Modeling the Spatial Consequences of Payday Loan Interest Rate Cap

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This study demonstrates the relevance of the spatial analysis in payday loan research and policy design and evaluation. The examination of the interplay between the regulatory and institutional environments and the need for cash permits to show the relevance of the spatial analysis. Results indicate that counties located near borders have more access to payday loans compared to distant counties. Loan acquisition costs resulting from the interest rate cap make it hard for distant Arkansans who desperately need some cash. Payday loan 'plenty' is visible around Arkansas borders and loan 'desert' is visible in the interior of Arkansas.

INTRODUCTION

The financial situation of typical American households is dire for the last decade because of stagnant and declining incomes, decreasing asset values and increasing debts, but expenses related to basic needs (food, housing, transportation, health care, education, etc.) are still raising. Many low- and moderate-income U.S. households visit payday loan storefronts to obtain small dollars. They present the most recent pay stubs, have checking accounts and do not have an outstanding loan to be paid in the next 14 days (Elliehausen, 2009). Payday loan is defined as small dollar, two-week maturity, and unsecured loans whose borrowers are expected to make a single payment of the principal and the financial charges in the next two weeks coinciding with the payday (Graves, 2003; Stegman, 2007; Caskey, 2010; Melzer, 2011; Edminston, 2011; Montezemolo, 2013). The main purpose of this study is to search and discover a model that best portrays the spatial consequences of the payday loan interest cap using the case of the state of Arkansas.

Putting this study into context, the state of Arkansas constitutes an interesting example because the Attorney General McDaniel asked 239 payday loan businesses to stop providing new loans and to cancel current and past due loans on March 18, 2008. Consequently, 162 payday businesses closed their storefronts by February 2009 and the remnant 27 closed by July 31, 2009. Since then, there is no payday loan business operating in the state of Arkansas. The Arkansas legislators passed Amendment 89 in November 2010 to increase the interest rate cap to 17 percent from 10 percent by a vote of 431,724 for and 260,735 were against the amendment. In the meantime, the need for quick cash or other financial arrangements for many households in Arkansas did not go away. The nearby states that surround Arkansas are the permissive states and have many payday loan storefronts. Despite this new policy, some Arkansans cross the borders to obtain small dollar loans. The question is that what are the spatial consequences of this amendment?

Three main regulatory environments have been identified in the literature, which include 27 permissive states that allow single payment loans with the annual percentage rates of 391 percent or higher; 9 hybrid states that have loan establishments and enforce lower limits on fees, loan usage or longer repayment periods; and, 15 restrictive states that have no payday loan facilities (Shackman & Tenney, 2006; Kaufman, 2013; Foster, 2014; Montezemolo, 2013). The State of Arkansas is a restrictive state. It is surrounded by six permissive states, Louisiana, Mississippi, Missouri, Oklahoma, Tennessee, and Texas. Evidence suggests that state prohibitions and interest rate caps have been associated with reductions in the number of payday loan storefronts (see McKernan et al., 2013 for more details). Consistent with other studies, the main hypothesis is that Arkansas consumers cross borders to obtain small dollar loans in the nearby states and the distance reduces access to payday loan for Arkansas who live far from the surrounding states.

Research indicates that payday loan has been at the forefront of many policy debates. These lending practices have garnered supports and have been subject to criticism. Proponents argue that payday lenders provide a valuable service or financial arrangement to consumers who desperately need cash or short-term credit to finance some emergencies (unexpected medical bills, unpredicted spending, etc.) or daily expenses (Caskey, 2010; Edminston, 2011). On the other hand, opponents lament the predatory behavior and practices of payday lenders that strategically located or relocated in low income or disproportionately minority populated communities with African Americans or Hispanics (Graves, 2003; Stegman, 2007; Melzer, 2011). This study is built upon, Graves (2003), Graves and Peterson (2005), and Gallmeyer and Roberts (2009), Barth et al. (2016) and many other researchers' work on spatial analytical perspectives of payday loans.

Since the map analysis and the a-spatial statistical methods were frequently used in previous studies, this study contributes to the existing literature in three important ways: (1) conduct the exploratory spatial data analysis to uncover the spatial autocorrelation or dependence using the well-known Moran's *I* statistic in the spatial statistics literature; (2) build, compare, and evaluate the spatial regression models and select the appropriate specifications that best portray the payday loans usage in the study area; and, (3) evaluate the spatial effects of the additional loan acquisition costs due to the interest cap.

This reminder of the study is organized as follows. Section 2 summarizes the relevant literature on the payday lending regulatory environments and the related spatial analyses. Section 3 discusses the methods, that is, the exploratory spatial data analysis, the model specifications, and the data description. Section 4 presents the results while section 5 discusses the significance of the main findings.

RELATED LITERATURE

Payday Lending and Regulatory Environments

Several studies in consumer finance in the United States, as well as ongoing discussions and debates in policy centers, governmental agencies, academic circles and kitchen tables, have underscored the need for a better understanding of the relationships among consumer loan, regulatory and institutional environments, and relative locations of payday loan businesses. The urgent needs to obtain small dollar loans to cope with emergencies or to pay regular bills have in part resulted in a growing number of payday loan storefronts. Traditional bank credit is not an option for the working poor. Historically, the payday loan has been one of the five commonly known alternative financial services including auto loans, pawn broker loans, tax refund anticipation loans, and rent-to-own transactions (Burke et al., 2014). This study focuses on the payday loan. A payday loan is often defined as a small dollar, short term maturity, and unsecured consumer loan (Graves, 2003; Prager, 2009; Burke et al., 2014). According to some estimates, the payday loan is a $46 billion industry. Consumers obtain these loans in exchange for a post-marked checks tendered to the payday lenders. The loan is approved as result of a documented source of income, physical address, and a good standing checking account. There is a consensus that the demand for payday loans is the reflection of the need for quick cash.

In a recent economic education newsletter from the Federal Reserve Bank of St. Louis, Bennett (2014) puts in perspective the emergence and widespread growth of payday storefronts in America. The author indicates that the 1980s and 1990s is the spring of the payday lending and thereafter becomes prevalent in many communities across America. Bennett (2014) finds about 20,000 payday storefronts, which is a higher number of establishments compared with 14,157 McDonald's restaurants across the United States of America. The review of existing literature suggests two groups: proponents and opponents of the instalment lending. To illustrate, proponents argue that payday lenders provide a valuable service or financial arrangement to consumers who desperately need cash or short-term credit to finance some emergencies (unexpected medical bills, unpredicted spending, etc.) or daily expenses (Caskey, 2010; Edminston, 2011). On the other hand, opponents lament the predatory behavior and practices of the payday lenders by strategically located or relocated in low income or disproportionately minority populated communities with African Americans or Hispanics (Graves, 2003; Stegman, 2007; Melzer, 2011). In the State of Lending in America & its Impact on U.S. Households, Montezemolo (2013) of the Center for Responsible Lending, warns that payday loan businesses create a debt treadmill, which does more harm rather than good to struggling families in the United States. She mentions that a lack of underwriting for affordability, high fees, short-term due dates, single balloon payment, and collateral in the form of post-dated check or access to a bank account are the main contributing factors creating repeat borrowers and a vicious cycle of debt. Furthermore, recent contributions to the payday discourse are found in Bennett (2014), Burke et al. (2013) the Consumer Financial Protection Bureau, the second report of the Pew Charitable Trusts Payday lending in America (2013), and the Consumer Financial Protection Bureau (2014).

Spatial Perspectives on Payday Lending

On the spatial analytical perspectives, the first effort in the spatial data analysis of payday lenders is from the seminal work of Graves (2003) entitled "Landscapes of Predation, Landscapes of Neglect: A Location Analysis of Payday Lenders and Banks" published in the Professional Geographer. The author examines the locational strategies of banks and payday lenders in metropolitan Louisiana and in Cook County, Illinois using the landscape analytical tool to better understand the working of culture and economics in daily transactions. Graves (2003) formulates three main hypotheses: (1) there is no difference between the average income and ethnic compositions of neighborhoods with payday lenders and the countywide means, (2) there is no difference in zoning regulations between banks and payday loan lenders in the study area, and (3) there is no difference between the data groups holding the population constant. To test this hypothesis, the author utilizes a *t*-test for the difference between population means. On the spatial perspectives, Graves (2003) utilizes the ArcGIS overlay operation to produce two thematic maps that render the geocoded locations of banks and payday lenders along with the median household on the first map and the percent of white on the second map, respectively. His statistical analysis, the *t*-test for the difference between population means, reveals a stronger spatial pattern showing higher concentrations of payday lenders in poorer and minority neighborhoods and banks are located in wealthier and whiter than countywide means. In fact, the size of the population matters. The local analysis yields mixed and conflicting results. The map analysis is considered as an exploratory analysis and the formulation of the testable hypothesis paves the way for more advanced analysis.

In investigating the effects of predatory lending business practices on the financial vulnerability of military personnel using 20 states, 1516 counties, 13,253 Zip codes, about 15,000 payday storefronts, and 109 military bases in the United States, Graves and Peterson (2005) report high concentrations of payday loan business facilities nearby military bases after controlling for the commercial development patterns and zoning ordinances. The authors note different legal and regulatory environments and lament a lack of consumer protection using the existing laws. However, the only exception is the enforcement of civil and criminal usury law in its full extent. Their paper is a harmonious combination of legal and geographic analysis, which allows to show the spatial consequences of law and legal institutions. The latter is designed to structure and influence events in the physical world (Graves & Peterson, 2005). The interplay between law and geography lends more support for the spatial data analysis. On the spatial perspectives, the authors employ buffering to create two areas. For the first area, a county is nearby to a military base when it is located within 3-mile radius of the base and a distant county falls beyond the 3-mile radius from the military base. They develop the location quotient to portray the density of payday loan storefronts, which is compared to the density of banks in the same area. The main GIS techniques used here are buffering and overlay (Chang, 2010, p. 223-225; Malczewski, 1999, p.41).

In analyzing the social ecology of payday lending in Colorado, U.S.A, Gallmeyer and Roberts (2009) take additional steps in the spatial data analysis compared to Graves (2003) and Graves and Peterson (2005). The authors employ the GIS overlay operation to produce three thematic maps. The first map displays the relative locations of payday lending sites in the state of Colorado (Fort Collins & Loveland, Greeley, Denver Metropolitan area, Colorado Springs, and Pueblo) to the major roadway and Front Range corridor. The second map shows the percent of foreign born and the payday lending sites in Denver Metro. The last map displays the percent of military personnel and the locations of payday loan facilities in Colorado Springs, Colorado. The authors conduct a parametric and non-parametric test to compare the means of locations with the presence of payday loan facilities against the locations without payday loan facilities using the *t*-test for the difference between population means and the Mann-Whitney test, respectively. They reach inconclusive results on the persistence of spatial disparity. Instead, the authors estimate the logistic model to evaluate the predictive effects of socio-demographic variables. They find that payday loan businesses are located in areas with lower income, moderate poverty, higher percentages of ethnic minorities, immigrants, young adults, elderly, military personnel, and people in non-management and professional occupations.

Recently, in their article entitled, do state regulations affect payday lender concentration? Barth et al. (2016) analyze a unique database from the state's regulatory authorities and find an association between the number of payday loan storefronts and the regulatory environments at the county level. That is, permissive regulatory environments have more payday loan storefronts compared with restrictive regulatory environments. The authors also report other limiting factors to payday loan accessibility including restrictions on operations, fees, size of the loan, and the number of renewals and rollovers. It should be noted that existing applied studies in consumer loans have not yet investigated the spatial dependence or spatial autocorrelation nor employed spatial regression models. In addition, current literature does not provide clear guidance regarding the exploratory spatial data analysis (ESDA) and the spatial regression analysis in the payday loan research. This study tries to fill this gap in the applied literature and takes advantage of recent developments in applied spatial statistics, spatial econometrics, and geographic information systems. The next section presents the exploratory spatial data analysis and briefly discusses the model specifications and describes the two main datasets built for this study.

METHODS

Exploratory Spatial Data Analysis

The exploratory spatial data analysis of payday loan usage provides a more adequate and specialized framework and methodology for the spatial dependence (Good, 1983; Anselin, 1990; Getis & Mur, 2004). Consistent with the First Law of Geography or Tobler's (1979) Law "everything is related to everything else, but near things are more related than distant things." that is, adjacent counties or counties in a close proximity in the study area may fairly have similar levels of payday loan usage. A wealth of data on payday loan usage collected by the American Financial Services Association (2014) has become increasingly available to researchers; thus, new analytical tools are needed in order to discover patterns and to suggest potential relationships between payday loan usage and socioeconomic and demographic characteristics of counties in the study area.

In this section, the exploratory data analysis is conducted to measure the spatial association between payday loan usage of a county in the study and its neighbors. The researcher employs a global statistic Moran's I to evaluate the presence or absence of a stable pattern of spatial dependence in the payday loan usage across the study area, and later, on the residuals of the standard linear regression and spatial models (Anselin, 1988b, 1990, 1995; Anselin & Florax, 1995; Anselin & Rey, 1991). Prior to that, it is imperative to define and construct the neighborhood structure by the means of a spatial weight matrix (LeSage & Pace, 2009, p.9; Haining, 2003, p.80). Mathematically, the spatial weight matrix, $\boldsymbol{W}$, is an n by n non-singular matrix, where $i = 1 \ldots n$ and $j = 1 \ldots n$. According to Anselin and Rey (2014, p.35), the elements, w_{ij}, of the spatial weight matrix $\boldsymbol{W}$ are positive for all neighbors $i \neq j$ and by construction w_{ij} equals zero for $i = j$ because a country i cannot be its own neighbor (Ord, 1975). There are several ways of representing this matrix depending on the research objective(s) and the spatial information product.

For this study, four types of spatial weight matrices are employed: queen contiguity, rook contiguity, general distance, and *k*-nearest neighbors (Anselin, 1999, 2002). Once a spatial weight matrix is specified, spatial patterns are typically identified and quantified through Moran's *I* statistic. Based on the spatial extent of the study area as shown in Figure 1, it is reasonable to use the Moran's *I* statistic (Moran, 1948; Cliff & Ord, 1981; Anselin & Rey, 1991) to measure and test the hypothesis of spatial randomness in payday loan usage across the study area. The Moran's *I* shown in Equation 1a measures the linear association between *y*, the deviations of the number of loans about its mean, say in Benton County, Arkansas and *Wy*, the weighted average of the deviations of the payday loan usage of the neighboring counties. The Moran's *I* for the OLS residuals and that of the spatial lag models and the spatial error models to be discussed in the regression analysis section is presented in Equation 1b. Both statistics are in matrix form below patterning the formula in Anselin and Rey (2014, p.108).

Moran's $\boldsymbol{I = y'Wy/ y'y}$ (1a) and **Moran's** $\boldsymbol{I = e'We/e'e}$ (1b) (1)

For the sake of clarity, Anselin (1988b, 1995) provides a nice interpretation of the Moran's *I* statistic equivalent to the simple regression model coefficient estimates when variables are in deviations about their means. Following the author, the Moran's *I* portrays the linear association between the payday loan usage rate in Benton County, Arkansas and the payday loan usage rate in nearby counties in the study area.

Model Specification

This section presents different model specifications to examine how the payday loan usage differs across the study area. The standard practice is to verify whether or not the residuals from the linear regression model (by letting $\Theta = \rho = \lambda = 0$ in equation (2)) are autocorrelated. The main assumption is that the 17 percent constitutional rate cap in the state of Arkansas introduces a change in payday loan. The results indicate that residents of the border counties obtain more payday loans than residents in the interior counties as shown on Figure 1. It is reasonable to assume that the data on the payday loan usage come from some spatial data generating process (DGP) to be revealed. The best effort is to uncover through a specification search and discovery process, the model that both best portrays the data and is useful to the purpose of this study. The specification begins with a general model, the spatial Durbin model, which represents different spatial regression models following LeSage and Pace (2009, p.32) and it is written as:

$$\mathrm{Y} = \alpha \iota_n + \rho \mathrm{WY} + \mathrm{X}\beta + \mathrm{WH}\Theta + \varepsilon, \tag{2}$$

From equation (2), four models can be derived by imposing restrictions on parameters Θ, ρ, and λ and assuming that the error term $\boldsymbol{\varepsilon}$ follows a normal distribution, that is, $\varepsilon \sim N(0, \sigma^2 I_n)$. The same assumption holds for equations (3)-(6). To be specific, the spatial lag model can be obtained by letting $\Theta = 0$ and assuming that the error term follows a normal distribution. The spatial lag model is presented as follows:

$$\mathrm{Y} = \alpha \iota_n + \rho \mathrm{WY} + \mathrm{X}\beta + \varepsilon, \tag{3}$$

The third model is the spatial error model, which introduces the spatial dependence in the error term by letting $\Theta = \rho = 0$ and assuming that the error term follows a standard normal distribution. It is written as:

$$Y = \alpha\iota_n + X\beta + u, \tag{4}$$

where $u = \lambda Wu + \varepsilon$.

Besides the above model specifications, the two last models incorporate the spatial lags into the dependent variable and the disturbance process. This requires the use of two distinct spatial matrices. The first spatial weight matrix W_1 captures global effects emanating from the spatial spillovers and the second matrix W_2 captures local effects emanating from nearby neighbors. Both the specification of the spatial weight matrices and disturbance processes differentiate these two models presented in equations (5) and (6). The spatial autoregressive process is written as:

$$Y = \alpha\iota_n + \rho W_1 Y + X\beta + u \tag{5}$$

where $u = \lambda W_2 u + \varepsilon$.

The spatial autoregressive moving average process (see Anselin & Bera, 1998 for more details) is specified as:

$$Y = \alpha\iota_n + \rho W_1 Y + X\beta + u \tag{6}$$

where $u = \lambda W_2 \varepsilon + \varepsilon$.

From the above models, ***Y*** represents the payday loan usage for 160 counties in the study area, ***X*** is a matrix of (1) two dummy variables indicating the access to loans; (2) a set of payday loan predictors/covariates such as total population, percent of minority, and median household income. **H** is a subset of X, which has spatially lagged explanatory variables. In equation (1), $\boldsymbol{\rho}$ is a measure of the strength of spatial autocorrelation in the sample of observations of payday loans from one country to its neighbors, ***W*** the spatial weight matrix represents the neighborhood structure, nearness or adjacency among counties. To be specific, two different types of spatial weight matrices may be used, $\boldsymbol{W_1}$ (queen, rook, distance) and $\boldsymbol{W_2}$ (kernel weights, *k*-nearest neighbor, or general distance) because the model has both spatial lag and error effects (LeSage & Pace, 2009, p.33). Each specification should have its own type of spatial weight matrix for the econometric procedures to be conducted in the standard routines of the spatial econometrics packages such as *GeoDaSpace, STATA or R*. It is important to note that in other specifications (spatial lag model or spatial error), only one type of spatial weight matrix shall be used at a time. $\boldsymbol{\lambda}$ is the measure of the strength of spatial dependence in the disturbances of the model, $\boldsymbol{u}$ is an innovation or a shock to be infused, $\boldsymbol{\varepsilon}$ represents the traditional error term which follows the standard normal distribution, and $\boldsymbol{\beta}$ is a vector of parameters associated with the explanatory variables. Based on the neighborhood structure defined by the spatial matrix weight **W** (share a common boundary, be within a specified distance of each other, and be 'nearest' neighbors…). **WY** is the spatially lagged response variable or the weighted average of the number of payday loans in counties *j* neighbor to a county *i*. It should be noted that **Wu** is the associated spatially lagged error term as shown in equation (5); **Wε** is the associated with the moving average process as shown in equation (6) and α_{in} represents the *y*-intercept or the vector of ones.

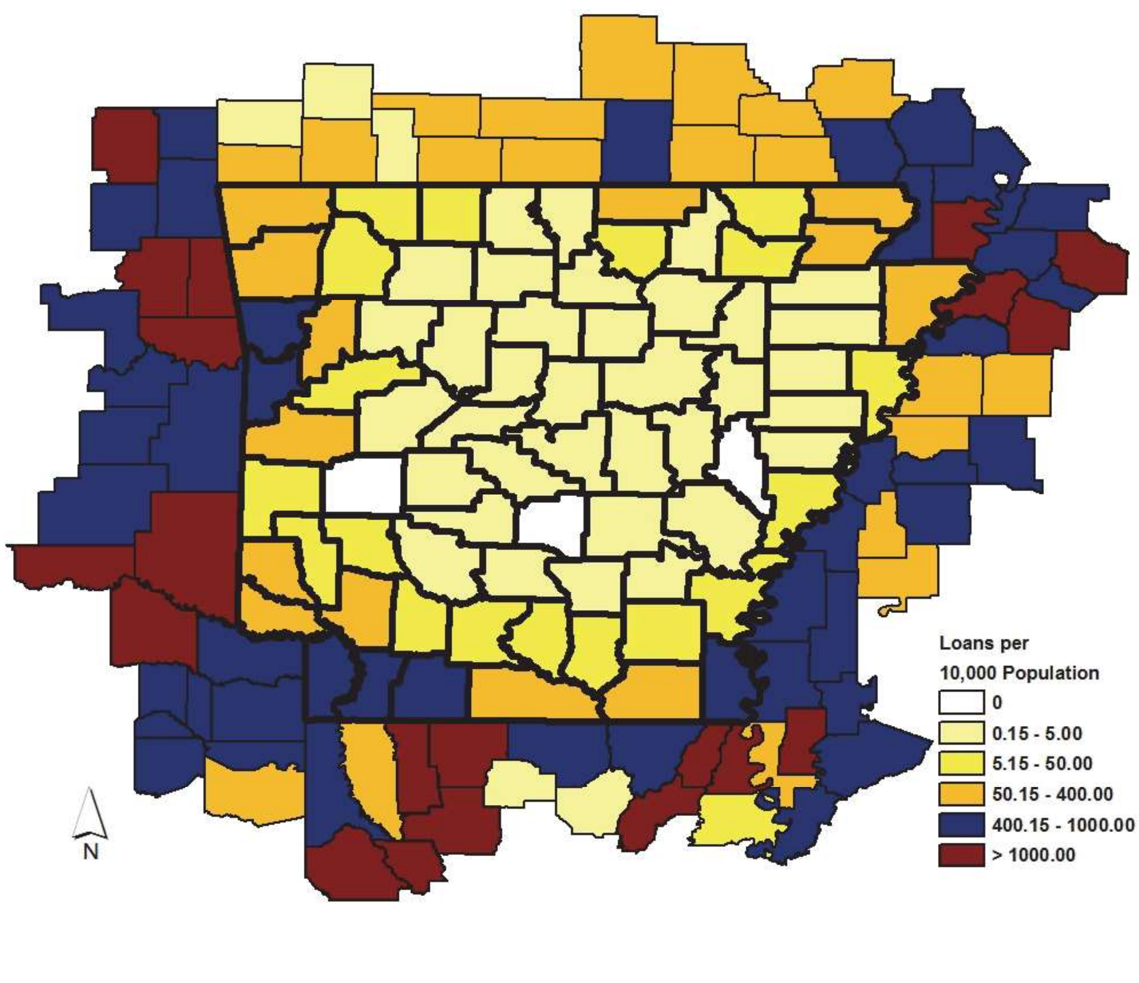
Data

Two datasets are used in the study. The first set was collected from the U.S. Census Bureau, 2006-2010 American Community Survey, which is the 2010 U.S. Census. The second set was generated from the ArcGIS package, two dummy variables. The response variable is the cash payday loan usage shown in Tables 2a-3b. The explanatory variables are two dummy variables built to examine how the payday loan usage changes as one approaches and then crosses the Arkansas borders. For the first dummy, a county takes on a value of 1 if it is located within 80 miles from the state of Arkansas borders, and for the second dummy, a county is takes on a value of 1 if it is located within 120 miles from the two nearest countries of five states surrounding Arkansas and 0, otherwise. Two dummy variables were generated from the

ArcGIS package using the distance measurement analytical tool (Mitchell, 2005; Chang, 2010, p.231). The latter calculates the distance between the borders and any county inside the study area based on the predefined distance threshold, within 80 miles from the state of Arkansas borders and 120 miles from the two nearest countries of six states surrounding Arkansas, respectively.

Note that a set of commonly used payday loan usage predictors were gathered from the 2010 U.S. Census (Caskey, 1994; Graves & Peterson, 2005; Gallmeyer & Roberts 2009; Prager, 2009; Zinman, 2010) and are employed in the statistical analysis. The control variables, which are the socioeconomic and demographic variables, were gathered at the county level. They include the total population, percent of management, business, science, and arts occupations, percent of service occupations, percent of sales and office occupations, percent of natural resources, construction, and maintenance occupations, percent of production, transportation, and material moving occupations, per capita income (in 2010 inflation-adjusted dollars), percent of poor (all families), percent of population age 15-19 years, percent population 20-24 years, percent population age 65 years and over, percent of non-white as a proxy of minority (100-percent of white, one race reported), percent of Black or African American (one race reported), percent of veteran calculated from the total non-veteran and veteran, percent of foreign born, median household income (in 2010 inflation-adjusted dollars), median age in years, percent of never married females 15 years and over, percent of high school graduate (includes equivalency), percent of bachelor's degree or higher, and percent of renters occupied.

FIGURE 1
PAYDAY LOAN USAGE IN ARKANSAS AND TWO-NEAREST COUNTIES FROM ITS SURROUNDING STATES



The payday loan usage thematic map was created by the author using the ArcGIS map package to render the distribution of the payday loan usage across the study area. Figure 1 portrays 75 counties of the state of Arkansas in the center and 21 counties of Missouri in the north, 15 parishes (counties) of Louisiana in the south, 14 counties Oklahoma in the west, 9 counties of Texas in south west, 16 counties of Mississippi in the east, and 10 counties of Tennessee in the north east. The payday loan usage and other covariates were added into the clipped area of interest shapefile using the tabular join. Six classes were created using the manual classification method in line with Dent's (1999, p.143) practical recommendation between 4 classes at the minimum and 6 classes at the maximum. The geographic coordinate system (GCS) is the GCS North American 1983 and the datum is North American Datum 1983, NAD83.

RESULTS

Exploratory Spatial Data Analysis

The first step in this analysis is to test the hypothesis of spatial randomness in the payday loan usage against the alternative hypothesis of spatial autocorrelation or dependence. These tests are performed using 42 alternative specifications of the spatial weight matrix—queen (10), rook (10), general distance (12), and *k*-nearest neighbors (10). The global Moran's *I* statistics are shown in columns 1- 3 of Table 1. One compares the calculated *p*-values associated with the global Moran's *I* statistics against the conventional critical values of 0.01, 0.05, and 0.10 to evaluate their significance. Results suggest strong evidence of a significant spatial autocorrelation or dependence between the payday loan usage in one county in the study area and a nearby county using four specifications of the spatial weight matrix. The left hand side of Table 1 displays Queen, Rook, Distance threshold, and k-nearest neighbor spatial weight matrices. These matrices introduce the neighborhood structure between counties in the study area in relation to payday loan usage.

TABLE 1
GLOBAL SPATIAL AUTOCORRELATION OR DEPENDENCE IN PAYDAY LOAN USAGE

Spatial weight matrix	Moran's *I*		
	Payday loan usage	OLS Residuals[+] (80mi Dummy)	OLS Residuals[++] (120mi Dummy)
	(1)	(2)	(3)
Queen			
Queen of order 1	0.296268***	0.2332***	0.1986***
Queen of order 2	0.188733***	0.1143***	0.1333***
Queen of order 3	0.133817***	0.0645***	0.0822***
Queen of order 4	0.0817313***	0.0524***	0.0662***
Queen of order 5	0.0375953***	0.0298***	0.0380***
Queen of order 6	0.0172033***	0.0179***	0.0233***
Queen of order 7	0.00718945***	0.0150***	0.0130***
Queen of order 8	-0.0105551	0.0028***	-0.0003*
Queen of order 9	-0.0195663***	-0.0063	-0.0072
Queen of order 10	-0.0195614***	-0.0126***	-0.0115**
Rook			
Rook of order 1	0.296603***	0.2336***	0.1994***
Rook of order 2	0.190929***	0.1164***	0.1340***
Rook of order 3	0.135197***	0.0658***	0.0837***
Rook of order 4	0.0835469***	0.0529***	0.0664***
Rook of order 5	0.0385455***	0.0305***	0.0386***
Rook of order 6	0.0170051***	0.0175**	0.0238***
Rook of order 7	0.00629917	0.0142***	0.0132***
Rook of order 8	-0.0114492	0.0020**	-0.0003*
Rook of order 9	-0.0197449***	-0.0067	-0.0077
Rook of order 10	-0.019461***	-0.0124***	-0.0116**
Distance threshold			
32.96 mi	0.30707***	0.2381***	0.1882***
40 mi	0.309202***	0.2371***	0.2000***
50 mi	0.266946***	0.2091***	0.1988***
60 mi	0.222392***	0.1498***	0.1470***
70 mi	0.198539***	0.1299***	0.1359***
80 mi	0.186778***	0.1169***	0.1262***
90 mi	0.152636***	0.0933***	0.1024***
100 mi	0.132391***	0.0771***	0.0882***
120 mi	0.0929464***	0.0645***	0.0732***
150 mi	0.0466504***	0.0379***	0.0452***
180 mi	0.0090561	0.0103***	0.0155***
200 mi	-0.00677852	0.0007	0.0034**

k-nearest neighbors			
1-nearest neighbor	0.315574***	0.2263**	0.2078**
2-nearest neighbor	0.378895***	0.2804***	0.2134***
3-nearest neighbor	0.324305***	0.2556***	0.2112***
4-nearest neighbor	0.310417***	0.2472***	0.2062***
5-nearest neighbor	0.303905***	0.2327***	0.1921***
6-nearest neighbor	0.285606***	0.2213***	0.1882***
7-nearest neighbor	0.26627***	0.1991***	0.1822***
8-nearest neighbor	0.26302***	0.1915***	0.1784***
9-nearest neighbor	0.259786***	0.1819***	0.1746***
10-nearest neighbor	0.249244***	0.1721***	0.1658***

Note: $^{+}$ the 80mi-dummy variable is included in the standard regression model, $^{++}$ the 120mi-dummy is included in the standard regression model. ;*** indicates *p-value* < 0.01, ** *p-value* < 0.05, * *p-value* < 0.10.

Column 1 of Table 1 shows evidence of spatial autocorrelation in payday loan usage with queen contiguity of orders 1-7. The Moran's *I* ranges from 0.0072 (Queen of order 7) to 0.2963 (Queen of order 1) is significant for positive spatial autocorrelation at the 1 percent level as shown in column 1 of Table 1. There is also presence of spatial dependence when using rook contiguity of orders 1 – 6. The Moran's *I* ranges from 0.0017 (Rook of order 6) to 0.2966 (Rook of order 1) is significant for positive spatial autocorrelation at the 1 percent level as shown in column 1 of Table 1. The distance approach yields similar results. As shown in column 1 of Table 1, using the arc distance weight matrix with predefined distances of about 32.96 to 150 miles between the centers (centroids) of two counties, the presence of dependence was detected in payday loan usage. To illustrate, the payday loan usage in Jackson County, Arkansas tends to be more similar to nearby counties than the payday loan usage at a greater distance such Adair, Oklahoma. The Moran's *I* ranges from 0.0467 (150 miles) to 0.3092 (40 miles) and is significant at the 1 percent level. Finally, the spatial dependence was tested using the *k*-Nearest-Neighbor specification of the spatial weight matrix, with *k* ranging from 1 to 10. The results, also shown in column 1 of Table 1, indicate a strong spatial dependence in payday loan usage when considering 1 to 10 nearest neighbors in the specification. The Moran's *I* statistics range from 0.2492 (tenth nearest neighbors) to 0.3789 (second nearest neighbors) and are significant at the 1 percent level. These results suggest a positive and significant spatial clustering of counties with fairly similar payday loan usage and corroborate with the map analysis results. Since, such strong evidence has been found for patterns of spatial association (spatial autocorrelation) using various specifications of the spatial weight matrix, the next step is to conduct the spatial regression analysis.

Spatial Regression Analysis

In addition to the detection of spatial autocorrelation in the dependent variable (the payday loan usage), one fits a standard linear regression model to the data using the ordinary least squares(OLS) technique, retains the OLS residuals and performs the spatial dependence on the OLS residuals (Ord, 1975; Anselin & Rey, 1991; Anselin & Florax, 1995; Anselin, 2002). Toward this end, the model preferred should demonstrate the best fit of the data based on a further investigation of spatial autocorrelation of the residuals of the chosen spatial regression models using the Moran's *I* statistic. Since there is evidence of spatial dependence among residuals of the linear regression model, the next step consists of the estimation of spatial regression models presented in equations (2)-(6). Researchers should be guided by the principle of parsimony when selecting the appropriate specification (Anselin, 1988b, 1999, 2002; Anselin & Rey, 2014, p.196, 251).

Testing for Spatial Dependence

Two separate explanatory variables represented by two dummy variables, (1) within 80 miles from the Arkansas borders and (2) within 120 miles from the two nearest counties borders of states surrounding

Arkansas were employed for testing the spatial dependence. Results are presented in Tables 2 and 3, respectively. At this stage, it is recommended to look at Columns 2 and 3 of Table 1 to examine the results of the appropriate diagnostics tests on the residuals of the standard regression model. Findings indicate that residuals are spatially autocorrelated as shown by the Moran's *I* statistic reported in Table 1. Several spatial weight matrix specifications were employed during this testing. To be specific, the spatial matric Queen of orders 1-8 and 10 show evidence of spatial autocorrelation among the OLS residuals. The Moran's *I* ranges from 0.0130 (Queen of order 7) to 0.1986 (Queen of order 1), which is significant for positive spatial autocorrelation at the 1 percent level as shown in column 2 of Table 1. Rook, distance threshold, and *k*-nearest neighbor specifications reveal spatial autocorrelation among the OLS residuals.

Model Comparison and Search for a Best Special Model Portraying Spatial Dependence

Overall, the Moran's *I* test on the residuals after fitting the standard linear regression model suggests that there is strong evidence of spatial autocorrelation among the OLS residuals. Given these results, the standard practice in applied spatial research is to conduct a specification search, using alternative models (spatial lag model, spatial error model or spatial Durbin model) with the same spatial weight matrix. Therefore, thirty-two spatial weights matrices were applied.

For comparison purposes, one utilizes the same explanatory variables in the standard linear model, the spatial lag model, spatial Durbin model, and the spatial error model. Similarly, the same spatial weight matrices were employed in estimating the spatial regression models and in investigating spatial autocorrelation among the residuals of the spatial regression models. The explanatory and control variables include: the within 80 miles from the Arkansas borders dummy variable, the within 120 miles from the Arkansas borders dummy variable, total population, percent of minority, median household income, etc. After conducting over ninety-six regressions, the number of potential spatial models was reduced to four for each dummy variable shown in Tables 2 and 3. For the spatial models using the within 80 miles distance from the Arkansas borders as shown in Columns 2-5 of Tables 2a-2b and the within 120 miles dummy as reported in Columns 2-5 of Tables 3a-3b, eight spatial models were retained using two optimal spatial weight matrices, the 120 miles threshold distance and the Queen of order 4. Since the standard practice in econometric analysis favors a parsimonious model, the spatial Durbin model, a more complex model, yielded less interesting results and are not reported here.

Tables 2a and 2b summarize the results of the models with 80 miles as a dependent variable. It is evident that the best specification is the spatial lag model for the following reasons. The coefficients associated with the within 80 miles from the Arkansas borders dummy and the within 120 miles from the two nearest counties of states surrounding Arkansas dummy variables are statistically significant at the 1 percent level as shown in columns 2-3 and 5 of Tables 2a and 3a. These two variables remain significant in the spatial lag model and the spatial error model after controlling for demographic and socioeconomic variables.

TABLE 2a
STANDARD REGRESSION MODEL, SPATIAL LAG MODEL, AND SPATIAL ERROR MODEL

Variables	Standard model	Spatial Lag Model	Spatial Lag Model	Spatial Error Model	Spatial Error Model
Dependent variable: Payday loan usage	(1)	(2)	(3)	(4)	(5)
Explanatory variable					
Within 80 miles from Arkansas borders	**1,726.695*****	**1,194.3160*****	**1,238.0920*****	**941.7599****	**1,034.1600*****
	(393.9185)	(357.6167)	(361.5872)	(401.8545)	(399.8310)
Control variables					
Percent services occupations	28.0276	27.0103	23.7985	29.0159	24.8124
	(41.9411)	(37.7653)	(38.4520)	(38.2637)	(39.1716)
Percent sales and office occupations	37.3999	53.1322	49.1110	69.6772	61.6352
	(47.6088)	(43.1839)	(43.6596)	(44.2156)	(44.6915)
Total population(000)	**11.8696*****	**12.6062*****	**12.6071*****	**12.1277*****	**12.3347*****
	(1.8130)	(1.6441)	(1.6621)	(1.6658)	(1.6972)
Percent of Minority(Nonwhite, once race)	**24.2443****	**18.3239****	**18.8887****	**23.1588****	**20.9936***
	(9.8988)	(8.9826)	(9.0780)	(11.2795)	(11.0744)
Percent of Veterans	71.1136	84.4378	80.9540	53.7591	50.7188
	(71.7525)	(65.3156)	(66.1265)	(67.7336)	(69.4228)
Percent of foreign born	-28.0869	**-43.7211***	**-48.3217***	**-53.3053****	**-57.0075****
	(27.6753)	(25.1117)	(25.3853)	(26.4723)	(27.1354)
Median household income(000)	**44.1340***	24.2190	27.3011	20.3158	21.00055
	(26.5168)	(24.0432)	(24.3044)	(25.2070)	(25.2922)
Moran's *I* for residuals	0.0524***	0.0173*(*pval*=0.0610)	0.0089(*pval*=0.1340)	0.0275**(*pval* =0.0230)	0.0189**(*pval*=0.044)
Spatial weights matrix	Queen of order 4	Distance 120 miles	Queen of order 4	Distance 120 miles	Queen of order 4

Note: *, **, *** statistically significant at 10%, 5%, and 1%. [a] p-values are reported in brackets to evaluate spatial dependence in column 1, [b] likelihood ratio test p-values in square brackets, [c] coefficients of spatial lag and error model standard errors are in parentheses. The sample is composed of 160 counties. From columns 2-5, pval stands for the p-value associated with the Moran's *I*

The selection of the best model was guided by both the higher levels of significance of the coefficients associated with explanatory, control variables, and spatial lag and error effects compared with other specifications. Statistics from which researchers base their decisions are reported in columns 2-5 of Tables 2a-2b and 3a-3b under the specification search heading. Results suggest that the coefficients of spatial lag and error effects are highly statistically significant and of expected signs. To illustrate, columns 3 and 4 of Tables 2b show that the coefficient associated with the spatial lag effects (*rho*, 0.8256) is statistically significant at the 1 percent level. The coefficient of the spatial error effects (*lambda*, 0.8486) is statistically significant at the 1 percent level. It is important to note that the standard errors for *rho* and *lambda* are listed in parentheses next to these coefficients as shown in columns 2 and 4 of Tables 2b-3b. The significance of the *p*-values associated was evaluated with the likelihood ratio test when applying to the spatial lag model (*p*-value = 0.0000) and spatial error model (*p*-value = 0.0001). These *p*-values are presented underneath the coefficients related to these spatial models as shown in columns 2-5 of Table 2b.

TABLE 2b
STANDARD REGRESSION MODEL, SPATIAL LAG MODEL, AND SPATIAL ERROR MODEL

Variables	Standard model	Spatial Lag Model	Spatial Lag Model	Spatial Error Model	Spatial Error Model
Dependent variable: Payday loan usage	(1)	(2)	(3)	(4)	(5)
Within 80 miles from Arkansas borders	**1,726.695*****	**1,194.3160*****	**1,238.0920*****	**941.7599****	**1,034.1600*****
	(393.9185)	(357.6167)	(361.5872)	(401.8545)	(399.8310)
Specification Search					
Spatial lag effects (rho)	-	0.8401*** (0.0929)[c]	0.8256***(0.1030)[c]		
Likelihood Ratio test (p-value)[+]	-	17.1185[0.0000][b]	14.4025[0.0001][b]		
Spatial error effects (lambda)	-	-		0.8486***(0.0907)[c]	0.8191***(0.1089)[c]
Likelihood Ratio test (p-value)[++]		-		13.9008[0.0001][b]	10.5301[0.0012][b]
Diagnostics					
Measures of fit					
Log likelihood	-1411.72	-1403.16	-1,404.52	-1,404.77	-1,406.46
Akaike Information Criterion (AIC)	2841.44	2826.33	2,829.04	2,827.54	2,830.91
Bayesian Information Criterion (BIC)	2869.12	2857.08	2,859.79	2,855.22	2,858.59
Spatial dependence~					
Lagrange Multiplier LM(lag)	22.0064 [0.0000][a]				
Robust Lagrange Multiplier LM(lag)	16.6133 [0.0001][a]				
Lagrange Multiplier LM(error)	10.3587 [0.0013][a]				
Robust Lagrange Multiplier LM(error)	4.9656 [0.0259][a]				
Lagrange Multiplier LM(lag & error)	26.9720 [0.0000][a]				
Moran's *I* for residuals	0.0524***	0.0173*(*pval*=0.0610)	0.0089(*pval*=0.1340)	0.0275**(*pval* =0.0230)	0.0189**(*pval*=0.044)
Spatial weights matrix	Queen of order 4	Distance 120 miles	Queen of order 4	Distance 120 miles	Queen of order 4

Note: *, **, *** statistically significant at 10%, 5%, and 1%. [a] p-values are reported in brackets to evaluate spatial dependence in column 1, [b] likelihood ratio test p-values in square brackets, [c] coefficients of spatial lag and error model standard errors are in parentheses. The sample is composed of 160 counties. From columns 2-5, pval stands for the p-value associated with the Moran's *I* statistics for results.

Furthermore, Tables 3a-3b summarize the results using the within-120miles-distance threshold as the dependent and the same set of control variables and the Queen of order 4 and 90-mile threshold distance spatial weight matrices. To be consistent, the selection of the preferred model specification was based on the higher levels of significance of the coefficients associated with explanatory, control variables, and spatial lag and error effects compared with other specifications.

TABLE 3a
STANDARD REGRESSION MODEL, SPATIAL LAG MODEL, AND SPATIAL ERROR MODEL

Variables	Standard model	Spatial Lag Model	Spatial Lag Model	Spatial Error Model	Spatial Error Model
Dependent variable: Payday loan usage	(1)	(2)	(3)	(4)	(5)
Explanatory variable					
Within 120 miles from surrounding state counties borders	**1,469.0270*****	**911.3357*****	**1111.4240*****	**623.3026***	**1,023.0270*****
	(335.1083)	(301.6681)	(305.9794)	(354.3094)	(340.0229)
Control variables					
Percent services occupations	14.6379	6.8588	13.4344	3.6894	17.8084
	(42.1173)	(37.7653)	(38.4141)	(37.3940)	(38.8631)
Percent sales and office occupations	29.2802	48.8627	43.2363	**77.1810***	59.4852
	(47.6244)	(42.7641)	(43.4570)	(43.4806)	(44.3386)
Total population(000)	**11.6897*****	**12.7250*****	**12.4963*****	**12.3324*****	**12.3056*****
	(1.8118)	(1.6237)	(1.6520)	(1.6086)	(1.6832)
Percent of Minority(Nonwhite, once race)	**27.4445*****	**15.8755***	**21.0728****	**20.7760***	**21.1827***
	(9.8640)	(8.8801)	(8.9947)	(12.0005)	(11.0077)
Percent of Veterans	83.3605	79.0464	90.3551	38.6379	59.9674
	(71.8062)	(64.5959)	(65.7796)	(67.3276)	(69.0399)
Percent of foreign born	-28.9488	**-50.6129****	**-49.6277****	**-68.7859*****	**-59.3338****
	(27.6891)	(24.8715)	(25.2818)	(26.6517)	(26.9386)
Median household income(000)	43.9193*	14.4457	27.0265	7.5734	18.7212
	(26.5153)	(23.7806)	(24.1782)	(25.3803)	(25.0583)
Moran's I for residuals	0.1024***	-0.0063(*pval*=0.3410)	0.0150*(pval=0.0650)	0.0036(*pval* =0.2580)	0.0207**(pval=0.0450)
Spatial weights matrix	Distance 90miles	Distance 90miles	Queen of order 4	Distance 90 miles	Queen of order 4

Note: *, **, *** statistically significant at 10%, 5%, and 1%. [a] p-values are reported in brackets to evaluate spatial dependence in column 1, [b] likelihood ratio test p-values in square brackets, [c] coefficients of spatial lag and error model standard errors are in parentheses. The sample is composed of 160 counties. From columns 2-5, pval stands for the p-value associated with the Moran's *I* statistics for results.

Overall, the spatial lag model and spatial error model reported in columns 2 and 4 of Table 3b have spatial effects coefficients, which are statistically significant at the 1 percent level. The coefficient associated with the spatial lag effects (*rho*, 0.7312) is statistically significant at the 1 percent level and the coefficient of the spatial error effects (*lambda*, 0.8000) is statistically significant at the 1 percent level. The standard errors for *rho* and *lambda* are listed in parentheses next to these coefficients as shown in columns 2 and 4 of Table 3. In addition, the significance of the *p*-values associated with the likelihood ratio test when applying to the spatial lag model (*p*-value = 0.0000) and spatial error model (*p*-value = 0.0000) was evaluated at the conventional levels of 0.01, 0.05, and 0.10.

TABLE 3b
STANDARD REGRESSION MODEL, SPATIAL LAG MODEL, AND SPATIAL ERROR MODEL

Variables	Standard model	Spatial Lag Model	Spatial Lag Model	Spatial Error Model	Spatial Error Model
Dependent variable: Payday loan usage	(1)	(2)	(3)	(4)	(5)
Explanatory variable					
Within 120 miles from surrounding state counties borders	**1,469.0270*****	**911.3357*****	**1111.4240*****	**623.3026***	**1,023.0270*****
	(335.1083)	(301.6681)	(305.9794)	(354.3094)	(340.0229)
Specification Search					
Spatial lag effects (rho)	-	0.7312*** (0.1077)[c]	0.8375***(0.0970)[c]		
Likelihood Ratio test (p-value)[+]	-	20.7056[0.0000][b]	15.8694[0.0000][b]		
Spatial error effects (lambda)	-	-		0.8000***(0.0945)[c]	0.8302***(0.1033)[c]
Likelihood Ratio test (p-value)[++]		-		19.5845[0.0000][b]	12.8911[0.0003][b]
Diagnostics					
Measures of fit					
Log likelihood	-1411.72	-1401.37	-1,403.79	-1401.93	-1,405.27
Akaike Information Criterion (AIC)	2841.44	2822.74	2,827.57	2821.86	2,828.55
Bayesian Information Criterion (BIC)	2869.12	2853.49	2,858.32	2849.53	2,856.23
Spatial dependence~					
Lagrange Multiplier LM(lag)	32.8678 [0.0000][a]				
Robust Lagrange Multiplier LM(lag)	11.6510 [0.0000][a]				
Lagrange Multiplier LM(error)	21.3411 [0.0000][a]				
Robust Lagrange Multiplier LM(error)	0.1243 [0.7244][a]				
Lagrange Multiplier LM(lag & error)	32.9921 [0.0000][a]				
Moran's I for residuals	0.1024***	-0.0063(*pval*=0.3410)	0.0150*(pval=0.0650)	0.0036(*pval* =0.2580)	0.0207**(pval=0.0450)
Spatial weights matrix	Distance 90miles	Distance 90miles	Queen of order 4	Distance 90 miles	Queen of order 4

Note: *, **, *** statistically significant at 10%, 5%, and 1%. [a] p-values are reported in brackets to evaluate spatial dependence in column 1, [b] likelihood ratio test p-values in square brackets, [c] coefficients of spatial lag and error model standard errors are in parentheses. The sample is composed of 160 counties. From columns 2-5, pval stands for the p-value associated with the Moran's *I* statistics for results.

Model Evaluation

The search for the best spatial model consists of testing spatial autocorrelation in the residuals of the spatial regression models. Empirical research suggests that the best spatial model should be free of spatial autocorrelation in its residuals. According to Anselin (1988b; 1990; 1999; 2002) and Anselin and Bera (1998), among others, the presence of significant residual spatial clustering undermines the potential of model to be the best candidate for portraying the generating process in the data. The standard practice in data-driven spatial empirical studies is to report the best model based on the optimal spatial weight matrix.

Looking at the very bottom of columns 2, 4, and 5 of Tables 2a-2b, the Moran's *I* statistic associated with the residuals from the spatial lag model and the spatial error models indicates significant spatial autocorrelation. The remaining spatial autocorrelation in columns 2, 4 and 5 casts doubt about the adequacy of these spatial regression models in explaining the payday loan usage in the study area. Across all four specifications, the spatial lag model in column 3 may be preferred because its residuals do not exhibit the remaining spatial autocorrelation.

A cross examination of the measures of fit and diagnostics are required to further validation of the results. The same standard rule was followed when comparing the preferred spatial lag models compared with the standard linear regression: the higher the log-likelihood, the better the fit and the lower the Akaike Information Criterion (AIC, thereafter) and Bayesian Information Criterion (BIC, thereafter), the better the fit. As shown in columns 1 and 3 of Table 2b, the log-likelihood, AIC, and BIC statistics (-1,404.52, 2,829.04, and 2,859.79) in the spatial lag model are preferred to the same statistics (-1,411.72, 2,841.44 and 2,869.12) in the standard linear regression model. These findings again imply that the spatial lag model is the best way to represent the spatial structure of payday loans among the counties of Arkansas and the two nearest counties from five surrounding states. The diagnostics for spatial autocorrelation and the evaluation of the model based on the measures of fit and specification search statistics suggest the spatial process is generated by a spatial lag model. The results of a final spatial autocorrelation test on the spatial lag model residuals using Moran's *I* are shown at the bottom of Table 2a. Since, there is no evidence of spatial dependence among these residuals (Moran's *I* =0.0089, *p-value* = 0.1340, not statistically significant), it should be concluded that the spatial lag model is the preferred specification. The queen spatial weight matrix is the most popular in the applied spatial econometrics studies. The queen of order 4 spatial weight matrix was selected as the optimal weighting scheme because it yields interesting results when compared with other schemes. The *p-value* of the likelihood ratio test also favors the queen of order 4 spatial weight matrix.

The same cross examination was conducted in the second model reported in Table 3a, which employs the within-120-miles from the borders of the two nearest counties of five states that surround Arkansas as the explanatory variable and the set of control variables. The review of the spatial autocorrelation among the residuals of the spatial lag model and the spatial error model shows the absence of spatial autocorrelation. The bottom of the columns 2 and 4 of Table 3b indicates the absence of spatial autocorrelation among the residuals of the spatial lag model (Moran's *I* = -0.0063, *p-value* = 0.3410) and the spatial error model (Moran's *I* = 0.0036, *p-value* = 0.2580), respectively. Based on these results, two competing specifications seem to fit the purpose of the study, their coefficients associated with the explanatory variables, the control variables, and the spatial lag, and error effects are statistically significant. However, it is important to note that the coefficient estimate associated with the within 120-mile threshold dummy variable in the spatial error model has a low level of significance (*p-value* = 0.079) compared with the same coefficient estimate in the spatial lag model, which is highly significant at less than 0.01 (*p-value* = 0.003). This tilts the balance in favor of the spatial lag model. Again, the standard rule applied in this study is that the higher the log-likelihood, the better the fit and the lower the AIC and BIC, the better the fit when comparing the spatial lag model and the spatial error model results. That is, a further investigation of the measures of fit suggests the log-likelihood, AIC, and BIC statistics (-1,401.37, 2,822.74 and 2,853.49) in the spatial lag model are preferred to the same statistics (-1,401.93, 2,821.86 and 2,849.53) in the spatial error model. Given the above results, the spatial lag model is the preferred model and the 90- mile threshold distance is the optimal spatial weight matrix.

DISCUSSION AND CONCLUSIONS

The main purpose of this study was to model the spatial consequences of interest cap in payday lending. Two dummy variables were introduced as the potential explanatory variables of the payday loan usage in Arkansas. These variables measure payday loan accessibility. In addition, a set of demographic and socioeconomic variables was added to this analysis as controls. Among the eight control variables, three remain statistically significant across various specifications, namely, the percent of foreign born, the percent of minority and the county population size.

From the spatial lag model reported in column 3 of Table 2a, estimates suggest that counties located within 80 miles from the Arkansas borders post higher payday loan usage rate compared with the interior counties beyond 80 miles from the Arkansas borders. Payday loan usage rate is more likely and positively associated with the population size and racial or ethnic minority population. The findings are consistent with Graves (2003), Temkin and Sawyer (2004) and Burkey and Simkins (2004) for minority population and, Damar (2009) and Prager for larger population size in Oregon 2002-2004. Furthermore, counties with more foreign born populations are likely to have lower payday loan usage rate compared to the communities with more born American citizens. It is quite interesting that the relationships for foreign-born are different, which strongly suggests that different mechanisms work in the foreign-born population. Some researchers suggest that foreign born segment of the population has lower earning capacity and lower wealth holdings and lacks familiarity with the small dollar lending industry.

In addition, the key findings in the 2011 Federal Deposit Insurance Corporation national survey of unbanked and underbanked households suggest that about 18 percent of foreign-born non-American citizens are unlikely to engage with the banking system than American born. This may discourage lenders to extend credits to some foreign born population. Results also suggest that percent of veterans, percent services occupations and percent sales and office occupations all are positively associated with higher payday loan usage rate, but not significant at the conventional levels. The row data shows a low percent of veterans, which may be the reason the coefficient associated with this variable is not statistically significant. More interestingly, in very parsimonious model specifications not reported here, each of the following variables, percent veterans, percent services occupations, percent sales and office occupations, and median household income are positively associated with higher payday loan usage across the study area. Nevertheless, the empirical results are location-specific and some sets of predictors appear to be significant based on the study area and the scale of the data.

As for the models with 120 miles as a dependent variable, results indicate that the spatial lag model is again the preferred model to the spatial lag model as shown in Table 3a because of the higher significance level and the size of the coefficient estimate associated with the explanatory variable. Also, the results of the diagnostics related to the measures of fit and spatial dependence favor the spatial lag model. However, the spatial error model has one more additional variable, percent of sales and office occupations, which is weakly significant at the conventional levels and of the expected sign. The significance of this coefficient estimate in the spatial error model, arguably, is a warning that the percent of sales and office occupations may not be significant at that level. Column 2 of Table 3a indicates that counties located within 120 miles from the Arkansas borders post higher payday loan usage rate compared with other counties within the study area.

Payday loan usage is more likely and positively associated with the population size and the racial/ethnic minority population. Again, the findings are consistent across alternative specifications. Since credit extensions and payments are made at the payday storefronts, the Amendment 89 did more harm than good to Arkansans located far from the borders and who still seek a temporary financial relief. Based on results, the spatial analysis is relevant to payday loan policy design and evaluation. Given the fact that the spatial lag model is the best fit for the data, the next research project will simulate the impact of population, median household income, and percent of minority changes on payday loan usage in Arkansas.

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