWLEDGMENTS

I would like to acknowledge all the help and support that I have received from the members of my committee and the faculty and staff of the Food and Resource Economics department at the University of Florida. A special thanks goes out to Dr. Wysocki who early on in my career as a master's student reached out to provide funding and work experience with UF/IFAS Extension. Dr. Wysocki's faith and generosity combined with his offer of an opportunity for a broader agricultural educational experience within my program fundamentally changed my experience during my time here at the university. I would also like to thank Dr. VanSickle who expanded my understanding of agricultural policy, provided opportunities for real-world analytical experience, and helped me explore future opportunities in the field. Additionally, I am very grateful to UF/IFAS Extension and Dr. Place, Dr. Dusky, and Dr. Adams who made the effort to continue funding my assistantship during my final year in the program. Finally, I would like to express my gratitude to Dr. Grogan for her help at every step in this research project. Without her guidance, patience, and advice, I would never have made it through this process. Thank you to you all, I will always fondly remember this experience.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
AFN	Alternative Food Network
Ag Census	USDA Census of Agricultural
AMS	Agricultural Marketing Service
ARMS	Agricultural Resource Management Survey
ARS	Agricultural Research Service
BEBR	Bureau of Economic and Business Research
CSA	Community Supported Agriculture
ERS	Economic Research Service
FGDL	Florida Geographic Data Library
FM	Farmers’ Market model
FSAO	Florida Statistical Abstract Online
GSPRE	Generalized Spatial Random-effects model
MLE	Maximum Likelihood Estimation
NCSS	National Cooperative Soil Survey
NRCS	Natural Resources Conservation Service
SAIPE	Small Area Income and Poverty Estimates
SAC	Spatial Autocorrelation model
SAR	Spatial Autoregressive model
SDM	Spatial Durbin model
SEM	Spatial Error model
SF	Small Farm model
USDA	United States Department of Agriculture
WSS	Web Soil Survey

Abstract of Thesis Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Master of Science

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August 2014

Chair: Kelly Grogan
Major: Food and Resource Economics

The past three decades have generated strong academic and public interest in Alternative Food Networks (AFNs) generally and farmers' markets in particular. AFNs tend to encourage shorter supply networks and emphasize social, nutritional, and environmental considerations over profit. Facing higher barriers to entry to the conventional agricultural supply chain, small farms are increasingly turning to AFNs and farmers' markets to diversify into alternative value-added activities and sell their production. Farmers' interest in AFNs in conjunction with increasing consumer demand for local foods has had a dramatic impact on the growth in farmers' markets in the last two decades.

The results from this research contribute to the existing literature by describing the relationship between markets and their small farm suppliers. It establishes that the location of farmers' markets does not have a statically significant impact on the number of small farms in the region. On the other hand, the analysis suggests that recent trends in farmers' market location patterns have been positively influenced by the number of small farms in an area.

CHAPTER 1
INTRODUCTION

Participants at both ends of our conventional food distribution system are seeking alternatives to mitigate real or perceived grievances with the current supply chain. Consumers are increasingly seeking locally sourced foods with the belief that they are more nutritious, safer, and encourage more environmentally friendly agricultural practices. Farmers, facing pressures on their production margins, are attempting to regain control of a larger slice of the agricultural value chain. Together these forces represent much of the driving energy and support for today's Alternative Food Networks (AFN).

Farmers' markets are one of the more popular examples of an AFN and have experienced tremendous growth in the past twenty-years. While a good deal of research explores the demand-side of the relationship between consumers and farmers' markets, less research has focused on the supply-side and the economic linkage with farmers.

This research explores the connection between farmers and farmers' markets in an effort to determine exactly how that relationship functions. The analysis here shows that the location of farmers' markets is positively correlated with the location of small farms. More importantly, this research shows that this is a causal relationship; the location of small farmers drives the location of farmers' markets.

Conventional Agricultural Supply Chain

The development of today's global conventional agricultural supply chain has diminished farmers' production profit margins. Technological advancement and increased production scales exert pressure on farm resources and provoke an economic necessity to improve operating profits by increasing volume and improving efficiency (Marsden, 1998). The increasing pressure on farm income has forced many farms to consolidate production in an effort to obtain scale economies in their operations. Increasing efficiency and volumes have led to market saturation in some areas, further reducing production margins (Renting, 2003).

This scaling-up of production in conjunction with the growth in the food processing industry has created a delinking effect in the conventional distribution system as these sections of the value chain have grown ever proportionally larger and more removed from consumers (Renting, 2003). Product requirements from food companies have become surprisingly complex over time. Not only do farmers have to meet minimum safety requirements and quality standards, but today's major food purchasers often times require that farmers be able to supply a minimum amount of product in order to become a supplier (Sonnino, 2006). These increasingly high market entry barriers are costly for farmers, further reinforcing consolidation and specialization pressures. Together, these forces tighten the linkage between farms, wholesalers, and processors while weakening the bond with the end consumer.

In this delinked environment, food safety has increasingly relied on objective quality standards established and monitored by experts (Renting, 2003). Increasingly intricate regulatory issues regarding environmental regulations, animal-welfare standards, and sanitary measures require specialized knowledge, large capital investments, and dedicated resources. While greatly improving safety, the black box regulatory regime has greatly reduced transparency from outside the distribution network and many claim it has come at a cost to quality, nutrition, and sustainability (Sonnino, 2006).

Alternative Food Networks

In this environment, farmers face two strategic options if they want to continue to farm. They can either grow to maintain scale efficiencies and compete on volume or diversify into alternative value-added activities. This has lead to increased interest in Alternative Food Networks (AFN) by farmers. From the farmers' perspective, the AFN approach was an active attempt to recapture a portion of the value chain (Renting, 2003). Shortening the supply chain creates new relationships and institutional support that require new methods of competition that realign power structures (Sage, 2012).

As such, AFNs have attracted a great deal of attention in the last twenty years (Sonnino, 2006). AFN's tend to encourage Short Food Supply Chains (SFSC) that emphasize social, nutritional, and environmental considerations in addition to profits. Broadly speaking, AFNs and SFSCs are an emerging network of producers, distributors, retailers, and other actors that offer a substitute to the conventional food supply chain. These arrangements present an alternative to the conventional agricultural distribution system that is commonly charged with having a heavy environmental footprint, encouraging the production of less nutritious foods, and abetting the proliferation of food deserts especially in poorer neighborhoods (Sonnino, 2006 and Jarosz, 2008).

Diverse in nature and founded on different social constructions, AFNs proclaim a different relationship to ecology, locality, and consumption economics (Sage, 2012). As such, these networks can impact trends in farming practices, rural development, and sustainable resources relative to more conventional supply chains (Renting, 2003). Expanding ideological goals beyond the profit motive reestablishes the social linkages between farmers and their customers, supplementing the current fragmented supermarket relationship (Jarosz, 2008).

Increasingly reported outbreaks of food-borne illness in the last couple of decades combined with the industry's tendency to obscure transparency with bureaucracy has caused consumer trust in the conventional food system to wane (Conner et al., 2010). Combined with an increased concern for ecology, health, and animal-welfare, consumers have begun to demand more food choice options and transparency in the food supply chain. These new public concerns prove difficult to ameliorate in today's delinked food distribution construct (Sonnino, 2006).

"Local foods" is one such AFN that has recently attracted a good deal of consumer support. Consumers have identified three primary factors in their desire for increased access to local foods. The first is their perception that local is a higher quality food product. The second is the ability to avoid food-borne illnesses; followed closely by their desire to support local farmers (Conner et al., 2010). The primary constraint to the expansion of local foods is the lack of a distribution mechanism allowing local foods entry into mainstream markets. This has increased farmers' reliance on specialty or direct marketing techniques and farmers' markets in particular (Martinez et al., 2010).

Consumers' growing suspicion of the conventional agricultural supply chain, their desire for alternative food choices, and the barriers small farms face in accessing the conventional distribution chain have all increased the attractiveness of AFNs. In turning to AFNs, farmers have implicitly embraced, and increasingly utilize, direct marketing practices. However, shorter supply chains and direct farmer-to-consumer relationships remove the middlemen, thereby requiring the farmer to take on more responsibility for marketing his produce. This naturally begs the question: do these alternative marketing channels and direct marketing efforts benefit small farms?

Direct Marketing

As part of the Agricultural Resource Management Survey (ARMS), the USDA's Economic Research Service (ERS) collects information on sources of farm income. ERS defines direct marketing as one of seven different marketing activities including (i) roadside stores, (ii) on-farm stores, (iii) farmers' markets, (iv) regional distributors, (v) state branding programs, (vi) direct sales to local grocery stores, restaurants, or other retailers, and (vii) community-supported agriculture (CSA) (ERS, 2014). Over time, ARMS surveys have found that direct marketing to consumers accounts for an ever-larger share of small farms' sales relative to larger farms (Martinez et al., 2010).

Direct marketing participation by farmers has dramatically increased in the last decade. The number of farms with direct marketing income has increased 17% since 2002 and direct sales have increased 50% (Uematsu, 2011). Survey data of farmers using direct marketing strategies determined that smaller farms using organic production methods, but without USDA certification, more often make use of these channels. Smaller farm and household size as well as high-value crops all correlated with a higher percentage of direct marketing (Monson, 2008). Research has also shown that market location is key to direct marketing success (Morgan, 2001).

SFSCs allow farmers to get a better price by selling directly to consumers thereby recapturing a larger share of the value chain (Darby, 2008). However, these direct-to-consumer efforts can impose additional burdens on farmers. Specialty marketing techniques like value added products, such as jellies or sauces, produced on a small scale impose additional labor requirements on farmers including packaging, storage, transportation, and advertising (Martinez et al., 2010).

Farmers' Markets

Of the direct marketing channels utilized by small farms, the farmers' market is considered by the local food movement to exemplify all of an AFN's most desirable characteristics by benefitting small farms, consumers, and communities (Brown, 2008). For farmers, it is a good market entry-point because there are few upfront requirements or costs, and the markets tend to attract a desirable customer base without the expense of a middleman. Farmers' markets also provide a platform for testing new value-added products such as artisan cheeses or canned goods. Consumers benefit from the availability of local foods that, many believe, are fresher and more nutritious. The community benefits from the local reinvestment of food dollars and from civic pride.

The United States Department of Agriculture (USDA) defines a farmers' market as: "A multi-stall market at which farmer-producers sell agricultural products directly to the general public at a central or fixed location, particularly fresh fruit and vegetables (but also meat products, dairy products, and/or grains)" (FNS, 2014). Farmers' market managers have identified the three most important reasons their customers shop with them as: their products' freshness, its better taste, and the availability of locally grown food (Ragland, 2009).

More than 80% of all farmers' markets are seasonal markets open on average 4.5 months per year. Markets open less than six months each year typically have 25 vendors per week, earn $20,770 per month, and serve 565 customers weekly. Markets open for more than six months each year but not year round have on average 51 vendors per week, earn an average of $57,290 per month, and serve an average of 942 customers weekly. Finally, year-round markets reported, on average, 58 vendors weekly, earn $69,497 per month, and serve 3,578 customers weekly (Ragland, 2009).

Little is known about the prototypical farmers' market farmer beyond their sales and travel distances. The average monthly sales for a southeastern farmer at a farmers' market are just under $1,000 per month. However, this can vary markedly depending on the market's age and the number of months it is open annually. Market managers also report that nearly three-quarters of farmers travel less than 10 miles to their site (Ragland, 2009).

Over the past two decades, the number of farmers' markets has grown at a 13.6% annual growth rate, reaching more than 8,100 markets across the country today (AMS, 2014). The concerning aspect of this growth trend is that while the number of markets is increasing rapidly, total sales are growing at a much slower rate of 2.4% (Ragland, 2009).[1] Farmers' markets now account for about $1 billion in annual sales (AGMRC, 2014).

The Agricultural Marketing Service (AMS) conducted a national survey of farmers' market managers in 2006 and found that 40% of farmers' markets are less than five years old. Markets open for less than five-years have, on average, fewer vendors (22 versus 31 weekly), fewer customers (430 versus 959 weekly), and lower sales volume ($15k versus $32k monthly) (Ragland, 2009). Most of these markets are still establishing themselves economically. This may help explain the disparity between

[1] Some of the disparity in growth in the number of farmers' markets relative to the growth in farmers' market sales can be attributed to the difficulty in obtaining reliable sales data from markets and the fact that the little data that is available comes from different sources.

the growth in the number of markets and overall sales volume. It also raises questions about long-term viability of these new markets.

Although farmers' markets are enjoying increasing popularity, many are failing. Failing farmers' markets tend to be smaller, have less product variety, and lack administrative resources. They tend to have inexperienced management and experience high turnover in vendors, making revenue generation a challenge (Stephenson, 2008). Managers have identified their three top needs for improvement which include a need for additional support in market advertising, improved strategies for overcoming low customer attendance, and approaches for boosting vendor sales (Ragland, 2009). Increased competition between markets affect their ability to attract both customers and suppliers (Stephenson, 2008). Ironically, the increased popularity of these markets has hurt existing markets through this increased competition.

Space and location are important factors for farmers' markets because the distances between farms and market infrastructure can impact the channel's efficacy. The literature consistently questions whether farmers' markets follow a different location pattern than the traditional supermarket. Since the two channels are founded on different operating principles, one could reasonably expect differences in their location choices. It is possible that farmers' markets tend to locate near small farms. However, a number of studies have compared the demographic and geographic patterns of farmers' markets and supermarkets and found them to be similar in nature.

The complementary question is: Is the location of small farms influenced by the location of farmers' markets? If AFN networks, and farmers' markets in particular, are important outlets for farmers, then their presence might influence the location of small farms. This study used a spatial econometric analysis and two model formulations to determine if a significant, causal relationship could be identified between farmers' markets and small farms.

The results of this research showed that, during the recent past, farmers' markets began locating in areas with small farms and away from areas with larger farms. This relationship was determined to be causal whereby smalls influenced the location of farmers' markets. Further, it was determined that farmers' markets did not have a significant affect on the location of small farms.

It is important to understand how these factors influence citizens and their communities. While farmers' markets occupy a small niche in the overall food distribution value chain, it is a passionate corner of the market and the community. As in the discussion about AFNs, the mission of the farmers' market is different from that of other food retailers and the impacts to the local economy and community morale are important.

CHAPTER 2
LITERATURE REVIEW

Historically, researchers have compared and contrasted AFNs and their marketing channels to those of the conventional agricultural supply chain. One key aspect of these contrasts, and the focus of this research, has been on the identification of spatial influences in the location pattern of farmers' markets. As observed by Ragland, location is a critical factor and most successful markets are located in densely populated areas (Ragland, 2009). Unfortunately, there is not a lot of literature available on this subject for guidance (Berning, 2013).

A natural first location comparison would be with other traditional retail food outlets such as grocery stores or supermarkets. One of the local food movement's objectives has been for farmers' markets to improve access inequalities, such as those created by food deserts. Using a bivariate spatial point pattern analysis, Sage (2012) attempted to assess whether farmers' market have different location strategies from those of grocery stores and supermarkets, the very type of retail outlets from which they are trying to differentiate themselves. The analysis determined that farmers' markets tend to locate close to other food retail outlets instead of opting for a different strategy (Sage, 2012). Sage goes on to make an interesting comparison of farmers' markets as today's version of periodic markets studied by economic geographers in the '50s and '60s. Periodic markets served a number of diverse economic roles for the trade of goods and services and were generally associated with the rural areas in economically underdeveloped regions. These markets were known to locate centrally within the community within the proximity of other services. He further points out that while farmers' market vendors and managers face different economic considerations from those of conventional food retailers, they still face constraints on the location of viable markets (Sage, 2012).

Other research has shown that as population increases, so does the number of farmers' market per person. According to Berning, total market size is a key determinate for the location of farmers' markets, and there may be efficiencies for farmers' markets in the pursuit of co-location strategies with grocery stores (Berning, 2013).

Morgan measured the impact of certain economic and demographic factors on the number and types of direct marketing operations in an area, including farmers' markets. This research determined that economic factors such as income, employment, and farmed acreage were all positively correlated with the number of farmers' markets in a county (Morgan, 2001). Interestingly, the analysis did not identify any competitive forces between farmers' markets and traditional grocery stores. Very small towns and cities had a negative effect on the number of farmers' markets at the county level. Demographic factors affecting the number of farmers' markets in a county were population and the size of cities within its boundaries. More generally, it was determined that farmers' markets were located near urban areas (Morgan, 2001).

Berning's research employed an industrial organization theoretical framework and zip code level analysis to determine the socio-economic, structural, and competitive factors affecting the number of farmers' market in a given area. The industrial organization approach recognizes that both demand and supply side factors impact location decisions. The study employed a two-stage equilibrium outcome entry game where farms had to first decide to participate in the farmers' market and then they had to compete with other farms in the market. This approach to the analysis necessitated two conditional assumptions. First, there had to be enough farms as potential market entrants in the area. Then secondly, at least some farms had to decide that it would be profitable to compete (Berning, 2013).

Berning's empirical analysis showed that on the demand side, factors such as population size, increased education levels, households with children, and population participation in the SNAP program were all positively correlated with the number of farmers' markets. On the supply side, increased farming activities and reduced farm size were positively correlated with the number of farmers' markets. Again, researchers found a positive association between the location of farmers' markets and the presence of grocery stores (Berning, 2013). Interestingly, increased farm size and the presence of large-scale fruit and vegetable wholesaling were negatively correlated with farmers' markets; the presence of the conventional supply chain represented an opportunity cost to farmers for adopting alternative direct marketing efforts (Berning, 2013).

Jarosz (2008) proposes a slightly different approach to the location determination and development of AFNs. In general, she views the growth in farmers' markets as a sociopolitical process propelled by the restructuring of large-scale agricultural areas into urban and rural areas nearer to larger metropolitan regions. Her hypothesis is that urbanization fuels the growth of AFNs and farmers' markets through both the economic and political processes. First, urbanization attracts wealthier, middle class citizens who in turn demand more organic, seasonal, and locally sourced foods. Once relocated, this politically active demographic participates in interest groups and organizations involved with food politics in support of farmers and farmland preservation; this activity favors farmers' markets (Jarosz, 2008).

Jarosz also contends that AFNs, including farmers' markets, do not tend to stray far from the conventional, market-oriented food distribution models. This includes their location decisions. "One farmers market manager observes that as farms and farmland are further displaced outside the city's boundaries, the numbers of farmers markets increases as the urban demand for fresh, locally grown fruits and vegetables grows" (Jarosz, 2008). Young, upwardly mobile urban professionals drive the demand for locally grown and organic produce, and it is this demand and their presence that drive the growth in the number of farmers' markets (Jarosz, 2008).

This has led to reconsideration of the generally held perspective that AFNs are separate from the conventional food networks. The two market channels may not be separate supply chains but highly competitive retail formats. The fact that the research consistently points to the existence of similar location strategies for both farmers' markets and traditional grocers lends support to the need for additional analysis along this line of reasoning. Some have argued that these networks are interconnected but that an imbalance of power exists due to regulatory arbitrage whereby farmers' markets and their suppliers are subject to less oversight and regulations (Sonnino, 2006).

In summary, farmers' markets tend to locate in populated urban areas near other supermarkets and grocery stores. Farmers' markets are positively correlated with demographic indicators like income, population, and higher education. Economic factors associated with farmers' markets include a larger degree of farming activity in an area with a higher proportion of small farms. Areas with larger farms and a conventional agricultural supply chain tend to have a negative effect on the location of farmers' markets in an area.

Research reviewing the impact that farmers' markets have on the location of small farms could not be located. Two primary contributions of this research to the body of existing literature come from this analysis. First, it identifies the positive, causal relationship of small farms on the location of farmers' markets not previously found in the literature. Second, it also demonstrates that the reverse is not true and that farmers' markets do not have an effect on the location of small farms. To the best of our knowledge, this latter effect has not been analyzed in previous literature.

CHAPTER 3
SPATIAL MODEL OVERVIEW

This study's approach builds upon previous work by modeling the location of farmers' markets as well as small farms. The analysis tests whether or not farmers' markets lead to an increase in the number of small farms in the surrounding area or if small farms lead to an increase in the number of farmers' markets in the surrounding area. The analysis also identifies other factors that drive the spatial distribution of farmers' markets and small farms.

To ascertain if a relationship between farmers' markets and small farms exists, two general models are estimated. The Farmers' Market (FM) model estimates the number of farmers' markets in a county as a function of possible determinants of farmers' markets. These determinants could include socioeconomic variables as well as the number of small farms in the county. The Small Farm (SF) model estimates the number of small farms as a function of possible determinants of small farms. These determinants could include some demographic characteristics, soil types, climate, and number of farmers' markets in the county. As will be discussed below, two size categories are considered for the SF model.

Any geographic measure used for the analysis could potentially misrepresent the spatial relationships present because customers shopping at farmers' markets as well as farmers supplying farmers' markets have no spatial boundaries limiting their movement. As a result, spatial models must be used to allow for correlation across the spatial unit of observation.

To examine spatial relationships in the data, a formulation of the Manski model was selected (Manski, 1993). The model expands on the concept of spatial crosssectional models to include the ability to test for spatial correlations between the variables in panel datasets. The methodology allows for the estimation of spatially correlated dependent and independent variables, the identification of spatial error autocorrelation, and the estimation of random and fixed effects. The Hausman test can then be used to determine whether the random effects specification or the fixed effects specification is more appropriate.

The general specification of spatial models for panel data is explained here and summarized in Table 3-1 below. The general model is:

$$y_t = \tau y_{t-1} + \rho W y_t + X_t \beta + W X_t \theta + \alpha + \gamma_t + \nu_t \tag{3-1}$$

$$\nu_t = \lambda W \nu_t + u_t \tag{3-2}$$

$$\alpha = \phi W \alpha + \mu \tag{3-3}$$

The weight matrix W models the various spatial correlations in the panel dataset. If the dependent variable is autocorrelated, that is captured by τ. If the dependent variables are correlated across space, this correlation is modeled by $\rho W y_t$ where the spatial autoregressive coefficient is ρ. β is the vector of unknown parameters in $X_t \beta$ and X is the *k* by *n* matrix of independent observations, where *k* is the number of independent variables in *X,* and n is the number of observations in each time period. If the independent variables associated with nearby observations affect the observed dependent variable, this spatial correlation is modeled by $W X_t \theta$, where θ is a vector of fixed unknown parameters. α is the unobserved county-level factor that is fixed over time. If spatial correlation exists among the county-level unobservable factors, this correlation is modeled by $\phi W \alpha$. γ_t is an unobservable effect that occurs in time *t* across all observations. ν_t is the vector of random error terms. Any spatial correlation in the error terms is identified by $\lambda W \nu_t$ where λ is the spatial autocorrelation coefficient.

Finally, this general formulation cannot be utilized with all four spatial interactions included. At least one of the spatial interactions needs to be excluded from a model's formulation in order to identify all included spatial parameters. Therefore, a series of five models can be estimated to determine if the various kinds of spatial correlation exist.

The first formulation is the Spatial Autoregressive (SAR) model (Anselin, 1988) where the neighboring dependent variables are correlated with dependent variable *i*. τ, θ, ϕ, and λ are assumed to be zero thereby eliminating the autocorrelation, spatial correlation between the neighboring independent and dependent variables, spatial correlation of the unobserved county-level terms, and the spatially correlated error term. The resulting model is:

$$y_t = \rho W y_t + X_t \beta + \alpha + \gamma_t + u_t \tag{3-4}$$

The second formulation is the Spatial Durbin (SDM) model (Anselin, 1988) where τ, λ, and ϕ are assumed to be zero thereby eliminating the spatially correlated residual and the autoregressive interaction of unobserved county-level interactions. In this formulation, it is the neighboring dependent and independent variables that are a factor in determining the observed independent variable resulting in the following specification:

$$y_t = \rho W y_t + X_t \beta + W X_t \theta + \alpha + \gamma_t + u_t \tag{3-5}$$

The Spatial Autocorrelation (SAC) model (LeSage, 2009) specification assumes τ, θ, and ϕ are zero eliminating the lagged dependent variable, the spatially lagged explanatory variables, and any unobserved county-level spatial correlations. For this model, the spatial correlation across the dependent variables and residuals are tested for significance. This model cannot be estimated with random effects. It is formulated as follows:

$$y_t = \rho W y_t + X_t \beta + \alpha + \gamma_t + \nu_t \tag{3-6}$$

$$\nu_t = \lambda W \nu_t + u_t \tag{3-7}$$

The fourth specification assumes τ, ϕ, ρ, and θ are zero, which eliminates all spatial correlations except for spatial correlation in the error terms. This specification is referred to as the Spatial Error (SEM) model (LeSage, 2009) as shown below:

$$y_t = X_t \beta + \alpha + \gamma_t + \nu_t \tag{3-8}$$

$$\nu_t = \lambda W \nu_t + u_t \tag{3-9}$$

The final specification, the Generalized Spatial Random-effects (GSPRE) model (Belotti, 2013), assumes τ, ρ, and θ are zero eliminating the lagged dependent variable, the spatial correlation in the dependent variable, and the spatial effects of the explanatory variables. The model allows for spatial correlation in the unobserved county-level effects as well as the spatially correlated error term. This model cannot be estimated with fixed effects. It is formulated as follows:

$$y_t = X_t \beta + \alpha + \nu_t \tag{3-10}$$

$$\alpha = \phi W \alpha + \mu \tag{3-11}$$

$$\nu_t = \lambda W \nu_t + u_t \tag{3-12}$$

All models can be estimated using Stata's xsmle package. This package fits balanced spatial panel data using maximum likelihood estimation (MLE) and has a number of flexible options. This subroutine also handles the five model formulations of interest to the study. More importantly, the three different panel datasets assembled were balanced and could be analyzed using the xsmle command.

Spatial correlation of the independent variables indicates that the observations of the dependent variable in a given county are affected by the independent variables of neighboring counties. For the FM model, this kind of spatial correlation could be present if the socioeconomic composition of a bordering county increases or decreases the number of farmers' markets in the observed county. Without geographic or economic barriers, there is little cost for consumers and farmers to freely travel to neighboring markets. In the SF model, an adjoining county's agricultural, demographic, and environmental factors would likely be positively correlated with small farms because the presence of agricultural knowledge and capital assets tend to encourage more farming in the broader area.

Spatial correlation between the dependent variables may be particularly important for the FM model, as it captures the effects of competition between markets and could be negatively correlated. In the SF model, the presence of this correlation would indicate the presence of infrastructure and institutionalized knowledge in the vicinity. In the case of small farms, we hypothesize that this correlation will be positive.

Also of interest are the spatial correlations in the residuals and the unobserved county-level factors. An example of the former would be a onetime event such as a hurricane which would affect multiple, neighboring counties in a given time period. An example of the latter could be soil types or environmental variables that are similar across counties in a region but relatively fixed over time.

Together, these spatial characteristics will help researchers and policy makers better understand how farmers' markets and small farms relate to each other. This knowledge can then be used to inform rural policy considerations to better support sustainable small-scale farms that emphasize food and its relationship to surrounding communities (Jarosz, 2008).

Table 3-1. Manski Model Summary of Equations (3-1), (3-2), and (3-3)

Parameter/Term	Interpretation	Example
$\rho W y_t$	Dependent variable spatial correlation	Effects of neighboring farmers' markets on the number of farmers' markets in a county may dissipate for counties farther apart
$W X_t \theta$	Independent variables spatial correlation	Effects of neighboring infrastructure on the number of small farms in a county may dissipate for counties farther apart
$\phi W \alpha$	Spatial correlation of unobserved county level effects	Onetime event such as a hurricane which would affect multiple, neighboring counties
$\lambda W \nu_t$	Spatial correlation of error terms	Environmental variables that are similar across counties in a region but relatively fixed over time.
τy_{t-1}	Lagged dependent variable correlation	Effects of the number of small farms in the previous period on the observed number of farms
$X_t \beta$	Vector of unknown parameters and matrix of independent observations	Independent agricultural, demographic, and environmental variables
γ_t	Unobservable effect that occurs in time	Economic trends such as inflation or recessions

CHAPTER 4
DATA

Several spatial levels of analysis were considered. Due to limitations in data availability at a smaller spatial scale, county-level units of observations were used. In addition to data availability, this unit of measure may be most appropriate for two reasons. First, each county in Florida has an extension office, and the activities of the extension service in the county may influence the number of small farms. The county-level fixed effect will account for this unobservable factor. Second, many farmers' markets are organized by county-level organizations. Although appropriate for this analysis, county-level data limit the number of observations in each time period to sixty-seven.

Three types of data were pooled for analysis in the two models and each panel element was designated by county and year. The information collected included county-level agricultural and demographic data that were then combined with environmental assessments of the county's soils and climate. Due to changes in methodology used by the USDA in collecting and tabulating the Census of Agriculture (Ag Census) the study was limited to the period of 1996 through 2013. Fortunately this time period coincides nicely with the period of most interest. Table 4-1 summarizes the dataset for Florida's sixty-seven counties for all years in the study.

Farmers' Market Data

In 1994, the USDA began publishing a self-subscribed directory of farmers' markets from across the United States entitled the *National Directory of Farmers' Markets*. The directories were compiled every two years until 2008 when they became an annual event. Directories for the years 1996, 1998, 2000, 2002, 2006, and 2008 through 2013 were obtained from the USDA's AMS (AMS, 2014). While the lists may not be inclusive of every market that existed in every county for every year covered by the analysis, any bias should be consistent throughout the state and across time. The basis for this assessment rests on the assumption that a well-managed farmers' market, one that would be effective as a direct-to-consumer channel for small farms, would be motivated to register in the national directory for its own self-promotion. Markets that did not self-register would likely have been of a short-lived nature or suffered from poor management.

For both the FM and SF models, data from the *National Directories of Farmers' Markets* was used to determine the number of farmers' markets (*Farmers' Markets*) in each county. Four modifications were made to the published data. First, wholesale farmers' markets were removed from all years since the intent of the analysis was to assess the impact of direct-to-consumer marketing channels for small farms. These markets were state sponsored wholesale markets that, while allowing some direct-to-consumer retail sales, primarily served as wholesale markets.[1] Second, duplicate registrations or registrations for companion markets or incomplete registrations that could not be verified were removed.[2] These removals amounted to fifteen markets from the 2011 directory and nine markets in the 2013 directory. The third modification was to the 1996 directory, which consisted of only fourteen state operated and supported wholesale markets. Therefore, the 1996 USDA directory needed to be supplemented with retail farmers' market information. A survey of more than 300 existing farmers'

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[1] This is consistent with the literature where only markets that conducted at least 51 percent of their retail sales directly with consumers where included in the analysis (Ragland, 2009)

[2] Companion markets are defined as markets located in the same location and run by the same management team but operating during a different time period of the year.

markets was conducted during February and March of 2014 by phone and email. When it could be established that a market had begun operations prior to 1997, it was included in the data for the year 1996.

The final modification was to interpolate the number of markets for the years 2001 and 2003. Since the USDA had originally conceived of the national directory as a biennial exercise, the *National Directory of Farmers' Markets* did not exist for the years 2001 and 2003. Moreover, AMS could not find the 2004 *National Directory of Farmers Markets* and a published copy could not be located. On a county-by-county basis, the number of farmers' markets in 2001 was estimated to be halfway between the number of farmers' market between the 2000 and 2002 directories. For 2003, a weighted average of the number of farmers' market in the 2002 and 2006 directories, with 2002 receiving 75% of the weight and 2006 receiving 25% of the weight. In general, there is an upward trajectory of farmers' markets across time, so these extrapolations should approximate the actual number well.

USDA Agricultural Census Data

Every five years the USDA conducts the Census of Agriculture (Ag Census) to determine key agricultural statistics by state and county across the United States. The Ag Census was the limiting resource in this study because it was the only source for determining the number and size of farms in each of Florida's sixty-seven counties (NASS, 2014). Although the Ag Census dates back more than 150 years, the USDA changed its accounting methodology for farms in 2002. The department adjusted the 1997 data, but not prior periods. Thus, farm count comparisons prior to 1997 were incompatible and were excluded from the study. Data are utilized from the 1997, 2002, 2007, and 2012 censuses (NASS, 2014).

The USDA defines small farms as those with sales of less than $250,000. A consistent alternative definition for small farms based on acreage could not be identified (NASS, 2014). Therefore for completeness, two different categories of small farms were created from the Ag Census. The first small farm designation was less than 50 acres (*Farms <50 Acres*) and the second was less than 180 acres (*Farms <180 Acres*). This second measure also includes the farms that are less than 50 acres. Farms that were greater than 180 acres were considered “big farms” (*Farms >180 Acres*). An intermediate category of medium sized farms was created for farms between 50 and 180 acres (*Farms 50 to 180 Acres*). Finally, the variables for all the agricultural acreage in the county (*Farmed Acres*) and the total number of farms in a county (*Total Number of Farms*) were also collected from the Ag Census.

For two counties, data were not available for all years. The numbers of acres farmed in Franklin and Nassau counties were not explicitly reported for 2002. Using the number of farms and total state farmed acreage from the 2002 census and the trend in the average size of farms in these two counties from the 1997 and 2007 Ag Censuses, the number of farmed acres in these counties was interpolated for 2002.

Bureau of Economic and Business Research (BEBR) Data

Several categories of demographic information were obtained from the *Florida Statistical Abstract*, which is published by the Bureau of Economic and Business Research (BEBR) at the University of Florida. The bureau publishes annual intercensal estimates of state and county demographic data by using the Census Bureau’s decennial census counts and augmenting those with intercensal estimates and revisions. The county-level data for population (*Population*) used in this analysis was downloaded from the bureau’s Florida Statistical Abstract Online (FSAO) located on its website (BEBR, 2014). BEBR's median household income is based on the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program generating the most reliable annual estimates of county-level median income. The county-level data for median income (*Medium Income*) used in the study were downloaded from the FSAO located on its website (BEBR, 2014). BEBR calculates population density as the number of people per square mile.[3] The county-level data for population density (*Population Density*) used in this analysis were downloaded from the FSAO located on its website (BEBR, 2014).

Educational Attainment

An important demographic statistic not published by BEBR was a county-level indicator of educational attainment. Throughout much of the literature, higher levels of education have been linked with more enthusiasm for farmers' markets along with higher spending levels and greater usage (Gallons, 1997). The only Florida county-level estimates found were the *Annual Educational Attainment Estimates for U.S. counties 1990–2005* (Bode, 2011). However, these estimates, generated by an algorithm calibrated for the entire country, were inconsistent with the American Community Survey (ACS) estimates for Florida counties for the years 2009, 2010, 2011, and 2012 (Census Bureau, 2014).

Consequently, estimates of educational attainment for Florida's sixty-seven counties were imputed using a basic fixed effects panel regression model:

$$y_{it} = \alpha_i + X'_{it}\beta + \varepsilon_{it} \tag{4-1}$$

[3] Land area is not adjusted for undevelopable or uninhabitable land such as parks, reserves, or water bodies.

α_i is a scalar representing the individual county-level fixed effects, and β is the vector of unknown parameters in $X_{it}\beta$ where X is a *k* x 1 vector of independent variables in time *t*. ε_{it} is the error term representing the differences between the observed and predicted value of the dependent variable y_{it}.

Equation (13) was estimated using county demographic data and both linear and quadratic forms of explanatory variables were considered. Two educational categories were imputed: percent of individuals 25 years old or older with a high school degree or higher and percent of individuals 25 years old or older with a bachelor's degree or higher. Decennial census data from the 1990 and 2000 censuses were combined with ACS five-year estimates for 2009, 2010, 2011, and 2012 for the regression analysis (Census Bureau, 2014).

The predicted values from the linear and quadratic models were compared to the ACS five-year estimates and the difference between the predicted and actual values were squared and summed. A model for each educational attainment category was then chosen based on minimizing the sum of the squared errors. For both the high school (*>High School Degree*) and bachelor's degree (*>Bachelor's Degree*) educational attainment categories, a linear model using year and medium income and individual county intercepts generated the most accurate estimates of educational attainment.[4]

Soil Data

Soil types are a prominent factor when determining crop types and subsequently the location of major farming regions. To aid with local planning, the USDA Natural

[4] BEBR did not publish medium income data for 1996. In its place, 1995 and 1997 medium income data were averaged and substituted for 1996 medium income data. Estimates included calculated County intercepts when significant; otherwise intercept was zero.

Resources Conservation Service (NRCS) conducts the National Cooperative Soil Survey (NCSS) detailing soil data for more than 95% of the nation's counties. The NRCS has also developed a farmland classification system from the soil data to help with identifying good production locations. NCSS's soil survey information and county land area (*Total Acres*) data can be accessed through the Web Soil Survey (WSS) link on the NRCS home webpage (NCSS, 2014).

Three of the NRCS's soil designations were used to describe different types of useful farmland in a county. The information was used in the small farms model (SF) as a possible determinant of the location of small farms in the county. The best classification for agricultural land is prime (*Prime Acres*) and is defined as " . . . land that has the best combination of physical and chemical characteristics for producing food, feed, forage, fiber, and oilseed crops and that is available for these uses" (NRCS, 2014). The other two classifications were farmland of local importance (*Local Importance Acres*) and unique importance (*Unique Importance Acres*). Both of these designations indicate that, while the soil characteristics may not be nationally recognized as especially good for all crops, it has been identified as regionally or locally important for farming (NRCS, 2014).

Hardiness Zones

In addition to soil data, regional climate affects the probable success and location of farms as well as the type of crops grown. For the purposes of this research, an index indicative of a county's climate was needed for comparison between counties. The USDA Agricultural Research Service (ARS) publishes the Plant Hardiness Zone Map (Figure 4-1) which is the standard used by farmers to assess crop suitability for their location. The ARS constructs the hardiness zone map in 5 degree Fahrenheit increments based on the average annual extreme minimum winter temperatures during the 1976 to 2005 period. A copy of the ARS Plant Hardiness Zone Map is included in Figure 4-1 (ARS, 2014).

These zones were used to create a hardiness index value (*Hardiness Zone Index*) for each county. Florida's counties' hardiness zones range from 8a to 11a corresponding to minimum extreme temperatures of 10 – 15 degrees Fahrenheit and 40 – 45 degrees Fahrenheit respectively. To develop the hardiness index value, each hardiness zone was assigned an increasing value based on rising minimum temperatures beginning with 8a being assigned the value 1 up to 11a receiving the value 7. An average value for each county was then calculated based on all zones located geographically within a county's borders. Calculated hardiness index values ranged from 1.5 for Holmes and Okaloosa, the coldest counties in the state, up to 6.0 for Monroe County.

Empirical Models

As mentioned above, the analysis contains two main models: The Farmers' Market (FM) model and the Small Farms (SF) model.

The FM model includes the number of *Farmers' Markets* at the county-level as the dependent variable. The explanatory variables include two categories: agricultural variables and demographic variables.

The agricultural variables include *Farmed Acres* and the number of farms by size: *Farms <50 Acres*, *Farms 50 to 180 Acres*, and *Farms >180 Acres*. It is hypothesized that the agricultural characteristics of the observed county, and its neighbors, will be positively correlated with the number of *Farmers' Markets* in a county.

Having a good supply of farmers' market products nearby would likely encourage the establishment for an outlet for those products.

The demographic data include *Population*, *Medium Income*, *Population Density*, and both educational attainment categories, *>High School Degree* and *>Bachelor's Degree*. Much of the existing farmers' market research and literature has identified these as drivers of demand that lead to the establishment of markets in the region (Conner et al., 2010 and Brown, 2008).

In order to determine causality instead of correlation, all independent variables are lagged relative to the dependent variable. Consequently, the farmers' markets correspond to the years 1998, 2003, 2008, and 2013, while the agricultural and demographic variables correspond to the years 1997, 2002, 2007, and 2012, respectively. This generated 268 observations.

The SF model includes the number of "small farms" at the county level as the dependent variable. Two classifications are used for small farms: less than 50 acres (*Farms <50 Acres*) and less than 180 acres (*Farms <180 Acres*), both of which are defined above. For this model, the years include 2002, 2007, and 2012, leading to 201 observations. Just like the FM model, the independent variables are lagged to avoid endogeneity. Since the agricultural data from the Ag Census are only available every five years, the explanatory variables in the "number of farms" categories and *Farmed Acres* are lagged by five years. This resulted in the 1997 Ag Census information being used as lagged independent data for the 2002 observations. The demographic data are lagged one year and environmental explanatory variables are constant across time.

The independent variables include agricultural, demographic, and environmental variables. The agricultural variables were the total number of farms by size and the total *Farmed Acres*. Higher values of these variables indicate increased presence of infrastructure and institutional knowledge, which encourage farming. The number of *Farmers' Markets* was also included as an explanatory variable to test the hypothesis that the presence of a favorable direct-to-consumer marketing channel, like farmers' markets, would encourage more small farms.

The demographic data included in the SF model were *Median Income*, *Population Density*, and both educational attainment categories, *>High School Degree* and *>Bachelor's Degree*. The goal was to determine if these factors have an influence on the choice to farm.

The county's size and its climatic and soil characteristics were also included as independent variables in the SF model. *Total Acres* describes the county's size and restricts the amount of land ultimately available for farming. A larger county would have more capacity for small farms and so should be positively correlated with the number of small farms. The environmental characteristic *Hardiness Zone Index* is a proxy for relative minimum temperature. A higher index value implies a longer growing season, which should also positively correlate with the number of small farms. Finally, the soil designations of *Prime Acres*, *Local Importance Acres*, and *Unique Importance Acres* all indicate salient agricultural land. Higher availability of important farming land should positively correlate with more small farms.

Weight Matrix

In all of the spatial models estimated, a weighting matrix is needed for the spatial correlation components. For county *i*, counties closest to county *i* are likely most spatially correlated with county *i*. The weighting matrix, *W*, contains assumptions about how this correlation dissipates as counties get farther and farther from county *i*. Common weighting matrixes include using a 0-1 measure to only account for spatial correlation between adjacent neighbors. Other matrixes make use of the inverse of the distance between two observations, or transformations of the inverse.

Different weighting matrixes could have been used to model each of the spatial dependencies ($\rho W y_t, WX_t\theta, \lambda W \nu_t, and\ \phi W \alpha$). However, the inverse of the distances between the centers of each county was used for all weighting matrixes. The distances were determined using a county-level dataset from the Florida Geographic Data Library (FGDL). FGDL's *2002 Census Counties* provides an ArcGIS compatible spatial description of Florida's sixty-seven counties (FGDL, 2014). These spatial references are two-dimensional, polygon shape files. Using the centroid command in ArcGIS to establish the geometric center of each county, the distances between each county's centroid and those of its sixty-six neighboring counties were calculated. The inverse of these distances were used to create a 67 x 67 symmetric matrix to be used as the spatial weight matrix in each model's analysis.

Regional Analysis

The county-level information for the entire state overlooks interesting regional differences. For comparison purposes, the study's data were divided into North and South Florida regions. The South Florida region consists of the thirty-one counties that are approximately south of Marion County, Florida and the city of Ocala. The North Florida region is comprised of the state's remaining thirty-seven counties. Table 4-2 summarizes the data for South Florida's thirty-one counties and North Florida's thirty-six counties.

A quick review reveals that South Florida has more than twice the number of farmers' markets and small farms, on average, per county. North Florida has only sixty-percent of the South's total number of farms and nearly two-thirds fewer total farmed acres. While medium incomes and graduation rates are similar between the two regions, the South has four-times the population density. It is interesting that all of the best soil for farming is located in the North while a larger share of the farmed acreage is in the South.

The panel dataset was compiled from a large number of sources and provides a good view of the wide-ranging agricultural, demographic, and environmental factors present within the peninsula. Comparing North and South Florida highlights the contrast between the two regions of the state. It also indicates that the southern region looks more like the state as a whole. The results of the FM model buttress this observation by establishing that the South Florida region drives the overall statewide results of the models.

Table 4-1. Summary Statistics of County-level Data

	Mean	SE	Min	Max
Dependent Variables				
Farmers' Markets	1.40	2.76	0.00	31.00
Farms <50 Acres	461.00	537.12	11.00	2,968.00
Farms <180 Acres	594.91	625.14	12.00	3,598.00
Agricultural				
Total Number of Farms	690.64	675.89	15.00	3,870.00
Farms 50 to 180 Acres	133.91	123.80	0.00	663.00
Farms >180 Acres	95.74	77.76	0.00	425.00
Farmed Acres (1,000s)	148.71	150.33	0.10	652.67
Demographics				
Population (1,000s)	257.81	418.38	6.65	2,551.29
Medium Income (1,000s)	38.44	9.95	21.98	94.13
Population Density	312.48	506.71	8.20	3,388.90
>Bachelor’s Degree (%)	17.86	8.74	1.40	43.19
>High School Degree (%)	78.97	7.73	54.48	93.32
Environmental				
Hardiness Zone Index	3.27	1.14	1.50	6.00
Prime Acres	16,615.70	41,443.94	0.00	250,570.00
Local Importance Acres	21,670.19	47,910.76	0.00	192,500.00
Unique Importance Acres	90,577.93	156,063.24	0.00	744,220.00
Total Acres	512,519.40	222,131.68	66,000.00	1,286,600.00

Table 4-2. Summary Statistics of County-level Data by Region

	North Florida		South Florida		Difference in Means
	Mean	SE	Mean	SE	t-test
Dependent Variables					
Farmers' Markets	0.88	1.35	2.01	3.71	-3.42***
Farms <50 Acres	305.50	421.90	641.58	598.43	-5.37***
Farms <180 Acres	443.06	519.97	771.24	689.68	-4.43***
Agricultural					
Total Number of Farms	528.26	569.54	879.22	740.14	-4.38***
Farms 50 to 180 Acres	137.56	126.58	129.66	120.86	0.52
Farms >180 Acres	85.19	72.57	107.98	81.98	-2.41**
Farmed Acres (1,000s)	81.77	67.45	226.45	180.07	-8.94***
Demographics					
Population (1,000s)	95.53	148.63	446.27	536.34	-7.52***
Medium Income (1,000s)	37.42	11.33	39.62	7.93	-1.82*
Population Density	129.66	192.76	524.78	655.43	-6.90***
>Bachelor’s Degree (%)	15.73	9.24	20.33	7.42	-4.45***
>High School Degree (%)	78.15	6.91	79.91	8.52	-1.86*
Environmental					
Hardiness Zone Index	2.35	0.47	4.34	0.64	-29.20***
Prime Acres	30,902.06	52,562.03	25.10	138.02	6.54***
Local Importance Acres	34,956.47	58,233.53	6,240.97	24,363.42	5.12***
Unique Importance Acres	4,491.53	17,917.56	190,549.23	183,697.78	-12.09***
Total Acres	463,761.11	151,487.39	569,141.94	272,789.23	-3.98***

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure 4-1. ARS Hardiness Zone Map

CHAPTER 5
RESULTS

For both the FM and SF models, all 5 spatial models were estimated. In cases where the spatial parameters were insignificant or the MLE estimation failed to converge, the spatial specification was discarded. Estimations were conducted using both the random and fixed effects specifications for the SAR, SDM, and SEM models. The Hausman test was then run to determine which model was more appropriate. The GSPRE model was only estimated using the random effects specification and the SAC formulation was only estimated using the fixed effects specification.

Farmers' Market Model

For the Farmers' Market (FM) model at the statewide level, all possible spatial models were estimated. Time interaction variables where included to check for structural changes over time. Each year of interaction variables were tested for joint significance, and years for which the interaction terms were insignificant were removed from the model.

Only the linear Spatial Autoregressive (SAR) model and the linear Generalized Spatial Random-effects (GSPRE) model correctly modeled the spatial relationships in the data. The spatial parameters in the other models were insignificant. While it would have been optimal to estimate a model that allows for nonzero values of ρ, λ, and ϕ in a combined model, the xsmle subroutine does not allow for such a model.[1]

Table 5-1 presents the results of the two spatial models. Results are robust across both spatial models. The variables pertaining to the number of farms are of

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[1] The fixed effects specification for SAR did not converge to a solution using maximum likelihood estimation (MLE) and GSPRE is by definition a random effects specification. Consequently, random effects models were used for both spatial models.

primary interest to this analysis. Interestingly, the coefficients on all three variables representing the count of farms are statistically insignificant before considering the year interactions. While the number of farms in each size category is insignificant, total *Farmed Acres* are positively correlated with the number of markets. This supports the earlier hypothesis that having a good supply of farmers' market products nearby would likely encourage the establishment of market outlets for those products and is consistent with the findings of both Morgan and Berning (Morgan, 2001 and Berning, 2003). A one standard deviation change in the number of *Farmed Acres* has an equivalent impact of 1/3 of a farmers' market in the county.

Among the other variables, *Population* size and the percentage of residents with a bachelor's degree (>*Bachelor's Degree*) were positively correlated and significant demographic factors at the 10% level. These results are also consistent with the findings of Morgan and Berning (Morgan, 2001 and Berning, 2003). For both factors, one standard deviation change has the equivalent impact of approximately 1/3 of a farmers' market in the county, which agrees with Gallons (1997).

While the base effect of *Farms <50 Acres* and *Farms 50 to 180 Acres* are insignificant, in 2012, the effect of *Farms <50 Acres* on number of markets becomes positive while the effect of *Farms 50 to 180 Acres* becomes negative. Berning (2013) identified these same relationships in his research. It appears that farms less then 50 acres in size might be attracting more farmers' markets to their area with a one standard deviation change in the number of *Farms <50 Acres* increasing the number of markets in a county by a factor of 1.5. At the same time, somewhat larger farms, farms that are less likely to target farmers' markets due to scale effects have a negative effect with a one standard deviation change in the number of *Farms 50 to 180 Acres* decreasing the number of markets in a county by a factor of 1.2. This is likely due to constraints on agricultural land. More intermediate sized farms reduce the amount of land remaining for smaller farms and decreases demand for farmers' markets as a marketing outlet.

Dummy variables for 2002, 2007, and 2012 were included in the model to identify any time trends. Both 2002 and 2012 were positive and significant indicating a natural growth in the number of farmers' markets over time. The variable 2007 was not significant. This was likely due to the onset of the recession that began in 2007, which would have had a negative impact of farmers' market. Farmers' markets are more susceptible to poor economic conditions because they do not typically compete on price.

In terms of other structural changes, the interactions with the 2002 dummy variable were jointly insignificant so were excluded from the model. The 2007 and 2012 interactions were jointly statistically significant, indicating that some structural changes have occurred over time. While the base effect of *Population Density* is insignificant, in 2007 *Population Density* has a positive effect on farmers' markets.

The spatial parameters in both models are statistically significant at the 0.01 level. The strongly significant and negative ρ indicates that the presence of farmers' markets in surrounding counties has a negative effect on the number of markets in a county. This is likely due to the effects of competition. The existence of established markets in neighboring counties makes it more difficult to open a new market and draw a sustainable number of both shoppers and farmers. The negative λ indicates a negative spatial correlation across error terms and the positive ϕ indicates positive spatial correlation in the county-level unobserved effects. This latter correlation may be the result of cultural effects that increase demand for farmers' markets and are likely correlated across neighboring counties.

The recent effect of small farms positively influencing the location pattern of farmers' markets is robust across specifications at the state level and similarly observed in South Florida when estimating the models by region. The analysis was run by state regions using the same models and methodology. These regional FM results are summarized in Tables 5-2 and 5-3. The key outcome of the regional analysis was an indication that the southern region of the state appears to be driving the statewide results. Unlike the results of North Florida, farmers' markets in South Florida have become positively correlated with small farms in recent years.[2]

Overall, the South Florida's results were similar to those statewide; both ρ and λ were significant and negative. However, unlike at the state level, ϕ is insignificant for South Florida indicating no spatial correlation in the county-level unobserved effects. The other results of the South Florida model resembled the state level analysis, only with approximately twice the impact. The base effect of *Farms <50 Acres* and *Farms 50 to 180 Acres* are insignificant, and Farmed Acres is positively correlated with the number of farmers' markets in a county. A one standard deviation change in the number of *Farmed Acres* in South Florida has an equivalent impact of more than 2/3 of a farmers' market in the county.

In 2012, the effect of *Farms <50 Acres* on number of markets becomes positively correlated with the number of farmers' markets in the county while the effect of *Farms*

[2] It should be noted that by dividing the state into regions, each regional model utilizes about half of the data as the model at the state level.

50 to 180 Acres becomes negatively correlated. A one standard deviation change in the number of *Farms <50 Acres* increases the number of markets in a county by a factor of 2.8, while a one standard deviation change in the number of *Farms 50 to 180 Acres* decreases the number of markets in a county by a factor of 2.4.

Estimation of the model for the North Florida region revealed no spatial significance and exhibited little explanatory value among the model's variables. In terms of base effects, only the percentage of the population with a bachelor's degree (*>Bachelor's Degree*) was significant, indicating a positive effect of a more educated population on the number of markets. A one standard deviation change in the percentage of the population with a bachelor's degree increases the number of markets in the county by a factor of 0.6.

While the North Florida regional had less overall explanatory power, the model did identify some structural change in 2012 with regards to the effects of *Population*, *Farmed Acres*, and *Population Density*. The changes indicate an increased positive effect of education. As with the South region, observations were limited in the analysis and may lack the degrees of freedom to precisely fit the estimates.

Small Farms Model

For the Small Farms (SF) model at the statewide level, the farms of less than fifty acres definition of small farms was considered first. Again, all spatial models were estimated and those models without statistically significant spatial parameters were discarded. As was the case for FM, the Spatial Autoregressive (SAR) and the Generalized Spatial Random-effects (GSPRE) models best specify the spatial relationships. However, this time a log model was preferred to the linear model, based on comparison of R^2 values and the ease of variable interpretation.[3] Both of these random-effects models exhibited high R^2 values. Results are presented in Table 5-4.

The primary variable of interest is *Farmers' Markets*, and it was not statistically significant in terms of its base value or when interacted with the 2007 or 2012 year dummy variables. This suggests that farmers' markets do not encourage the development of more small farms in the surrounding area.

Not surprisingly, the number of intermediate and large farms in a county are positively correlated with *Farms <50 Acres*. The presence of intermediate and large farms leads to various kinds of infrastructure, which are necessary for the viability of small farms. A one percent increase in the number of *Farms 50 to 180 Acres* would increase the number of *Farms <50 Acres* by 0.5 percent; this would translate to a 44.0 percent increase in *Farms<50* for a one standard deviation increase in *Farms 50 to 180 Acres* or approximately 55 small farms. A one percent increase in the number of *Farms >180 Acres* would increase the number of *Farms <50 Acres* by 0.4 percent; this would translate to a 32.1 percent increase for a one standard deviation increase in *Farms 50 to 180 Acres* or approximately 25 small farms.

Other significant explanatory variables include *Population Density*, county size (*Total Acres*), and *Farmed Acres*. These indicate that counties with a higher population density, more total acres, and fewer agricultural acres would likely have more farms of less than 50 acres. *Population Density* and fewer *Farmed Acres* indicate more urbanized areas so the relationships found likely capture relationships with hobby farms.

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[3] The MLE of the SAR fixed-effects specification converged to a result, but showed little significance and failed to meet the asymptotic assumptions of the Hausman test. The model was discarded in favor of the random effects specification.

The interactions of the time dummy variables with the explanatory variables indicate that there has been some structural change in relationships during the last decade. A test for joint significance of interactions by year indicated that only the 2007 and 2012 sets of interactions were statistically significantly different than zero. Some of these structural changes indicate a change in location of small farms to areas with locally important acreage and away from areas with land designated as *Uniquely Important Acres*. As of 2012, small farm operators appear to be moving south to the warmer areas of the state as indicated by the positive coefficient on the *Hardiness Zone Index*.

For this model, two of the spatial correlation parameters were significant. A positive ρ indicates that the presence of small farms in the larger region encourages small farms in the observed county. This is likely due to the effects of infrastructure, knowledge, and a shared sense of community. Having the retail outlets, agricultural skills and services and the local knowledge of how to farm encourages more small farms. The negative λ indicates spatially correlated error terms. For this model, ϕ was found to be insignificant, indicating no spatial correlation across the county-level unobservable terms.

Finally, the Small Farms (SF) model at the statewide level using a definition of small farms as *Farms <180 Acres* was analyzed. Again, all spatial models were estimated and those models without statistically significant spatial parameters were discarded. As was the case for FM, the Spatial Autoregressive (SAR) and the Generalized Spatial Random-effects (GSPRE) models best specify the spatial relationships. A Hausman test was conducted on the estimates generated under both the random and fixed-effects specification for the SAR model and the fixed-effects formulation was rejected. Both model specifications exhibited high R^2 values. Results are presented in Table 5-5.

As was the case when small farms were defined as less than 50 acres, when defined as less than 180 acres, the coefficient on *Farmers' Markets* is statistically insignificant, both in terms of its base value and for the interaction terms.

Under the new small farm designation of less than 180 acres, the presence of large farms is still positively correlated with the number of small farms. A one percent increase in the number of *Farms >180 Acres* would increase the number of *Farms <180 Acres* by 0.3 percent; this would translate to a 22.1 percent increase in *Farms <180 Acres* for a one standard deviation increase in *Farms >180 Acres* or approximately 17 small farms for a county with the average number of *Farms >180 Acres*. Other positively correlated explanatory agricultural variables include *Prime Acres* and county size (*Total Acres*). Like the previous small farm scenario of less than fifty acres, small farms are also positively correlated with *Population Density*. Unexpectedly, the percentage of high school graduates in a county (*>High School Degree*) is negatively correlated with small farms.

The interactions of the time dummy variables with the explanatory variables indicate that there has been some structural change in relationships during the last decade. A test for joint significance of interactions by year indicated that only the 2007 and 2012 sets of interactions were statistically significantly different than zero. Again, small farms seem to be moving to warmer regions of the state and making more use of *Local Important Acres* over time. Small farms also appear to be locating in less population dense regions and using less land designated as *Uniquely Important Acres* in 2012 relative to previous years.

The statistically significant and positive ρ indicates that the presence of other similarly sized farms in the larger region encourages small farms in the observed county. This again is likely due to the effect of infrastructure and knowledge in the region. Having the resources, skills, and agricultural services nearby supports the area's small farms. λ is not significant under this small farm specification indicating no spatial correlation in the error terms. However, ϕ is significant and positive. This implies that the county-level unobserved effects are spatially correlated.

Due to the limited number of observations available for the small farms models, the regional analysis was not included here. Both small farm categories require a large number of variables to estimate the SF log model. For *Farms <50 Acres*, the model requires 39 variables and has only 93 observations available for the South region. This means the model may not have enough degrees of freedom to accurately fit the estimates.

In summary, the results of this research aligned well with the literature in that it identified many of the same factors affecting farmers' markets. This study found support for Morgan's (2001) positive correlation between farmers' markets and income, population size, and farmed acreage. Berning (2013) determined that a combination of market size, education levels, farming activities, and decreased farm size were all positively correlated with farmers' markets. The research here supports those findings as well. Like Berning, this study also determined a negative relationship between larger farms and farmers' markets.

Table 5-1. Statewide Farmers' Market Linear Model Results

	SAR Model		GSPRE Model	
Variable	Coeff	SE	Coeff	SE
2002	0.4294**	0.1872	0.2292**	0.1066
2007	-0.2008	2.6089	-0.3791	2.6344
2012	6.0898**	2.5882	5.7939**	2.6033
Population (1,000s)	0.0009*	0.0005	0.0007*	0.0004
Farms >180 Acres	-0.0021	0.0033	-0.0013	0.0032
Farms 50 to 180 Acres	0.0011	0.0021	-0.0007	0.0021
Farms <50 Acres	-0.0001	0.0004	0.0002	0.0004
Medium Income (1,000s)	-0.0154	0.0175	-0.0153	0.0168
Farmed Acres	0.0025***	0.0010	0.0043***	0.0010
Population Density	-0.0000	0.0003	0.0002	0.0003
>High School Degree (%)	0.0202	0.0264	0.0219	0.0248
>Bachelor's Degree (%)	0.0382*	0.0223	0.0476**	0.0212
2007xPopulation	-0.0009	0.0007	-0.0008	0.0006
2007xFarms >180 Acres	0.0006	0.0054	0.0013	0.0055
2007xFarms 50 to 180 Acres	0.0004	0.0034	0.0002	0.0032
2007xFarms <50 Acres	0.0003	0.0005	0.0001	0.0005
2007xMedium Income	0.0046	0.0217	0.0063	0.0223
2007xFarmed Acres	-0.0010	0.0014	-0.0010	0.0014
2007xPopulation Density	0.0013***	0.0004	0.0013***	0.0004
2007x>High School Degree	0.0046	0.0392	0.0019	0.0395
2007x>Bachelor's Degree	0.0217	0.0324	0.0178	0.0339
2012xPopulation	0.0065***	0.0008	0.0072***	0.0007
2012xFarms >180 Acres	0.0081	0.0054	0.0071	0.0056
2012xFarms 50 to 180 Acres	-0.0095**	0.0038	-0.0075**	0.0036
2012xFarms <50 Acres	0.0027***	0.0006	0.0021***	0.0006
2012xMedium Income	0.0021	0.0215	0.0107	0.0224
2012xFarmed Acres	-0.0061***	0.0016	-0.0066***	0.0015
2012xPopulation Density	0.0004	0.0004	-0.0000	0.0004
2012x>High School Degree	-0.0515	0.0381	-0.0694*	0.0380
2012x>Bachelor's Degree	0.0028	0.0321	0.0098	0.0330
Constant	-1.4406	1.7085	-2.2008	1.6094
Spatial				
rho	-1401.9031***	479.5713		
lambda			-3234.1602**	1599.8225
phi			5165.7276***	344.3522
N	268.00		268.00	
R^2	0.8638		0.8432	

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5-2. South Region Farmers' Market Linear Model Results

	SAR Model		GSPRE Model	
Variable	Coeff	SE	Coeff	SE
2002	0.9664**	0.3894	0.6684*	0.3578
2007	-3.5991	5.2875	-6.1390	5.8107
2012	4.5626	4.8665	-0.5911	5.2112
Population (1,000s)	0.0003	0.0006	0.0004	0.0006
Farms >180 Acres	-0.0035	0.0047	-0.0062	0.0051
Farms 50 to 180 Acres	0.0002	0.0038	0.0010	0.0043
Farms <50 Acres	0.0003	0.0007	0.0004	0.0008
Medium Income (1,000s)	-0.1104	0.0766	-0.1501*	0.0884
Farmed Acres	0.0049***	0.0011	0.0051***	0.0013
Population Density	0.0003	0.0003	0.0001	0.0003
>High School Degree (%)	0.0207	0.0327	0.0253	0.0360
>Bachelor's Degree (%)	0.1245	0.0810	0.1572*	0.0953
2007xPopulation	-0.0010	0.0009	-0.0005	0.0010
2007xFarms >180 Acres	-0.0092	0.0110	-0.0011	0.0119
2007xFarms 50 to 180 Acres	0.0060	0.0078	0.0003	0.0083
2007xFarms <50 Acres	0.0007	0.0010	0.0006	0.0012
2007xMedium Income	0.1220	0.1125	0.1629	0.1299
2007xFarmed Acres	0.0010	0.0021	0.0001	0.0024
2007xPopulation Density	0.0018***	0.0005	0.0017***	0.0006
2007x>High School Degree	0.0333	0.0599	0.0416	0.0648
2007x>Bachelor's Degree	-0.1211	0.1345	-0.1666	0.1559
2012xPopulation	0.0057***	0.0011	0.0056***	0.0013
2012xFarms >180 Acres	0.0109	0.0079	0.0196**	0.0090
2012xFarms 50 to 180 Acres	-0.0198***	0.0075	-0.0296***	0.0082
2012xFarms <50 Acres	0.0043***	0.0012	0.0053***	0.0014
2012xMedium Income	0.3663***	0.1129	0.3319**	0.1305
2012xFarmed Acres	-0.0088***	0.0021	-0.0109***	0.0024
2012xPopulation Density	0.0009*	0.0005	0.0009	0.0006
2012x>High School Degree	-0.0442	0.0536	-0.0303	0.0576
2012x>Bachelor's Degree	-0.3948***	0.1213	-0.4105***	0.1384
Constant	0.2370	2.8561	-0.3424	3.2201
Spatial				
rho	-6448.0440***	1417.661		
lambda			-6596.855***	2528.4159
phi			-12788.2282	9.724e+08
N	124.00		124.00	
R^2	0.9182		0.9111	

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5-3. North Region Farmers' Market Linear Model Results

	SAR Model		GSPRE Model	
Variable	Coeff	SE	Coeff	SE
2002	0.2108	0.1605	0.3272***	0.1049
2007	-0.1311	3.0243	0.1352	3.0417
2012	-2.7188	2.9457	-2.6668	2.9842
Population (1,000s)	0.0003	0.005	-0.0021	0.0051
Farms >180 Acres	0.002	0.0047	0.0028	0.0049
Farms 50 to 180 Acres	0.00	0.002	0.00	0.0019
Farms <50 Acres	0.00	0.0006	0.0003	0.0006
Medium Income (1,000s)	-0.0076	0.0129	-0.0119	0.0135
Farmed Acres	-0.0005	0.0046	-0.0018	0.0049
Population Density	0.0005	0.0037	0.0022	0.0037
>High School Degree (%)	-0.0118	0.0363	-0.006	0.0365
>Bachelor's Degree (%)	0.0617***	0.0212	0.0554**	0.022
2007xPopulation	-0.0066	0.0055	-0.0084	0.0054
2007xFarms >180 Acres	0.0089	0.007	0.0094	0.0073
2007xFarms 50 to 180 Acres	-0.0013	0.0026	-0.0016	0.0026
2007xFarms <50 Acres	0.001	0.0007	0.0011	0.0007
2007xMedium Income	-0.0041	0.0152	-0.0032	0.0155
2007xFarmed Acres	-0.0103	0.007	-0.0109	0.0073
2007xPopulation Density	0.0045	0.0041	0.0058	0.004
2007x>High School Degree	-0.004	0.0463	-0.0032	0.0469
2007x>Bachelor's Degree	0.0600**	0.026	0.0515*	0.027
2012xPopulation	0.0161***	0.0056	0.0121**	0.0055
2012xFarms >180 Acres	0.0068	0.0069	0.0058	0.0071
2012xFarms 50 to 180 Acres	0.0015	0.0038	0.0004	0.0038
2012xFarms <50 Acres	0.0001	0.0007	0.0004	0.0007
2012xMedium Income	-0.0124	0.0145	-0.008	0.0152
2012xFarmed Acres	-0.0127*	0.007	-0.0099	0.0073
2012xPopulation Density	-0.0072*	0.0042	-0.0041	0.0041
2012x>High School Degree	0.046	0.0436	0.0498	0.0444
2012x>Bachelor's Degree	-0.0009	0.0256	-0.0156	0.0276
Constant	0.2547	2.3078	0.1018	2.3002
Spatial				
rho	998.8436	739.3718		
lambda			-2260.8127	2416.8602
phi			-4680.0374	6048.0262
N	144.00		144.00	
R^2	0.7642		0.7529	

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5-4. Statewide Small Farms Log Model Results (*Farms <50 Acres*)

	SAR Model		GSPRE Model	
Variable	Coeff	SE	Coeff	SE
2012	-3.0691	2.9678	-2.0982	2.9033
2007	-0.5225	2.8256	0.2898	2.7353
lnFarms >180	0.3950***	0.0887	0.3366***	0.0894
lnFarms 50 to 180	0.4762***	0.0783	0.5914***	0.0743
lnFarmers' Markets	0.0505	0.0963	0.0151	0.0912
lnHardiness Zone	1.0240***	0.2901	1.1047***	0.2831
lnPrime Acres	0.0109	0.0189	0.0135	0.0195
lnLocal Importance	-0.0009	0.0159	-0.0122	0.0157
lnUnique Importance	-0.0285*	0.0146	-0.0189	0.0153
lnTotal Acres	0.4113***	0.1329	0.3613***	0.1357
lnMedium Income	0.0958	0.2781	-0.1772	0.2724
lnFarmed Acres	-0.1965**	0.0884	-0.2069**	0.0858
lnPopulation Density	0.3733***	0.0696	0.3471***	0.0706
ln>High School Degree	-1.6299	1.1131	-0.7104	1.0958
ln>Bachelor’s Degree	0.0923	0.2355	0.0241	0.2326
2007xlnFarms >180	-0.0919	0.0959	-0.0778	0.0898
2007xlnFarms 50 to 180	-0.0357	0.0786	-0.0988	0.0709
2007xlnFarmers' Markets	0.0736	0.0922	0.1599*	0.0891
2007xlnHardiness Zone	0.2484	0.1879	0.1625	0.1543
2007xlnPrime Acres	0.0087	0.0115	0.0005	0.0115
2007xlnLocal Importance	0.0212**	0.0089	0.0191**	0.0092
2007xlnUnique Importance	-0.0158	0.0097	-0.0257***	0.0089
2007xlnTotal Acres	-0.0435	0.0858	-0.0466	0.0830
2007xlnMedium Income	-0.0185	0.1876	0.0871	0.1742
2007xlnFarmed Acres	0.0656	0.0732	0.1104	0.0694
2007xlnPopulation Density	-0.0576	0.0539	-0.0493	0.0548
2007xln>High School Degree	0.5194	0.6818	0.3461	0.6498
2007xln>Bachelor’s Degree	-0.2302	0.1549	-0.3048**	0.1536
2012xlnFarms >180	-0.1023	0.1015	-0.0712	0.0961
2012xlnFarms 50 to 180	-0.0384	0.0880	-0.1303	0.0846
2012xlnFarmers' Markets	0.0384	0.0929	0.0770	0.0872
2012xlnHardiness Zone	0.5220***	0.1788	0.4809***	0.1472
2012xlnPrime Acres	0.0090	0.0116	-0.0021	0.0120
2012xlnLocal Importance	0.0035	0.0090	0.0035	0.0092
2012xlnUnique Importance	-0.0258**	0.0105	-0.0441***	0.0105
2012xlnTotal Acres	-0.0832	0.0857	-0.1383	0.0843
2012xlnMedium Income	-0.0964	0.1915	0.0506	0.1857
2012xlnFarmed Acres	0.1207*	0.0731	0.2021***	0.0704
2012xlnPopulation Density	-0.0765	0.0572	-0.0689	0.0570
2012xln>High School Degree	1.2080*	0.7309	1.0450	0.7034

Table 5-4. Continued

Variable	SAR Model Coeff	SE	GSPRE Model Coeff	SE
2012xln>Bachelor's Degree	-0.2073	0.1679	-0.2081	0.1681
Constant	0.1938	4.5470	-1.5849	4.5765
Spatial				
rho	301.1818*	155.9988		
lambda			-9302.308***	2492.6669
phi			118.2120	2338.0989
N	201.00		201.00	
R^2	0.8863		0.8831	

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5-5. Statewide Small Farms Log Model Results (*Farms <180 Acres*)

	SAR Model		GSPRE Model	
Variable	Coeff	SE	Coeff	SE
2012	-2.8050	2.5506	-3.0354	2.5106
2007	-1.1624	2.4142	-1.2897	2.3760
lnFarms >180	0.2727***	0.0856	0.2475***	0.0829
lnFarmers' Markets	0.0244	0.0848	0.0100	0.0867
lnHardiness Zone	0.2329	0.3784	-0.7278	0.5442
lnPrime Acres	0.0529**	0.0253	0.0430*	0.0243
lnLocal Importance	0.0020	0.0213	-0.0003	0.0196
lnUnique Importance	-0.0138	0.0191	-0.0162	0.0212
lnTotal Acres	0.7380***	0.1685	0.7621***	0.1608
lnMedium Income	0.0225	0.3068	0.0082	0.3081
lnFarmed Acres	0.0207	0.0797	0.0114	0.0794
lnPopulation Density	0.5635***	0.0780	0.4811***	0.0802
ln>High School Degree	-2.7190*	1.4640	-3.0287**	1.4293
ln>Bachelor’s Degree	-0.1954	0.3075	-0.0728	0.2949
2007xlnFarms >180	0.0454	0.0638	0.0380	0.0628
2007xlnFarmers' Markets	0.0645	0.0780	0.0767	0.0803
2007xlnHardiness Zone	0.2792*	0.1513	0.2504*	0.1493
2007xlnPrime Acres	0.0098	0.0098	0.0090	0.0098
2007xlnLocal Importance	0.0223***	0.0076	0.0218***	0.0075
2007xlnUnique Importance	-0.0052	0.0079	-0.0063	0.0079
2007xlnTotal Acres	-0.0664	0.0722	-0.0672	0.0714
2007xlnMedium Income	0.1084	0.1610	0.1138	0.1607
2007xlnFarmed Acres	-0.0763	0.0603	-0.0651	0.0596
2007xlnPopulation Density	-0.0550	0.0355	-0.0551	0.0348
2007xln>High School Degree	0.5688	0.5797	0.6131	0.5697
2007xln>Bachelor’s Degree	-0.2355*	0.1338	-0.2409*	0.1318
2012xlnFarms >180	0.0039	0.0621	-0.0002	0.0612
2012xlnFarmers' Markets	0.0635	0.0792	0.0741	0.0830
2012xlnHardiness Zone	0.6547***	0.1468	0.6145***	0.1439
2012xlnPrime Acres	0.0104	0.0099	0.0094	0.0100
2012xlnLocal Importance	0.0105	0.0075	0.0100	0.0074
2012xlnUnique Importance	-0.0234***	0.0080	-0.0245***	0.0082
2012xlnTotal Acres	-0.1195	0.0731	-0.1171	0.0746
2012xlnMedium Income	-0.0060	0.1635	-0.0014	0.1619
2012xlnFarmed Acres	-0.0043	0.0597	0.0051	0.0597
2012xlnPopulation Density	-0.1520***	0.0390	-0.1523***	0.0396
2012xln>High School Degree	1.1717*	0.6276	1.2273**	0.6167
2012xln>Bachelor’s Degree	-0.1569	0.1494	-0.1531	0.1458
Constant	2.7438	6.0899	6.5944	6.0412

Table 5-5. Continued

	SAR Model		GSPRE Model	
Variable	Coeff	SE	Variable	Coeff
Spatial				
rho	627.4741***	194.7893		
lambda			-218.9295	1509.5403
phi			4949.6839***	453.5149
N	201.00		201.00	
R^2	0.7765		0.5492	

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

CHAPTER 6
CONCLUSIONS

The results of the FM model demonstrate that small farms, and farms in general, have not historically had an impact on the location and number of farmers' markets in Florida. However, in 2012 we see a structural transition in this relationship as farmers' markets not only become positively correlated with *Farms <50 Acres* and negatively correlated with *Farms 50 to 180 Acres*, but this relationship is likely causal. The use of a lagged *Farms <50 Acres* variable in the FM model combined with the lack of significance of *Farmers' Markets*, also lagged, as an explanatory variable in the SF model demonstrates this causal relationship. From 2012 forward, the number of farmers' markets in a county is spatially related to the number and size of farms surrounding the county and appear to form as a result of increases in the number of farms less than 50 acres in size. The resulting impact is not small as the magnitude of the effect implies the gain or loss of more than one farmers' market in a county as the number of small farms moves one standard deviation from the mean number of small farms.

Another structural shift that has occurred in the state is that farmers' markets have become more prevalent in the southern region of the state. The northern region of the state has fewer small farms (*Farms <50 Acres*) and, on average, more intermediate sized *Farms 50 to 180 Acres*. In addition, the SF models demonstrate that small farms are also shifting south seeking a warmer climate as farmers of small farms transition from using *Uniquely Important Acres* to producing on *Locally Important Acres*. This result implies that the northern parts of Florida could see fewer farmers' markets in the future when it already has less than half the number of markets as the southern part of the state.

Two policy implications arise from this result. First, it provides confirmation that there is a causal relationship between the location of farmers' market and the location of small farms. This suggests that markets are responding to the availability of fresh local produce and are seeking to provide a market outlet for small farms in the region. Conversely, it could be the case that small farms are actively attempting to form farmers' markets to use as an outlet for their produce. For communities in areas with a large number of small farms less than 50 acres, primarily in South Florida, it indicates that they should expect an increase in the number of markets and should prepare to effectively support them.

The second policy implication relates to the northern part of the state, which has less than one-half the number of small farms (*Farms <50 Acres*) as compared to South Florida. North Florida also has a larger number of farms in the 50 to 180 acre category, implying fewer farmers' markets in the region thereby potentially restricting the availability of locally produced foods. More important may be the implications of the effectiveness of rural development policies in this area of the state. These policies tend to encourage the development of small farms to support of the local economy and, as suggested by these findings, may not be working as effectively as would be hoped in this part of Florida.

This research has also confirmed that farmers' markets do not have an effect on the location and number of small farms. Instead, small farms develop around farming communities with larger local farms. Also, the SF model results suggest that small farms are moving south in the state and transitioning from farming *Uniquely Important Acres* to producing on *Locally Important Acres*. This appears to be consistent regardless of whether you define small farms as *Farms <50 Acres* or as *Farms <180 Acres*.

The faster growth of small farms in the southern part of the state is an interesting observation since the region is four times more densely populated and contains vast regions of environmentally sensitive land. This is even more striking when considered with the transition to production on locally important acreage, which is in relatively short supply in the area. This would suggest impending pricing pressures on an ever-shrinking land resource. Considering that this tendency is relatively new and small farms generally obtain small margins on their production, this appears to be an unsustainable trend.

The other concerning trend is that beginning in 2007 small farms have become negatively correlated with more highly educated populations as demonstrated by the significant and negative coefficient on >Bachelor Degree. This could indicate that as more residents obtain higher education, they are choosing careers other than farming. A long-term implication of this trend could be a loss in innovation in the industry.

This research is limited by several factors. First, the analysis was constrained to the state of Florida and may not be applicable to some other areas of the county. Although many of the results of this study align well with Berning's (2013) research from New England, future research needs to assess these effects generally across all regions of the country. As the regional analysis here demonstrates, the effects of small farms less than 50 acres on farmers' markets vary even within the state Florida.

This last point highlights Berning's (2013) first order constraint of the two-stage equilibrium outcome entry game: there have to be enough (small) farms as potential market entrants in the area. It would be helpful to better understand what it is about North Florida's agricultural, demographic, and environmental factors that inhibit a correlation between farmers' markets and small farms. In a sense, what are the thresholds that give rise to this associative relationship? Then, how could community leaders identify those thresholds and make the best use of the knowledge in its application to rural development policy?

Finally, some improvements to the dataset would allow better estimates of these effects and should be considered for future research. Zip code or Metropolitan Statistical Area (MSA) level data would improve the understanding of geographical relationships and better estimate spatial impacts. These small spatial scales would also provide more observations in each time period, for better estimation of structural changes over time. For the farmers' market data, this would entail a simple translation of the markets' location address. For the agricultural data, observations would have to be drawn from a source with more detail such as the USDA's annual ARMS research. An added benefit of using ARMS data would be an improvement in the frequency of the agricultural data from five years to annual. Increasing the frequency of observations would improve the estimation ability of the models and provide a better picture of trends over time.

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BIOGRAPHICAL SKETCH

William Barker earned his Master of Science from the Food and Resource Economics department at the University of Florida in the summer of 2014. He previously earned a Bachelor's of Science degree with a double major in economics and applied mathematics from Yale University in the spring of 1996. Born and raised in Plant City, FL, Will graduated salutatorian from Plant City High School and served six years in the United States Navy.