Clusters of Organic Operations and their Impact on Regional Economic Growth in the United States

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Introduction

The organic agriculture industry has gained momentum in recent decades as consumer demand for organic products has gone up for reasons such as perceived health benefits (e.g., Hughner, 2007). Organic agriculture has also been linked to regional economic development (e.g., Pimentel et al., 2005; and Darnhofer, 2005), with much of the research focusing on organic sales. To our knowledge, the impact of organic operations on general economic indicators has not been widely addressed in existing literature. The purpose of this paper is to analyze the impact of organic operations on county-level general economic indicators. In order to systematically identify counties that have statistically significant "high levels" of organic operations, we focus on the spatial econometrics method, the Local Moran's I, to identify "hotspots" (in our case, counties with positively correlated high numbers of organic operations). We then calculate the treatment effect of being in a hotspot on county-level economic indicators, thereby quantifying the impact of organic operation hotspots. In order to differentiate the effects of hotspots of organic operations from those of other types of establishments, we also analyze and compare the effects of hotspots of agricultural establishments. Our research, we believe, is the first to estimate the effect of organic clustering on general economic indicators, and the first to consider organic clustering as an endogenous treatment, thereby accommodating potential selection bias in the formation of clusters.

Much of the research on clustering of firms or industries generally finds that clustering can be advantageous to economic development (Morrison Paul and Seigel, 1999; Feser, 1998; Chevassus-Lozza and Galliano, 2003; Cainelli, 2008; Glaeser et al., 1992; Greenstone et al., 2010; Barkley and Henry, 1997; Duranton and Puga, 2003; Gibbs and Bernat, 1997; Gabe, 2004 and 2008; Graham and Kim, 2008; Rocha and Sternberg, 2008; and Feser et al., 2008). Specifically, Morrison Paul and Seigel (1999), Chevassus-Lozza and Galliano (2003), Cainelli (2008), Greenstone et al. (2010), Duranton and Puga (2003), and Graham and Kim (2008) discuss the industry-level scale economies brought on by agglomeration externalities, while Glaeser et al. (1992), Greenstone et al. (2010), Gibbs and Bernat (1997), Henderson (1997), Gabe (2008), and Feser et al. (2008) discuss the advantages of clustering for local growth (e.g., growth of employment/wages, industries, and business activity within a city/county). Gabe (2004) and Rocha and Sternberg (2008) find that agglomeration encourages investment and entrepreneurship, respectively, in affected industries.

The economic intuition behind why clustering is beneficial to economic development is primarily centered on positive agglomeration externalities. For example, agglomeration implies a higher availability and specialization of inputs (e.g., workers, suppliers) and the opportunity for information sharing and knowledge spillovers, which can lead to cost reductions and advantages in competition (e.g., University of Wisconsin-Extension's Center for Community Economic Development; Barkley and Henry, 1997; and Duranton and Puga, 2003). It also implies a quicker flow of goods, which leads to better industry organization (e.g., Barkley and Henry, 1997 and University of Wisconsin-Extension's Center for Community Economic Development). Clustering may also promote local economic and business growth because manufacturers may want to take advantage of the existing agglomeration externalities (e.g., Delgado, 2012; Gabe, 2008; and University of Wisconsin-Extension's Center for Community Economic Development). Additionally, agglomeration externalities (e.g., higher availability of inputs) may lead to fewer barriers to entry, which can promote innovation (University of Wisconsin-Extension's Center for Community Economic Development).

Clustering is frequently addressed as it pertains to food and agriculture. For example, Goetz (1997) finds that state-level agglomeration economies are present in most of the food manufacturing industry, and Chevassus-Lozza and Galliano (2003) find that agglomeration economies encourage exportation and give firms advantages in competition in the French food industry.

Although research on clustering in the food and agriculture industry in general is prevalent, it is important and interesting to address the organic food sector separately, as a special case of agriculture. First, Marasteanu and Jaenicke (2013) demonstrate that while hotspots are present in the organic sector, they are not consistent with those of agricultural operation in general. In addition, operations in the organic sector display different characteristics from those of the conventional food industry, including more restricted production methods (United States Department of Agriculture's National Organic Program), higher input costs (USDA's Economic Research Service), need for more specialized labor (Klonsky and Tourte, 1998), and more frequent use of their own resources (Argiles and Brown, 2010; and Schmidtner et al., 2011). The organic food industry is also growing at a quicker rate than the conventional food industry, and has seen an increase in retail sales from $3.6 billion in 1997 to $21.1 billion in 2008, with organic cropland more than doubling between 1997 and 2005 (Dimitri and Oberholtzer, 2009). These factors imply that organic operations may see a more significant impact from clustering (e.g., they may have a greater need for or ability to take advantage of agglomeration externalities brought on by clustering). With a few exceptions, however, the specific impact of clustering on the organic sector has not, to our knowledge, been widely addressed. Two examples of the scarce literature on this topic are Naik and Nagadevara (2010), who find economic benefits to clustering in organic farming in Karnataka, India; and Jaenicke et al. (2009), who find that clustering positively impacts the output (in sales per employee) of organic handling firms in the United States.

Methodology:

Hotspot Identification:

To perform our analyses, we start with the hotspot maps generated in Marasteanu and Jaenicke (2013), who use the Local Moran's I to identify statistically significant hot-spots (positively correlated counties with high attribute values), cold-spots (positively correlated counties with low attribute values), and outliers (negatively correlated counties). The Local Moran's I test statistic, which is used to test the null hypothesis of no spatial autocorrelation, is defined as follows (Anselin, 1995; Lesage, 1998; and Anselin, 1999):

$$I_i = (x_i - \bar{X})\Sigma_{j \neq i} w_{ij}(x_j - \bar{X})$$

$x_i = attribute\ level\ for\ section, i$

$\bar{X} = mean\ attribute\ level\ for\ entire\ area$

$w_{ij} = weighting\ value\ between\ sections\ i\ and\ j$,

where the sections are United States counties, the entire area is the United States, the attribute level for county i is the count of organic operations, and the weighting matrix is a queen contiguity matrix. The significance of the Local Moran's I is determined via a permutation method implemented in GeoDa (GeoDa Center). In order to better interpret our results and facilitate a comparison, we also identify hotspots for general agriculture.

Impact of hotspots:

Using the hot spots obtained through the Local Moran's I method, we then analyze the effect of being in a hotspot on county-level economic indicators. In order to capture causal effects, we calculate the average treatment effects:

The average treatment effect is given by (Cameron and Trivedi, 2005):

ATE = $E[y_1|\boldsymbol{x}, D=1]- E[y_0|\boldsymbol{x}, D=0]$,

and the average treatment effect on the treated is given by:

ATET = $E[y_{1i}| D_i=1]- E[y_{0i}| D_i=1]$.

The indicator variable, D, represents the treatment (and takes a value of 1 if the treatment is applied and 0 otherwise), $\boldsymbol{x}$ represents a matrix of characteristics that are associated with the outcome, and y_{1i} represents the outcome when the treatment is applied, and y_{0i} represents the outcome when the treatment is not applied. In the case of our research, the treatment variable (our "D") is an indicator variable that takes a value of 1 if a county is in a hotspot and 0 otherwise, our outcome is some county-level economic indicator (we estimate four different models, using poverty, unemployment, income per capita, and median household income as the indicator), and $\boldsymbol{x}$ is a matrix of county-level variables that are consistent with literature on factors associated with economic growth.

We do not observe what the value of the outcome would be for treated individuals were they not treated, and vice-versa. Two common methods of addressing this are propensity score matching and treatment effects models. A propensity score is simply the probability of being treated conditional on $\boldsymbol{x}$. It is assumed that observations with the same propensity score have the same values of ***x***. To calculate what the value of a treated observation would be were it not treated and vice-versa, it is matched with an untreated observation that has a similar propensity score, and therefore similar values of ***x*** (Rosenbaum and Rubin, 1983; Cameron and Trivedi, 2005).

To estimate the average treatment effect and average treatment effect on the treated using propensity score matching, we first estimate a probit model with the treatment as the dependent variable, and characteristics that affect both the outcome and the probability of treatment as the independent variables. These variables are chosen based on consistency with literature on economic growth and hotspot formation (see Table 3).[1] We then use the predicted probabilities of being in a hotspot as our propensity score (Grilli and Rampichini, 2011). Then, using our estimated propensity score along Mahalanobis matching (Leuven and Sianesi, 2003), we estimate the average treatment effect, average treatment effect on the treated, and average treatment effect on the untreated for our four chosen economic indicators.

To assess whether or not we can be confident in our results, we check if our model satisfies the balancing hypothesis, which implies that the treatment is random for a given propensity score so that the ***x*** matrix of treated and control units with the same propensity score is identical (Becker and Ichino, 2002). To do this, we test the null hypothesis that the difference between the means (the bias) of the treated and control is equal to 0 for all independent variables given a propensity score, as well as the null hypothesis that all of the biases are equal to 0 (Leuven).

Because hotspots may affect their non-hotspot neighbors, we run the risk of violating the Stable Unit Treatment Value Assumption, which states that the treatment does not indirectly

[1] Our selection of these variables was also partially based on whether or not they allowed to model to satisfy the balancing hypothesis.

affect non-treated observations (Cameron and Trivedi, 2005). For example, a violation would occur the treated counties (i.e., organic hot spots) benefited at the expense of neighboring counties that were not also hotspots. To address this, we drop the observations for non-hotspot counties that are within two counties of a hotspot. We perform this analysis for organic hotspots, as well as general agricultural hotspots.

One drawback of the propensity score method is that it does not take into account the possibility that there may be variables that affect the treatment variable, but not the outcome variable. For example, the certifying agent may impact the presence of hotspots, but not the economic indicators. In such a case, we can use an instrumental variable approach to estimating a treatment regression model:

$$y_{ti} = \boldsymbol{x}_i{}'\beta_t + \mu_{ti}$$

where here *t* indexes the treatment status (takes a value of 1 if the observation is treated, and 0 otherwise), and *i* indexes the observation. To account for the endogeneity of the treatment variable, we also consider the following decision equation:

$$D*_i = \boldsymbol{z}_i{}'\gamma + \varepsilon_i$$

$$D_i = 1\ iff\ D*_i > 0$$

$$D_i = 1\ iff\ D*_i \leq 0$$

where $D*_i$ is a latent variable that may represent the actual level of the treatment, and D_i is a dummy variable that takes a value of 1 if the treatment is implemented, and 0 otherwise. The matrix, $\boldsymbol{z}$, represents variables that explain D_i. There must be at least one variable in this matrix that is uncorrelated with y_{1i} and y_{0i} except through D_i (Cameron and Trivedi, 2005). For ease of comparison, the specification for this equation is identical to that of the probit model used in the propensity score matching method, with the exception of two variables related to the type of certifying agent.

This estimation method accounts for selection bias, which occurs if any non-randomness in organic hotspot formation is still present even after conditioning on the variables in the z matrix. Even after selection bias is accounted for, estimation of the treatment regression model can be compromised by potential endogeneity or simultaneity. To account for the possibility of simultaneity, we use time lags (i.e., the clusters and x variables are from 2009 and before, while the county-level economic indicators, i.e., the y variables, are from 2011 – 2012). For comparison, we present the results obtained using both the propensity score matching approach as well as the instrumental variable approach that accounts for endogenous treatment formation.

As shown in the Marasteanu and Jaenicke (2013), certain characteristics spill over county lines; therefore, we need to account for the possibility of spatial lag and spatial error in our outcome equations. To do this, we implement Lagrange Multiplier tests for the presence of spatial lag and spatial error in the outcome equations.

Data

To obtain data on county-level factors affecting economic growth and development (the independent variables that comprise x), as well as on factors affecting the presence of clusters and organic and agricultural operations (the instrumental variables that comprise z), we use publicly available sources such as the U.S. Census, the Bureau of Labor Statistics, the USDA's Census of Agriculture, and the USDA's *Agricultural Resource Management Survey (ARMS).*

Our data on certified organic operations come from the National Organic Program and are publicly available online. They contain a list of all certified organic operations, along with information such as operation name, certifying agent, primary scope (i.e. handling, crops, livestock), address, phone number, and products produced. Approximately 60% of the operations have crops as their primary scope, while 28.5% have handling, 11.4% have livestock, and less than 1% have wild crops as their primary scopes. The data on county-level variables related to politics, infrastructure, demographics and economic activity come from several publicly available sources such as the U.S. Census and the USDA's Census of Agriculture. Further information regarding the certifier (i.e., whether it is a government agency or provides outreach), is publicly available on the certifiers' websites.

Table 1 lists the variables we use in our analysis (including description, summary statistics and source). Tables 2 and 3 offer explanations as to how the variables are expected to affect economic growth and hotspot formation, respectively, based on rationales found in existing literature.

Results

Figures 1 and 2 show maps of clusters of certified organic operations and clusters of agricultural establishments in general, respectively, calculated using the Local Moran's I statistic and a queen contiguity matrix.[2] There are three large areas of organic hotspots along the West coast, in part of the Midwest, and in the Northeast, and smaller area of hotspots in the West. There is a large area of organic coldspots that encompasses almost the entire south, and some smaller areas in the West, Midwest, Alaska and Hawaii, and outliers are scattered throughout the country. Comparing Figures 1 and 2 suggests that hotspots of agricultural establishments do not necessarily match to hotspots of organic operations, with hotspots of agricultural establishments

[2] Maps obtained using a distance band weighting matrix show hotspots and coldspots that are larger, but in the same general locations, and more outliers.

existing in Florida and parts of the Southeast, and fewer hotspots of agricultural establishments in the Northeast and Midwest.

Table 4 shows the treatment effects of being in an organic hotspot, as calculated via propensity score matching. For each outcome variable, it is informative to look at the difference column, which shows the difference between the mean outcome of the treated group (counties that are organic hotspots) and the mean outcome of the control group (counties that are not organic hotspots or within two counties of an organic hotspot) for observations before matching ("Unmatched"), after matching (Average Treatment Effect, or "ATE"), treated observations (Average Treatment Effect on the Treated, or "ATET"), and untreated observations (Average Treatment Effect on the Untreated, or "ATU"). For poverty rate and unemployment, we see a negative ATET, ATU and ATE, which implies that being in a hotspot negatively impacts poverty rate and unemployment rate. Conversely, for income per capita and median household income, we see a positive ATET, ATU and ATE, which implies that being in a hotspot positively impacts income per capita and median household income. The main conclusion that can be drawn from this is that being in an organic hotspot is beneficial to county-level economic indicators. The tests for the balancing condition all suggest that the bias (difference between mean of the treated and the mean of the control given a propensity score) is not significant in our model, and we can, therefore, be confident in the validity of our results.

Similarly, Table 5 shows the treatment effects of being in a general agricultural hotspot, as calculated via propensity score matching. These results are almost exactly opposite to the results for organic hotspots, as agricultural hotspots have positive effects on poverty rate and unemployment rate, and negative effects on income per capita and median household income.

This suggests that that it is the organic nature of hotspot that leads to a positive impact on the local economy.

Our tests of the balancing condition again suggest that we can be confident in our results. The Lagrange Multiplier Tests for Spatial Autocorrelation suggests the presence of spatial autocorrelation in both the dependent variable and in the error term, which implies that we cannot be sure if we should specify a spatial lag or a spatial error model. We, therefore, implement a Spatial Durbin Model, which includes spatial lags on the dependent variable as well as on the independent variables, following the suggested solution in LeSage and Pace (2009). To account for the endogeneity of the spatially lagged dependent variable, we use the two stage residual inclusion (2SRI) method, which is shown to be a consistent method of solving linear and non-linear models with endogenous regressors by Terza et al. (2008). In the first stage, the endogenous regressor, D, is estimated with a probit regression. Then, the estimated residuals from this regression are included, along with D, in the second-stage model, which is the treatment regression model, in our case. If the estimated coefficient on the estimated residuals is significantly different from zero, it means, it means that the variables are indeed endogenous.

Table 6 shows the results of instrumental variable treatment regression models using organic hotspots as the treatment. Models 1, 2, 3, and 4 represent the treatment regression models with poverty rate, unemployment rate, income per capita, and median household income, respectively, as the y variable. The estimates for ATE and ATET are consistent with those of the propensity score matching method and show a negative effect of organic hotspots on poverty rate and unemployment rate, and a positive effect on income per capita and median household income, for a more general conclusion that organic hotspots are beneficial to county –level economic indicators. The magnitudes of the effects are larger, however, in the propensity score matching method.

The covariates fit into different rationales described in Table 2. For Model 1, the positive and significant coefficient for *uic03* and *dist_highway_km* are consistent with the market access rationale, while the positive and significant coefficient for *popdensity09* is consistent with the protection from urban sprawl rationale. The negative and significant on *highschool09* is consistent with the human capital rationale and the negative significant coefficient for *valuelandperacre07* is consistent with the resources rationale. The negative significant coefficient for *ptaxpercap02* is consistent with the rationale that taxes can be used to establish better infrastructure and public services, which can attract more households to the area. In the second model, the negative significant coefficients on *totalphysicians09* and highschool09, and the positive significant coefficient on *numviolentcrime08* are consistent with the human capital rationale. The positive and significant coefficient for *uic03* is consistent with the market access rationale. In the third model, the positive significant coefficient for *totalphysicians09* and *highschool09*, as well as the negative significant coefficients for *nohealthins_18to64_07* and *numviolentcrime08* are consistent with the human capital rationale. The positive and significant coefficient for *valuelandperacre07* is consistent with the resources rationale, and the positive and significant coefficient for *ptaxpercap02* is consistent with the rationale that taxes can be used to establish better infrastructure and public services. The results of the fourth model are similar, with the exception of the negative and significant coefficient on *uic03*, which is consistent with the protection from urban sprawl rationale, and the negative and significant coefficient for *dist_highway_km*, which is consistent with the market access rationale.

The significant coefficients for the spatially lagged independent variables indicate that certain characteristics of a county impact the economic indicators of neighboring counties. The positive and significant coefficients on the spatially lagged dependent variables imply that observations in a county are partially explained by their neighbors. The significant coefficients on the residuals of the spatially lagged dependent variables imply that they are endogenous and that the results of the two stage residual inclusion model are valid.

Table 7 shows the same analysis for hotspots of agricultural establishments in general. The interpretations of the coefficients are similar. Again, the estimates of ATE and ATET are consistent with the results from the propensity matching method. This solidifies our conclusion that the benefits of hotspots are due to the organic component.

Conclusions and Further Steps

The purpose of this paper is to determine whether or not organic agriculture is good for local economies. To answer this question, we establish a rigorous idea of what constitutes organic agriculture at a local level by identifying hotspots of organic operations. We then determine an appropriate analysis that accounts for non-random formation or hotspots and potentially endogenous formation of hotspots by using propensity score matching and an endogenous regressor treatment effects model to quantify the impact of organic hotspots on four economic indicators: poverty rate, unemployment rate, income per capita, and median household income. We also perform the same analysis for general agricultural hotspots to determine whether or not any benefits associated with hotspots were, in fact, due to the organic component. Our results consistently show that organic hotspots are beneficial to economic indicators, while general agricultural hotspots are not. From this, we are able to conclude that organic agriculture is beneficial to the economy, and that the benefits are due to the organic component. This provides strong motivation for considering organic hotspots as a local economic development tool.

A few issues need to be addressed in the future. First of all, there do not, to our knowledge, exist tests for model specification and overidentification for a treatment regression. Finding and performing a few of these tests would increase our confidence in our results. Additionally, it may also be interesting and helpful to compare several different methods that account for the endogeneity of the spatially lagged dependent variable.

In the future, we plan to study the role of the organic certifier on hotspot formation, as well as to determine whether or not it has a significant indirect effect on the economic indicator variables. For example, when looking at the results of the selection equations, we can see that the type of prevalent certifier is significantly correlated with the presence of hotspots. Specifically, if 30% or more of a county's organic operations are certified by a governmental agency or if 30% or more of a county's organic operations are certified by an agency that provides outreach and networking opportunities, there is a higher chance that the county will be an organic hotspot. We also plan to examine the impact of coldspots and outliers on economic indicators, as well as to determine whether the impact of organic hotspots is due to the clustering of organic operations, or merely to the presence of organic operations.

Table 1: Variable Description and Summary Statistics

Variable	Description	Obs	Mean	Std. Dev	Min	Max
Economic Indicators						
poverty2012	poverty rate in 2012	2726	17.0201	6.207434	4	45.8
unemployment2011	unemployment rate in 2011	2726	8.595965	2.912345	1.1	29.7
inc_per_cap2011	income per capita in 2011	2726	35289.83	8254.619	17385	95861
med_hh_inc2012	median houshold income in 2012	2726	44802.68	10895.99	22126	118934
Factors associated with economic growth						
totalphysicians09	total number of physicians in 2009	2726	283.628	1103.658	0	32056
uic03	urban influence code in 2003[3]	2726	5.295671	3.360739	1	12
nohealthins_18to64_07	number of people, ages 18-64 without health insurance in 2007	2726	19.85165	6.059045	8.3	54.3
highschool09	percentage of people who have completed high school and above in 2009	2726	82.69879	7.285127	46.5	97.3
numviolentcrime08	number of violent crimes in 2008	2726	410.0657	1864.331	0	59788
indus_entropy00	industry entropy index, which measures economic diversity in 2000 [4]	2726	2.509517	0.572627	0.0705	3.3103
farm_receipt_per_op07	receipts of income and farm related totals measured in dollars per operation, 2007	2726	15441.15	13452.72	665	199181
dist_highway_km	distance of the county from an interstate highway measured in kilometers	2726	12.24956	22.01827	0	154.004
popdensity09	population density in 2009	2726	151.8245	395.945	0.26522	11295.26
valuelandperacre07	value of land and buildings per acre, 2007	2726	3235.653	3245.764	0	69192
ptaxpercap02	property tax per capita in 2002	2726	740.6764	520.1098	74	10747
Factors associated with the formation of hotspots						

[3] Lower UIC means higher level of urban influence (USDA's Economic Research Service, 2003)

[4] Calculated as $IE_i = -\sum_j^n p_{ij} \log_2 p_{ij}$, $p_{ij} = \dfrac{RCA_{ij}}{\sum_k^n RCA_{ik}}$, $RCA_{ij} = \dfrac{EMP_{ij} \cdot \sum_{s,t} EMP_{st}}{\sum_s EMP_{sj} \cdot \sum_t EMP_{it}}$ where EMP_{ij} is the number of employees of industry j in the county i and n is the number of industrial sectors in US economy. High IE means higher diversity (Goetz et al., 2010)

govt30	takes a value of 1 if 30% or more of the organic operations in the county are certified by a government agency	2726	0.175715	0.380648	0	1
outreach30	takes a value of 1 if 30% or more of the organic operations in the county are certified by an agency (non-governmental) which provides outreach (e.g., conferences, workshops, education, networking)	2726	0.351431	0.477505	0	1
Hotspots						
hh_org09	takes a value of 1 if the county is an organic hotspot, and 0 otherwise	2726	0.075569	0.264355	0	1
nohh_noneighbors_org09	takes a value of 1 if the county is not an organic hotspot and is not within two counties of an organic hotspot	2726	0.491563	0.500021	0	1
hh_totag09	takes a value of 1 if the county is a a general agricultural organic hotspot, and 0 otherwise	2726	0.070433	0.255922	0	1
nohhag_noneighbors_totag09	takes a value of 1 if the county is not a general agricultural hotspot and is not within two counties of an organic hotspot	2726	0.493397	0.500048	0	1

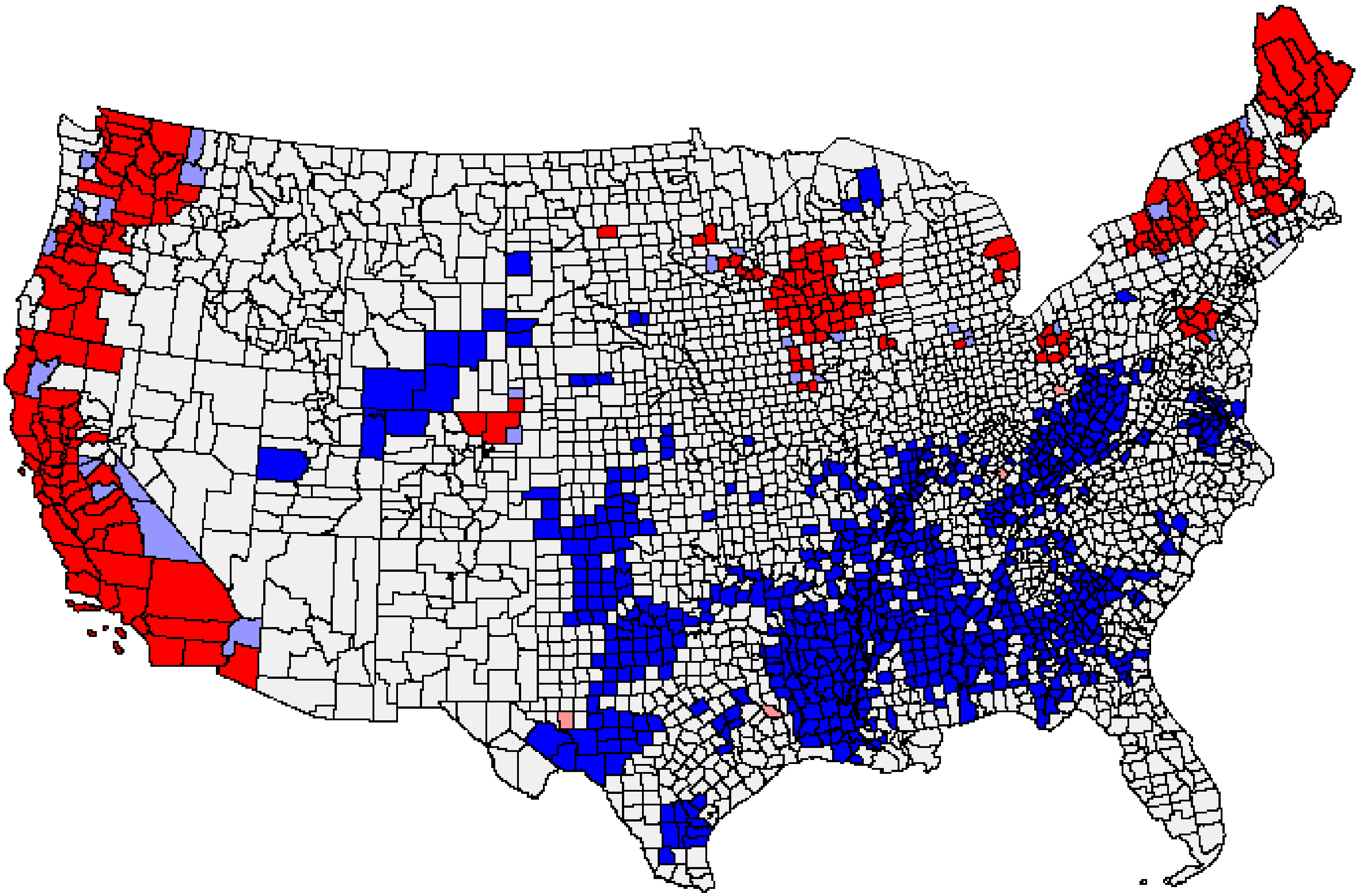
Table 2: Factors affecting regional economic growth/development

Factor	Variables	Effect on Economic Growth and Development	Source
Supply Side Factors			
Human Capital: The amount and quality of human capital impacts regional income or wealth; the ability to attract and retain human capital can also be beneficial to regional development. Education, health services, crime rate, and types of occupations can be indicators of human capital.	nohealthins18to64_07/ totalphysicians09 numviolentcrime08 valuelandperacre07 highschool09	Negative/Positive: Health insurance can be seen as an investment in human capital, and has been shown to have a small positive effect on regional development Negative: Crime can have a detrimental effect on human capital, and therefore regional development Positive: Amenities and high value of land and buildings attract and retain a population with high levels of education and skills Positive: Level of education is an indicator of human capital	Florida et al., (2008), Terluin (2003), Deller et al., (2001),
Resources: Presence and efficient use of resources may impact regional development	popdensity09/ dist_highway_km/ uic03 valuelandperacre07	Negative/positive/positive: This may indicate protection from sprawling development, which may be detrimental to natural resources Positive: rural areas that have more natural amenities can better manage their resources	Mishra et al. (2004), Ilberry (1991), Brown et al. (2012)
Demand side factors			
Factors related to market size, market access, and consumption ability affect regional development	popdensity09 popdensity09/ dist_highway_km/ uic03 farm_receipt_per_op07	Positive: May be an indicator of market size Positive/negative/negative: This may indicate level of market access Positive: higher farm income may imply higher market access	Deller et al., (2001)
Government and Policy			
The priorities and effectiveness of policy makers can impact regional growth	ptaxpercap02	Positive/Negative: High taxes are often found to be detrimental to growth; however, they can also be used to establish better infrastructure and public services, which can attract more households to the area	Deller et al., (2001), Terluin (2003)
Economic diversification			
Regional development can be linked with economic diversification, which includes things such as agritourism, organic farming, conservation, and landscape management	indus_entropy00	Positive: high industry diversity may imply economic growth	Van der Ploeg et al., (2000), Terluin (2003), Goetz et al., 2010)

Table 3: Factors affecting the presence of hotspots of organic/agricultural operations

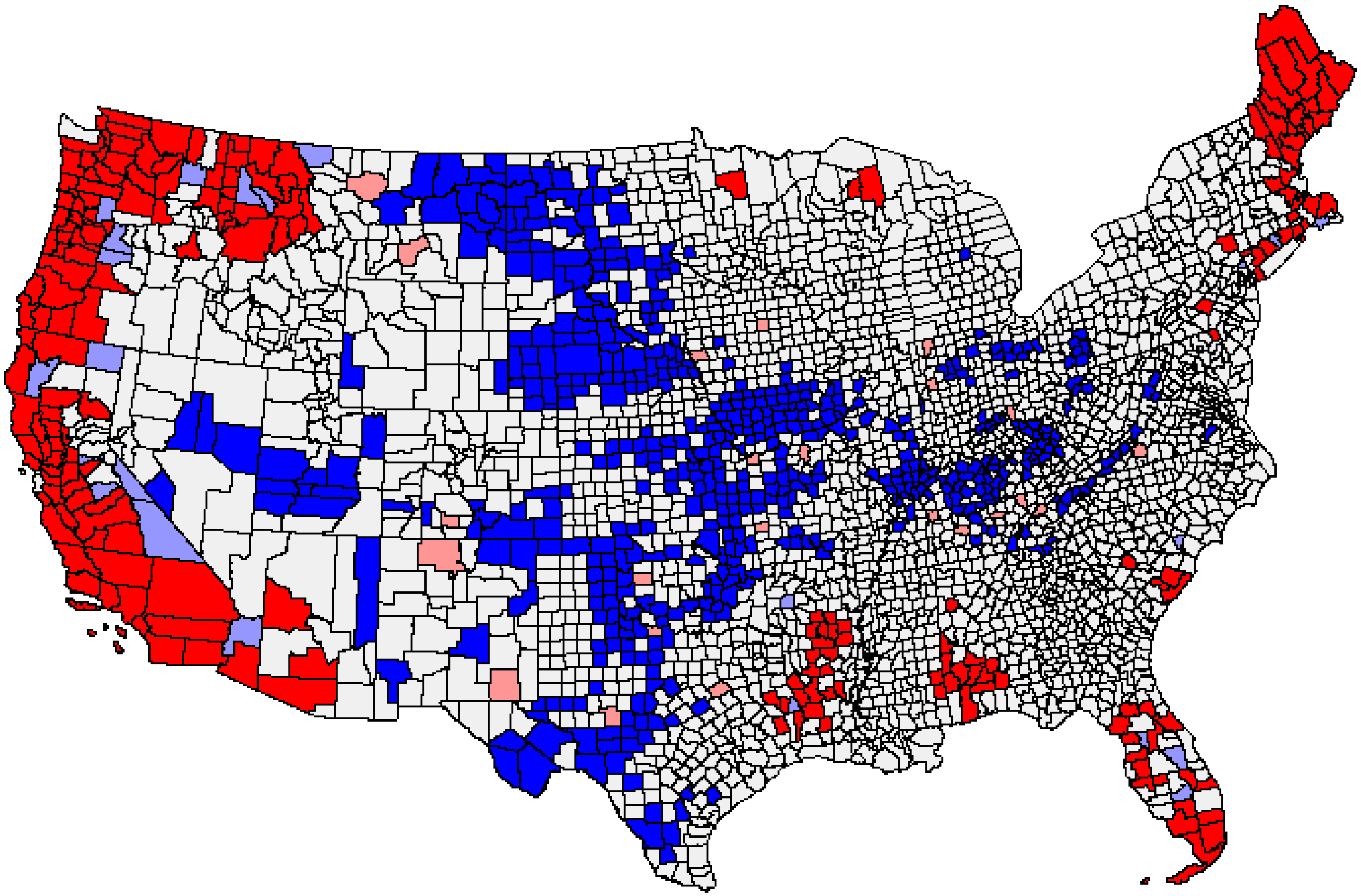
Rationale	**Variables**	**Expected Effect on share of organic operations**	**Sources**
State level fiscal policies negatively affect the formation of clusters	ptaxpercap02	Negative: state level fiscal policies negatively affect the formation of clusters	Goetz (1997)
Clustering is driven by workforce heterogeneity and diversity of a region	indus_entropy00	Positive: this indicates economic diversification	Davis and Schulter (2005), Duranton and Puga (2003), Delgado et al. (2012)
Resources	valuelandperacre07	Positive: This may indicate presence of resources	Kamath et al. (2012)
Demand conditions	farm_receipt_per_op2	Positive: may indicate high demand for agricultural goods	Kamath et al. (2012), Deller et al., (2001)

Figure 1: Organic Hotspots, Coldspots, and Outliers (based on operation counts)*



*Notes: grey = not significant; red = hotspot, blue = coldspot, purple = low-high, pink = high-low
While not pictured, Alaska and Hawaii are included in the analysis

Figure 2: Hotspots, Coldspots, and Outliers of All Agricultural Establishments*



*Notes: Grey = not significant; red = hotspot, blue = cold-spot, purple = low-high, pink = high-low
While not pictured, Alaska and Hawaii are included in the analysis

Table 4: Treatment Effects of organic hotspots estimated via Propensity Score Matching

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
poverty2012	Unmatched	14.4407767	17.4469403	-3.00616359	0.456785	-6.58
	ATET	14.4407767	16.0563107	-1.615534	0.577346	-2.8
	ATU	17.4469403	14.3576119	-3.08932838	.	.
	ATE			-2.89294957	.	.
unemployment2011	Unmatched	9.07912621	8.71	0.369126214	0.223287	1.65
	ATET	9.07912621	9.20631068	-0.127184466	0.349616	-0.36
	ATU	8.71	8.10298507	-0.607014925	.	.
	ATE			-0.543078913	.	.
inc_per_cap2011	Unmatched	38402.2136	34628.8015	3773.4121	590.6868	6.39
	ATET	38402.2136	36804.3592	1597.85437	933.3237	1.71
	ATU	34628.8015	37240.4657	2611.66418	.	.
	ATE			2476.57697	.	.
med_hh_inc2012	Unmatched	51443.7961	43888.4813	7555.31477	771.9225	9.79
	ATET	51443.7961	47934.5194	3509.2767	1276.854	2.75
	ATU	43888.4813	47716.6985	3828.21716	.	.
	ATE			3785.71928	.	.

Testing for balance condition

Variable	Mean Treated	Mean Control	%bias	t	p>t
valuelandperacre07	5251.4	4619.1	17.2	1.38	0.169
indus_entropy	2.7677	2.8027	-6.8	-0.82	0.41
ptaxpercap02	870.08	920.95	-10.9	-1.02	0.309
farm_receipt_per_op2	22818	23034	-1.2	-0.09	0.925

Pseudo R2	LR chi2	p>chi2	MeanB	MedB
0.01	5.57	0.233	9	8.9

Table 5: Treatment Effects of general agricultural hotspots, estimated via Propensity Score Matching

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
poverty2012	Unmatched	17.790625	16.8987361	0.891888968	0.461321443	1.93
	ATET	17.790625	16.5125	1.27812501	0.834173888	1.53
	ATU	16.8987361	18.6104089	1.71167282	.	.
	ATE			1.65751461	.	.
unemployment2011	Unmatched	10.7963542	8.42773234	2.36862182	0.222208303	10.66
	ATET	10.7963542	9.3109375	1.48541667	0.398282276	3.73
	ATU	8.42773234	10.183197	1.75546468	.	.
	ATE			1.72173064	.	.
inc_per_cap2011	Unmatched	36287.6302	34884.8045	1402.82575	611.8862	2.29
	ATET	36287.6302	37555.6458	-1268.01563	1200.97582	-1.06
	ATU	34884.8045	33084.603	-1800.20149	.	.
	ATE			-1733.72154	.	.
med_hh_inc2012	Unmatched	46813.1615	44534.2543	2278.90718	823.362941	2.77
	ATET	46813.1615	50121.7604	-3308.59896	1731.27988	-1.91
	ATU	44534.2543	41330.7569	-3203.4974	.	.
	ATE			-3216.62655	.	.
Testing for balance condition						
Variable	**Mean Treated**	**Mean Control**	**%bias**	**t**	**p>t**	
valuelandperacre07	7221.5	6162	27.5	1.53	0.126	
indus_entropy	2.757	2.7896	-6.5	-0.73	0.464	
ptaxpercap02	823.25	818.96	0.9	0.07	0.948	
farm_receipt_per_op2	33497	26649	34.2	1.94	0.053	
Pseudo R2	**LR chi2**	**p>chi2**	**MeanB**	**MedB**		
0.015	6.3	0.178	17.3	17		

Table 6: Instrumental Variable Treatment Effects Model for organic hotspots

	Model 1	Model 2	Model 3	Model 4
Outcome:	**poverty2012**	**unemployment2011**	**inc_per_cap2011**	**med_hh_inc2012**
totalphysicians09	-0.0002	-0.0005***	2.4099***	2.3731***
uic03	0.2244***	0.0622***	-92.4824	-797.8421***
nohealthins_18to64_07	0.03775	-0.0786***	-70.373**	-99.8549**
highschool09	-0.3816***	-0.1266***	387.6997***	594.2953***
numviolentcrime08	0.0002	0.0003***	-1.1248***	-1.3528***
indus_entropy00	0.4694*	0.434***	-785.4378**	-13.3626
farm_receipt_per_op07	-0.00001	0.00002*	0.061***	0.06042***
dist_highway_km	0.01167*	0.0008	0.0241	-19.2716**
popdensity09	0.0016***	-0.0001	0.7414	-1.3747
valuelandperacre07	-0.0001**	0.0001*	0.2228***	0.4807***
ptaxpercap02	-0.0018***	-0.0002	3.4255***	3.3684***
wx_totalphysicians09	0.0011	0.0011	-6.6674	-1.9515
wx_uic03	0.09711	-0.2782**	462.7733	1744.1545***
wx_nohealthins_18to64_07	-0.2573***	-0.2066***	81.5636	169.1942**
wx_highschool09	-0.12345***	-0.022	-601.9133***	-1046.2724***
wx_numviolentcrime08	-0.0021	0.0047***	1.9457	7.9327***
wx_indus_entropy00	2.5716**	1.3688**	273.0006	83.6286
wx_farm_receipt_per_op07	0.0002***	-0.0001	0.03069	0.0939
wx_dist_highway_km	-0.1463**	-0.0096	-40.1831	102.3195
wx_popdensity09	-0.0071*	-0.01282***	20.0262***	16.7326*
wx_valuelandperacre07	-0.0007***	-0.0002	-0.7405**	-2.0532***
wx_ptaxpercap02	0.0035**	0.0002	-9.7791***	-14.5847***
hh_org09	-1.6807**	-0.9613	1375.6849	1215.2188
wy_ poverty2012	0.4551***			
wy_ poverty2012_residual	1.1516***			
wy_ unemployment2011		0.4835***		
wy_ unemployment2011_residual		1.7919***		
wy_inc_per_cap2011			1.5184***	
wy_ inc_per_cap2011_residual			1.0627***	
wy_ med_hh_inc2012				1.9276***
wy_ med_hh_inc2012_residual				0.3225**
_cons	51.0209***	20.5021***	-404.1568	-11120.828***
Selection Equation	**hh_org09**	**hh_org09**	**hh_org09**	**hh_org09**
govt30	0.5832***	0.5808***	0.5812***	0.5767***
outreach30	1.2047***	1.2044***	1.2011***	1.1986***

valuelandperacre07	0.00005***	0.00005***	0.00005***	0.00005***
indus_entropy00	0.4146***	0.4307***	0.4254***	0.4226***
ptaxpercap02	0.0003***	0.0003***	0.0003***	0.0003***
farm_receipt_per_op07	0.00001***	0.00001***	0.00001***	0.00001***
_cons	-3.5546***	-3.5864***	-3.5914***	-3.586***

legend: * p<.1; ** p<.05; *** p<.01

Treatment Effects

	pctpovall2012	**unemp11**	**incpercap11**	**medhhinc012**
ATE	-0.5379	-0.2032	903.7709	1603.889
ATET	-0.7484	-0.3431	990.9332	1532.193

Table 7: Instrumental Variable Treatment Effects Model for general agricultural hotspots

	Model 1	Model 2	Model 3	Model 4
Outcome:	**pctpovall2012**	**unemp11**	**incpercap11**	**medhhinc012**
totalphysicians09	-0.0003*	-0.0006***	2.0632***	1.8737***
uic03	0.2423***	0.0627***	-100.58*	-752.4248***
nohealthins_18to64_07	0.025	-0.0762***	-28.9139	-113.9458***
highschool09	-.03485***	-0.1137***	379.4***	563.3638***
numviolentcrime08	0.0002*	0.0003***	-0.9768***	-1.1136***
indus_entropy00	0.1864	0.2626**	-239.6229	-102.6773
farm_receipt_per_op07	-0.00003***	0.00001	0.0699***	0.0528***
dist_highway_km	0.0074	0.0005	-5.7146	-20.7206**
popdensity09	.002***	-0.0001	1.2003*	-0.3198
valuelandperacre07	-.0003***	0.00003	0.3157***	.4631***
ptaxpercap02	-.0018***	-0.0003**	3.3497***	3.5581***
wx_totalphysicians09	-0.0034	-0.0022	-2.5189	9.3122
wx_uic03	0.2311	-0.1039	323.9087	1323.6665***
wx_nohealthins_18to64_07	-.01734**	-0.202***	93.8045	218.3158**
wx_highschool09	-0.1662***	-0.0575***	-494.6615***	-1075.0437***
wx_numviolentcrime08	-0.0018	0.0055***	0.92101	5.8068
wx_indus_entropy00	3.4221***	2.2368***	-1869.8937	197.199
wx_farm_receipt_per_op07	0.0002***	.00001	0.0329	0.1264
wx_dist_highway_km	-0.1168**	-0.0224	-82.2758	62.7661
wx_popdensity09	0.0018	-0.0088***	9.4337	-10.458
wx_valuelandperacre07	-0.0007***	-0.0003**	-0.1633	-1.3309***
wx_ptaxpercap02	0.0034**	0.0009	-8.7876***	-13.1576***
hh_org09	5.3794***	1.6113***	-4179.3281***	-3015.1581***
wy_ poverty2012	0.3639**			
wy_ poverty2012_residual	1.142***			
wy_ unemployment2011		0.4250***		
wy_ unemployment2011_residual		1.943***		
wy_inc_per_cap2011			1.3947***	
wy_ inc_per_cap2011_residual			0.875***	
wy_ med_hh_inc2012				1.9836***
wy_ med_hh_inc2012_residual				0.3241**
_cons	47.8054***	18.975886***	-798.5299	-9124.8747**

legend: * p<.1; ** p<.05; *** p<.01

Selection Equation	**hh_totag09**	**hh_totag09**	**hh_totag09**	**hh_totag09**
govt30	0.3833***	0.4165***	0.4063***	0.4021***
outreach30	-0.0295	-0.0459	-0.0484	-0.0429

valuelandperacre07	0.0001***	0.0001***	0.0001***	0.0001***
indus_entropy00	.3559***	0.3712***	0.4209***	0.3952***
ptaxpercap02	-0.0003**	-0.0003**	-0.0004***	-0.0004**
farm_receipt_per_op07	0.00002***	0.00002***	0.00002***	0.00002***
_cons	-2.6748***	-2.7183***	-2.7706***	-2.7456***

Treatment Effects

	pctpovall2012	**unemp11**	**incpercap11**	**medhhinc012**
ATE	1.0304	1.1974	-854.8308	-1153.487
ATET	1.4601	1.2405	-1216.999	-1352.565

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