Chapter 13
A Spatial Analysis of Methamphetamine Lab Seizures in the Midwest High-Intensity Drug Trafficking Area Before and After Federal Precursor Legislation

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Abstract This chapter uses spatial zero-inflated negative binomial regression to assess the relationship between methamphetamine lab seizures and county characteristics in the states of the Midwest High-Intensity Drug Trafficking Area for the years 2000–2010. I regressed meth lab seizure statistics from the El Paso Intelligence Center with county characteristics obtained from the 2000 and 2010 censuses. Two models were run to determine if the significant covariates for meth lab seizures changed as a result of the National Combat Methamphetamine Epidemic Act of 2005, which restricted precursor sales nationwide. The study does not find a significant difference in the covariates of the two models. In both cases, the most significant predictor of the presence of any meth lab in a county was their presence in neighboring counties, suggesting the agglomeration of methamphetamine production. In the count portion of the models, lab seizures were closely correlated with counties that were highly white but possessed the other characteristics associated with social disorganization.

Keywords Methamphetamine • Precursor legislation • Spatial regression • Zero-inflated models • Zero-inflated negative binomial regression

13.1 Introduction

This study, which assesses the relationship between domestic methamphetamine production and county characteristics in the Midwest High-Intensity Drug Trafficking Area (HIDTA) before and after the Combat Methamphetamine Epidemic Act of 2005, is positioned at the intersection of two burgeoning strands

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M. Leitner (ed.), *Crime Modeling and Mapping Using Geospatial Technologies*, Geotechnologies and the Environment 8, DOI 10.1007/978-94-007-4997-9_13,

of literature regarding the illegal stimulant methamphetamine. The first deals with attempts to determine the covariates associated with domestic methamphetamine production in clandestine laboratories (Lu and Burnum 2008; Weisheit and Wells 2010; Gilbreath 2010). The second assesses the impact that various attempts to control domestic methamphetamine production have had on methamphetamine indicators (Cunningham and Liu 2003, 2005; Rueters and Caulkins 2003; McBride et al. 2008; Dobkin and Niciosa 2009).

The study fills holes in both literatures. First, it applies a spatial version of a zero-inflated negative binomial regression (ZINB) to seizure data to determine the significant covariates of methamphetamine production. Previous studies either did not use a zero-inflated model or were aspatial in their methodologies. Second, the study assesses the spatial impact of precursor laws. Other studies of this type have focused entirely on differences in the observation of methamphetamine indicators over *time* (before and after implementation), but not across *space*.

To conduct the analysis, I correlated seizure data at the county level from the El Paso Intelligence Center (EPIC) with demographic data from the United States Census using spatial zero-inflated negative binomial models. The goal is to determine what county characteristics were most closely associated with the domestic, clandestine production of methamphetamine before and after precursor legislation.

13.2 History of the Problem

13.2.1 Methamphetamine in the Midwest

The Midwest has a long and complicated history with methamphetamine. In the 1930s, when amphetamine products were first introduced as asthma medications, inhalers containing the drugs were abused by members of the Kansas City jazz scene (Rasmussen 2008). In the late 1960s high-dosage methamphetamine injection became a serious concern for the medical community nationwide, particularly in centers of the 1960s counter culture such as San Francisco and the East Village of New York. However, other locales not considered part of the hippie movement also experienced serious outbreaks of abuse. St Louis, for example, began to see intravenous methamphetamine use as early as the late 1950s (Rawlin 1968). When police crackdowns began to limit the supply of diverted, legally produced liquid methamphetamine, the country's first clandestine methamphetamine labs began to appear in 1962 and 1963. In 1971 the government made methamphetamine a Schedule II substance, greatly limiting its legal uses and forcibly reducing production.

Without legally produced meth available for diversion, clandestine production became the nation's primary source. Outlaw motorcycle gangs (OMGs) controlled most production and distribution between the drug's scheduling in 1971 and the late 1980s. These groups were responsible for bringing methamphetamine back to the Midwest from its enduring base in California. The drug supposedly gets one of its

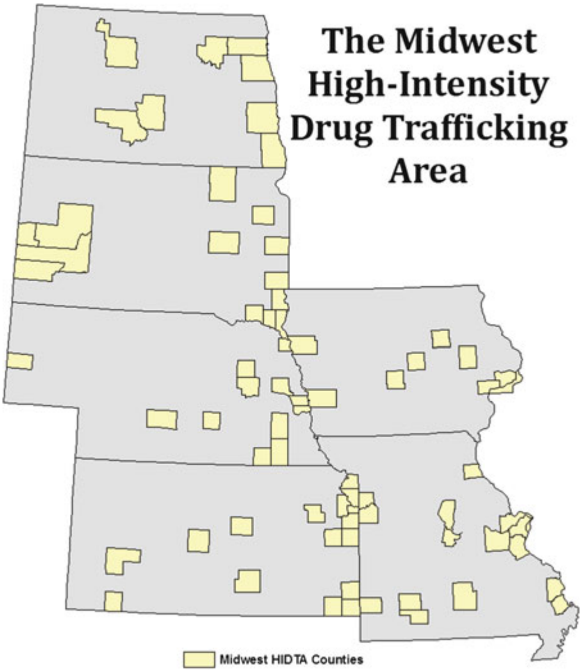

Fig. 13.1 The Midwest HIDTA

many nicknames, "crank," from the fact that OMGs frequently smuggled it in the crankcases of their bikes. Owen (2007) claimed that members of the Hell's Angels first brought meth production to southwestern Missouri in the 1970s, setting up labs in Mark Twain National Forest. The OMG meth presence in the region grew from there. In 1984 and 1985 members of a different biker gang, the Bandidos, were arrested throughout the Midwest for attempting to make and sell meth (*Los Angeles Times* 1985).

During the 1990s, new production methods that relied on easy-to-acquire precursors such as cold pills, rather than costly chemicals, spread among the drug-using populace, and caused a boom in methamphetamine labs and seizures. As one veteran member of the Independence, Missouri, Police Drug Taskforce put it, "in a matter of months [after the introduction of the new recipes], everyone was trying to cook dope" (Sweeny 2010). As availability of methamphetamine grew, so did demand. Between 1993 and 2003 admissions rates for people seeking treatment for methamphetamine abuse in the states of the Midwest HIDTA grew by an average of over 1,300%, and all but North Dakota exceeded the average national rate of 56 admissions for every 100,000 members of the population (DASIS 2006).

The federal government responded to the boom in methamphetamine use and production with the creation of the Midwest HIDTA in 1996. It is comprised of 73 counties in 6 states (Fig. 13.1). Cedar Rapids, Des Moines, Fargo, Kansas City, Omaha, Rapid City, Sioux City, St. Louis, and Wichita all fall within its scope. The HIDTA program had begun 8 years earlier as a way to fund and organize police efforts in key locations of drug trafficking and production. The program's goal is to disrupt drug smuggling and sales by coordinating the efforts of federal, state, and local police agencies. The program in the Midwest has produced mixed results. As mentioned above, rates for people seeking treatment have not been significantly reduced. The rate of labs seized per 100,000 people for the region (107.5 labs per 100,000 people) is also significantly higher than that for the nation as a whole (59.12 labs per 100,000) for the years 2000–2010, which are the focus of this study.

In 2005, the federal government passed the Combat Methamphetamine Epidemic Act, which removed all products containing ephedrine or pseudoephedrine from over-the-counter sales and required customers to show photo identification and to sign for their purchases. The law was an attempt by the government to remove the key ingredients of methamphetamine manufacture from the marketplace as a means to slow the continued growth of the drug's use and production across much of the country (Hunt et al. 2006).

The federal government has a long history of attacking the nation's methamphetamine problem through such supply-side interventions. The first attempt came with the rescheduling of phenyl-2-propanone in 1980. Further attempts occurred in 1988 with the Chemical Diversion and Trafficking Act, in 1993 with the Domestic Chemical Diversion and Control Act, and in 1996 with the Comprehensive Methamphetamine Control Act. In addition to federal action, in the early 2000s many states began to pass their own more stringent precursor legislation (McBride et al. 2008).

13.2.2 Previous Supply Side Intervention Analyses

Several studies have been undertaken to assess the efficacy of methamphetamine supply-side interventions. Cunningham and Liu (2003, 2005) found that the laws of 1988, 1993, and 1996 were effective in reducing both methamphetamine arrests in California and meth-related hospital admissions in California, Nevada, and Arizona. However, Rueter and Caulkins (2003) argued that the same laws had neither reduced methamphetamine use among the general population or arrestees nor significantly lowered the number of methamphetamine-related deaths. Dobkin and Niciosa (2009) observed that the Domestic Chemical Diversion Control Act had enabled the government to significantly disrupt the methamphetamine market in California, where prices soared, purity plummeted, and usage declined in the 18 months after the law was put into place. Weisheit and Wells (2010) found that the 2005 Combat Methamphetamine Epidemic Act significantly reduced the number of clandestine labs in operation across the country. McBride et al. (2008) argued that state precursor legislation generally resulted in significant reductions in the seizure of small toxic methamphetamine labs. To date, however, no study has explored the spatial ramifications of methamphetamine precursor laws by assessing whether the characteristics of the places that tended to have meth labs were changed by the Combat Methamphetamine Epidemic Act.

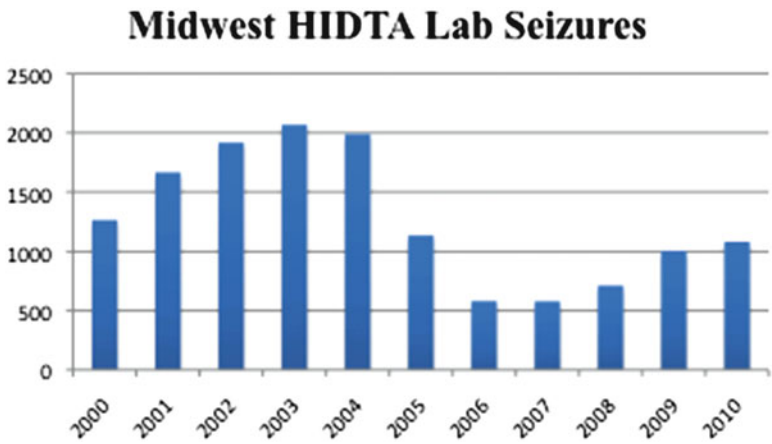

Fig. 13.2 Lab seizure totals by year for the Midwest HIDTA courtesy of the El Paso Intelligence Center

The 2005 Combat Methamphetamine Epidemic Act definitely reduced the number of labs seized nationwide (Weisheit and Wells 2010) and within the Midwest HIDTA.[1] However, the Midwest area has experienced significant growth in domestic methamphetamine production as producers sought to compensate for a dip in the availability of Mexican methamphetamine due to that country's restrictions on ephedrine- and pseudoephedrine-based products (NDIC 2009a, 2009b, 2010). That uptick in production is reflected in the total number of seizures in the region at the end of the decade (Fig. 13.2).

13.3 Methamphetamine Laboratories

13.3.1 Problems Created by Clandestine Laboratories

This study focuses on the domestic production of methamphetamine in clandestine labs in the Midwest HIDTA. Though a large percentage of the drug in the region comes from Mexico, domestic production is still a significant source and problem (NDIC 2010). Numerous ways exist to make methamphetamine. They have risen and declined in popularity over time as a result of police actions and varying demands for product. Some recipes for making the drug, such as the "Nazi Method," have distinctive odors associated with them and must occur far away from population centers to avoid detection. Other procedures have little tell-tale odor and can be

[1] The average annual number of labs seized per county between the years 2000 and the year 2005 was 3.14, and for 2007 through 2010 it was 1.59.

conducted virtually anywhere with enough space to shake a two-liter bottle full of precursors. Labs have been found in hotel rooms, homes, deserted outbuildings, trailers, and even the trunks of cars.

Labs vary in size and can produce quantities from a few grams to 50 pounds or more. Most labs found in the Midwest HIDTA are small-scale, designed to produce enough product for the cook's own use and some extra to sell to others. These operations are alternately referred to as STLs (small toxic labs) or "mom-and-pop" labs. "Superlabs," those producing quantities greater than ten pounds of the drug per batch, are generally associated with highly organized drug-trafficking organizations (DEA 2005). They are not common within the Midwest HIDTA.

Meth labs are incredibly dangerous places. Without any kind of intervention they often end in fires or explosions. Even when such calamity does not occur, a simple raid can be extremely hazardous. Taking apart an active lab can be like defusing a bomb because the production process involves numerous highly flammable solvents, explosive reactants like lithium and water, and noxious gasses.

The DEA estimates that, for every pound of methamphetamine created, five pounds of toxic waste are produced (DEA 2005). Not surprisingly, these byproducts are rarely disposed of properly. More often than not, they are dumped down a drain or left outside to leach into the ground, thus extending contamination well beyond the structure in which the meth was cooked. Though the police are responsible for removing lab equipment from a location, property owners must pay for "the cleanup of residual contamination after gross removal has occurred" (EPA 2009, 3). This can be a costly process. In a Rand Corporation study, Niciosa et al. (2009) estimated that meth labs alone (not including the social cost of meth use) cost the United States $61 million in 2005, not just in clean up and remediation, but also in injuries associated with their operation and seizure.

13.3.2 Understanding Lab Location

To better direct prevention efforts, and for other reasons, it is important to have a thorough understanding of where meth labs tend to locate. Much has been made of the fact that methamphetamine, unlike cocaine or heroin, is a synthetic drug. The nature of its method of production has caused many commentators to believe that it can be produced and used anywhere (Jenkins 1999). If that were the case, we would expect that traditional crime and drug market indicators would be insufficient for predicting the location of methamphetamine labs.

A number of different criminological perspectives exist from which one might select variables to explain lab location (Shaw and McKay 1942; Cohen and Felson 1979; Clarke 1980; Clarke and Felson 1993). But, given the scale at which we are operating (that of entire counties), variables associated with routine activity and rational-choice perspectives are not easily incorporated. We can, however, assess the efficacy of traditional social disorganization variables in predicting lab seizure locations.

Higher crime rates and drug markets tend to cluster in areas where a community has little ability to organize against them. Such lack of neighborhood efficacy is termed social disorganization. It frequently occurs in areas with high population turnover, a large number of renters, and high percentages of poverty, minorities, and single mothers (Shaw and McKay 1942; Sampson and Groves 1989; Kubrin and Weitzer 2003; Rengert et al. 2005, McCord and Ratcliffe 2007; Banerjee et al. 2008; Grattet 2009). If traditional indicators of social disorganization prove to be significant correlates to methamphetamine lab location, then we must reassess the way in which we discuss and analyze synthetic drugs.

Because the actual number and location of all methamphetamine labs is unknown and unknowable, we use lab seizures as a proxy. Obviously, no proxy is perfect, but seizures are the best measure available for domestic production and precedent exists in the literature for using such data to assess the spatial correlates of meth production. Lu and Burnum (2008), in an analysis of lab seizures around Colorado Springs, found lab location to be correlated with neighborhoods that had low median ages, predominantly white populations, and low levels of educational attainment. The authors used a Poisson regression model to assess the covariates, but do not appear to have accounted for spatial effects in their model. As will be made clear below, any analysis of spatial data that does not explicitly assess and account for spatial effects within its model is inherently flawed (see Sect. 13.4.1). Weisheit and Wells (2010) similarly failed to incorporate spatial effects in the regression portion of their analysis, which attempted to determine the covariates for lab seizures for the entire United States. Finally, in a study of lab seizures in Jefferson County, Missouri, Gilbreath (2010) found lab seizure locations correlated with census tracts having high unemployment, low population density, and longer distances from the center of the tract to the nearest police station.

13.4 Data

The seizure data for this project was acquired from the multiagency El Paso Intelligence Center (EPIC) via a Freedom of Information Act request. EPIC is the national clearinghouse for meth lab seizure data. They provided seizures by county for each year from 2000 to 2010. Rather than use just the 73 counties that officially make up the HIDTA, I included each county in the region's six states.[2] Although most of the officially designated counties of the Midwest HIDTA are found in the region's urban centers, methamphetamine has a reputation of being a rural drug, so I thought it was important to include these counties as well.

County-level data offers several advantages in this type of study (Messner et al. 1999). They are a resolution at which data from a number of other sources,

[2] Rather than sample all of Illinois, only Rock Island County was included, as it is the only Illinois county in the Midwest HIDTA.

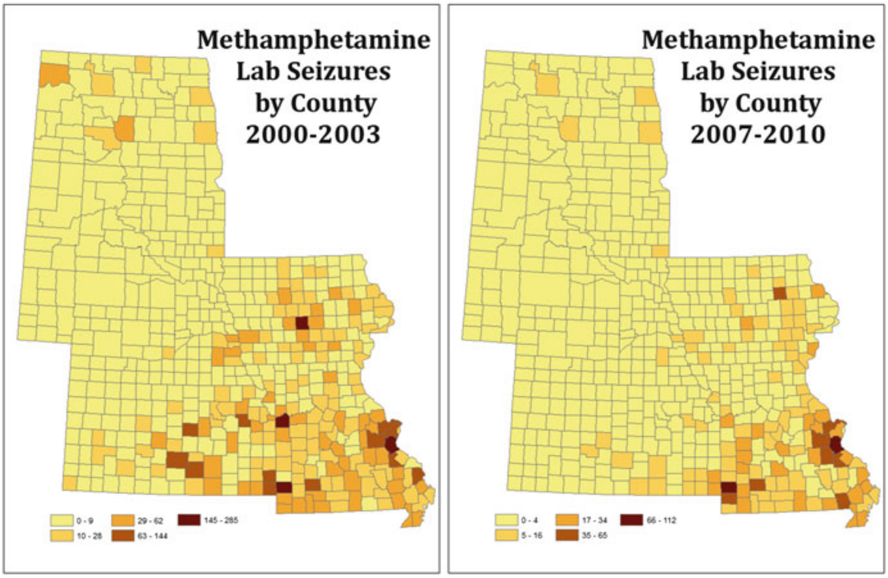

Fig. 13.3 The dependent variables of labs seized per county for the states of the Midwest HIDTA

particularly government agencies, are readily available. Counties also run the gamut from rural to urban, and from poor to rich, and the sheer number of counties in the study, 532, ensures adequate variation within the study area. Finally, this county-level data maintained by EPIC is the most detailed available for a study of this spatial scope.

Because the goal of this study is to assess the potential covariates for lab location both before and after the national precursor law went into effect, I created two dependent variables based on these distinct time periods (Fig. 13.3). The first is the total number of labs seized between 2000 and 2003, the peak years before state and federal precursor laws went into effect (McBride et al. 2008). The second is the total number of labs seized per county between 2007 and 2010.[3]

I selected potential explanatory variables based on a number of theoretical considerations. The goal was to select variables that combined the characteristics of users obtained from the Substance Abuse and Mental Health Services Administration (DASIS 2008; SAMHSA 2009; Hunt et al. 2006) with variables that are consistent with social disorganization theory and the existing geographic literature regarding methamphetamine lab location. [4]After testing a larger number of variables for collinearity, eleven were included in the model (Table 13.1).

[3] Because the Combat Methamphetamine Epidemic Act was not fully implemented until September 2006, my post-precursor law analysis begins with 2007. For the sake of covering the same time span between the two samples, peak years were cut at 2003.

[4] No study exists on the typical methamphetamine cook.

Table 13.1 Descriptive statistics for all variables

	2000–2003				2007–2010			
Variable	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
Count	0	285	12.99	26.79	0	112	4.35	10.51
Spat. Lag	0	119	13.52	18.26	0	59.75	4.54	8.32
Rent Occ.	12.8	56.8	26.03	6.54	12.8	58.2	26.64	6.65
Med. Age	20.6	51	38.88	4.36	23.5	53.4	41.90	5.55
Male Bach.	2.8	34.1	11.09	3.84	1.6	35.5	12.45	4.55
Poverty	3.5	42	11.45	4.55	4.2	62	14.29	5.97
Sing. Moth.	0.3	20.6	5.11	2.21	0.3	20.6	5.11	2.21
Vacant	3.5	52.9	13.20	7.04	4.8	53.7	15.30	7.37
Live Alone	13.2	40.3	27.44	3.48	14.8	42.6	29.01	3.77
Families	52.3	84.5	68.82	3.95	47.5	82.4	66.33	4.27
Mexican	0	35.5	1.96	4.03	0	49.5	3.39	5.74
White	4.5	99.7	93.25	12.00	2.9	99.2	91.69	12.58
PopDens	0.51	5624.12	56.49	281.47	0.47	5157.39	58.75	269.72
N=532								

Population density was included to test the connection between methamphetamine production and rural areas, as well as to control for differences in county sizes and populations (Herz 2000, United States Congress 2000).[5] I expected that lab seizures would have a positive correlation with population density, as anyone producing methamphetamine with the intent to sell would need to have a market. The percentage of a county whose population is white, the median age, the percentage of males over 25 with a bachelor's degree, and the percentage living in poverty were included based on the general characteristics of methamphetamine users, who tend to be white, young, poor, and under-educated (DASIS 2008; SAMHSA 2009; Hunt et al. 2006). These variables are also closely associated with social disorganization, the exception, of course, being percentage white. I expected the percentage of a county whose population is of Mexican origin to exhibit a negative correlation, assuming that such a county would have the potential of market penetration by Mexican drug-trafficking organizations and thereby eliminate the necessity for local production. I included the percentage of households with a single mother, percentage of homes occupied by renters, and percentage of vacant properties as additional indicators of social disorganization. I expected the percentage of households containing a family to have an opposite correlation to that of the social disorganization variables. The final variable in the models, spatial lag, is explained below (see Sect. 13.4.1). I collected two sets of independent variables: one from the 2000 census, and one from the 2010 census.[6]

[5] Unfortunately, the county level data for rural populations from the 2010 Census will not be available until October of 2012, so the percent of a county's population that is rural could not be used as our rural indicator.

[6] 2010 education attainment variables had to be obtained from the 5-year estimates of the *American Community Survey* after the long-form questionnaire was eliminated for the 2010 census. Economic data for 2010 variables are from the 2009 economic census.

13.5 Methods

13.5.1 Spatial Regression Models

To assess the covariates associated with lab seizures, this study uses a modified version of spatial regression models developed by Anselin (1988) and outlined in Ward and Gleditsche (2008). Such regression techniques are necessary because spatial data frequently exhibits what Getis (2007)) has called *the* fundamental concept of spatial analysis: spatial autocorrelation. Spatial autocorrelation is the clustering of similar values in space. It is frequently present in spatial data because collection units such as census tracts or neighborhoods have porous borders or exist only on maps. Human beings, biological vectors, economic forces, information and infrastructure all cross them at will. Actors in one area thus frequently have an impact on their neighbors. This impact is referred to in the literature as spatial dependence. The presence of spatial dependence, indicated by the significant clustering of similar values (significant spatial autocorrelation), is a sign of the violation of the independence assumptions inherent in most parametric inferential statistics. If significant spatial autocorrelation exists, and is not taken into account within a multivariate analysis, then "false indications of significance, biased parameter estimates, and misleading suggestions of fit" can result (Messner et al. 1999, 427).

Fortunately, several ways exist to account for spatial dependence within a model. If an investigator believes such spatial dependence is a result of actual interaction between observations, then he/she should consider using a *spatial lag* model. In such a model, a new independent variable is added to the regression equation to account for the existing spatial dependence. The lag variable, created using a spatial weights matrix, is usually some combination of the value of the dependent variable for all nearby units to each observation. Depending on the understanding one has of the process being modeled, the weights matrix can be based on some order of contiguous neighbors or on a distance-decay threshold.

It makes sense to use a lagged variable when one thinks of a dependent variable as continuous and potentially influenced by its neighbors. Baller et al. (2001) have associated a significant lag variable in the study of homicide with processes of diffusion, while Mennis et al. (2011) consider it evidence of spatial spillover in their study of juvenile delinquent recidivism. In the case of drug markets, Rengert et al. (2005) associated a significant lag variable with agglomeration.

On the other hand, if one assumed that the spatial effects in their model derives not from actual evidence of interaction between observations, but rather from model misspecification, missing independent variables, or some other statistical nuisance, then he/she might consider a *spatial error model*, in which the spatial dependence is accounted for in the error term.

In the case of the present study, spatial effects almost certainly result from interaction between counties as producers, suppliers, and information travel across borders. As such, a spatial lag model is most appropriate. To that end, I added a spatially lagged variable (based on first-order queen contiguity) to both regression

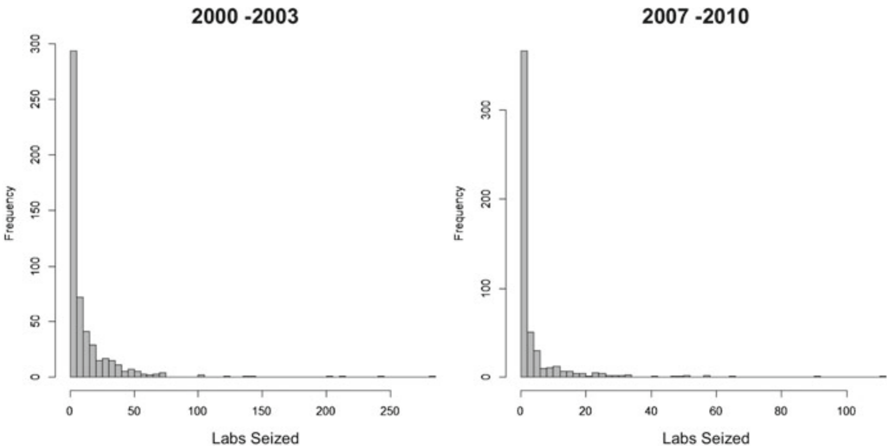

Fig. 13.4 Histograms of the two dependent variables

models. That is, for each county, the spatial lag variable is the average value of labs seized in all the neighboring counties it touches. This type of analysis has a long history in the study of crime, and was recommended by Anselin et al. (2000). The recent special issue of *The Professional Geographer* on the spatial analysis of crime also contains several good examples (e.g. Mennis et al. 2011, Andresen 2011). Baller et al. (2001) produced a spatial regression analysis of nationwide homicide rates that used county-level data much as this study does.

13.5.2 Zero-Inflated Regression Models

Most of the studies cited used ordinary least squares regression (OLS) for their analyses. However, count data (such as the number of labs seized) have several characteristics that make them ill suited for OLS techniques. They often contain a large number of zeros (areas with no observations of the dependent variable) and exhibit a severe positive skew. The two independent variables included here are no exception, since 24.4% of the counties in the 2000–2003 model had no labs seized within their borders and so did 47% in the 2007–2010 model (Fig. 13.4). When data have a disproportionate number of zeroes, a zero-inflated model should be substituted for the OLS one (McDonald and Lattimore 2010). Generally, either a zero-inflated Poisson regression, or a zero-inflated negative binomial regression is necessary.

One chooses between the two regression models based upon whether the distribution of the dependent variable is over-dispersed or not. In order to use a zero-inflated Poisson regression, the dependent variable's mean should be equal to its variance. If this is not the case, and the variance is significantly larger than the mean, then the distribution is overly dispersed, and a zero-inflated negative binomial model should be used (Atkins and Gallop 2007). In this study, the data were over-dispersed, making a zero-inflated negative binomial model the appropriate tool.

A zero-inflated regression model produces two different equations. For this reason it is often referred to as a mixed model. The first equation, sometimes referred to as the hurdle function, is essentially a logistic regression that determines the covariates associated with the probability of finding zero labs within a county. The second model, which is similar to a traditional OLS model (or a Poisson regression), determines which independent variables account for increasing lab seizures within those counties that have passed the hurdle of having no labs within them. It is entirely permissable to include different predictors in the two different models, although in this case I did not. A spatially lagged variable can be included in either side of the equation to account for spatial autocorrelation within the data. McCord and Ratcliffe (2007) and Rengert et al. (2005) used zero-inflated models with a spatial lag variable in their analyses of crime-count data.

For this study, I used *Open GeoDa* (Anselin et al. 2006) to create a spatial weights matrix based on first-order county contiguity, and then used this weights matrix to calculate a spatial lag variable for each county (mean labs seized in neighboring counties), which I then included in the zero-inflated regression models. The zero-inflated models were conducted using *R.* In addition, I assessed several characteristics of the spatial distribution of the dependent variables using the spatial statistics toolbox in *ArcGIS 10.*

13.6 Results

To begin the spatial regression process, I mapped the dependent variables and assessed them for spatial autocorrelation. Getis (2007), Baller et al. (2001), Messner et al. (1999), Anselin et al. (2000), and Eck et al. (2005) have all recommend such a test as the first step in exploratory spatial data analysis before any attempt at regression. An assessment of our dependent variable for 2000–2003 and 2007–2010 using Moran's I showed significant global spatial autocorrelation (2000–2003: $z = 13.4$ $p < .001$ and 2007–2010: $z = 20.7$ $p < .001$). An analysis of local autocorrelation, assessed using Anselin's Local Indicators of Spatial Autocorrelation (LISA) showed significant clustering of high values of lab seizures, indicating a violation of the independence assumption, and the necessity of spatial regression (Fig. 13.5).

Given the distribution of the data, the high number of zeroes, and the presence of significant spatial autocorrelation, I determined that a spatial zero-inflated model needed to be run. Analysis of the level of dispersion indicated that my data were overly dispersed, and that a zero-inflated negative binomial model was necessary ($=1.396$ (00–03) and 1.389 (07–10). In both cases the ZINB model compared favorably to a model containing only the intercept (likelihood ratio test chi square $= 595.91$, $p < .001$ (00–03), and 477.54, $p < .001$(07–10)) and to a zero-inflated Poisson regression model using the same variables (Vuong test V statistic : -5.25, $p < .001$ (00–03) and -5.53 $p < .001$(07–10)).

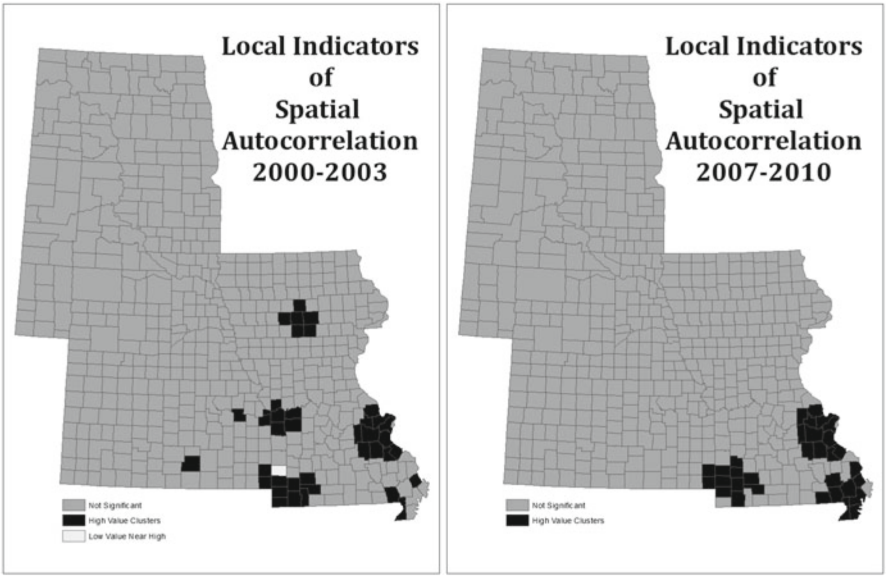

Fig. 13.5 Measures of local spatial autocorrelation in the dependent variables

For the 2000–2003 sample, the likelihood of no labs being seized within a county was negatively correlated with the spatially lagged count variable and with population density, and positively correlated with the percentage of homes that were vacant within the county. This means that an increase of one in the average number of labs seized in a county's neighbors reduced the likelihood of there being no labs seized within that county between 2000 and 2003 by 78.21%[7]. Similarly, an increase in a county's population density of one person per square mile further reduced the likelihood of no labs being found within the county over that time period by 12.95%. On the other hand, an increase of one in the percentage of housing units that were vacant in a county increased the probability of no labs being seized within its borders over the time period by approximately 25% (Table 13.2).

The count model of the ZINB regression determines coefficients for variables that contribute to increases in the number of labs seized. From 2000 to 2003, the spatial lag variable, the percentage of vacant properties, male educational attainment, the percentage of households with a single mother, and the percentage of the population that is white were all positively correlated with increasing lab seizures. In contrast, the percentage of households that contained families was the only negatively correlated variable. The poverty rate, population density, median age, percentage of properties that were renter-occupied, and percentage of the population that was Mexican were not significantly correlated with increasing lab seizures at $p \leq .05$ (Table 13.3).

[7] This value is calculated using the formula $(100^* (e^{-1.523904} - 1))$ where −1.523904 is the coefficient for the lagged variable (Atkins and Gallop 2007).

Table 13.2 Results for the logistic (zero predictor) portion of the ZINB model

	2000–2003				2007–2010			
	Estimate	S.E.	Z Score	Sig.	Estimate	S.E.	Z Score	Sig.
(Intercept)	−7.268903	17.207764	−0.422	0.673	1.744774	13.621925	0.128	0.898
Spat. Lag	**−1.523904**	**0.422713**	**−3.605**	**0.000**	**−1.544425**	**0.625519**	**−2.469**	**0.014**
Median Age	0.028997	0.191388	0.152	0.880	0.046823	0.086871	0.539	0.590
% Renter Occ.	0.047019	0.087023	0.54	0.589	0.007018	0.088431	0.079	0.937
% Vacant	**0.229066**	**0.079699**	**2.874**	**0.004**	0.012687	0.045984	0.276	0.783
% Sing. Moth.	−0.004149	0.402144	−0.01	0.992	−0.20066	0.294809	−0.681	0.496
% Poverty	−0.209626	0.165603	−1.266	0.206	0.152678	0.099806	1.53	0.126
% Male Bach.	0.030335	0.112135	0.271	0.787	0.090454	0.084447	1.071	0.284
Pop. Density	−0.138677	0.081793	−1.695	0.090	−0.012794	0.012149	−1.053	0.292
% White	−0.055387	0.059863	−0.925	0.355	−0.083181	0.067633	−1.23	0.219
% Mexican	−0.237321	0.209022	−1.135	0.256	−0.046148	0.056175	−0.821	0.411
% Families	0.178082	0.117213	1.519	0.129	0.03961	0.093412	0.424	0.672

Table 13.3 Results for the count portion of the ZINB model

	2000–2003				2007–2010			
	Estimate	S.E.	Z Score	Sig.	Estimate	S.E.	Z Score	Sig.
(Intercept)	−4.4920098	2.868234	−1.566	0.117	−2.7211056	3.7011464	−0.735	0.462
Spatial Lag	**0.0290827**	**0.0037927**	**7.668**	**0.000**	**0.0658063**	**0.0074477**	**8.836**	**0.000**
Median Age	−0.0470126	0.0249149	−1.887	0.059	**−0.0580102**	**0.0270718**	**−2.143**	**0.032**
% Renter Occ.	−0.0318169	0.0181003	−1.758	0.079	−0.0407613	0.0251276	−1.622	0.105
% Vacant	**0.0232354**	**0.0109036**	**2.131**	**0.033**	0.0021277	0.0121768	0.175	0.861
% Sing. Moth.	**0.5914383**	**0.0562411**	**10.516**	**0.000**	**0.5760556**	**0.0852761**	**6.755**	**0.000**
% Poverty	0.0399136	0.0211323	1.889	0.059	**0.0639268**	**0.0211418**	**3.024**	**0.002**
% Male Bach	**0.0756812**	**0.0199509**	**3.793**	**0.000**	0.0315928	0.0220197	1.435	0.151
Pop. Dens,	0.0003797	0.0002534	1.498	0.134	0.0003792	0.0003265	1.162	0.245
% White	**0.0726599**	**0.0129066**	**5.63**	**0.000**	**0.0738632**	**0.0207655**	**3.557**	**0.000**
% Mexican	0.0175243	0.0144087	1.216	0.224	−0.0262415	0.0184519	−1.422	0.155
% Families	**−0.038357**	**0.0200949**	**−1.909**	**0.056**	**−0.0632768**	**0.02635**	**−2.401**	**0.016**

For the sample of seizures after the precursor laws were in effect (2007–2010), the results were similar. The only significant covariate for the presence of lab seizures in the zero-inflation model was the spatially lagged count variable. Once again, it was negatively associated with the probability of no labs being seized within a county between 2007 and 2010. In this case, an increase of one in the lagged count variable decreased the probability of a zero count within the county by 78.66%. None of the other predictors were significantly associated with the zero-inflation model.

The covariates associated with increasing lab seizures were also similar to the 2000–2003 model. Once again, the spatial lag variable, the percentage of a population that was white, and the percentage of households with a single mother were all positively correlated with increasing meth lab seizures. Of these variables, the percentage of households with a single mother had the largest impact, raising the number of labs seized within the county by 3.32 for each increase of a percentage point.[8] In the 2007–2010 model the percentage of people living below the poverty level was also a significant positive covariant of increasing lab seizures, but the percentage of males over 25 with a bachelor's degree was no longer significant. The percentage of homes occupied by families was once again a significant negative covariate. In this model, the median age was also a negative covariate.

13.7 Discussion

As mentioned above, the 2005 Combat Methamphetamine Epidemic Act caused a dramatic dip in the number of labs seized both nationally and in the Midwest HIDTA. Seizures in the 2007–2010 period were only 35% of that for 2000–2003 (6,912 vs. 2,314). However, the their spatial distribution was much the same as before. The weighted mean center of lab seizures moved 66.4 miles southeast, but the size and orientation of the standard deviation ellipses for each time period were similar enough to argue that the general distribution of lab seizures was not significantly affected (Fig. 13.6).

The covariates of methamphetamine lab seizures also were not much affected by the Act. The most significant indicator of methamphetamine lab presence in a county (from the logistic portion of the ZINB) in both models was the presence of seizures in the counties that surrounded it (Table 13.1). In studies of drug markets, this is usually interpreted as the agglomeration of drug sales (Rengert and Robinson 2006, Rengert et al. 2005). That would also be an appropriate interpretation here.

Both of the count models similarly showed more similarities than differences. In the second model, more user characteristics proved to be significant in the manner that one would suspect, with median age being negatively correlated and the percentage of peo-

[8] This value is calculated by multiplying the percentage change (calculated in the same manner explained in the previous footnote) by the mean of the dependent variable for the data.

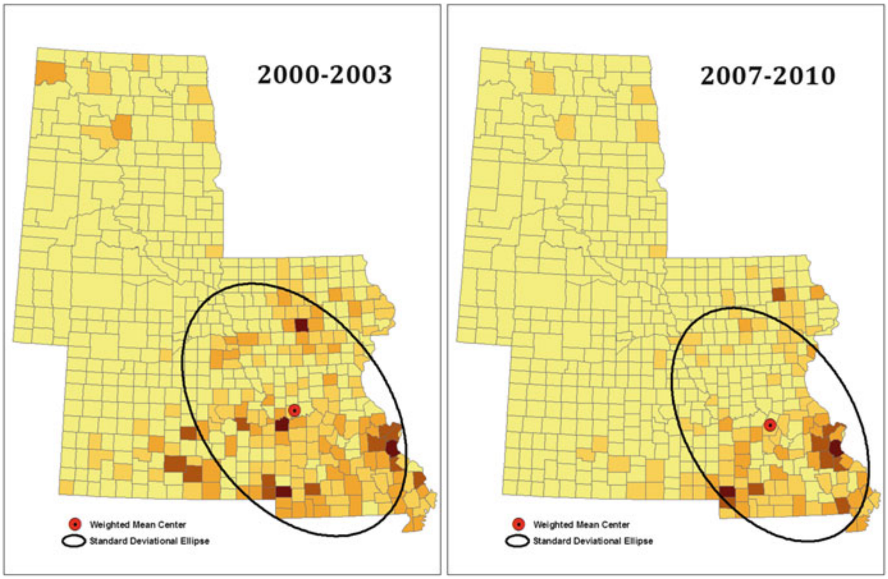

Fig. 13.6 Weighted mean center and standard deviational ellipse for lab seizures

ple living below the poverty level positively so. The percentage of white residents, even in a region deemed by many to be relatively homogenous, was consistently significant and was also the most impactful of the user characteristics in either model.

Percentage Mexican was clearly a poor proxy for methamphetamine market penetration by Mexican DTOs. Population density also was not significant in either count model, which might argue against the association between methamphetamine production and rural areas. When the percentage rural variable is made available for the 2010 census, this particular relationship will need to be reassessed.

Two of the social disorganization variables, percentage of households containing families and percentage of households with single mothers, were consistent across both models and had the expected correlation. The impact that the mothers variable had was surprising, as it surpassed many other variables that are more frequently associated with methamphetamine use or production, such as poverty or whiteness. Other social disorganization variables were less consistent. The percentage of homes occupied by renters was not significant in either model, and percentage of properties that were vacant was only significant in the first.

Given the overlap between the variables for user characteristics and social disorganization, it seems clear that methamphetamine production does indeed cluster in counties that exhibit social disorganization. The fact that the percentage of the county that is white (which is the opposite of a common indicator of social disorganization, the racial heterogeneity of a place, or percentage minority) was consistently significant does not alter this conclusion because whites make up the great majority of methamphetamine users (SAMHSA 2009).

Several limitations to this study exist that could be addressed in the future. The first is the temporal resolution of the data from EPIC, which was aggregated to yearly totals. The creation of the models' dependent variables was a negotiation between proximity to the date of the precursor law's implementation and the decennial census, which had the best available data. The best previous studies on precursor impacts used monthly data to assess their impact (Cunningham and Liu 2003, 2005; McBride et al. 2008; Dobkins and Nisocia 2009). However, none of them was dependent upon census data for independent variables. All of the seizure studies mentioned in the literature review relied on census data.

The spatial resolution of the data also limited this study. By operating at the county level, a number of variables associated with routine activities, rational choice, or a more nuanced ecological perspective could not be included in the model (Cohen and Felson 1979; Clarke 1980; Clarke and Felson 1993). For example, production might be highly correlated with the presence of pharmacies or big-box stores from which essential precursors and other materials might be purchased, or producers might situate labs near common commuter thoroughfares.

This study, the first of its kind to assess the covariates of methamphetamine production using a spatial zero-inflated negative binomial model, represents a significant step forward in our understanding of methamphetamine lab location. It proves that methamphetamine production at the county level, by concentrating in counties that exhibited most of the standard characteristics of social disorganization, behaves similarly to criminologists' basic understanding of other drug markets despite the unique nature of its synthesis. In addition, the study demonstrates that, although the Combat Methamphetamine Epidemic Act of 2005 did significantly reduce the number of lab seizures in the region, it did not alter the spatial characteristics of domestic methamphetamine production. In combination, these two conclusions argue that the strategy for policing methamphetamine does not need to be significantly different from that for other drugs and drug markets.

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