Missouri State Highway Patrol
Research and Development Division

Domestic Violence in Missouri: Examining the Impact of Individual and Contextual Factors Using Regression and Mapping Techniques

SPECIAL REPORT

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and

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INTRODUCTION

Domestic violence has existed since colonial times in the United States, although its recognition as a distinct type of offense in criminal codes did not materialize until the late 1900s. The earliest domestic violence legislation focused on assault, rape, and homicides exclusively within marital relationships, but statutes have been revised to include "parents or caretakers, dependent children, siblings, grandparents, and grandchildren" (Buzawa, Buzawa, & Stark, 2017, p. 33). The classification of violent criminal acts as "domestic" within law enforcement agencies is typically expansive. For example, domestic violence incidents as defined on the Missouri State Highway Patrol website "include any dispute arising between spouses, persons with children in common regardless of whether they reside together, persons related by blood, persons related by marriage, non-married persons currently residing together, and non-married persons who have resided together in the past" (Missouri State Highway Patrol, 2017).

Scholarly attention to the prevalence and consequences of domestic violence has grown dramatically since the 1980s (Johnson & Ferraro, 2000; Tjaden & Thoennes, 2000). Most of the academic literature focuses on either intimate partner violence (IPV) or family-related conflicts occurring inside the home. Reports from the U.S. Department of Justice indicate the rate of IPV committed against women dropped by 72% from 1994 to 2011 (Catalano, 2013). During the same time period, this rate fell 64% for men. Since 2011, IPV rates have not changed significantly (Truman & Langton, 2014, 2015; Truman & Morgan, 2016). Findings from the National Intimate Partner and Sexual Violence Survey from 2010 and 2011 showed that approximately 36% of women and 29% of men in the United States had been stalked, raped, or beaten by an intimate partner at least once during their lifetime (Black, Basile, Breiding, Smith, Walters, Merrick, Chen, & Stevens, 2011). Additionally, 14% of men and 22% of women had fallen victim during their lifetime to severe physical violence from an intimate partner such as an attack with a hard object, kicking and punching, or burning (Breiding, Smith, Basile, Walters, Chen, & Merrick, 2014).

Domestic violence poses very serious physical and psychological consequences. Campbell (2002) examined the literature on ailments stemming from IPV. She noted experiencing this kind of violence can reduce one's quality of life through chronic headaches, back pain, gastrointestinal problems, and central nervous system dysfunction resulting in seizures and loss of consciousness. Campbell also points out the most common mental health problems emanating from IPV are depression and post-traumatic stress disorder. Other psychological effects include anxiety, sleeplessness, impaired social functioning, and substance abuse disorders. Breiding, Black, and Ryan (2008) found that intimate partner victims compared to nonvictims had more problems related to breathing, physical activity, and drinking. Intimate partner victims were also more likely to possess HIV risk factors and avoid medical visits. A separate study identified that psychologically-based abuse had a more profound impact on health problems than physical abuse for both male and female victims (Coker, Davis, Arias, Desai, Sanderson, Brandt, & Smith, 2002).

The National Center for Injury Prevention and Control (2003) reported that over half a million female victims of domestic violence required medical attention for their injuries in the past year. Financial costs are obviously attached to medical treatment and the recovery process.

Arias and Corso (2005) estimated the "average cost per man victimized by a female intimate partner was $80 in mental health services and $224 in productivity losses. The average cost per man victimized by physical IPV for medical services was $83" (p. 386). For women victimized by male intimate partners, the average cost "was $207 in mental health services and $257 in productivity losses. The average cost per woman victimized by physical IPV for medical services was $483" (Arias & Corso, 2005, p. 386). Women with a history of IPV victimization have reported health care expenses almost 20% greater than those with no history (Rivera, Anderson, Fishman, Bonomi, Reid, Carrell, & Thompson, 2007). Moreover, the National Center for Injury Prevention and Control (2003) estimates that approximately 8 million days of financially compensated work time are lost by IPV victims per year.

Several in-depth scholarly research reviews have examined the damage domestic violence inflicts upon children. A meta-analytic review of over 41 studies published in peer-reviewed journals identified that children exposed to domestic abuse are more likely to suffer emotional and behavioral difficulties than other children (Wolfe, Crooks, Lee, McIntyre-Smith, & Jaffe, 2003). Kitzmann, Gaylord, Holt, and Kenny's (2003) meta-analytic review of 118 studies pulled from journal articles, book chapters, theses, and dissertations determined "63% of child witnesses [to IPV] were faring more poorly than the average child who had not been exposed to interparental violence" (p. 345). Holt, Buckley, & Whelan's (2008) literature-based review of studies from 1995-2006 found that "growing up in an abusive home environment can critically jeopardize the developmental progress and personal ability of children" which can "contribute significantly to the cycle of adversity and violence" (p. 802). Interestingly, Carrell and Hoekstra (2010) identified a potential spillover effect in their single study by finding that reading and math scores and classroom behavior were negatively affected when youths interacted with children who had been exposed to domestic violence.

Due to the wide variety of negative effects associated with domestic violence victimization, scholars have sought to identify personal and contextual factors influencing this type of offending. At the individual level, research indicates age, socio-economic status, employment status, race/ethnicity, relationship dissatisfaction, the presence of psychological syndromes (e.g. depression, posttraumatic stress disorder, borderline personality disorder, and substance abuse), prior relationship violence, witnessing parental spousal abuse, and experiencing child abuse are significantly related to male domestic violence perpetration (Aldarondo & Sugarman, 1996; Dutton, Van Ginkel, & Landolt, 1996; Holtzworth-Munroe & Smutzler, 1996; Jordan, Marmar, Fairbank, Schlenger, Kulka, Hough, & Weiss, 1992; Leonard & Senchak, 1996; Maiuro, Cahn, Vitaliano, Wagner, & Zegree, 1988; Pan, Neidig, & O'leary, 1994; Riggs, Caulfield, & Street, 2000). Compared to men arrested for domestic violence, women arrested for this crime are more likely to be younger than their partner, unemployed, have witnessed severe interparental violence, have attempted suicide, and have displayed clinical syndromes (e.g., delusional disorder, major depression, bipolar disorder, and thought disorder) and personality disorders (e.g., compulsive, histrionic, and borderline personality disorders) (Henning & Feder, 2004; Henning, Jones, & Holdford, 2003).

The academic literature also suggests contextual (or geographically-driven) factors play an important role in shaping aggregate patterns of domestic violence. For instance, Browning (2002) used neighborhood-level predictors from the Project on Human Development in Chicago

Neighborhoods (PHDCN) to examine the frequency in which women were murdered by male partners from 1994-1995. The results from this study indicated neighborhoods with a higher percentage of female residents and lower levels of collective efficacy had a higher number of intimate-partner homicides. Piquero, Brame, Fagan, and Moffitt (2006) examined domestic violence offense specialization, escalation, and de-escalation in four U.S. cities. The findings showed substantial differences across cities, such as the percentage of domestic violence specialists in Milwaukee was 23.4% compared to 4.4% in Omaha. Unfortunately, the authors did not examine whether contextual factors were capable of accounting for these differences.

Researchers have also investigated domestic violence using multilevel models that include both individual- and community-level predictors in the same model to examine individual-level outcomes. When controlling for individual-level characteristics, researchers have found that physical and sexual IPV incidents were more likely to occur in communities with a higher percentage of female-headed households, a higher percentage of residents under the age of 18, higher levels of concentrated disadvantage, lower levels of collective efficacy, higher levels of residential instability, and a stronger commitment to norms that stress non-intervention among residents (Benson, Fox, DeMaris, & Van Wyk, 2003; Benson, Wooldredge, Thistlethwaite, & Fox, 2004; Browning, 2002; Gage & Hutchinson, 2006; Jain, Buka, Subramanian, & Molnar, 2010; Lauritsen & Schaum, 2004; Wright & Benson, 2010). The findings from these studies suggest contextual variables should be incorporated when examining the occurrence of domestic violence incidents.

Despite the scholarly interest in exploring the causes of domestic violence, few empirically-grounded policies and programs exist to effectively guide efforts to prevent and reduce this crime. Battering intervention programs were promoted as a solution to spousal abuse during the 1980s but have offered few signs of success (Babcock, Green, & Robie, 2004). As part of a broader meta-analysis project, Ramsay and colleagues (2009) identified that advocacy intervention programs seeking to empower IPV victims by assisting with goal identification and community resource acquisition have generated reductions in physical abuse victimization. Interestingly, Exum, Hartman, Friday, and Lord (2014) observed benefits from a police-oriented approach to addressing domestic violence. These researchers examined the Charlotte-Mecklenburg North Carolina Police Department's domestic violence unit. This unit conducted intensive investigations of domestic violence cases and facilitated the provision of extensive services to victims, such as crisis intervention, shelter, counseling, safety planning, and help navigating the criminal justice process. Cases assigned to the domestic violence unit resulted in approximately 50% less recidivism compared to those assigned to standard patrol.

The current study addresses four research questions. First, the individual-level predictors associated with a number of arrest-based outcome measures are examined. Using data from the Missouri State Highway Patrol's Criminal History Reporting System, this study seeks to determine whether an offender's prior criminal history and demographic characteristics are influencing whether the person is rearrested for another domestic violence offense or any other form of criminal activity within five years of his or her first domestic violence arrest. Building on the research of Piquero and his colleagues (2006), this study examines whether individual-level predictors affect domestic violence specialization and escalation within five years of the initial domestic violence arrest.

Research Question #1: What are the individual-level predictors associated with the likelihood an offender was rearrested for any crime, was rearrested for another domestic violence incident, specialized in domestic violence, and escalated the severity of his or her domestic violence?

Second, this study examines the county-level predictors associated with aggregate patterns of domestic violence recidivism. In order to examine patterns in domestic violence, the individual-level recidivism variables previously discussed are aggregated to provide county-level outcome measures. Although aggregation to the block, neighborhood, and census tract levels is typically preferred over aggregation to county units, privacy considerations stemming from the nature of the available datasets made county-level aggregation necessary. Using data from the U.S. Census Bureau and governmental publications, this study investigates whether a variety of county-level contextual factors are associated with aggregated measures of recidivism.

Research Question #2: What are the contextual factors associated with county-level rearrests for any crime and domestic violence recidivism, specialization, and escalation?

Third, the distribution of domestic violence recidivism across Missouri counties is examined. Given that the Charlotte-Mecklenburg study provides evidence law enforcement can positively influence domestic violence and that this type of offense can vary considerably from place to place, identifying where domestic violence is most prominent appears to be very important. Police agencies and other government entities should benefit sizably from receiving intelligence that more efficiently guides resource utilization and distribution. In addition, informing agencies about characteristics related to domestic violence across locations should prove useful in targeting interventions to reduce its prevalence and reoccurrence. As a result, the current study employs advanced mapping technologies to demonstrate potential fluctuations in domestic violence across Missouri and over time as well as to provide more vivid descriptive information highlighting key empirical relationships.

Research Question #3: How does the distribution of rearrests for any crime, domestic violence recidivism, specialization, and escalation vary across Missouri counties?

Finally, this study examines the recidivism outcome measures using mixed effects models. In these models, both the individual- and the county-level variables are incorporated into the same model to predict the individual-level recidivism measures. The use of multilevel modeling is an appropriate strategy because offenders are nested within counties, and these models are capable of accounting for the invalid standard errors that occur when observations are not independent. The use of multilevel models will also allow for the determination of whether contextual variables are significantly related to the individual-level dependent variables, while simultaneously controlling for offender-specific characteristics.

Research Question #4: What individual- and county-level predictors are significantly associated with individual-level rearrests for any crime, domestic violence recidivism, specialization, and escalation.

METHODOLOGY

Data

The primary data source used in this study is the Criminal History Reporting System (CHRS), which is maintained by the Missouri State Highway Patrol. The CHRS repository contains information on offenders' criminal history and demographic characteristics. The first step for generating this study's dataset involved searching the CHRS for offenders who were charged and arrested for a domestic violence offense. Domestic violence is defined here as whether an offender was charged with a first, second, or third degree domestic violence offense. Domestic violence ordinance offenses are also included in our definition. Because domestic violence specific charge codes were not adopted in the state of Missouri until the turn of the new century, the search parameters were limited to the period from 2000 to 2016. The initial search of the CHRS yielded 86,114 offenders who were charged and arrested for at least one domestic violence incident during this time period. Table 1 contains the yearly number of domestic violence charges and arrests in Missouri from 2000 to 2016.

The second step for generating the final dataset involved establishing an appropriate recidivism time frame. As described above, the dependent variables used in this study examine whether offenders recidivated within five years of their first domestic violence arrest. In order to ensure all offenders were allotted five years to recidivate, only offenders who were arrested for their initial domestic violence incident between 2000 and 2010 were included in the individual-level dataset. With the exclusion of offenders who were arrested for their first domestic violence incident after 2010, the final individual-level database contains 49,814 offenders.

In addition to the individual-level information obtained from the CHRS, this study incorporates a number of variables that are measured at the county level. The data used to create these county-level predictors were drawn from the U.S. Census Bureau and governmental publications. County-level socioeconomic and demographic data were obtained by combining data from summary file 3 (SF3) of the 2000 Decennial Census, 2005-2009 American Community Survey (ACS) 5-year estimates, and 2011-2015 ACS 5-year estimates. The ACS replaced what had historically been referred to as the "long form" SF3 data, and data users must now use ACS datasets to obtain the rich set of data that was once provided by SF3 data. Data for the 2000 Decennial Census and ACS were downloaded via the *American FactFinder* website (https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml). TIGER/Line Shapefiles provide the county boundary files used for mapping and spatial analysis in Geographic Information Systems (GIS) and were downloaded from the *Missouri Spatial Data Information Service* website (http://msdis.missouri.edu/). (See Appendix A for a figure listing the locations of all Missouri counties.)

Individual-level Variables

Dependent Variables

Five individual-level recidivism variables are examined in this study. The first dependent variable, *Any Recidivism*, is designed to capture whether an offender was rearrested for any form of criminal activity after his or her first domestic violence arrest. This dummy variable is coded as *1* if an offender was rearrested for any form of criminal activity within five years of the first domestic violence arrest and *0* if the person was not rearrested for another crime. *Domestic Violence Recidivism* is a dummy variable coded as *1* if the offender was rearrested for another domestic violence offense within five years of the initial domestic violence arrest and *0* if he or she was not rearrested for this type of crime. *Number of Domestic Violence Rearrests* measures the number of rearrests for domestic violence within five years of the first domestic violence arrest. *Specialization* is coded as *1* if an offender was only rearrested for domestic violence incidents within five years of the first domestic violence arrest and the person had not been arrested for any other form of criminal activity before his or her first domestic violence arrest. Offenders who did not meet this requirement are coded as *0*. The final individual-level dependent variable, *Escalation*, is coded as *1* if an offender was rearrested for a more serious form of domestic violence within five years of his or her initial domestic violence arrest and *0* if there was no escalation.

Independent Variables

A number of individual-level variables are used to account for offenders' prior criminal history and demographic characteristics. The first set of predictors are designed to capture the frequency at which offenders were arrested for *Violent*, *Drug Sales/Distribution*, and *Drug and Alcohol* related offenses. The prior criminal history variables capture the number of times offenders were arrested for each type of criminal activity before their first domestic violence arrest.

A set of dummy variables are also included to account for offender gender and race. The gender variable is coded as *1* if the offender is a *Male* and *0* if the person is female. Three dummy variables were also used to capture whether an offender is *African American*, *Native American*, or *Asian*, with Caucasians serving as the reference group. There were five offenders with missing data for gender and 203 offenders with missing information for race.

Finally, two variables are included to account for the age of an offender at their first arrest. The first age variable captures an offender's *Age of First Domestic Violence Arrest*. The second age variable captures an offender's *Age of First Arrest* for any crime. These variables were calculated by determining the differences between the offenders' dates of birth and the dates at which they were first arrested for a domestic violence offense and any type of crime. There were two offenders with missing data for age of first domestic violent arrest and 18 with missing data for age at first arrest for any crime.

County-level Variables

Dependent Variables

Seven county-level dependent variables are examined in this study. The first outcome variable is the *Domestic Violence Charge Rate*. This variable was created by calculating the yearly number of domestic violence charges within each of the 114 counties and the city of St. Louis. The number of domestic violence charges was then divided by the total number of residents within each county and the city of St. Louis. This value was multiplied by 100,000 to create a rate. The yearly domestic violence charge rates for each county from 2000 to 2016 were then averaged to create the final measure. The second county-level dependent variable is the *Domestic Violence Arrest Rate*. Similar to the method used to construct the previous outcome measure, the number of yearly domestic violence arrests within each county and the city of St. Louis was divided by the total population and then multiplied by 100,000 to create a rate. The final variable represents the average domestic violence arrest rate in each county from 2000 to 2016. All offenders, regardless of when they were arrested for their first domestic violence incident, were included when creating both the domestic violence charge and arrest rate variables.

The remaining five county-level dependent variables represent each of the individual-level outcome measures aggregated to the county level. The *Any Recidivism*, *Domestic Violence Recidivism*, *Specialization*, and *Escalation* variables are created by calculating the *proportion* of offenders who were originally coded as *1* out of the total number of offenders within each county. Because offenders who were charged with a first degree domestic violence assault at the time of their first domestic violence arrest cannot escalate, these offenders were removed when calculating the county-level escalation variable. Finally, the *Number of Domestic Violence Rearrests* variable is calculated as the average number of times all of the offenders within each county were rearrested for a domestic violence incident. Since all the recidivism outcome measures are constructed using the final individual-level database, offenders who were not arrested for their first domestic violence incident between 2000 and 2010 were excluded when creating these county-level outcome measures. Furthermore, although offenders could be arrested for a domestic violence incident in multiple counties, only the county in which offenders were initially arrested for their first domestic violence offense was used when aggregating the individual-level outcome measures.

Independent Variables

A number of county-level variables are included in the models to account for criminal activity within jurisdictions. The *Violent Crime Rate* for each county is calculated based on the rate of homicide, robberies, and rapes per 100,000 residents. The county-level rates from 2000 to 2016 have been averaged to produce the final violent crime rate variable. Aggravated assaults were excluded when calculating the violent crime rate due to the overlap between this type of crime and domestic violence. The violent crime rate variable has been log transformed to reduce skewness. Similar to the previous variable, the *Property Crime Rate* variable consists of the average rate of these offenses within jurisdictions for the period from 2000 to 2016. Data used in the construction of both measures came from the Uniform Crime Report and the Missouri State Highway Patrol webpage (https://www.mshp.dps.missouri.gov/MSHPWeb/Root/index.html).

Additional variables are included to account for *drug and alcohol* related arrests across counties. Since the Uniform Crime Report does not publish reported instances of drug and alcohol offenses, the arrest rate for these crimes is designed to serve as a proxy measure for the frequency at which these offenses occur. The *Arrest Rate for All Drug Sales and Distribution* variable is constructed by dividing the total number of yearly arrests for all drug-related sales and distribution offenses by the total population within counties. This value was multiplied by 100,000 to produce a rate. The final variable consists of the average rate of arrests for all drug sales and distribution offenses for each county from 2000 to 2012. *Arrest Rates for the Possession of Opium and Cocaine* and their derivatives (i.e., morphine, heroin, codeine, etc.), *Possession of Marijuana*, *Possession of Synthetics* (i.e., Demerol, methadone, etc.*)*, and the *Possession of Other Substances* (i.e., barbiturates, Benzedrine, etc.) are also included in the analyses to account for drug-related offenses. Similar to the drug sales and distribution variable, yearly arrest rates for each crime were first calculated, and the final variables consist of the average rate of arrest for each type of drug-related offense from 2000 to 2012. Finally, two variables are used to examine the arrest rate for alcohol-related offenses. The *Arrest Rate for Drunkenness* and *Driving under the Influence (DUI)* are calculated using the same procedures involved with the creation of the drug-related arrest rate variables. The arrest rate for all drug sales/distribution, possession of opium and cocaine, possession of synthetics, possession of other substances, and the drunkenness variables are positively skewed; therefore, these measures have been log transformed to reduce skewness. Data for all of the arrest variables were drawn from the Uniform Crime Report.

The variables *Percentage of Population 20-54 Years of Age*, *Percentage Minority*, and the *Disadvantage Index* were created by averaging each county's estimate for that variable for the 2000 Decennial Census, 2005-2009 ACS 5-year, and 2011-2015 ACS 5-year to create a combined 2000-2016 county-level estimate for each respective variable. The *Percentage of the Population 20-54 Years of Age* represents the percent of each county's population that is 20-54 years of age. *Percentage Minority* represents the percent of each county's population that is a racial minority or Hispanic (*i.e.*, all persons except non-Hispanic whites).

The *Disadvantage Index* measures the level of socioeconomic disadvantage in each county wherein higher scores represent greater levels of disadvantage than do lower scores. The *Disadvantage Index* incorporates variables commonly found in the criminal justice and related literature to measure disadvantage: the unemployment rate, welfare rate, poverty rate, and female-headed households with kids.[1] The unemployment rate represents the percentage of the population 16+ years of age that are part of the civilian labor force but currently unemployed. The welfare rate represents the percentage of households receiving public assistance income. The poverty rate represents the percentage of the population living below the federally mandated poverty level. Female-headed households with kids represents the percentage of all families (married or unmarried) that are female-headed single parent households. The standardized value (mean of 0, variance of 1) for each variable was summed together and divided by the total number of variables in the index to create the final measure. Each variable of the index contributes equally to the final *Disadvantage Index*. The index has a Cronbach's alpha of 0.86, indicating it is a reliable (or consistent) measure of disadvantage.[2]

ANALYTIC STRATEGIES

Three sets of analyses are used to examine the key research questions associated with this study. The first set of analyses focus on the five individual-level recidivism outcome measures. These analyses are designed to capture whether offenders' prior criminal history and

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[1] Each of the four variables represents the average for the combined 2000-2016 time frame as previously detailed.
[2] We use a summative index rather than alternative methods (*e.g.*, factor analysis or principle components analysis) because of its computational simplicity and interpretation by policymakers and non-specialists.

demographic characteristics are associated with recidivism. Based on the binary nature of the *Any Recidivism*, *Domestic Violence Recidivism*, *Specialization*, and *Escalation* dependent variables, logistic regression models are used to analyze the predictors associated with these outcome measures. Odds ratios have been included in all tables that provide output for the logistic regressions. For continuous independent variables, an odds ratio can be interpreted as the expected percentage change in the odds of the dependent variable occurring with a one-unit increase in the independent variable, while holding the remaining variables in the model constant. For dichotomous variables, the odds ratio reflects the expected percentage change in the odds of the dependent variable occurring when the value of the dummy variable moves from a value of zero to one, while holding all other variables constant. If an odds ratio is greater than one, the percent change in the odds can be calculated by subtracting one from the odds ratio and then multiplying this number by 100. If the odds ratio is less than one, the percentage change in the odds can be calculated by subtracting the odds ratio from one and then multiplying this number by 100. For the count-based *Number of Domestic Violence Rearrests* variable, the results from the likelihood ratio test indicated the data for this dependent variable ($p < .001$) violated the traditional Poisson assumption; therefore, negative binomial models are estimated because this procedure allows the conditional variance to exceed the conditional mean (Long, 1997).

The second set of analyses incorporate the county-level outcome measures. These analyses are designed to examine the predictors that are associated with the seven county-level dependent variables. When the individual-level recidivism dummy variables are aggregated to the county level, these variables are expressed as the proportion of offenders within each county that recidivated. Furthermore, when the number of domestic violence rearrests variable is aggregated to the county level, this variable represents the average number of rearrests for domestic violence incidents. Since all county-level dependent variables are continuous in nature, Ordinary Least Squares (OLS) regression models are used here.

In addition to regression analyses, ArcGIS software was used to create univariate thematic maps showing the geographic distribution of the seven county-level dependent variables. To ease presentation and facilitate comparison among univariate maps, every county was rank ordered and assigned to one of five categories (quintiles) from low to high depending upon its value for any particular variable (e.g., Domestic Violence Arrest Rate). Because there are 114 counties and the city of St. Louis (or 115 county equivalents for the purposes of this study) in Missouri, this non-overlapping classification scheme assigns approximately 23 counties into each of the five categories.[3] Furthermore, while each variable is divided into five categories, the value range each category represents will vary depending on the distribution of the underlying variable. For example, the lowest quintile (i.e., 20th percentile) category for the variable *Domestic Violence Arrest Rate* represents a range of 6-38 arrests per 100,000 people; in comparison, the lowest quintile for the variable *Domestic Violence Recidivism* represents a range of 0 to 19.9%.

The *Spatial Statistic Toolbox* in ArcGIS was used to conduct a preliminary spatial analysis for each of the seven county-level dependent variables used in the OLS analysis. Specifically, ArcGIS was used to compute an index of *global* spatial autocorrelation (*Moran's I*),

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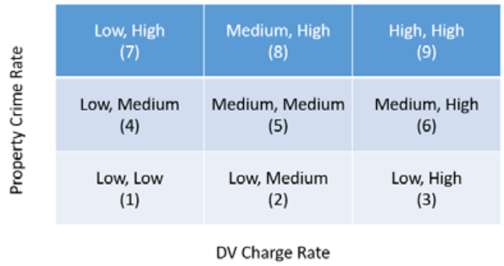
[3] Specialization was classified into three group rather than five due to the inconsistent value range for the 20th, 40th, and 60th percentiles.

which measures the extent to which the variable is correlated with itself though space.[4] The value for *Moran's I* ranges from -1.0 to +1.0 describing the extent to which a variable is dispersed or clustered throughout space. Values under 0 suggest a negative or inverse correlation of the variable throughout space (e.g., all of Missouri). For example, statewide counties with high domestic violence arrest rates tend to be located next to counties with low domestic violence arrest rates. A value of -1.0 represents a perfectly dispersed (i.e., inverse) correlation of the variable throughout space. In comparison, values greater than 0 suggest a positive or clustered correlation of the variable throughout space. For example, statewide counties with high domestic violence arrest rates tend to be located next to counties with high domestic violence arrest rates. This is the more common pattern of spatial autocorrelation with crime data. A *Moran's I* of 0 suggest a random distribution of the variable throughout space. Hence it suggests there is no relationship in the distribution of the variable throughout space, hence spatial autocorrelation is not present.

Additionally, ArcGIS was used to compute a *local* measure of spatial autocorrelation—the *Getis-Ord-Gi** statistic—for each of the seven county-level dependent variables. *Getis-Ord-Gi** identifies *localized clusters* of counties that are significantly higher or lower than expected (i.e., average) for a particular variable.[5] Unlike *Moran's I*, which provides a single *global* measure of spatial autocorrelation for all 115 Missouri counties, *Getis-Ord-Gi* provides a *local* unique measure for each county thereby facilitating the identification and mapping of significant clusters of hot or cold spots for each of the seven county-level dependent variables.

A series of bivariate choropleth maps were produced in ArcGIS to visualize the relationship between county-level dependent variables and predictor variables found to be statistically significant in the OLS analysis. In similar fashion to producing the univariate maps, for every dependent variable, each county was rank ordered and assigned to one of three mutually exclusive categories. Furthermore, for a particular predictor variable, each county was rank ordered and assigned to one of three categories depending on the county's value for that predictor variable. Each county was then "cross classified" based upon its classifications for the dependent and predictor variables. The resulting cross-classification scheme results in nine unique categories that are assigned unique colors for visual presentation. For example, each county can be classified into a low, medium, and high *Domestic Violence Charge Rate* category. Each county can also be classified into a low, medium, and high *Property Crime Rate* category. The resulting nine-category map classification legend takes the following form (please ignore color pattern):

[4] ArcGIS dataset information set to *conceptualization* = CONTIGUITY_EDGES_CORNERS, *distance method* = EUCLIDEAN, and *row standardization* = TRUE/ROW.
[5] ArcGIS dataset information set to *conceptualization* = CONTIGUITY_EDGES_CORNERS, *distance method* = EUCLIDEAN, and without FDR correction.



For example, counties found in Box 1 would evince both low *Domestic Violence Charge Rates* and low *Property Crime Rates*. Counties classified into Box 9 would show both high *Domestic Violence Charge Rates* and high *Property Crime Rates*. In comparison, counties in Box 7 are those counties categorized as having low *Domestic Violence Charge Rates* and high *Property Crime Rates*.

The final set of analyses incorporate both individual- and county-level variables into the same models. These multi-level analyses seek to determine the individual- and county-level independent variables associated with the individual-level dependent variables. Since offenders are located within counties, the nested nature of the data violates the basic assumption underlying an OLS regression. In order to account for the invalid standard errors that occur when observations are not independent, mixed effects models are estimated. This estimation procedure is appropriate because it accounts for the dependency among the observations within counties and it captures variation both within counties (Level 1) and across counties (Level 2) (Rabe-Hesketh & Skrondal, 2008). The Level 1 model includes both individual- and county-level variables to describe the likelihood of an offender recidivating. The Level 2 model incorporates a random intercept to capture variation in the recidivism measures across counties. Mixed effects logistic regression models are used with the binary dependent variables (i.e., *Any Recidivism*, *Domestic Violence Recidivism*, *Specialization*, and *Escalation)*, and a mixed effects negative binomial regression model is used with the *Number of Domestic Violence Rearrests* outcome measure.

Unless indicated otherwise, the threshold for determining statistical significance of relationships reported in the text of the results section is set at the .05 alpha level. Meeting this threshold requires 95% or greater confidence that the statistical finding is not due solely to chance. The multivariate tables provide additional information noting whether relationships reached the .01 and .001 alpha levels.

RESULTS

Individual-level Results

Table 2 contains descriptive statistics for all of the individual-level variables included in the models. According to this table, 66% of offenders were rearrested within five years of their first domestic violence arrest for any form of criminal activity (.664 x 100). Furthermore, 33% of offenders were rearrested for another domestic violence incident within five years of their first domestic violence arrest (.329 x 100), and the average number of times offenders were rearrested for a domestic violence offense within five years is .559. This table also indicates that 2% of offenders were specialists (.018 x 100), and 12% of offenders escalated within five years of their first domestic violence arrest (.123 x 100). In terms of offender demographic characteristics, Table 2 indicates that 81% of the offenders are male, 34% are African American, .3% are Asian, .2% are Native American, and 65% are Caucasian. Finally, the average age at which offenders were arrested for their first domestic violence incident is 32.77, and the average age at which offenders were arrested for any crime is 26.29. (Appendix B contains a correlation matrix that examines the bivariate relationship between all of the individual-level variables included in the models.)

Table 3 contains the multivariate results when the recidivism variables were regressed on the individual-level independent variables. Model 1 in Table 3 shows the individual-level predictors associated with the any recidivism outcome measure. The results indicate that offenders with a higher number of prior arrests for violent, drug sales and distribution, and drug- and alcohol-related offenses were more likely to be rearrested. Males were more likely to be rearrested in comparison to females. African Americans were more likely and Asians less likely to be rearrested than Caucasians. Model 1 results also show that offenders who were older at the time of their first arrest for any crime and their first arrest for a domestic violence incident were less likely to be rearrested for any crime. Odds ratio values for the statistically significant variables in Model 1 are explained here to illustrate how odds ratios are interpreted. Accordingly, for every additional prior violent arrest, one can expect the odds of an offender being rearrested for any type of crime within five years increases approximately 18% (1.18-1.0 = .18; .18 X 100 = 18). Further, for every additional drug-related, drug sales and distribution, and alcohol-related arrest, the odds of an offender being rearrested for any crime increased by 22.4%, 12.9%, and 30.7%, respectively. A one-year increase in age at first arrest was associated with a 2.4% decrease in the odds of a person being rearrested for any type of crime; similarly, as the age of an offender at first domestic violence arrest increased by one year, the odds of the person being rearrested for any type of crime decreased by 3%. The odds of a male offender being rearrested for any crime was 78.1% higher in comparison to females. Finally, the odds of rearrests for any crime were 15.6% higher for African Americans and 42.8% lower for Asian Americans in comparison to Caucasian offenders.

Model 2 in Table 3 reports the impact of individual-level variables on domestic violence recidivism. Similar to the results in Model 1, offenders with a higher number of prior arrests for violent and drug- and alcohol-related offenses were more likely to be rearrested for another domestic violence incident. The results also show that males and African Americans were more likely to be rearrested for this crime. Offenders who were older at the time of their first arrest for any crime and their first arrest for a domestic violence incident were less likely to be rearrested for another domestic violence offense.

Model 3 in Table 3 shows the individual-level predictors associated with whether or not an offender specialized in domestic violence. The prior criminal history and age of first arrest variables have been removed from this model because the definition of specialization states offenders can only be arrested for a domestic violence incident both before and within five years of their first domestic violence arrest. In contrast to the positive direction of gender and race effects in the first two models, Model 3 indicates that both males and African Americans were *less likely* to specialize in domestic violence. Unlike Model 1 and 2, age at first domestic violence arrest was not a significant predictor in Model 3.

Model 4 in Table 3 contains the results when escalation was regressed on the individual-level predictors. Since offenders who were charged with a first degree domestic violence assault at the time of their first arrest for this crime cannot escalate, these cases have been removed from the analyses. Consistent with the direction of effects in Models 1 and 2, Model 4 shows offenders with a higher number of prior arrests for violent and alcohol-based crimes and those who were male and African American escalated at greater rates. Similar to the first two models, offenders who were older at the time of their first arrest for any crime and their first arrest for a domestic violence incident were less likely to escalate.

Table 4 contains the results when the number of domestic violence rearrests was regressed on the independent variables. The results here are largely consistent with Models 1, 2, and 4 from the previous table. A higher number of domestic violence incidents were found when offenders had more prior arrests for violent and drug- and alcohol-related offenses and were male and African American. Finally, Table 4 illustrates negative relationships for age at first arrest for any crime and for a domestic violence incident; as the age decreases, the number of domestic violence rearrests increases.

County-level Results

Table 5 contains descriptive statistics for all of the county-level variables included in the models. These statistics indicate the average domestic violence charge rate across all 115 counties is 103.24, and the average domestic violence arrest rate is 96.56. Sixty-six percent of offenders across counties were rearrested within five years of their first domestic violence arrest for any form of criminal activity (.661 x 100). Furthermore, 30% of offenders across jurisdictions were rearrested for another domestic violence incident within five years of their first domestic violence arrest (.300 x 100), and the average number of times offenders within counties were rearrested within five years is .468. This table also indicates that 2% of offenders across jurisdictions were considered as specialists (.018 x 100), and 14% of offenders within counties escalated within five years of their first domestic violence arrest (.135 x 100). The remainder of this table presents descriptive statistics for all of the independent variables in the county-level analyses. (Appendix C contains information for all of these outcome measures for each county, and Appendix D contains a correlation matrix that examines the bivariate relationship between all county-level variables included in the models.)

Table 6 contains the multivariate results when the county-level outcome variables were regressed on the independent variables. Model 1 in Table 6 shows the predictors associated with county-level domestic violence charge rates. These findings indicate as violent and property crime rates increase, so does the domestic violence charge rate. The results also show as the rate of arrests for marijuana possession increases, the charge rate for domestic violence decreases. Figure 1 shows the spatial distribution of the county-level domestic violence charge rate throughout the State of Missouri. Informal visual inspection suggests *global* geographic clustering (*i.e.*, positive spatial autocorrelation) of county-level domestic violence charge rates *across* the whole state. In other words, the overall spatial pattern suggests counties with higher (or lower) domestic violence charge rates tend to be located next to one another. A statistically significant, albeit weak/moderate, global *Moran's I* (0.204, $p = 0.000$) verifies that the spatial process producing this geographic distribution is not due to an independent random process (*i.e.*, complete spatial randomness). Figure 2 presents the geographic distribution of statistically significant *local clusters* of county-level domestic charge rates. It shows two statistically significant Hot Spot clusters in the southwest and southeast portions of Missouri. These Hot Spots show a clustering of counties with comparatively "high" domestic violence charge rates. In contrast, a statistically significant Cold Spot occurs in the northwest section of Missouri. Cold Spots show a clustering of counties with comparatively "low" values for the domestic violence charge rate. Reynolds County stands alone as a statistically significant Cold Spot near the southeast section of Missouri because its domestic violence charge rate is significantly lower compared to that of the surrounding counties. Figures 3 and 4 complement Appendix D and the OLS regression findings in Model 1 of Table 6 by visualizing the (aspatial) correlation between county-level domestic violence charge rate and both the property crime and marijuana possession arrest rates.

Model 2 in Table 6 contains the results when the domestic violence arrest rate was regressed on the county-level predictors. These results indicate that counties with higher violent crime rates also have higher domestic violence arrest rates. The findings also show that as the rate of arrests for marijuana possession increases, the arrest rate for domestic violence decreases. Finally, counties with higher rates of arrests for possession of synthetics reported higher domestic violence arrest rates. Figure 5 presents the spatial distribution of the county-level domestic violence arrests rate throughout Missouri. Similar to the domestic violence charge rate, inspection of the map suggests a geographic clustering of county-level domestic violence arrest rates across the state. Again, a statistically significant *Moran's I* (0.200, $p = 0.000$) suggests the spatial process producing this pattern is not random. Examination of the Hot/Cold Spots shown in Figure 6 reveal the same pattern of Hot and Cold Spots as evinced in Figure 6. This finding is not surprising considering the relationship between domestic violence charge and arrest rates. Figures 7, 8, and 9 complement Appendix D and the OLS regression findings in Model 2 of Table 6.

Model 3 in Table 6 contains the findings when recidivism for any type of crime was regressed on the independent variables. The F-statistic for this model was not statistically significant and thereby the individual findings from the model are not interpreted. Figure 10 maps the spatial distribution of the percentage of persons rearrested for any crime. Unlike the findings for the previous county-level dependent variables rates, the *Moran's I* for any recidivism is very weak (0.068) and is not statistically significant. Therefore, one cannot reject the null hypothesis that the geographic distribution of county-level recidivism for any crime is randomly distributed. In other words, the spatial process producing the observed geographic pattern is random change (*i.e.*, complete spatial randomness). While the global *Moran's I* is not significant, Figure 11 suggests that several statistically significant local clusters exist for county-level recidivism for any type of crime. Hot Spots occur around Macon, Callaway, and Perry counties. There is a Cold Spot in southeast Missouri around Reynolds County. Additional Cold Spots exist in parts of northwest Missouri (*e.g.,* Clay County). Figures 12, 13, and 14 show maps related to property crime, arrests for drug sales and distribution, and arrests for possession of synthetics.

Model 4 in Table 6 shows the county-level predictors associated with the proportion of offenders who were rearrested for another domestic violence incident. This model indicates that counties with higher property crime rates also had a greater proportion of offenders who were rearrested for a domestic violence offense. Figure 15 shows the spatial distribution of the county-level domestic violence recidivism rate (*i.e.,* percent of persons rearrested for domestic violence). Visual inspection of the map suggests the geographic distribution of domestic violence recidivism is characterized by positive spatial autocorrelation statewide. The *Moran's I* (0.165, p = 0.003) is significant indicating the spatial process producing this pattern is not random. Figure 16 reveals several local clusters of counties having similar domestic violence recidivism rates. A seven-county Hot Spot occurs around Boone County. Two smaller Hot Spots occur around the areas of St. Genevieve and Polk Counties. Two multi-county Cold Spots are of note on the map. One multi-county Cold Spot occurs in the northwest (Holt County area) and the other in the southeast (Reynolds County area). Figure 17 complements Appendix D and the OLS regression finding in Model 4 of Table 6 by visualizing the (aspatial) correlation between the county-level property crime rate and the domestic violence recidivism rate.

Model 5 in Table 6 contains the county-level findings when the specialization variable was regressed on the independent variables. Similar to the any recidivism model, the F-statistic indicated this model was not significant and thereby the individual findings from the model are not interpreted. Figure 18 displays the county-level domestic violence specialization variable (i.e., the percent of persons rearrested only for domestic violence). The *Moran's I* (-0.053) is negative suggesting a *dispersed* spatial distribution of county-level domestic violence specialization statewide; it is not statistically significant (p = 0.439) thereby suggesting the spatial process producing the observed dispersed geographic pattern is random (*i.e.,* complete spatial randomness). Figure 19, however, points to the existence of several local Hot and Cold Spots that may characterize the clustering of county-level domestic violence specialization rates. Hot Spots occur around Pike, Scotland, and Harrison Counties. Cold Spots occur around Reynolds and Holt Counties. Figure 20 provides a visual of the (aspatial) correlation between county-level disadvantage and domestic violence specialization.

The results within Model 6 from Table 6 show the county-level predictors associated with the proportion of offenders who escalated. Similar to the individual-level analyses, offenders who were charged with a first degree domestic violence offense at their first arrest were removed when calculating the proportion of offenders who escalated at the county level. Consistent with Model 5, Model 6 indicates that as the level of disadvantage within counties increases, the proportion of offenders who escalate decreases. Figure 21 shows the spatial distribution of the county-level domestic violence escalation rate (*i.e.,* percent of persons rearrested for escalated domestic violence). Visual inspection of the map suggests the geographic distribution of domestic violence escalation is characterized by positive spatial autocorrelation. The *Moran's I* (0.169, p = 0.003) is significant suggesting the spatial process producing this pattern is not due to random chance. Figure 22 reveals several *local* clusters of counties having similar domestic violence escalation rates. A ten-county Hot Spot occurs around Boone County. Another Hot Spot occurs at St. Genevieve County. A multi-county Cold Spot occurs in the north/northwest portion of Missouri centering near Harrison County. Another Cold Spot occurs at Bates County. Figure 23 complements Appendix D and the OLS regression finding in Model 6 of Table 6 by visualizing the (aspatial) correlation between the county-level disadvantage index and domestic violence specialization.

Finally, Model 7 in Table 6 contains the county-based results when the average number of rearrests for domestic violence was regressed on all of the predictor variables. This model indicates that counties with higher property crime rates observed a larger average number of domestic violence rearrests. Figure 24 presents the spatial distribution of the county-level average number of domestic violence arrests throughout Missouri. Informal inspection of the figure suggests a *global* clustering for the county-level average number of domestic violence arrests. A statistically significant *Moran's I* (0.181, p = 0.001) indicates the spatial process producing this pattern is not random. Figure 25 presents the geographic distribution of statistically significant *local* clusters for the average number of domestic violence arrests. Three statistically significant Hot Spot clusters occur throughout Missouri in the following areas: Boone, Greene, and Jefferson. Additionally, three significant clusters of Cold Spots occur in the following areas: Atchison, Putnam, and Reynolds. Figure 26 complements Appendix D and the OLS regression finding in Model 7 of Table 6.

Multi-level Results

The final set of analyses examines the individual- and county-level independent variables that are associated with the individual-level outcome variables. Table 6 contains the results from these mixed effects models. The results from diagnostic tests indicated that there was collinearity between the total population, the property crime, and the violent crime variables, which created unstable coefficient estimates. In order to address this issue, the violent crime rate and the total population variables have been dropped from the multilevel models.[6]

Model 1 in Table 7 contains the results when recidivism for any type of crime was regressed on the county- and individual-level predictors. The county-level findings from Model 1 indicate offenders were more likely to recidivate for committing any crime when they were located in counties with higher property crime rates, higher arrest rates for drug sales and distribution, larger percentages of residents between the ages of 20 to 54, smaller percentages of minority residents, and lower arrest rates for DUI and possession of other substances. The individual-level results from Model 1 demonstrate that the offenders were at greater risk of recidivating for any type of crime when they had a larger number of prior arrests for violent, drug sales and distribution, and drug- and alcohol-related offenses and were male or African American. Asians and those offenders who were older at the time of their first arrest for any crime and their first arrest for domestic violence were less likely to be rearrested for committing any type of crime.

Model 2 in Table 7 examines the county- and individual-level predictors associated with whether an offender was rearrested for another domestic violence offense. The county-level property crime rate, the percentage of residents age 20 to 54, the percentage of minority residents, the arrest rate for possession of other substances, and the arrest rate for DUI were all significant predictors and in the same directions as in Model 1. The results for the individual-level predictors were also quite similar to Model 1. Offenders were more likely to recommit domestic violence when they had more prior arrests for violent and drug- and alcohol-related

[6]Based on the results from the diagnostic tests that indicated collinearity between the property crime, the violent crime, and the total population variables, additional models were estimated to determine which variable(s) to remove from the final analyses. In these models, each predictor was individually entered into the analyses one at a time. The results from these models indicated that the violent crime rate and the total population variables were not significantly related to any of the dependent variables in the mixed effects analyses. Therefore, both of these variables were removed from the models presented in Tables 7 and 8.

offenses, were male or African American, and were younger at the time of their first arrest for committing any crime and their first arrest for domestic violence.

Models 3 and 4 in Table 7 report results for the mixed effects models with specialization and escalation as outcomes, respectively. The county-level effects in these models diverge noticeably from the pattern observed in Models 1 and 2. Offenders were more likely to specialize in domestic violence when located in counties with lower arrests rates for drunkenness and drug sales and distribution and higher arrest rates for other drug possession. Interestingly, the only county-level variable to significantly affect escalation was arrest rate for other drug possession, but in an opposite direction from its influence on specialization; offenders located in areas with higher arrest rates for other drug possession were actually less likely to escalate. The odds of specialization were lower for males and African Americans and higher for Asians. The individual-level predictors of escalation resembled quite closely those identified in Models 1 and 2. Offenders were at greater risk of escalation when they had more prior arrests for crimes related to violence and alcohol, were male or African American, and were younger when first committing any type of crime and first engaging in domestic violence.

Table 8 shows the results when the number of rearrests for domestic violence was regressed on the individual- and county-level predictors. The county level predictors in this model were the same as for Model 2 in Table 7 where domestic violence recidivism was analyzed. According to Table 8, offenders had more rearrests for domestic violence when they were located in counties with higher property crime rates, larger percentages of residents between the ages of 20 to 54, fewer minority residents, and lower arrest rates for DUI and other drug possession. Domestic violence rearrests were more numerous when offenders had more prior arrests related to violent, drug, and alcohol offending and were male or African American. Rearrests for domestic violence were fewer for Asians and those who were older at their first arrest for any type of crime and for domestic violence.

DISCUSSION

Domestic violence is a social problem that can pose serious debilitating effects to children, families, neighborhoods, and broader communities. Unfortunately, empirical literature examining the underlying causes of domestic violence and the effectiveness of prevention-based policies and interventions is underdeveloped. The current research project aimed to combine and analyze existing databases from multiple government agencies covering approximately 16 years in an effort to better understand the extent and drivers of this crime at a state level. In particular, the study examined domestic violence charge and arrest rates as well as various measures of recidivism. The impacts of both county- and individual-level factors were explored to explain variation across locations and among individuals.

Perhaps the most obvious takeaway from this study is confirmation of past results indicating that domestic violence activity and recidivism vary from place to place. Piquero and his colleagues (2006) had observed variation in domestic violence offense specialization, escalation, and de-escalation across four U.S. cities. A review of Appendix C illustrates noticeable variation in all charge, arrest, and recidivism measures, except for specialization. State and local agencies can utilize this information to examine how different counties compare on outcome measures of interest.

A second important takeaway is that advanced mapping technology was utilized to identify specific hot and cold spots for domestic violence charges, arrests, and recidivism across the state. This information should prove useful to inform agency-level discussions about the most efficient distribution of state resources to combat domestic violence. Based on the results, distributing resources evenly statewide may not be the most successful strategy. This report also provides maps that offer observers the opportunity to examine locations where specific county-level characteristics are corresponding with varying degrees of domestic violence activity and recidivism.

A third important observation is that regardless of location, a very small proportion of Missouri offenders are specializing in domestic violence. Rather, offenders who commit domestic violence are almost always engaging in other types of criminal activities. This finding has implications for programmatic approaches, suggesting initiatives targeting domestic violence should be holistic in design and address a broad range of criminal behaviors and criminogenic needs.

A fourth key observation is that little consistency was observed for statistically significant county-level predictors across the county-level outcome models. Property crime had the most frequent impact. As expected, higher property crime rates were connected with higher domestic violence charge rates, greater proportions of recidivists committing any type of crime and domestic violence specifically, and higher average numbers of domestic violence crimes per offender. Somewhat surprisingly, the county violent crime rate only had an appreciable effect in two models.

Importantly, a counterintuitive result was found in the county-level analysis. Counties with lower arrest rates for marijuana possession had higher domestic violence charge and arrest rates. This finding might indicate that differing enforcement priorities across jurisdictions are affecting arrest practices. That is, law enforcement manpower and resources may be more limited to target and making arrests for marijuana-related crimes in areas where domestic violence receives greater enforcement emphasis, or vice versa.

Another interesting and unexpected result was that counties where residents experienced greater social disadvantage had smaller proportions of offenders who escalated their domestic crimes. The reason for this escalation finding may stem from data manipulation necessary to examine this outcome. Those offenders with first degree (the most serious) assaults were removed from the escalation analysis because, by legal definition, they could not escalate. However, the excluded offenders may have been those most likely to actually increase the severity of their actions.

Caution must be taken when comparing the findings for the county-level variables in the aggregated outcome analyses to the results from the multi-level models. The primary difference between these analyses is that the multilevel models include county-level predictors to explain individual-level behavior, whereas the county-level analyses seek to determine the contextual factors associated with aggregate behavior. Furthermore, the statistical procedures for these two types of analyses are different. For instance, the county-level analyses examine the relationship between the predictors and the continuous outcome measures using OLS regression models. However, the multi-level models examine the relationship between the predictors and the individual-level recidivism measures using logistic and negative binomial models. The decision to map the county-level relationships was guided in large part by OLS model results and the correlation matrix. Unfortunately, we are not aware of a method for directly mapping the relationships between variables in a multi-level model.

In contrast to the fluctuations observed in the county-level analysis, significant predictors were largely consistent across the individual-level models, with the exception of the specialization model. Notably, these individual-level findings were supported even when county-level factors were controlled as part of the multilevel models. The first consistent set of results was that offenders who had more extensive records of violence and alcohol-related offending were more likely to recidivate. This confirms what is generally known about offenders and supports the use of assessment procedures which commonly incorporate criminal history to predict risk of reoffending. Second, those who were younger at the time of their first arrests (for any crime or domestic assault) had more unfavorable recidivism outcomes. These results support the theory that early flirtations with criminal behavior and entry into the justice system can generate a hardening effect, resulting in more frequent and severe offending. Finally, males and African Americans were more likely to be recidivists than females and Caucasians. These findings make sense given that males and African Americans commit a greater proportion of domestic assault than females and Caucasians.

The individual-level model for specialization showed that males and African Americans were less likely to specialize, age of first arrest for domestic assault had no impact, and past criminal record and age at first arrest for any type of crime had to be excluded for definitional reasons. Although considerable attention could be directed at explaining why the specialization model defies the others, the more important point here is to re-emphasize that specialists are a very small percentage of domestic violence offenders. As a result, attempting to unravel the reasons behind the unique specialization models offers little practical benefit.

A few important limitations of this research should be noted. First and perhaps most important, the contextual variables for this study are measured by county characteristics. Counties are aggregates that include many sublevels, such as individuals who are nested in street blocks, street blocks that are nested in neighborhoods, and neighborhoods that are nested in towns and cities. Tremendous variation can exist in characteristics within and across these sublevels. Ultimately, all of this variation was aggregated at the county level due to privacy concerns. Wherever possible, future analyses should examine the aggregated variables utilized in this study at more basic levels to receive a clearer picture of their impact on domestic violence charges, arrests, and recidivism.

Another limitation is the reliance on arrest data as a proxy measure for crime. The collection of arrest data can be influenced by differences in agency enforcement and recording practices. Depending on the circumstances, police officers can possess substantial discretion when making a decision to arrest someone for domestic violence. Law enforcement agencies may also encourage or discourage arrests based on court backlog, the availability of jail space, and priorities given to grant-funded initiatives. In addition, agency capacity for maintaining and reporting arrest data may vary by jurisdiction and affect the accuracy of arrest statistics. Moreover, the underreporting of domestic violence by victims and witnesses is a well-established phenomenon. If variation exists in rates of resident reporting across locations, this will ultimately affect the value of arrest as an indicator of the actual number of crimes committed.

Given that data was analyzed over an approximately 16-year period, caution also should be exercised in generalizing the reported findings to the present. Significant changes in recent years might affect the relationships observed over this multi-year period. However, the value of looking at data over time is that the findings are less likely to be influenced by chance and irregular events and circumstances.

In all, the current research project sheds light on the extent and possible drivers of domestic violence in Missouri. Throughout the project, data sets have been merged which will enable subsequent analyses of domestic violence in this state. The project also provides a foundation for establishing a viable researcher-practitioner partnership and examining other types of crimes in a similar fashion, such as homicide, rape, burglary and theft.

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TABLES AND FIGURES

Table 1: The Number of Domestic Violence Charges and Arrests, 2000-2016

Year	Total Number of Charges	Total Number of Arrests
2000	1,128	1,041
2001	4,456	3,903
2002	5,584	5,010
2003	6,409	5,747
2004	7,055	6,540
2005	7,779	7,194
2006	8,786	8,120
2007	9,601	8,834
2008	9,823	8,978
2009	10,575	9,618
2010	11,357	10,721
2011	11,900	10,721
2012	11,345	10,246
2013	11,691	10,574
2014	12,467	11,207
2015	12,395	11,328
2016	12,551	11,496

Table 2: Description of Individual-level Variables in Models

Variables	N	Mean/Proportion	Standard Deviation	Min	Max
1 if any recidivism	49,814	.664	.472	.000	1.000
1 if domestic violence recidivism	49,814	.329	.470	.000	1.000
Number of domestic violence rearrests	49,814	.559	1.053	.000	24.000
1 if specialization	49,814	.018	.132	.000	1.000
1 if escalation	49,814	.123	.328	.000	1.000
Number of prior violent arrests	49,814	.937	2.306	.000	49.000
Number of prior arrests for drug-related offenses	49,814	.640	1.654	.000	40.000
Number of prior arrests for drug sales and distribution	49,814	.153	.569	.000	9.000
Number of prior arrests for alcohol-related offenses	49,814	.330	.887	.000	14.000
1 if Male	49,809	.805	.396	.000	1.000
1 if African American	49,611	.342	.474	.000	1.000
1 if Asian	49,611	.003	.058	.000	1.000
1 if Native American	49,611	.002	.039	.000	1.000
Age of first domestic violence arrest	49,812	32.770	10.593	12.880	95.360
Age of first arrest	49,796	26.288	9.842	10.180	95.360

Table 3: Individual-level Logistic Regression Models

	Model 1 (Any Recidivism)			Model 2 (DV Recidivism)			Model 3 (Specialization)		
	β	**SE**	**Exp(B)**	***β***	**SE**	**Exp(B)**	***β***	**SE**	**Exp(B)**
Number of prior violent arrests	.166***	.008	1.180	.076***	.005	1.078	-	-	-
Number of prior arrests for drug-related offenses	.202***	.011	1.224	.047***	.006	1.048	-	-	-
Number of prior arrests for drug sales and distribution	.122***	.025	1.129	.024	.018	1.024	-	-	-
Number of prior arrests for alcohol-related offenses	.268***	.015	1.307	.121***	.011	1.128	-	-	-
1 if male	.577***	.025	1.781	.666***	.028	1.946	-.273**	.080	.761
1 if African American	.145***	.023	1.156	.193***	.022	1.213	-.465***	.079	.628
1 if Asian	-.559**	.165	.572	-.345	.196	.709	.748	.388	2.114
1 if Native American	.362	.260	1.436	.315	.247	1.370	.694	.591	2.002
Age of first domestic violence arrest	-.031***	.001	.970	-.017***	.001	.983	.001	.003	1.001
Age of first arrest	-.024***	.002	.976	-.016***	.002	.984	-	-	-
Constant	1.543	.040		-.535	.043		-3.700	.127	
N	49,590			49,590			49,607		
Nagelkerke R^2	.169			.073			.007		

*p < .05; **p < .01; ***p < .001

Table 3: Individual-level Logistic Regression Models Cont.

	Model 4 (Escalation)		
	β	**SE**	**Exp(B)**
Number of prior violent arrests	.054***	.005	1.055
Number of prior arrests for drug-related offenses	.015	.008	1.015
Number of prior arrests for drug sales and distribution	.016	.024	1.016
Number of prior arrests for alcohol-related offenses	.075***	.015	1.078
1 if male	.552***	.044	1.737
1 if African American	.245***	.031	1.277
1 if Asian	-.163	.294	.850
1 if Native American	.549	.314	1.731
Age of first domestic violence arrest	-.010***	.002	.990
Age of first arrest	-.022***	.002	.978
Constant	-1.626	.066	
N	43,761		
Nagelkerke R^2	.040		

*p < .05; **p < .01; ***p < .001

Table 4: Individual-level Negative Binomial Regression Model

	(Number DV Recidivism)	
	β	**SE**
Number of prior violent arrests	.058***	.004
Number of prior arrests for drug-related offenses	.038***	.005
Number of prior arrests for drug sales and distribution	.005	.014
Number of prior arrests for alcohol-related offenses	.113***	.009
1 if male	.632***	.024
1 if African American	.190****	.018
1 if Asian	-.533**	.183
1 if Native American	.306	.198
Age of first domestic violence arrest	-.016***	.001
Age of first arrest	-.012***	.001
Constant	-.540	.037
N	49,590	
McFadden's R^2	.028	

*p < .05; **p < .01; ***p < .001

Table 5: Description of County-level Variables in Models (N = 115)

Variables	Mean/Proportion	Standard Deviation	Min	Max
Domestic violence charge rate	103.236	77.971	6.270	506.300
Domestic violence arrest rate	96.563	72.002	6.270	498.150
Proportion of offenders who recidivated within five years	.661	.113	.330	1.000
Proportion of offenders with a domestic violence arrest within five years	.300	.114	.000	.600
Average number of domestic violence rearrests within five years	.468	.224	.000	1.120
Proportion of offenders who specialized within five years	.018	.022	.000	.110
Proportion of offenders who escalated within five years	.135	.079	.000	.330
Log population	9.995	1.079	7.710	13.820
Ln violent crime rate (No Aggravated)	3.442	.793	1.570	6.710
Property crime rate	2152.869	1316.240	597.970	9463.160
Percentage of population 20-54	44.603	3.792	34.540	55.400
Disadvantage Index	.000	.842	-1.600	3.360
Percentage Minority	7.984	7.568	1.750	56.400
Ln arrest rate for drug sales and distribution	4.343	.570	2.890	6.290
Ln arrest rate for cocaine and opium possession	2.336	2.375	-13.820	5.860
Arrest rate for marijuana possession	269.904	127.540	9.690	821.230
Ln arrest rate for synthetic possession	3.652	.652	2.070	5.660
Ln arrest rate for other possession	3.700	.779	1.120	6.440
Ln arrest rate for Drunkenness	2.153	1.156	-.110	5.570
Arrest rate for DUI	494.362	161.010	173.950	1210.350

Table 6: County-level OLS Regression Models Cont. (N = 115)

	Model 1 (DV Charge Rate)			Model 2 (DV Arrest Rate)			Model 3 (Any Recidivism)		
	b	**SE**	**Beta**	***b***	**SE**	**Beta**	***b***	**SE**	**Beta**
Log population	5.231	7.356	.072	8.619	7.090	.129	.009	.015	.084
Ln violent crime rate (No Aggravated)	28.238*	12.872	.287	27.386*	12.406	.302	-.043	.027	-.302
Property crime rate†	.018*	.008	.303	.013	.007	.236	.004*	.002	.463
Percentage of population 20-54	1.579	1.992	.077	1.505	1.920	.079	.004	.004	.135
Disadvantage Index	4.341	8.885	.047	6.699	8.563	.078	.009	.019	.068
Percentage Minority	-.796	1.058	-.077	-.867	1.020	-.091	-.002	.002	-.139
Ln arrest rate for drug sales and distribution	10.353	12.640	.076	5.987	12.182	.047	.071**	.026	.356
Ln arrest rate for cocaine and opium possession†	1.962	2.642	.060	2.543	2.546	.084	-.023	.550	-.004
Arrest rate for marijuana possession†	-.136**	.047	-.223	-.139**	.045	-.247	.004	.010	.041
Ln arrest rate for synthetic possession	18.655	10.176	.156	21.359*	9.808	.193	-.047*	.021	-.269
Ln arrest rate for other possession	-2.318	8.431	-.023	-2.431	8.126	-.026	-.025	.018	-.174
Ln arrest rate for Drunkenness	5.462	4.589	.081	4.386	4.423	.070	.008	.010	.084
Arrest rate for DUI	.068	.041	.139	.058	.039	.130	-.005	.009	-.074
Constant	-266.462	85.084		-273.338	82.004		.428	.177	
R^2	.599			.563			.173		

*p < .05; **p < .01; ***p < .001

†The coefficients and standard errors are multiplied by 100 in the Any Recidivism model.

Table 6: County-level OLS Regression Models Cont. (N = 115)

	Model 4 DV Recidivism			Model 5 (Specialization)			Model 6 Escalation		
	b	**SE**	**Beta**	***b***	**SE**	**Beta**	***b***	**SE**	**Beta**
Log population	.019	.015	.180	.001	.003	.045	.002	.011	.022
Ln violent crime rate (No Aggravated)	-.038	.026	-.268	-.002	.005	-.061	.003	.018	.030
Property crime rate†	.004**	.002	.507	.001	.003	.103	.009	.001	.154
Percentage of population 20-54	.004	.004	.121	-.001	.001	-.091	.002	.003	.099
Disadvantage Index	.007	.018	.001	-.007*	.004	-.279	-.030*	.127	-.319
Percentage Minority	-.003	.002	-.189	-.000	.000	-.007	-.000	.002	-.012
Ln arrest rate for drug sales and distribution	.048	.026	.242	.004	.005	.100	.033	.018	.241
Ln arrest rate for cocaine and opium possession†	.007	.005	.138	-.002	.001	-.209	.003	.004	.099
Arrest rate for marijuana possession†	-.008	.010	-.090	.009	.002	-.053	-.001	.007	-.020
Ln arrest rate for synthetic possession	-.031	.021	-.176	-.003	.004	-.099	.008	.015	.062
Ln arrest rate for other possession	-.030	.017	-.209	-.001	.003	-.032	-.017	.012	-.167
Ln arrest rate for Drunkenness	-.002	.009	-.025	-.001	.002	-.044	-.011	.007	-.161
Arrest rate for DUI†	-.008	.009	-.113	.001	.002	.078	-.007	.006	-.137
Constant	.075	.174		.037	.035		-.058	.122	
R^2	.208			.126			.183		

*p < .05; **p < .01; ***p < .001
†The coefficients and standard errors are multiplied by 100.

Table 6: County-level OLS Regression Models Cont. (N = 115)

	Model 7 (Number DV Recidivism)		
	b	**SE**	**Beta**
Log population	.031	.029	.149
Ln violent crime rate (No Aggravated)	-.062	.051	-.218
Property crime rate†	.010**	.003	.566
Percentage of population 20-54	.011	.008	.192
Disadvantage Index	.010	.035	.036
Percentage Minority	-.007	.004	-.233
Ln arrest rate for drug sales and distribution	.069	.050	.176
Ln arrest rate for cocaine and opium possession†	.012	.011	.123
Arrest rate for marijuana possession†	-.028	.019	-.161
Ln arrest rate for synthetic possession	-.028	.040	-.081
Ln arrest rate for other possession	-.040	.033	-.140
Ln arrest rate for Drunkenness	-.015	.018	-.078
Arrest rate for DUI	-.022	.016	-.160
Constant	-.149	.338	
R^2	.236		

*p < .05; **p < .01; ***p < .001
†The coefficients and standard errors are multiplied by 100.

Figure 1. Univariate Map – Domestic Violence Charge Rate

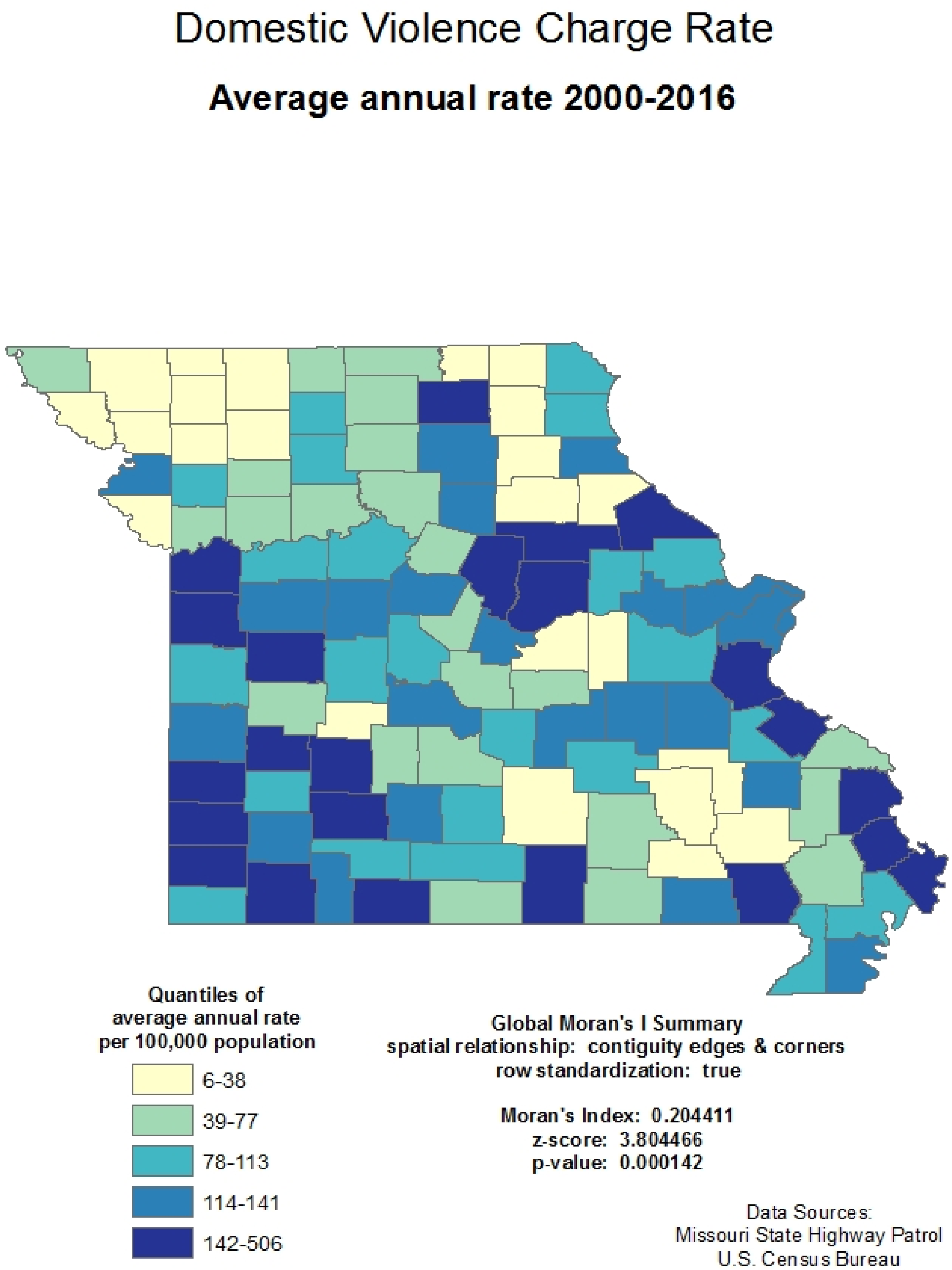


Figure 2. Hot Spot Map – Domestic Violence Charge Rate

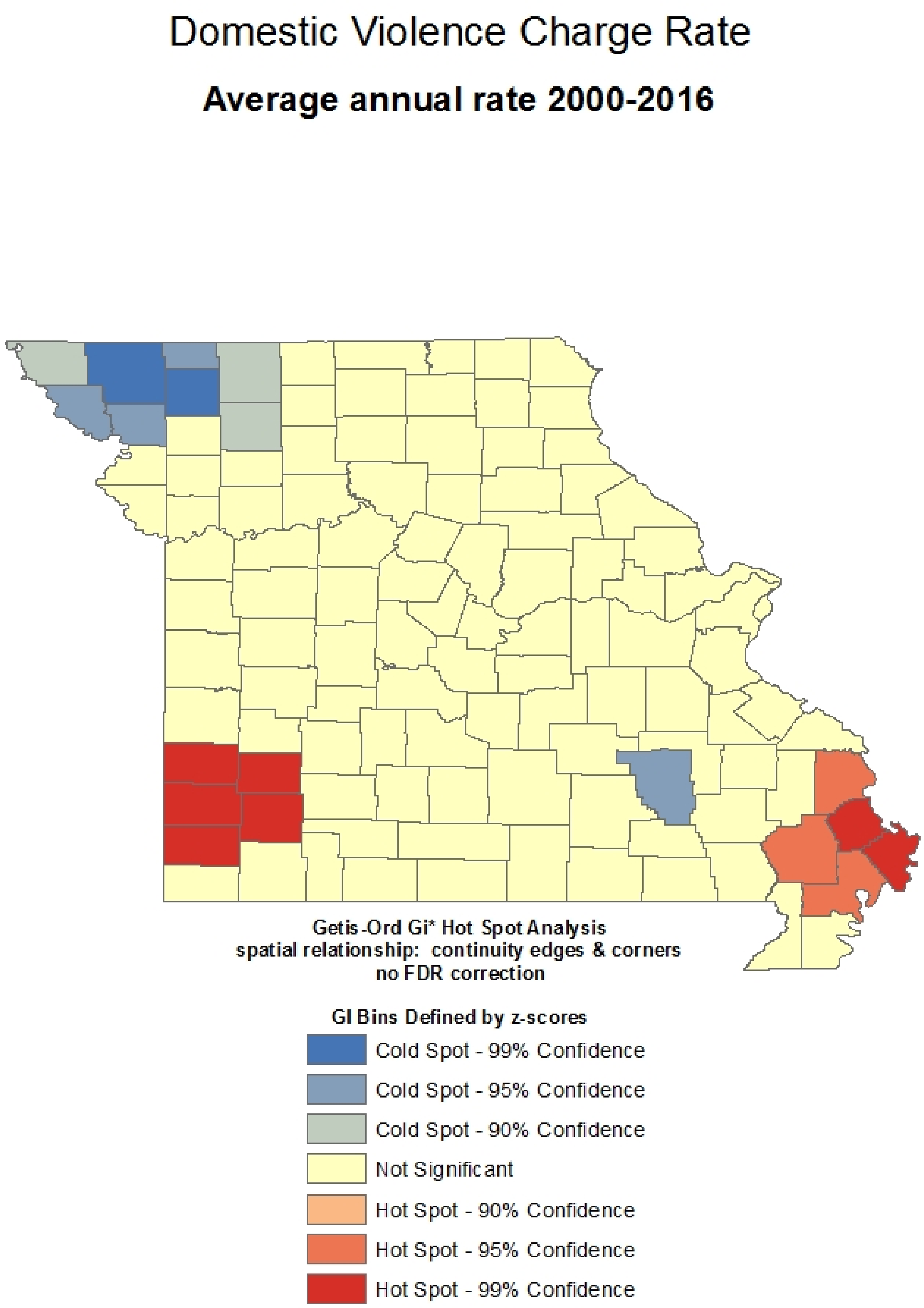


Figure 3. Bivariate Map – Property Crime Rate by DV Charge Rate

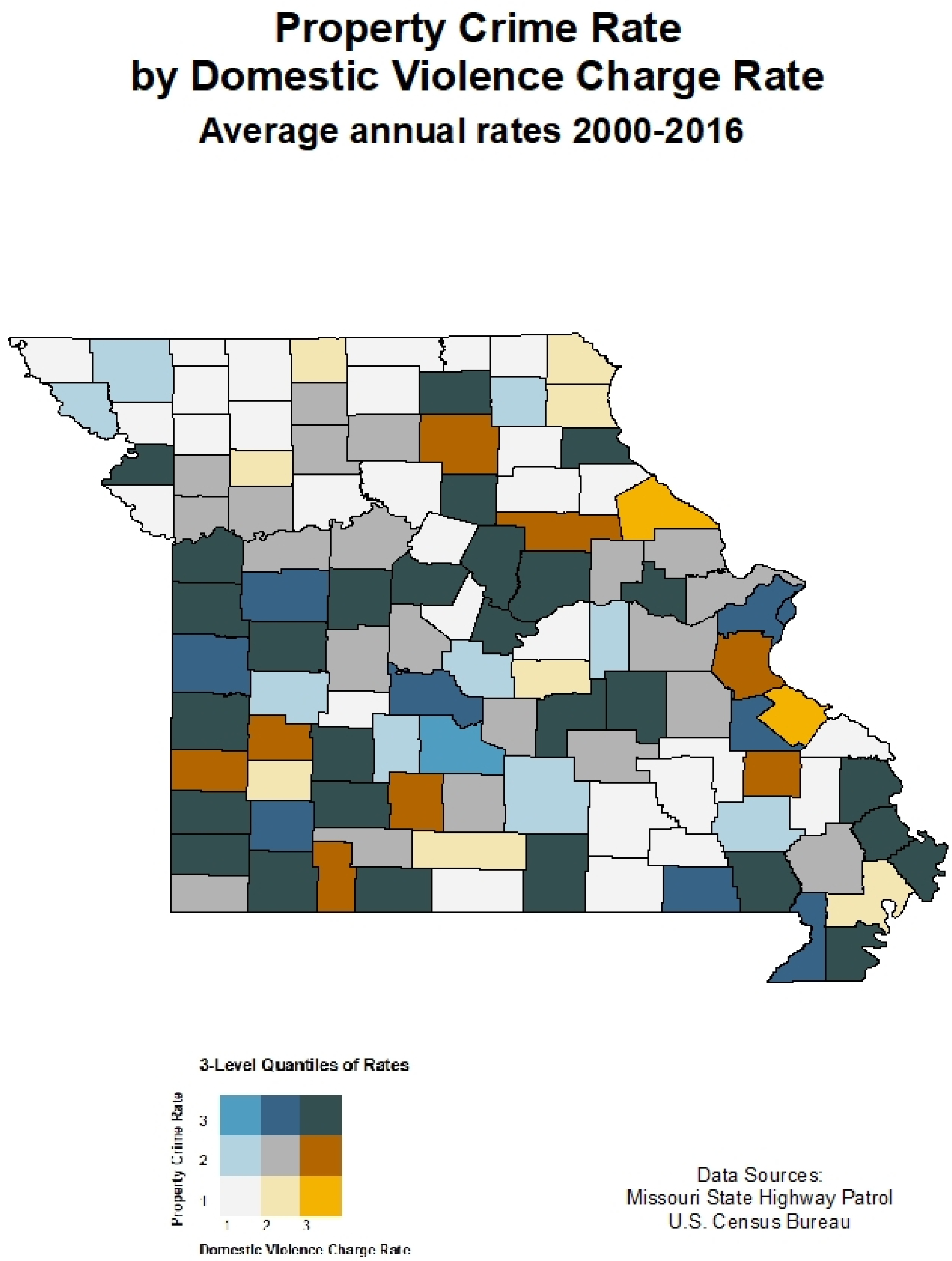


Figure 4. Bivariate Map – Marijuana Possession Arrest Rate by DV Charge Rate

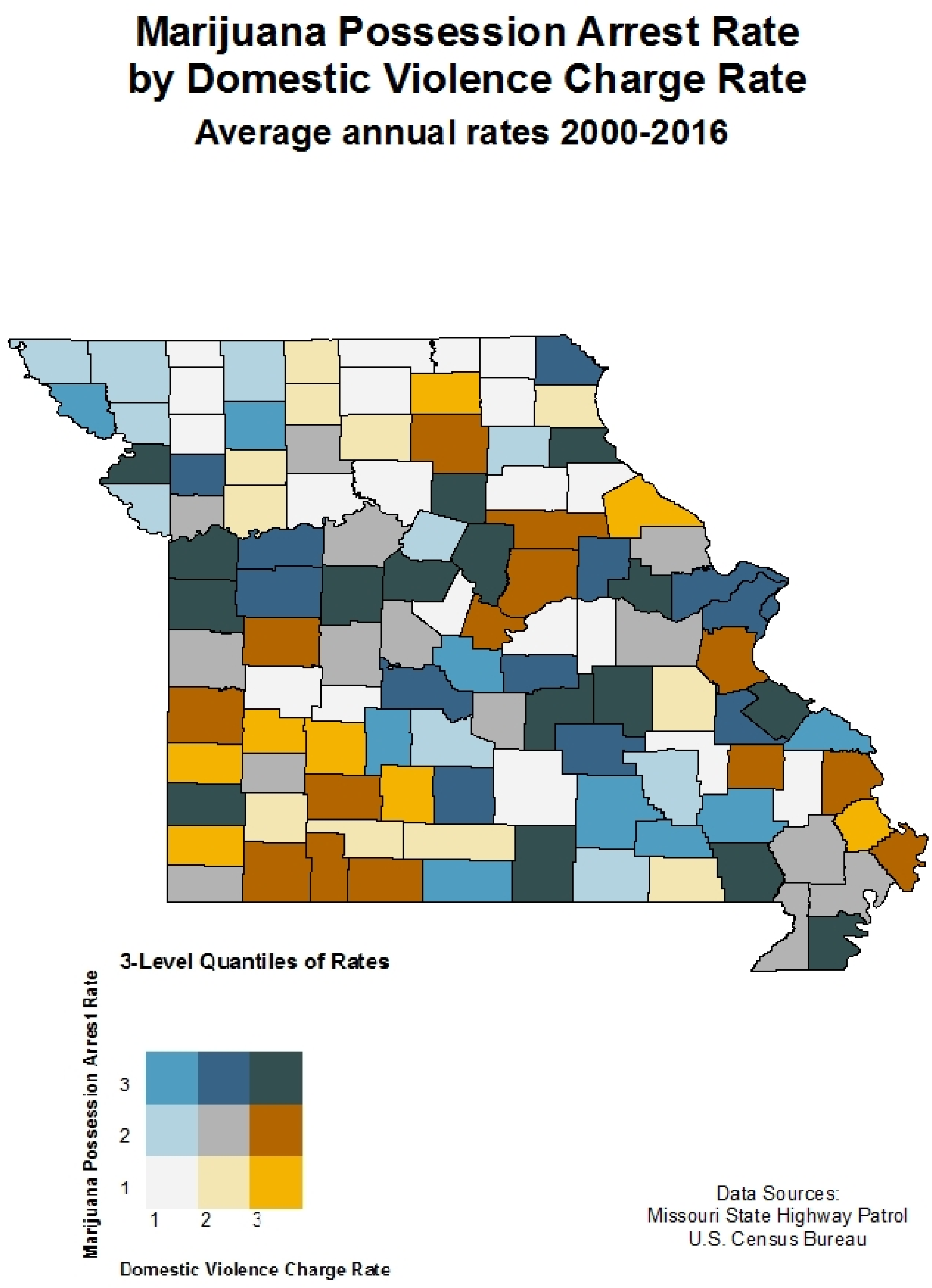


Figure 5. Univariate Map – Domestic Violence Arrest Rate

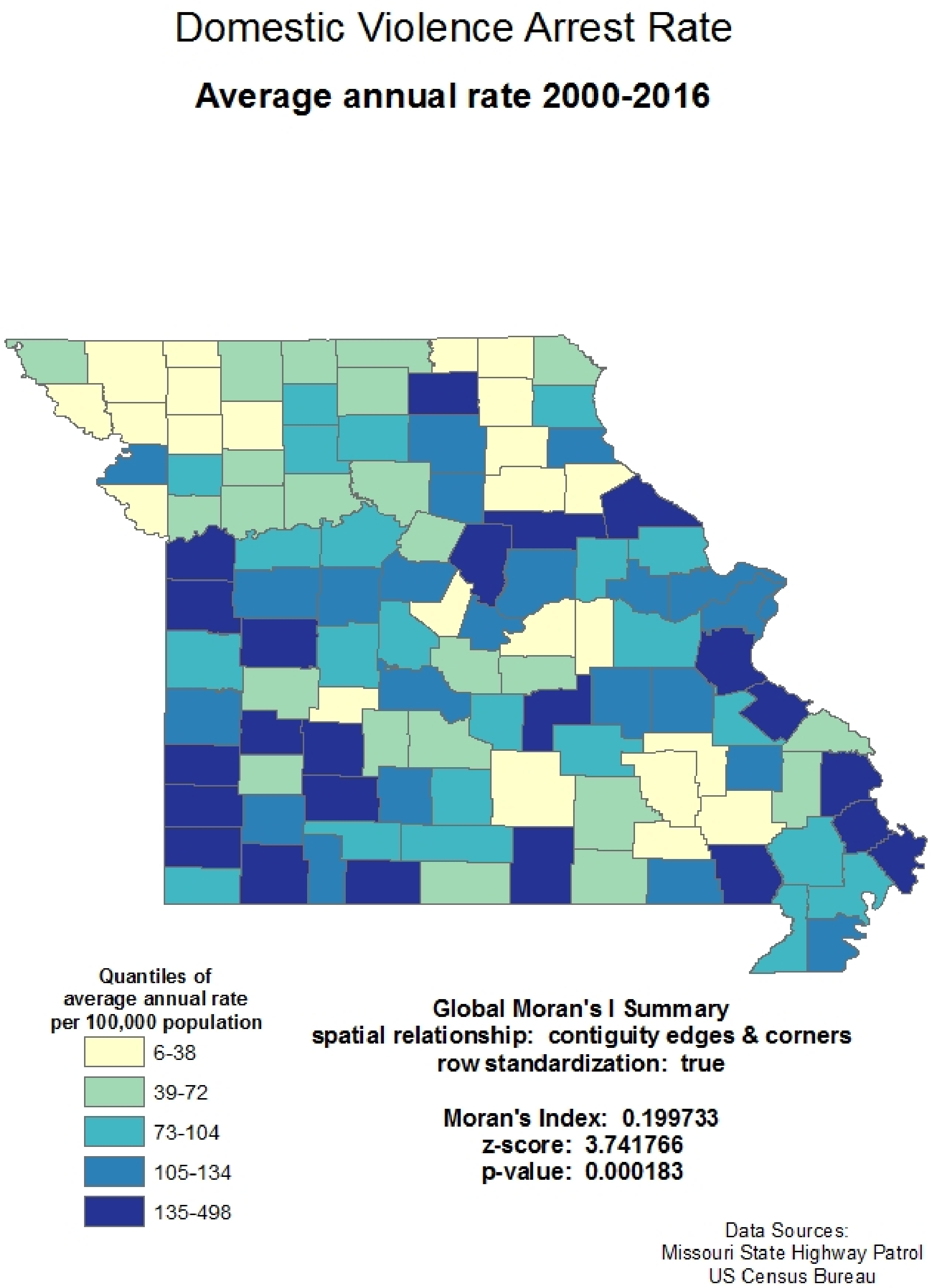


Figure 6. Hot Spot Map – Domestic Violence Arrest Rate

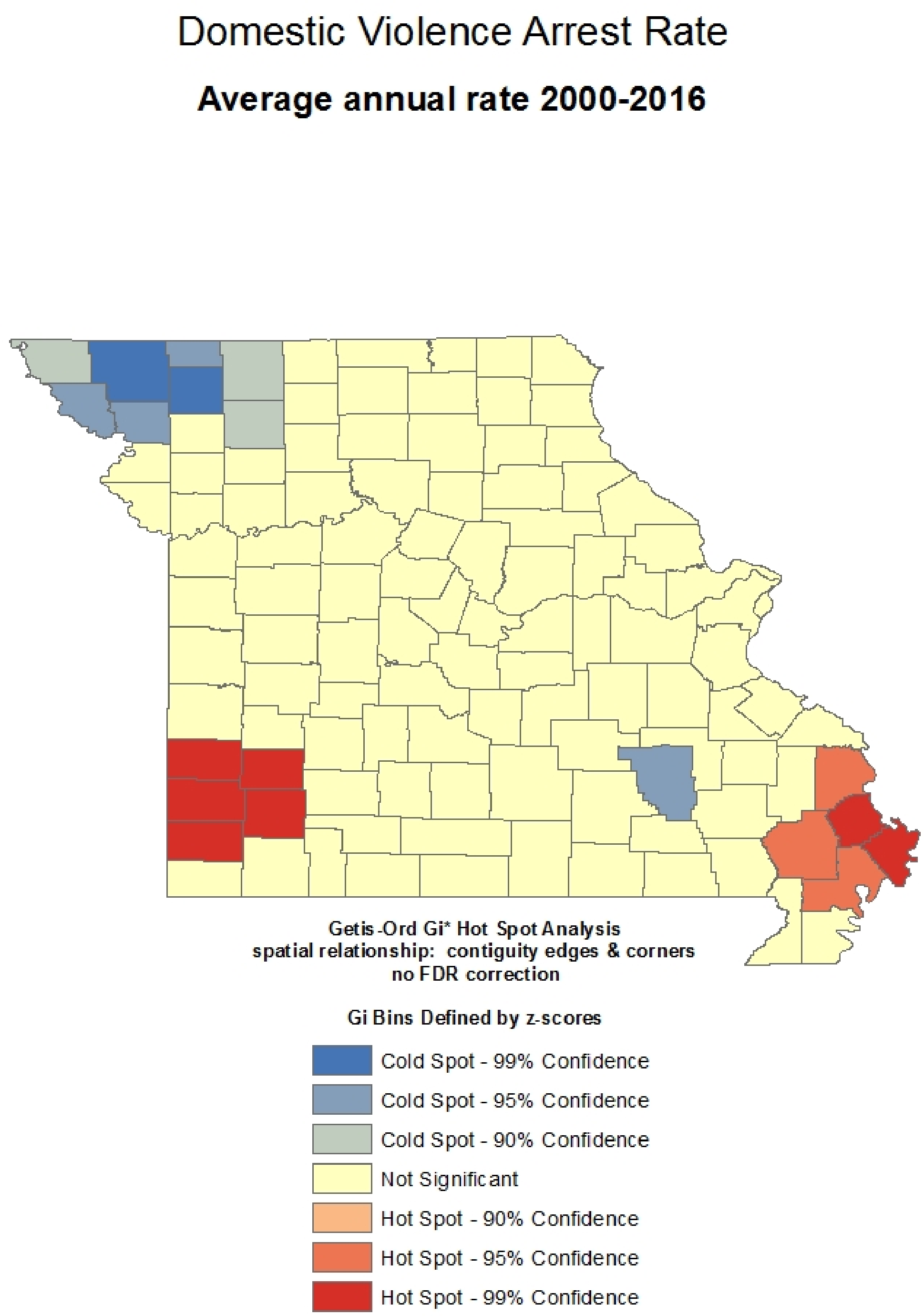


Figure 7. Bivariate Map – Non-Aggravated Violent Crime Rate by DV Arrest Rate

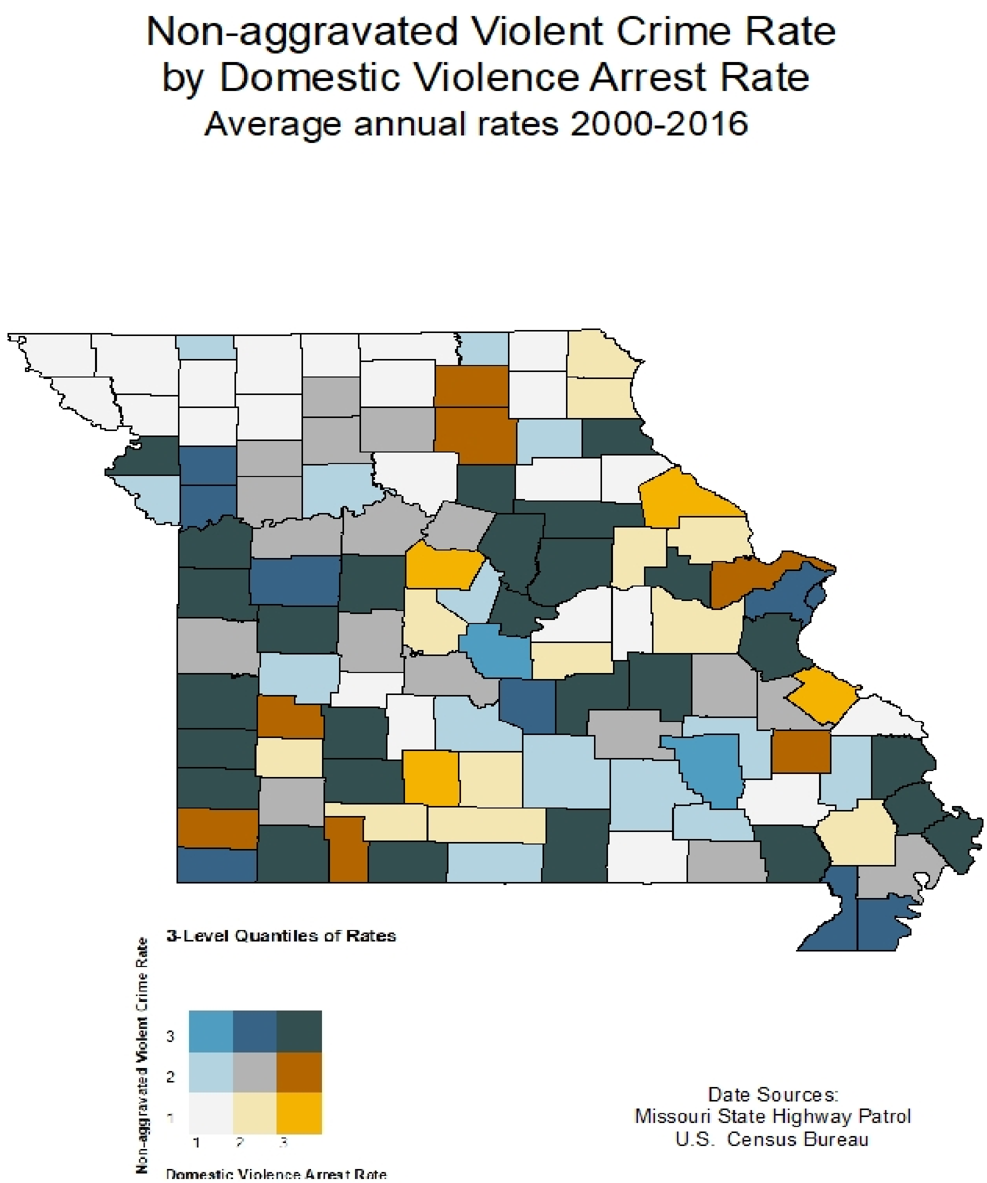


Figure 8. Bivariate Map – Marijuana Possession Arrest Rate by DV Arrest Rate

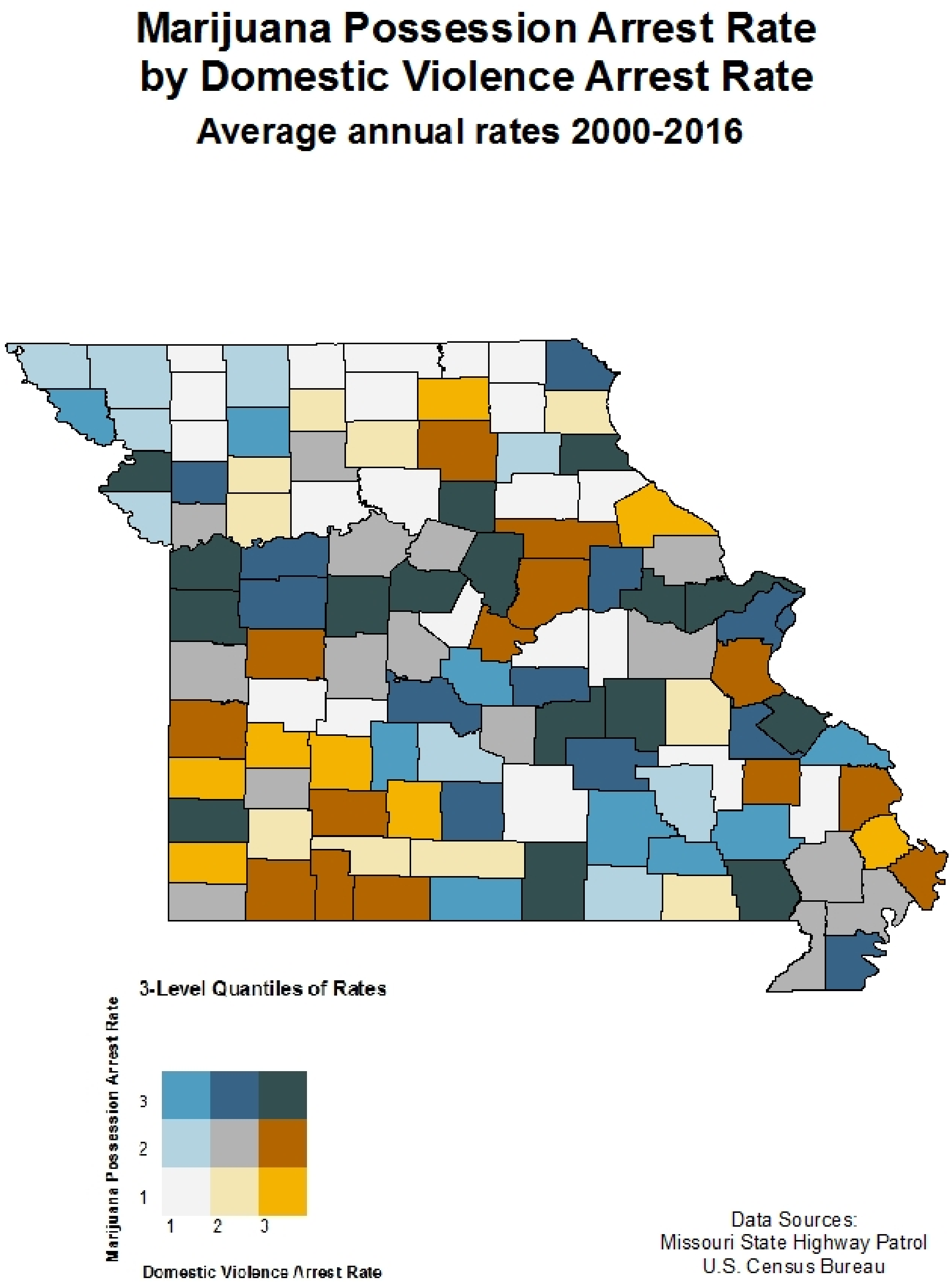


Figure 9. Bivariate Map – Synthetic Drug Possession Arrest Rate by DV Arrest Rate

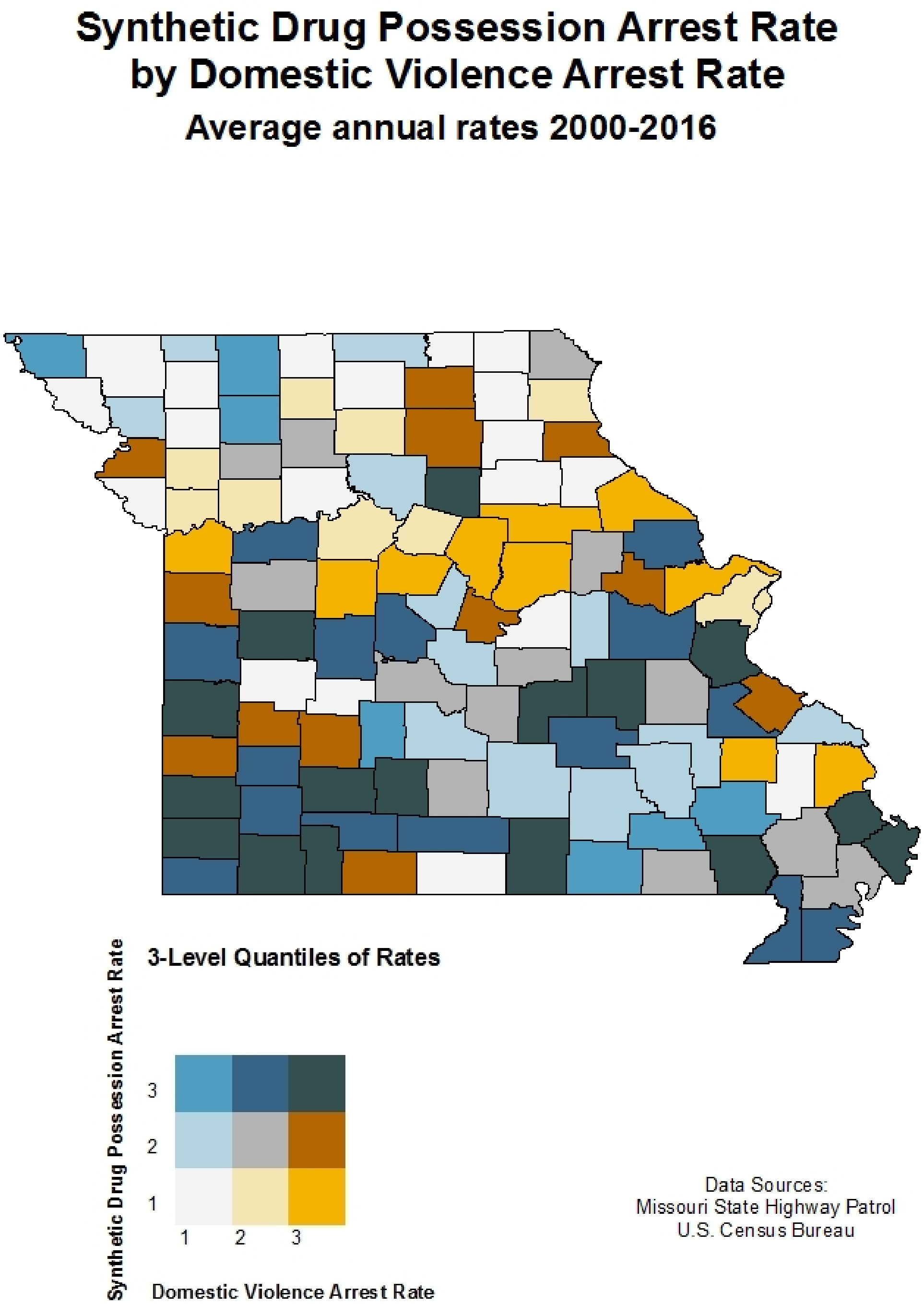


Figure 10. Univariate Map – Any Recidivism

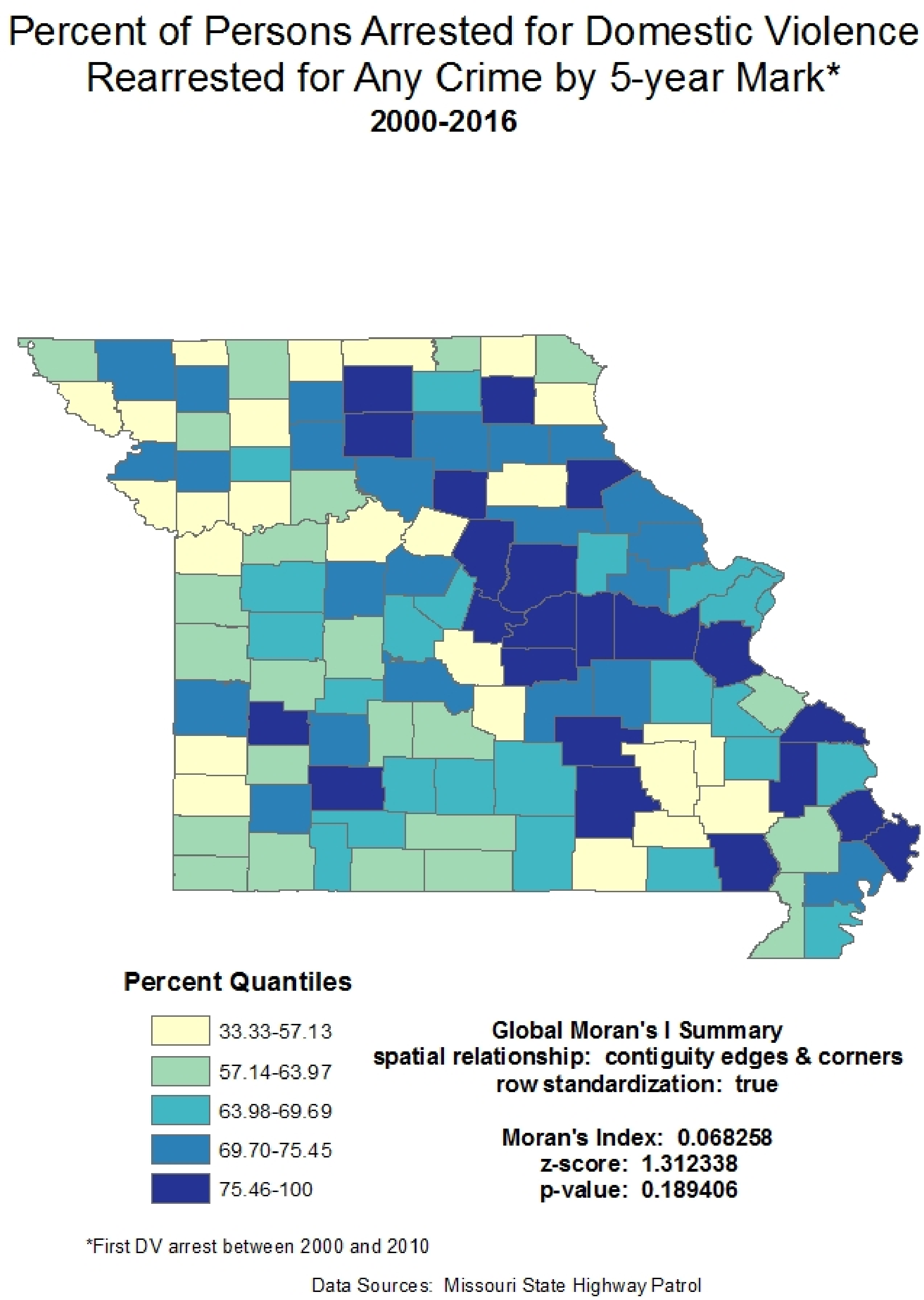


Figure 11. Hot Spot Map – Any Recidivism

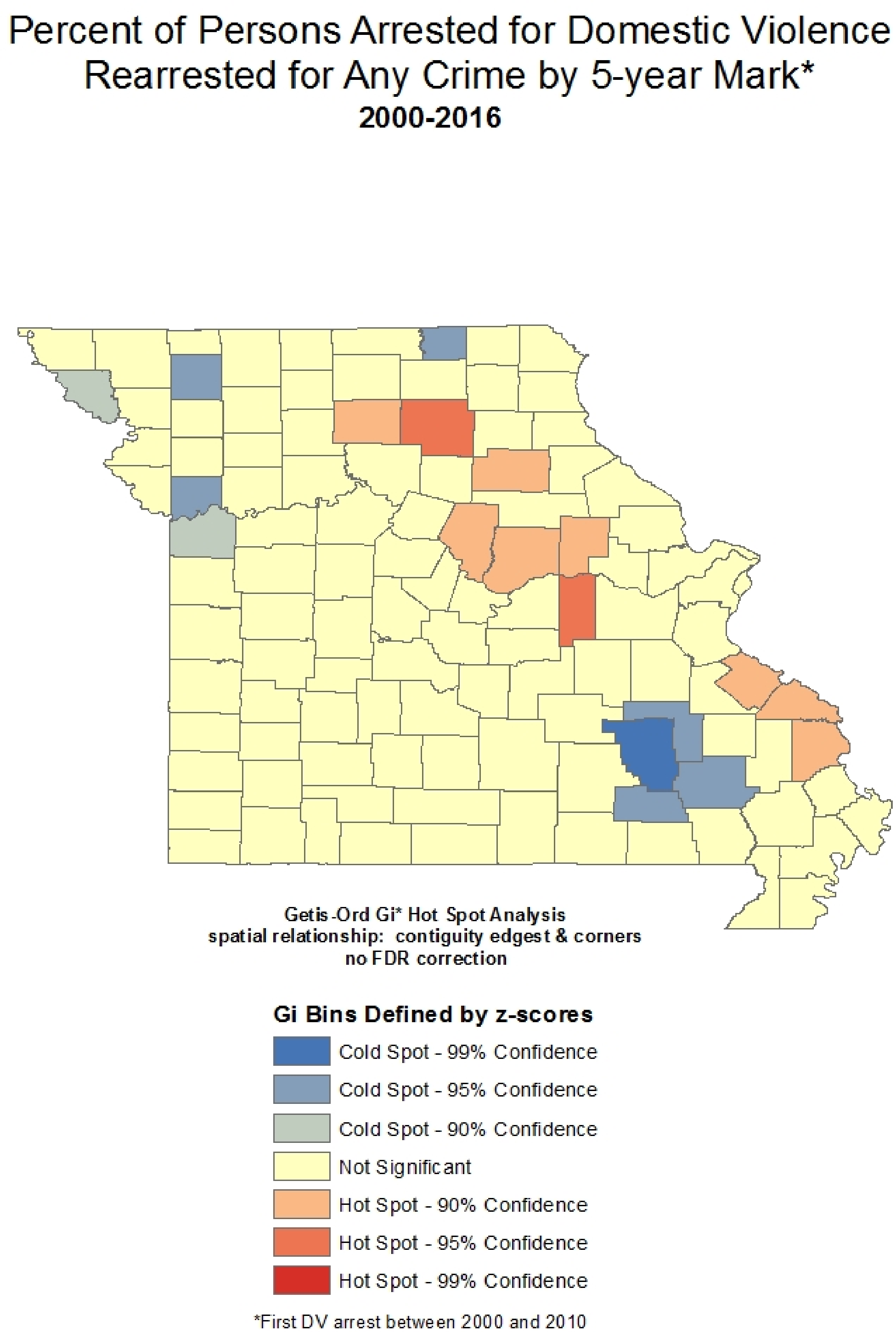


Figure 12. Bivariate Map – Property Crime Rate by Any Recidivism

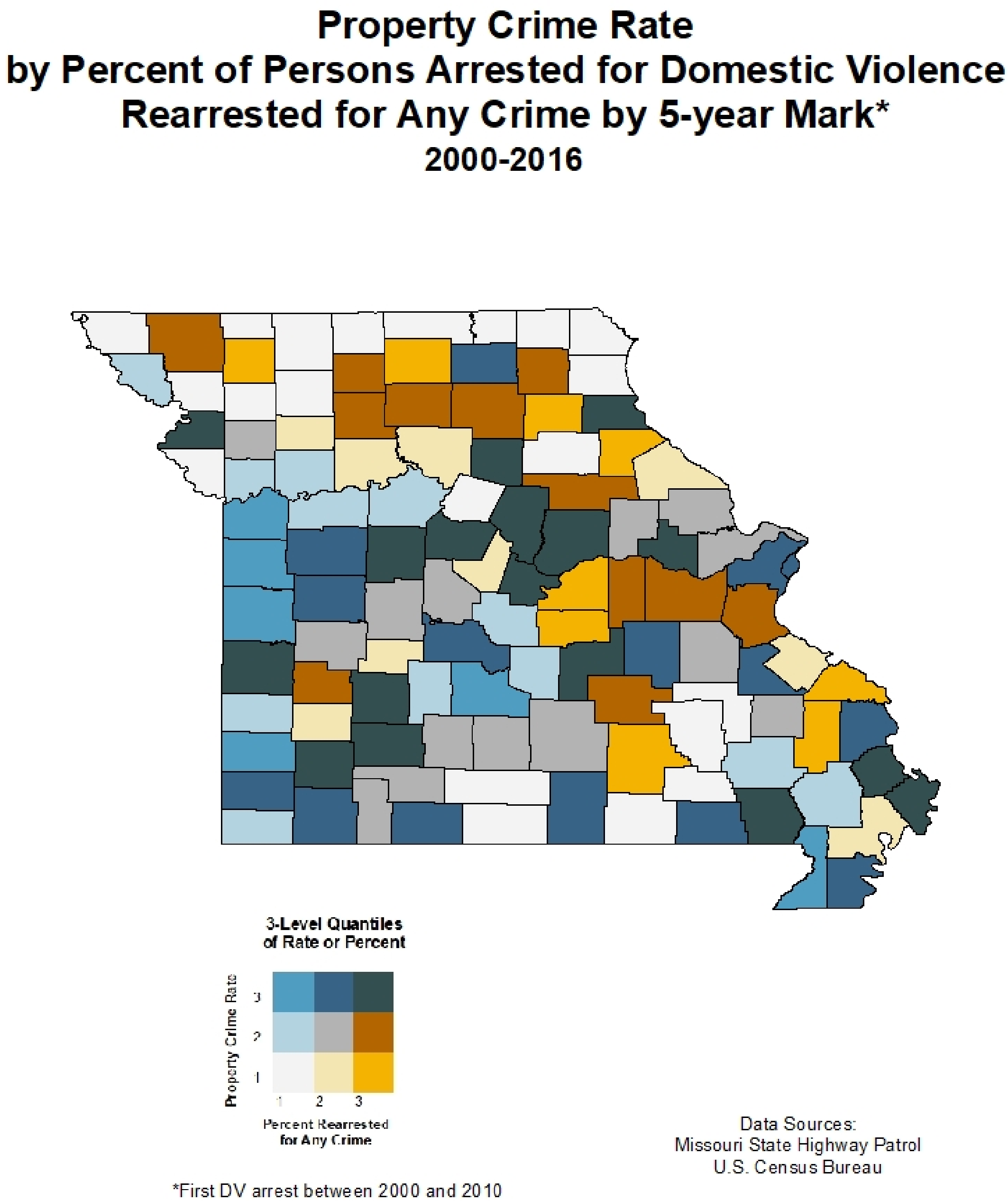


Figure 13. Bivariate Map – Drug Sales and Distribution Arrest Rate by Any Recidivism

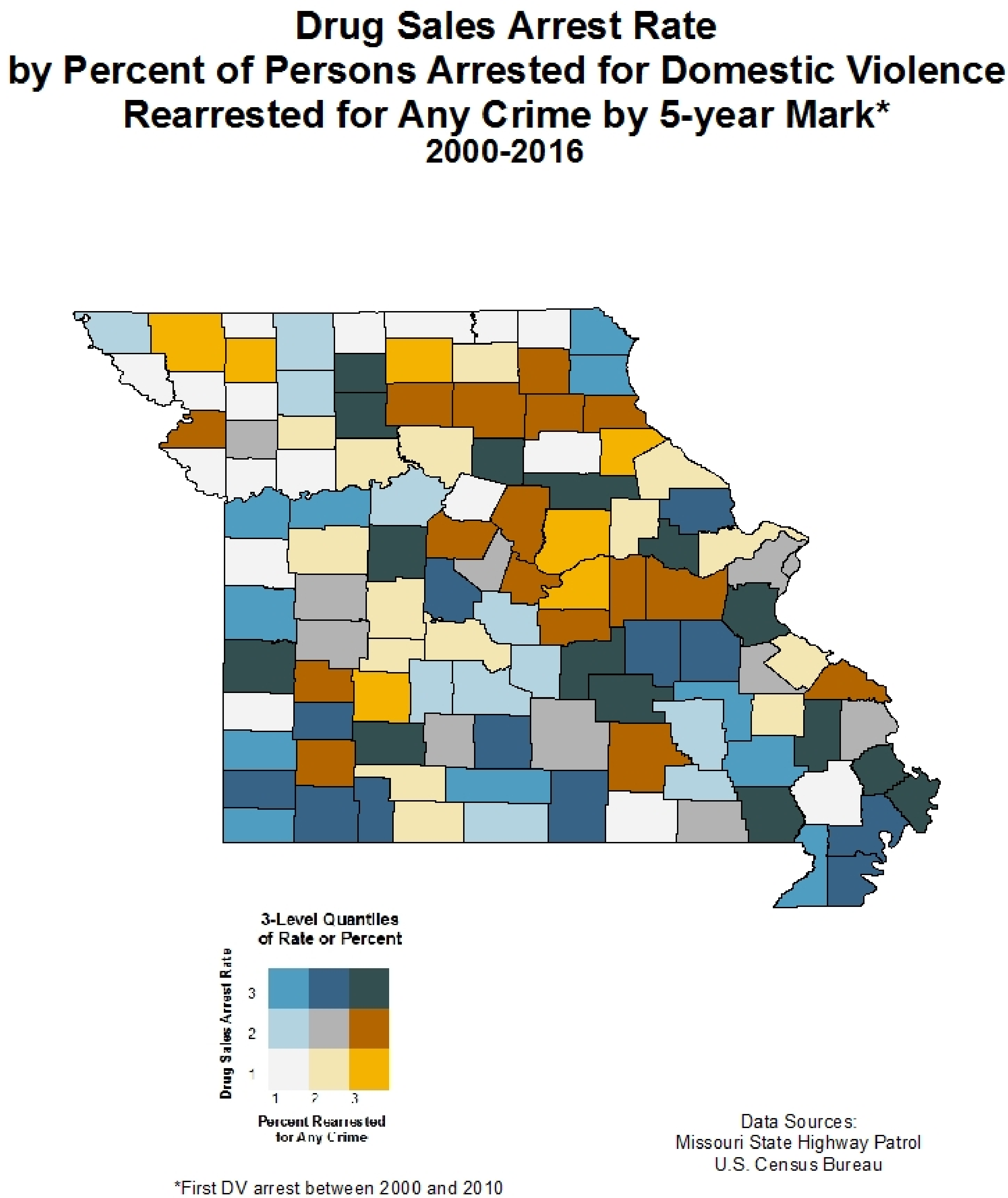


Figure 14. Bivariate Map – Synthetic Drug Possession Arrest Rate by Any Recidivism

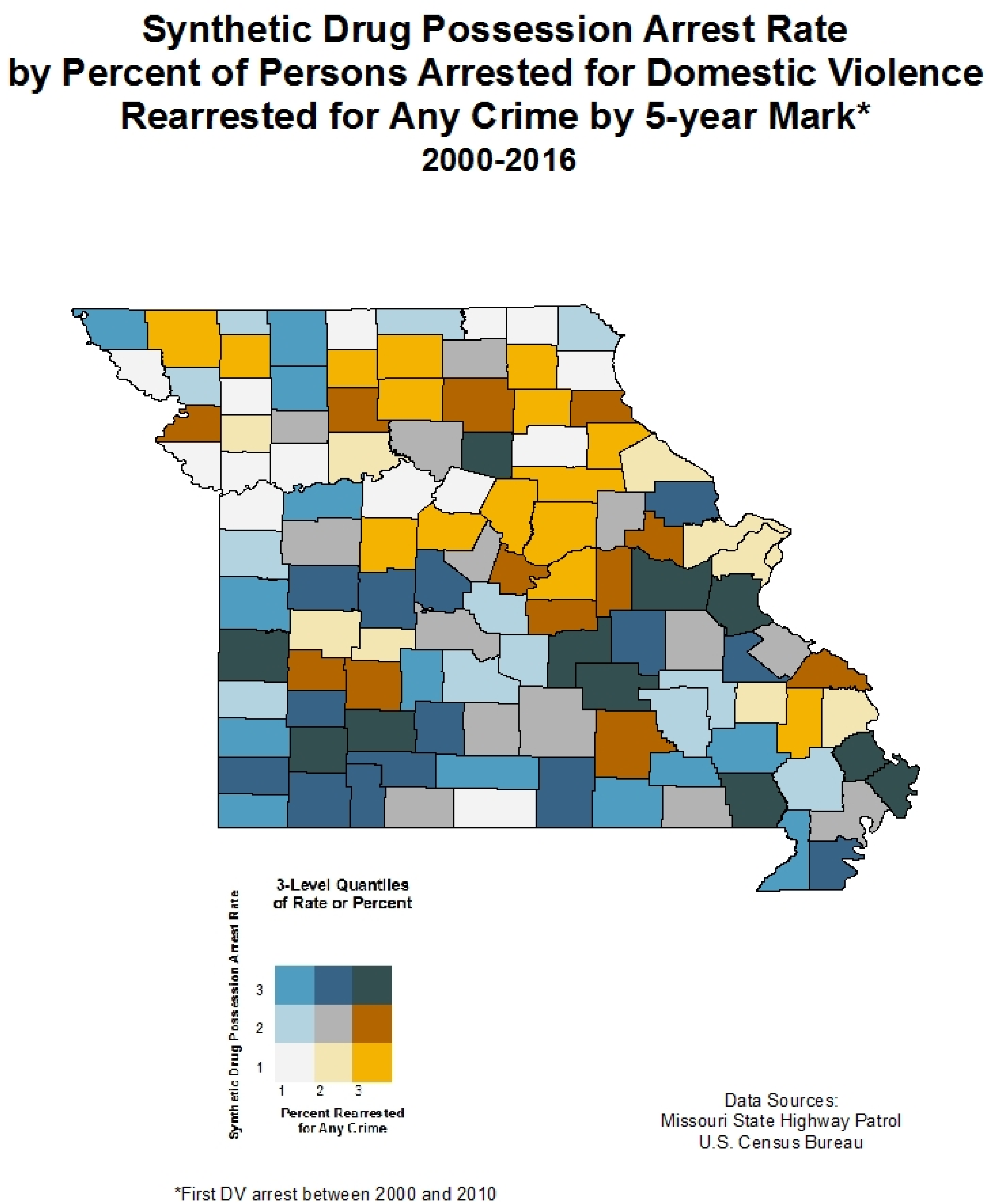


Figure 15. Univariate Map – Domestic Violence Recidivism

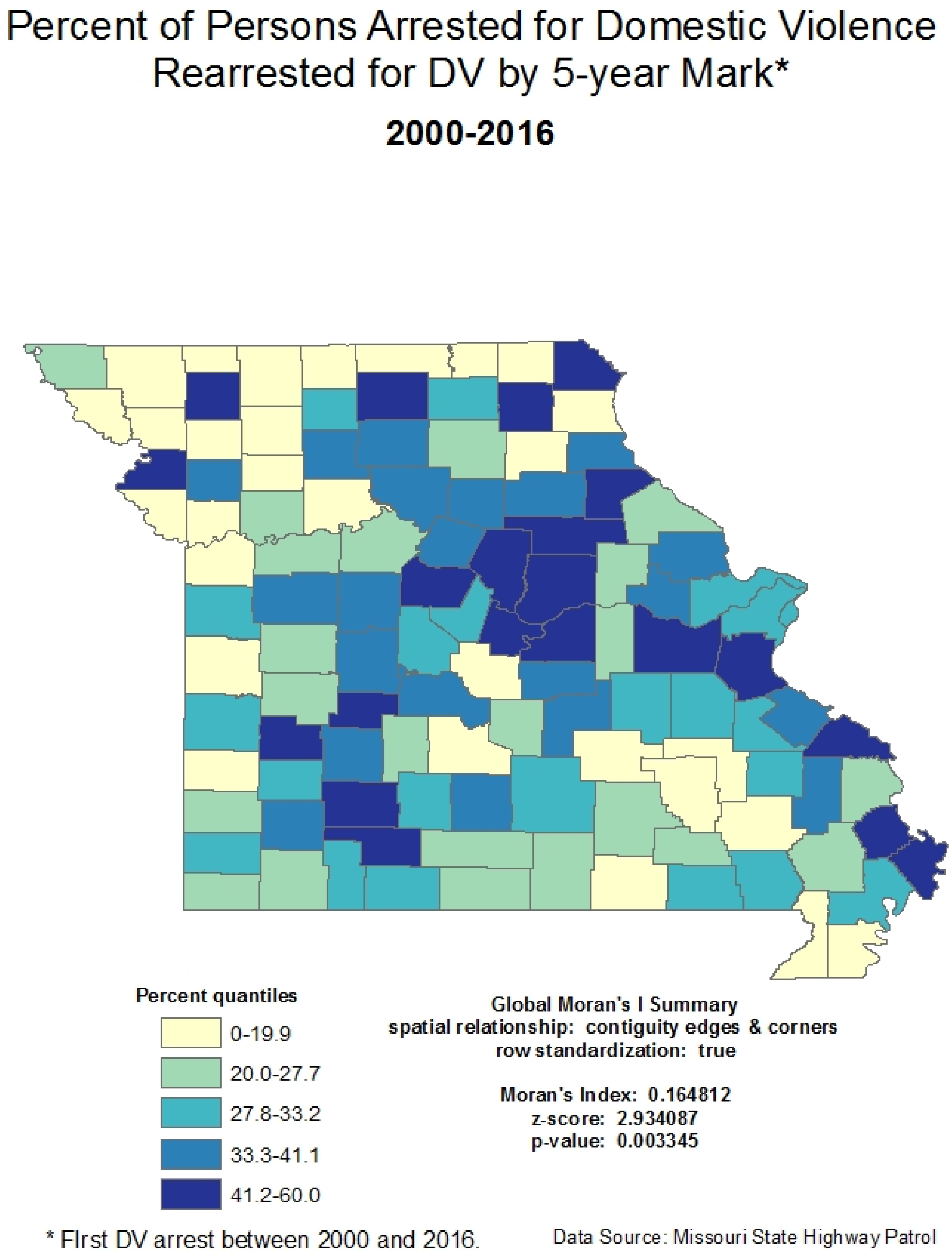


Figure 16. Hot Spot Map – Domestic Violence Recidivism

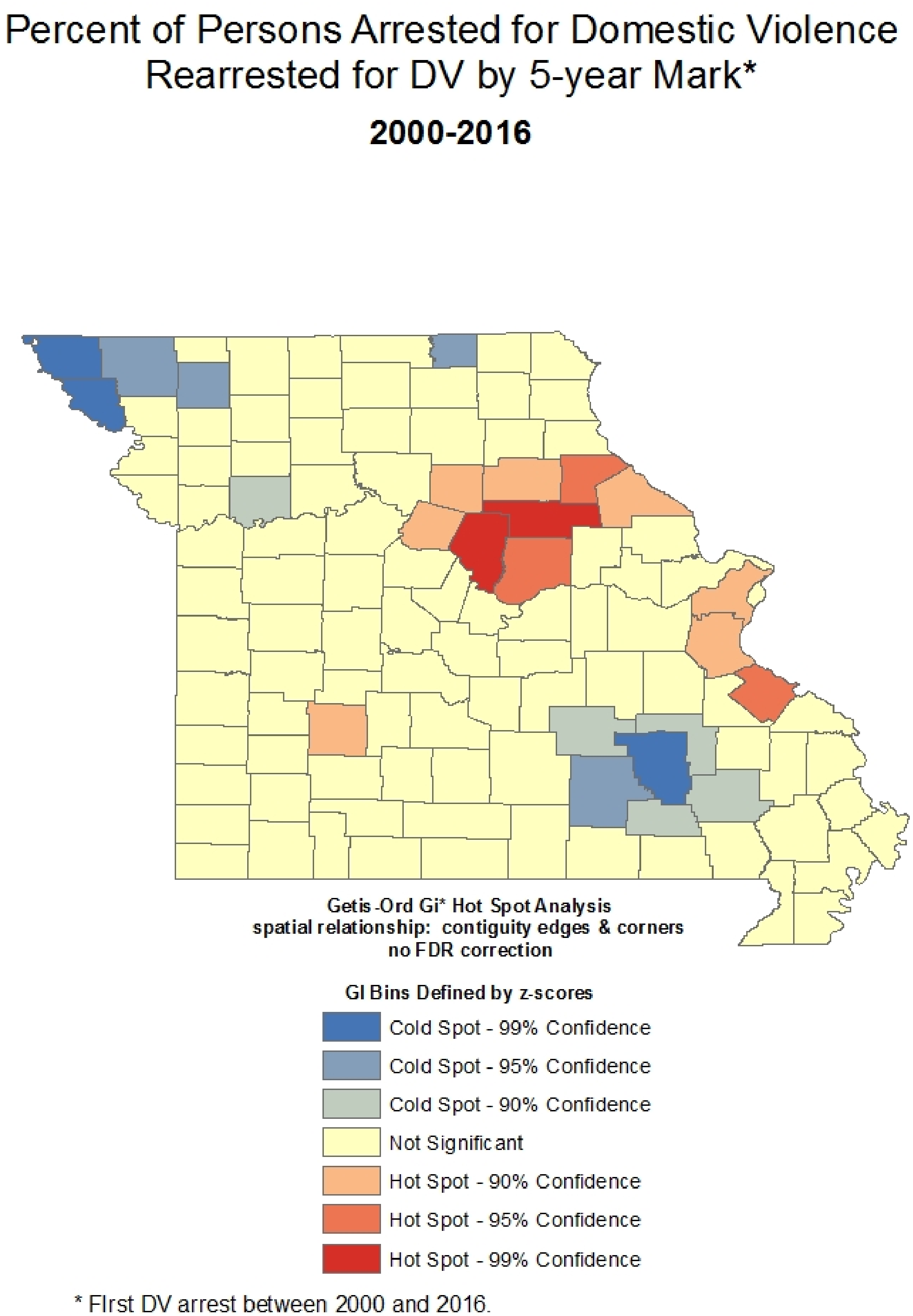


Figure 17. Bivariate Map – Property Crime Rate by DV Recidivism

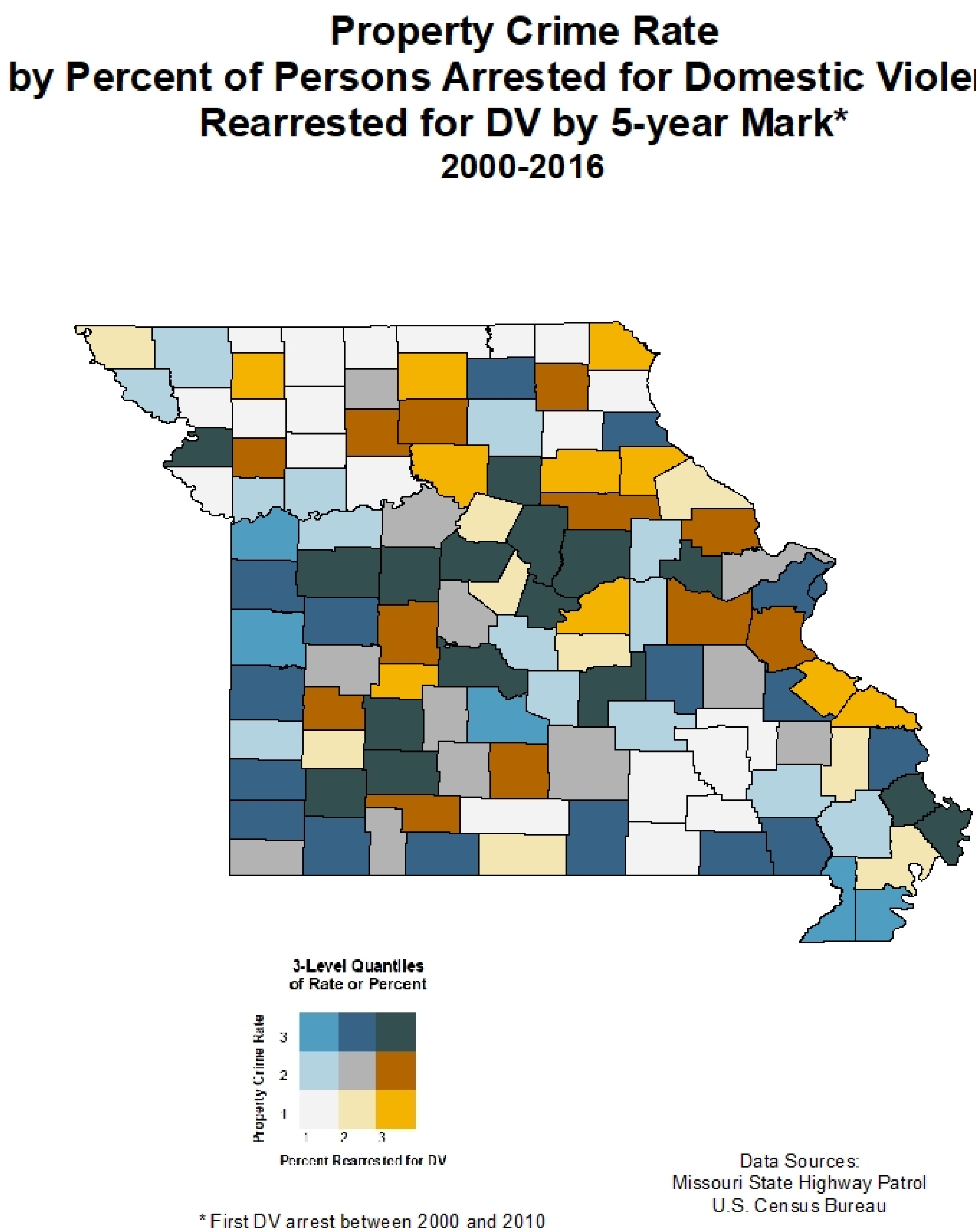


Figure 18. Univariate Map – Domestic Violence Specialization

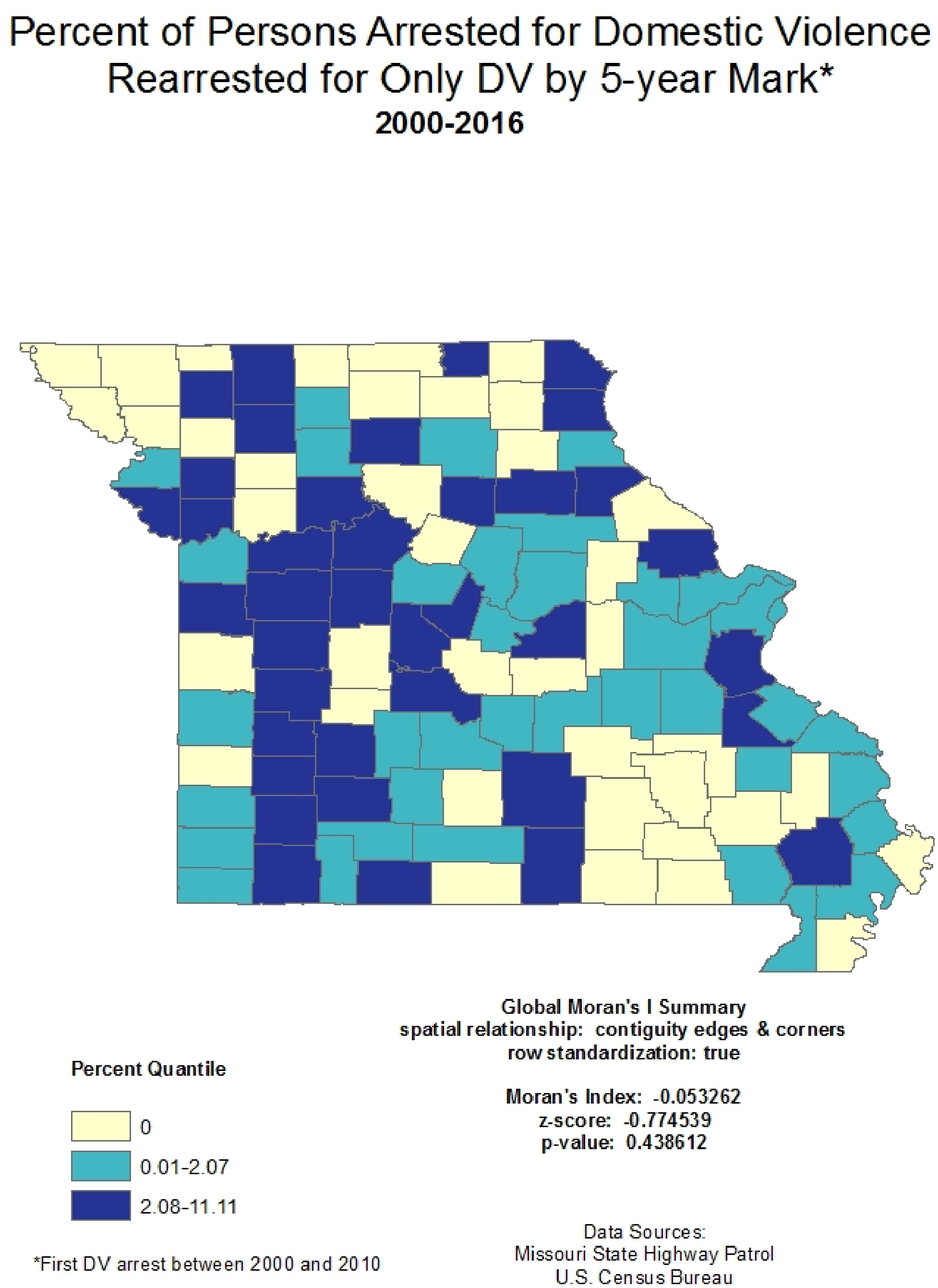


Figure 19. Hot Spot Map – Domestic Violence Specialization

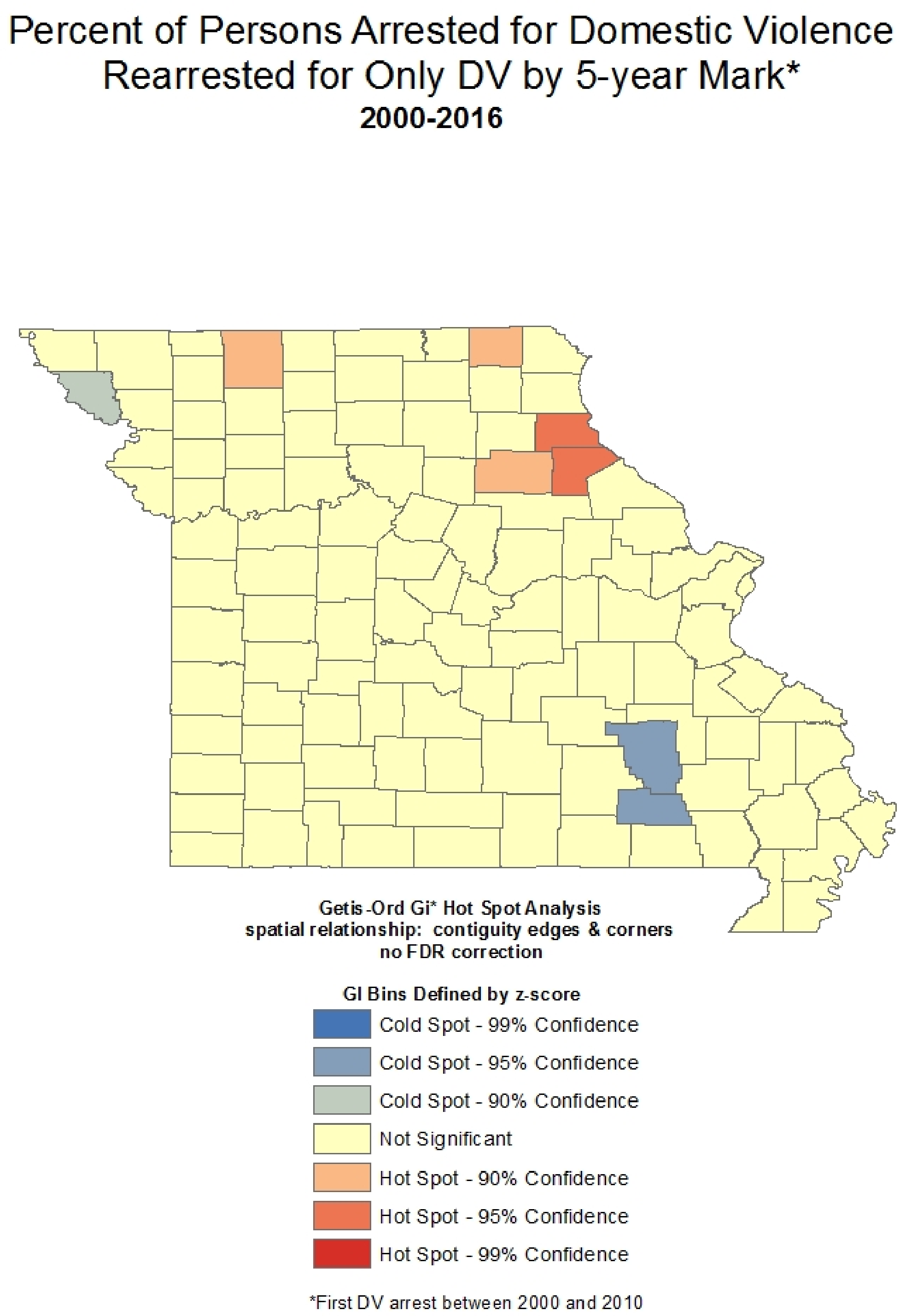


Figure 20. Bivariate Map – Disadvantage Index by DV Specialization

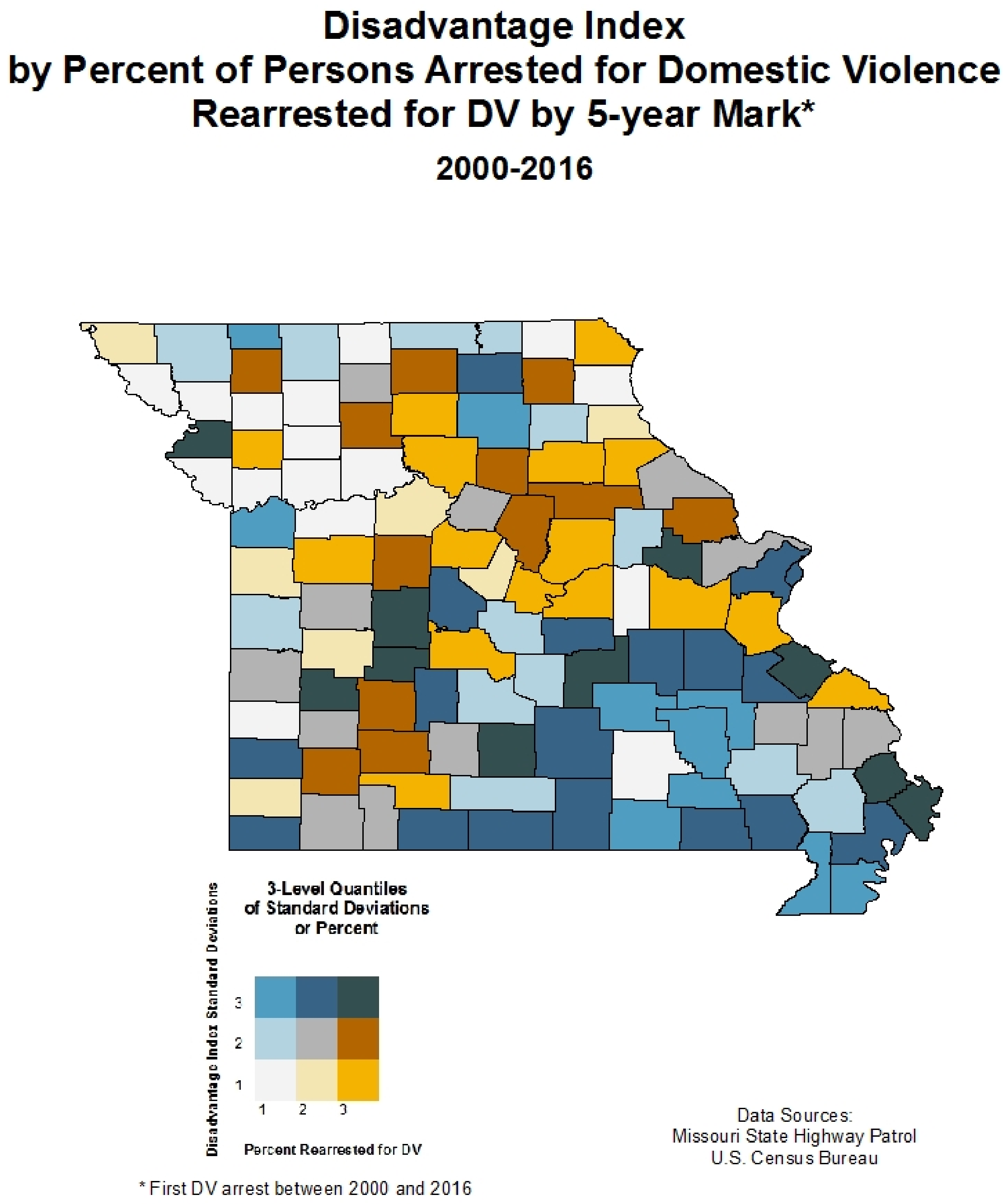


Figure 21. Univariate Map – Domestic Violence Escalation

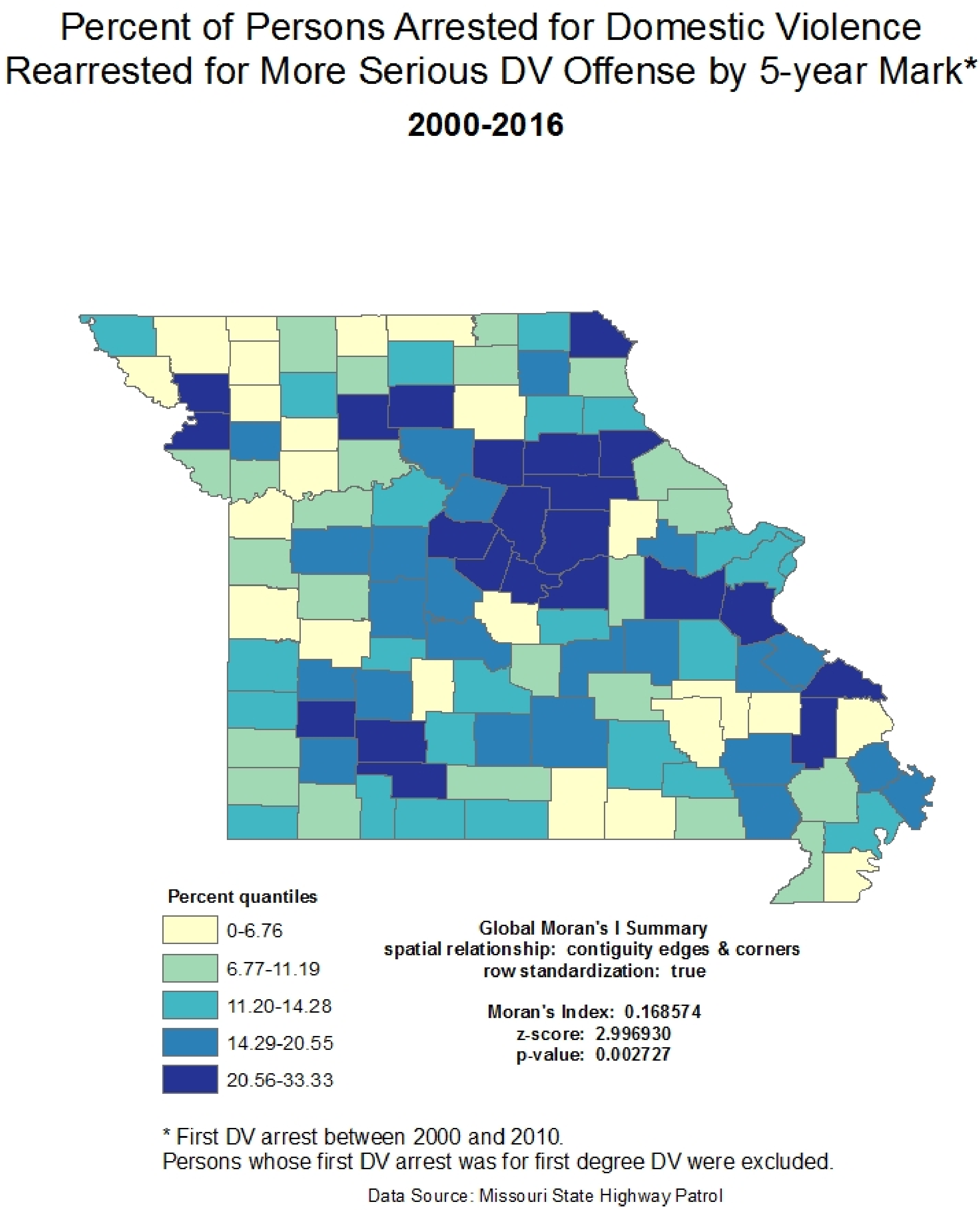


Figure 22. Hot Spot Map – Domestic Violence Escalation

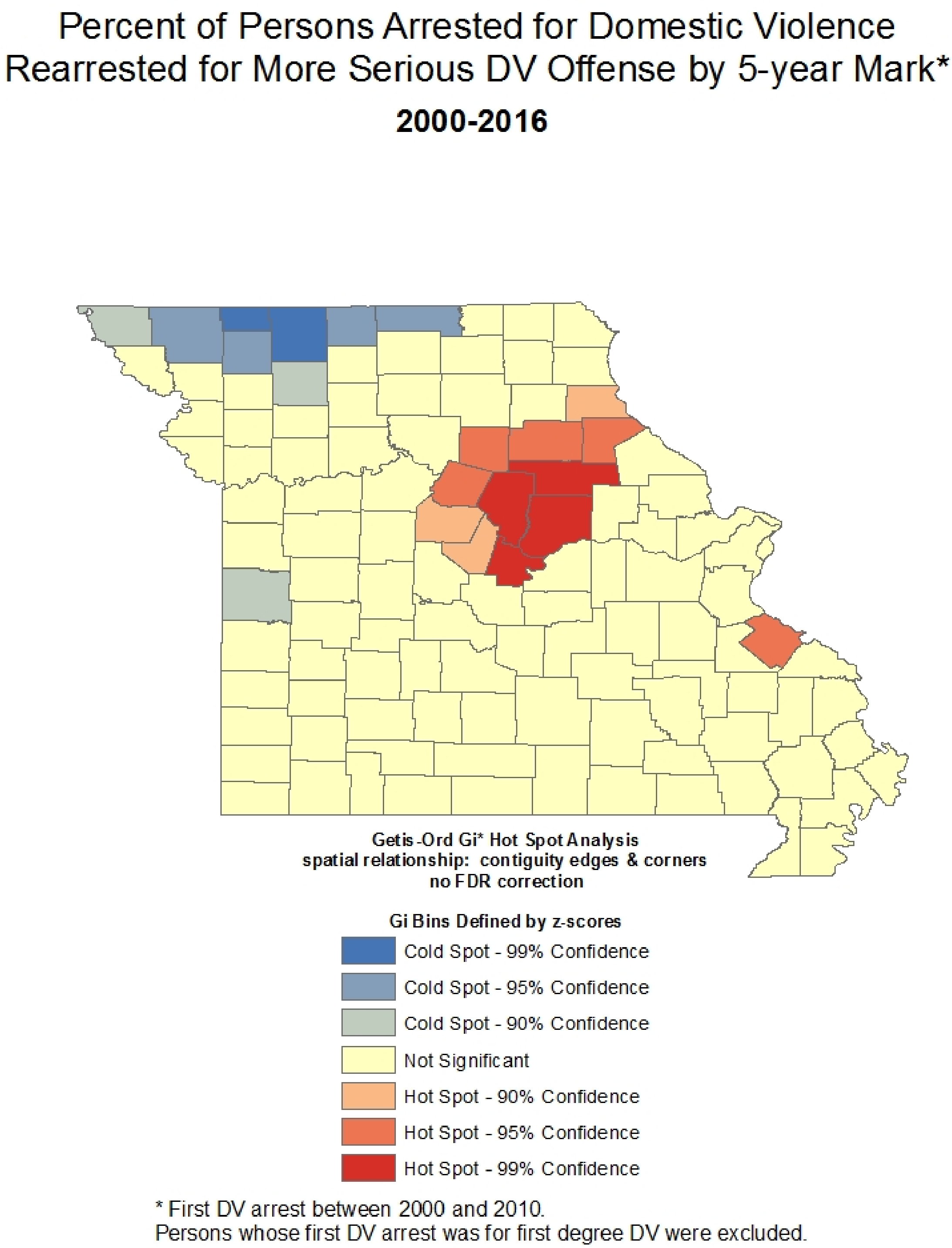


Figure 23. Bivariate Map – Disadvantage Index by DV Escalation

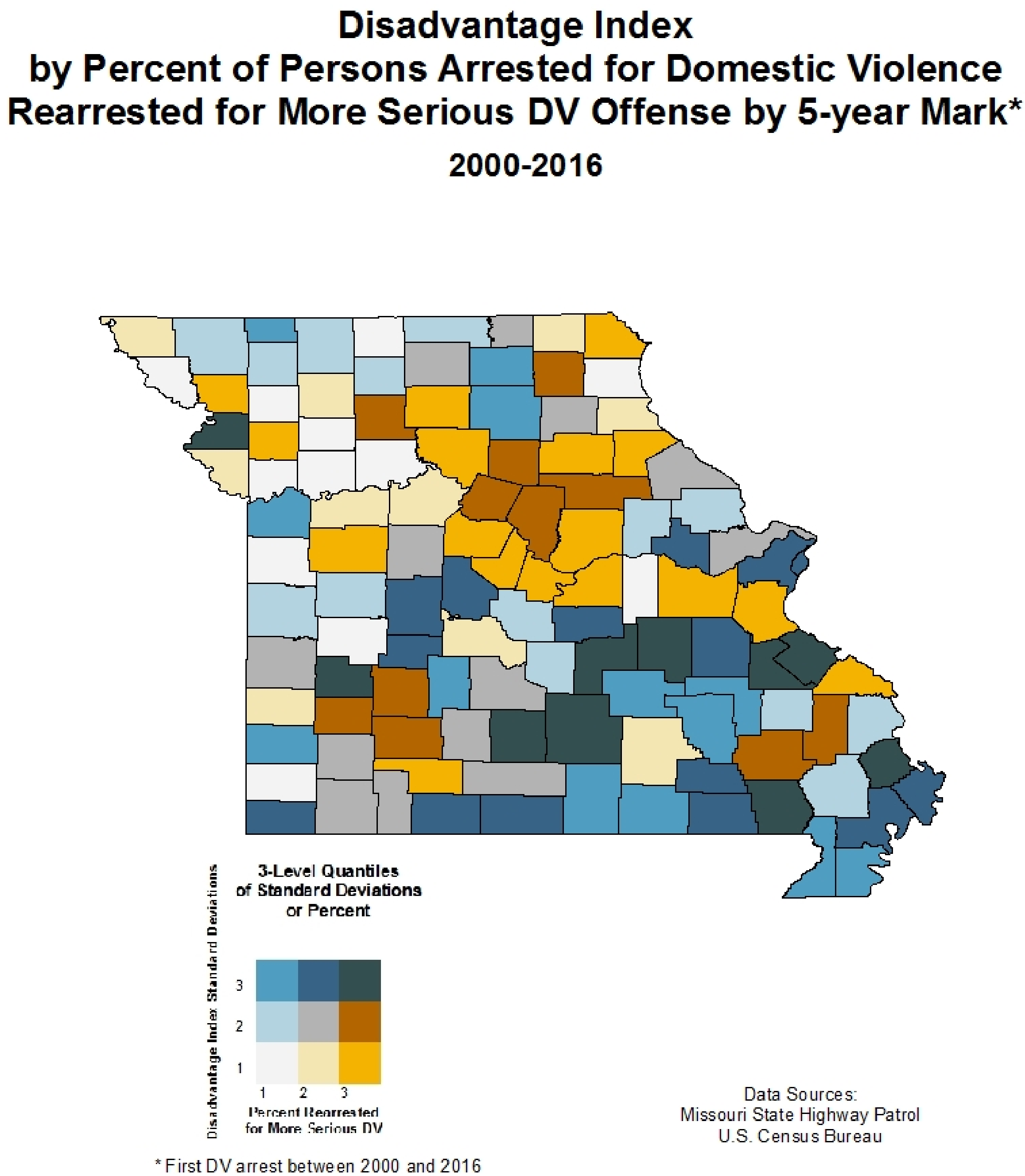


Figure 24. Univariate Map – Average Number DV Recidivism

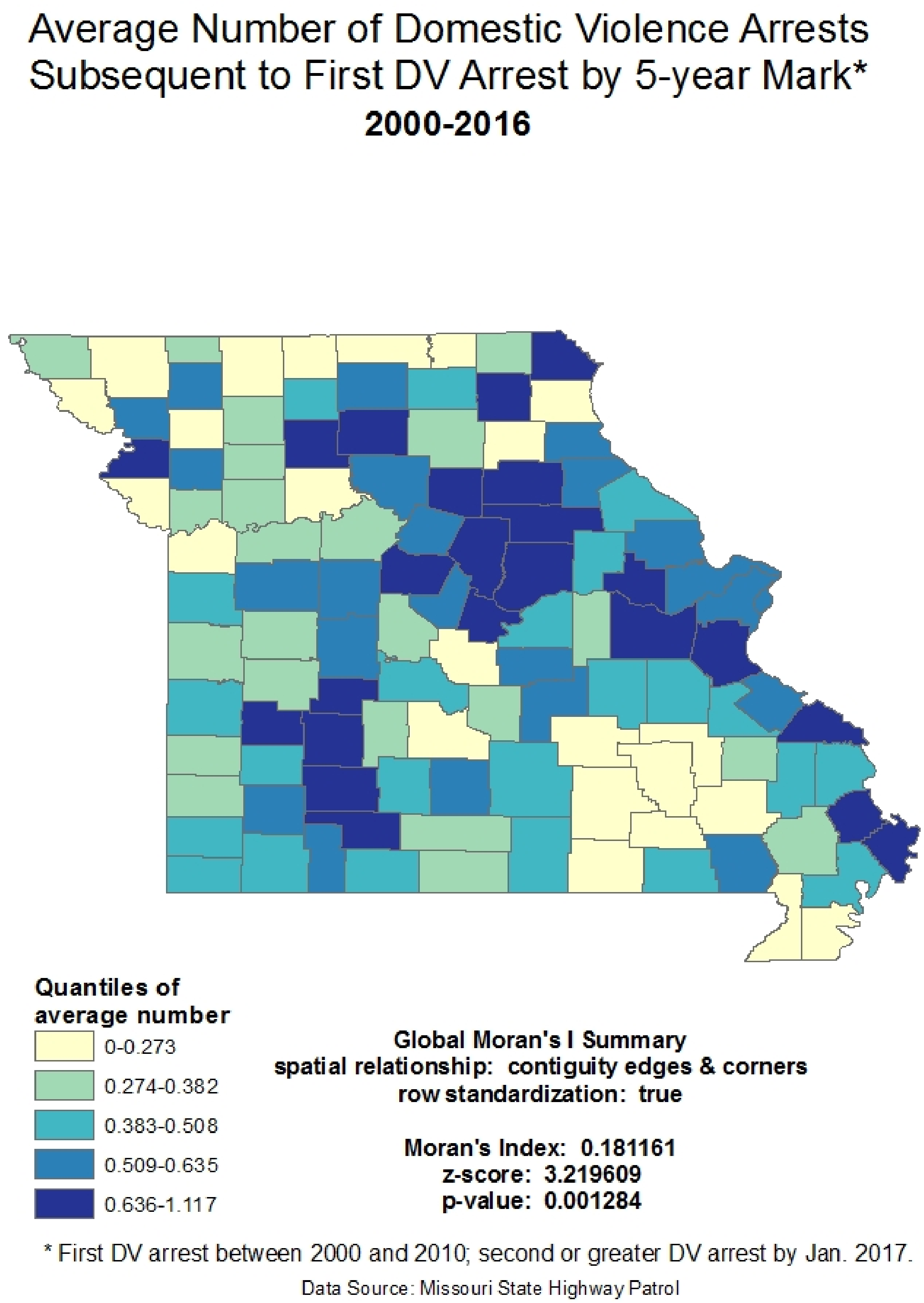


Figure 25. Hot Spot Map – Average Number DV Recidivism

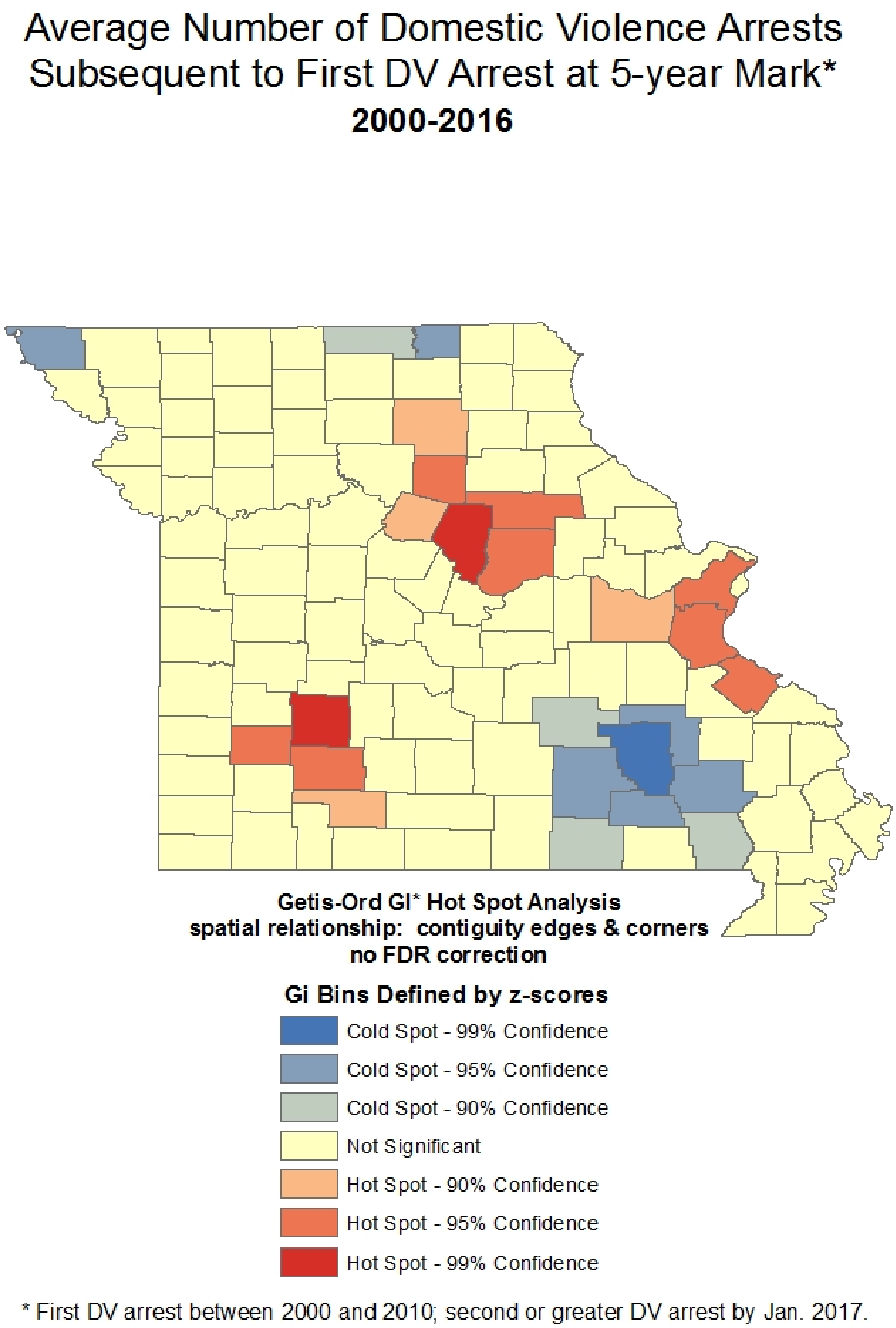


Figure 26. Bivariate Map – Property Crime Rate by Average Number DV Recidivism

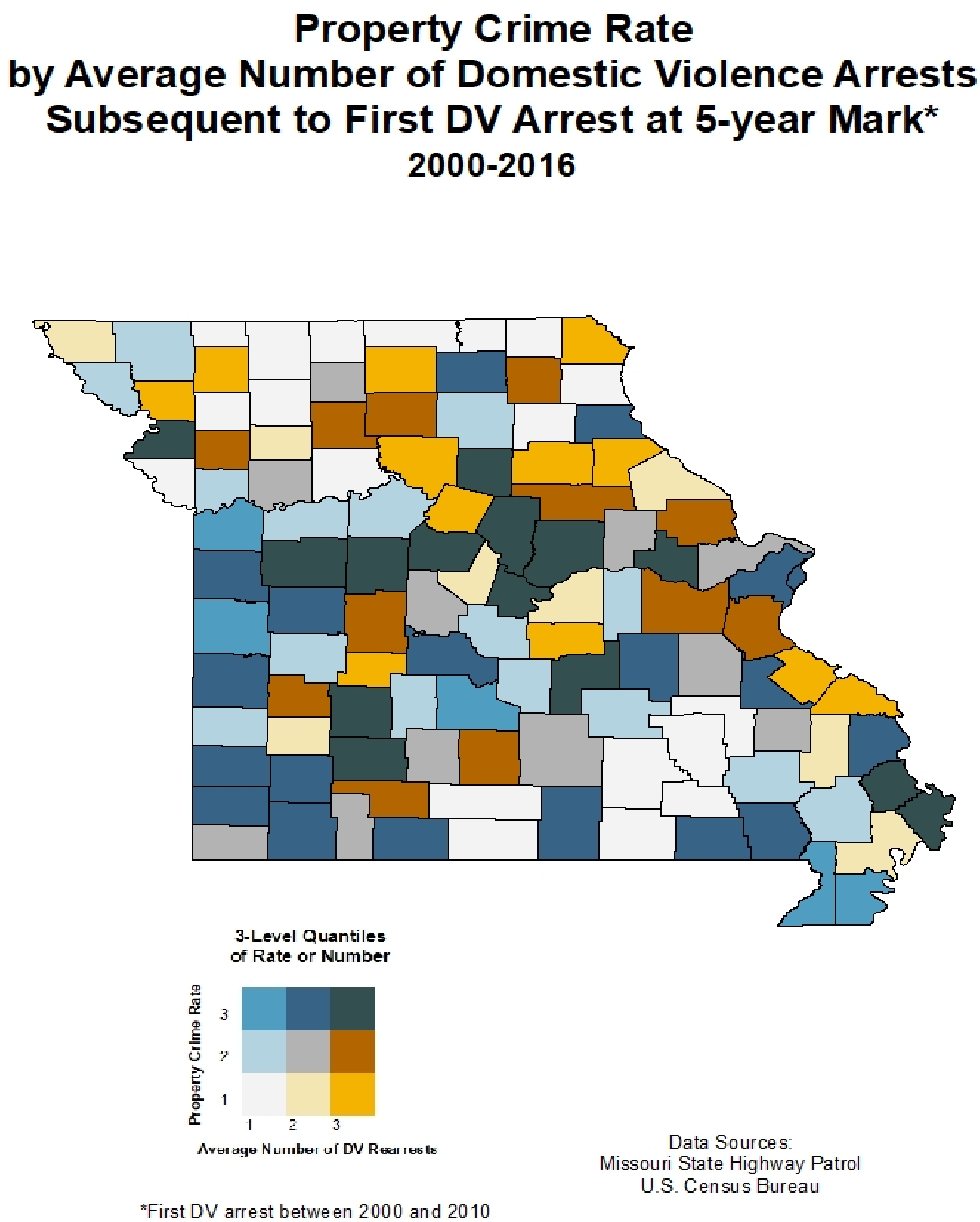


Table 7: Mixed-Effects Logistic Regression Models

	Model 1 (Any Recidivism) N = 49,589		Model 2 (DV Recidivism) N = 49,589		Model 3 (Specialization) N = 49,606		Model 4 (Escalation) N = 43,760	
	b	**SE**	***b***	**SE**	***b***	**SE**	***b***	**SE**
County-level Predictors								
Property crime rate†	.009**	.003	.012**	.004	.001	.005	.008	.005
Percentage of population 20-54	.020*	.010	.036**	.014	.021	.019	.024	.019
Disadvantage Index	.007	.048	-.038	.065	-.042	.106	-.138	.088
Percentage Minority	-.013*	.005	-.016*	.007	-.013	.010	-.008	.010
Ln arrest rate for drug sales and distribution	.213**	.070	.138	.096	-.260*	.126	.141	.130
Ln arrest rate for cocaine and opium possession	.007	.027	.030	.034	-.075	.052	.049	.052
Arrest rate for marijuana possession†	.032	.032	-.026	.043	-.092	.074	-.003	.058
Ln arrest rate for synthetic possession	.033	.055	.026	.075	.159	.092	.118	.102
Ln arrest rate for other possession	-.194***	.048	-.190**	.066	.261**	.091	-.181*	.089
Ln arrest rate for Drunkenness	.028	.025	-.019	.034	-.192***	.052	-.064	.047
Arrest rate for DUI†	-.079**	.023	-.066*	.032	.006	.043	-.081	.044
Individual-level Predictors								
Number of prior violent arrests	.149***	.008	.060***	.005	-	-	.045***	.006
Number of prior arrests for drug-related offenses	.192***	.011	.035***	.007	-	-	.007	.008
Number of prior arrests for drug sales and distribution	.126***	.025	.034	.018	-	-	.021	.025
Number of prior arrests for alcohol-related offenses	.253***	.015	.106***	.012	-	-	.057***	.015
1 if male	.552***	.025	.651***	.028	-.274**	.081	.501***	.044
1 if African American	.209***	.027	.236***	.027	-.309**	.092	.267***	.038
1 if Asian	-.484**	.166	-.280	.198	.801*	.390	-.124	.296
1 if Native American	.324	.265	.228	.254	.643	.592	.479	.321
Age of first domestic violence arrest	-.030***	.002	-.015***	.001	.001	.003	-.009***	.002
Age of first arrest	-.025***	.002	-.015***	.002	-	-	-.019***	.002
Intercept	.568	.497	-2.008	.679	-4.285	.938	-2.767	.919
Global Model Parameters								
County-level variance component	.038	.011	.099	.021	.021	.021	.172	.037

*p < .05; **p < .01; ***p < .001

† The coefficients and the standard errors are multiplied by 100.

Table 8: Mixed Effects Negative Binomial Regression Model

	(Number DV Recidivism) N = 49,589	
	b	**SE**
County-level Predictors		
Property crime rate†	.012**	.004
Percentage of population 20-54	.036**	.012
Disadvantage Index	-.006	.057
Percentage Minority	-.016*	.006
Ln arrest rate for drug sales and distribution	.063	.084
Ln arrest rate for cocaine and opium possession	.034	.030
Arrest rate for marijuana possession†	-.059	.038
Ln arrest rate for synthetic possession	.063	.066
Ln arrest rate for other possession	-.131*	.058
Ln arrest rate for Drunkenness	-.036	.030
Arrest rate for DUI†	-.057*	.028
Individual-level Predictors		
Number of prior violent arrests	.046***	.003
Number of prior arrests for drug-related offenses	.027***	.005
Number of prior arrests for drug sales and distribution	.004	.014
Number of prior arrests for alcohol-related offenses	.098***	.009
1 if male	.608***	.024
1 if African American	.233***	.021
1 if Asian	-.445*	.181
1 if Native American	.241	.194
Age of first domestic violence arrest	-.013***	.001
Age of first arrest	-.012***	.001
Intercept	-2.030	.589
Global Model Parameters		
lnalpha	.076	.022
County-level variance component	.078	.016

*p < .05; **p < .01; ***p < .001

† The coefficients and the standard errors are multiplied by 100.

APPENDIX

APPENDIX A:

Missouri Counties

Data Source: US Census Bureau

Appendix B: Individual-level Correlation Matrix

		1	2	3	4	5	6	7	8
1.	1 if any recidivism								
2.	1 if domestic violence recidivism	.497**							
3.	Number of domestic violence rearrests	.377**	.758**						
4.	1 if specialization	.095**	.192**	.086**					
5.	1 if escalation	.265**	.532**	.507**	.070**				
6.	Number of prior violent arrests	.154**	.128**	.136**	-.054**	.084**			
7.	Number of prior arrests for drug-related offenses	.158**	.099**	.098**	-.051**	.055**	.281**		
8.	Number of prior arrests for drug sales and distribution	.097**	.057**	.050**	-.036**	.031**	.149**	.373**	
9.	Number of prior arrests for alcohol-related offenses	.094**	.055**	.057**	-.050**	.029**	.078**	.085**	.026**
10.	1 if Male	.145**	.129**	.123**	-.015**	.080**	.120**	.103**	.093**
11.	1 if African American	.080**	.073**	.080**	-.027**	.041**	.233**	.134**	.120**
12.	1 if Asian	-.030**	-.016**	-.017**	.011*	-.008	-.018**	-.020**	-.014**
13.	1 if Native American	.001	.002	.004	.007	.006	-.003	-.012**	-.009
14.	Age of first domestic violence arrest	-.188**	-.097**	-.092**	.002	-.064**	.113**	.021**	.038**
15.	Age of first arrest	-.287**	-.156**	-.142**	.090**	-.099**	-.208**	-.212**	-.145**

*p = .05; **p = .01

Appendix B: Individual-level Correlation Matrix Cont.

		9	10	11	12	13	14
1.	1 if any recidivism						
2.	1 if domestic violence recidivism						
3.	Number of domestic violence rearrests						
4.	1 if specialization						
5.	1 if escalation						
6.	Number of prior violent arrests						
7.	Number of prior arrests for drug-related offenses						
8.	Number of prior arrests for drug sales and distribution						
9.	Number of prior arrests for alcohol-related offenses						
10.	1 if Male	.097**					
11.	1 if African American	-.155**	-.013**				
12.	1 if Asian	-.014**	-.004	-.042**			
13.	1 if Native American	-.003	-.000	-.028**	-.002		
14.	Age of first domestic violence arrest	.159**	.044**	-.046**	.009*	.001	
15.	Age of first arrest	-.060**	-.085**	-.161**	.040**	.017**	.678**

*p = .05; **p = .01

Appendix C: Domestic Violence Charge Rate, Domestic Violence Arrest Rate, and Recidivism Outcomes by County

County	Domestic Violence Charge Rate (2000-2016)	Domestic Violence Arrest Rate (2000-2016)	Proportion of Offenders who recidivated	Proportion of Offenders with Domestic Violence Rearrests	Average Number of Domestic Violence Rearrests	Proportion of Offenders who Specialized	Proportion of Offenders who Escalated
Adair	165.33	157.19	0.68	0.33	0.42	0.00	0.09
Andrew	22.92	20.88	0.40	0.20	0.60	0.00	0.27
Atchison	49.42	47.36	0.63	0.25	0.33	0.00	0.14
Audrain	159.40	146.39	0.73	0.44	0.64	0.02	0.24
Barry	183.20	178.58	0.63	0.26	0.39	0.03	0.11
Barton	154.70	146.16	0.57	0.20	0.28	0.00	0.13
Bates	85.70	80.41	0.60	0.20	0.31	0.00	0.05
Benton	102.03	99.54	0.64	0.36	0.55	0.00	0.15
Bollinger	57.24	50.58	0.83	0.34	0.46	0.00	0.27
Boone	184.15	168.56	0.76	0.46	0.83	0.01	0.21
Buchanan	126.06	113.77	0.73	0.43	0.90	0.02	0.24
Butler	146.22	142.75	0.76	0.33	0.53	0.01	0.18
Caldwell	74.75	71.53	0.69	0.20	0.33	0.00	0.05
Callaway	145.17	126.46	0.76	0.42	0.71	0.01	0.22
Camden	115.75	109.29	0.70	0.38	0.51	0.02	0.16
Cape Girardeau	250.42	238.28	0.66	0.28	0.43	0.01	0.07
Carroll	48.75	45.00	0.63	0.20	0.24	0.02	0.09
Carter	18.30	18.30	0.56	0.22	0.22	0.00	0.13
Cass	177.84	169.74	0.61	0.30	0.46	0.03	0.07
Cedar	198.59	171.57	0.82	0.48	1.07	0.02	0.20
Chariton	45.16	41.39	0.71	0.38	0.57	0.00	0.20
Christian	88.56	82.67	0.69	0.43	0.78	0.02	0.26
Clark	91.27	72.78	0.62	0.42	0.65	0.08	0.25
Clay	73.96	72.09	0.54	0.20	0.29	0.02	0.07
Clinton	104.04	100.05	0.71	0.39	0.58	0.02	0.21

Appendix C: Domestic Violence Charge Rate, Domestic Violence Arrest Rate, and Recidivism Outcomes by County Cont.

County	Domestic Violence Charge Rate (2000-2016)	Domestic Violence Arrest Rate (2000-2016)	Proportion of Offenders who recidivated	Proportion of Offenders with Domestic Violence Rearrests	Average Number of Domestic Violence Rearrests	Proportion of Offenders who Specialized	Proportion of Offenders who Escalated
Cole	132.84	126.83	0.79	0.45	0.81	0.02	0.26
Cooper	139.27	122.07	0.75	0.47	0.71	0.01	0.24
Crawford	138.78	134.20	0.71	0.30	0.42	0.02	0.17
Dade	79.55	72.72	0.63	0.31	0.49	0.03	0.21
Dallas	42.27	40.13	0.58	0.25	0.32	0.02	0.04
Daviess	38.99	28.36	0.41	0.12	0.29	0.06	0.13
De Kalb	26.02	25.56	0.59	0.18	0.27	0.00	0.00
Dent	79.19	76.15	0.76	0.18	0.20	0.00	0.08
Douglas	96.93	93.43	0.58	0.22	0.33	0.01	0.11
Dunklin	103.69	101.24	0.58	0.18	0.25	0.01	0.08
Franklin	97.24	85.94	0.76	0.44	0.72	0.02	0.24
Gasconade	30.80	30.03	0.77	0.23	0.31	0.00	0.08
Gentry	22.69	18.33	0.73	0.45	0.64	0.09	0.00
Greene	198.29	186.19	0.79	0.52	1.12	0.04	0.22
Grundy	99.32	95.87	0.74	0.33	0.43	0.02	0.08
Harrison	39.41	38.73	0.60	0.20	0.23	0.03	0.07
Henry	174.81	171.09	0.65	0.28	0.36	0.03	0.09
Hickory	16.89	13.70	0.67	0.44	0.78	0.00	0.13
Holt	6.27	6.27	0.50	0.00	0.00	0.00	0.00
Howard	59.86	58.69	0.57	0.34	0.59	0.00	0.18
Howell	161.67	152.34	0.65	0.28	0.40	0.03	0.05
Iron	21.33	20.77	0.47	0.06	0.06	0.00	0.00
Jackson	181.00	169.75	0.53	0.19	0.25	0.02	0.06
Jasper	506.30	498.15	0.56	0.24	0.38	0.02	0.07
Jefferson	162.57	146.69	0.79	0.51	1.07	0.02	0.24

Appendix C: Domestic Violence Charge Rate, Domestic Violence Arrest Rate, and Recidivism Outcomes by County Cont.

County	Domestic Violence Charge Rate (2000-2016)	Domestic Violence Arrest Rate (2000-2016)	Proportion of Offenders who recidivated	Proportion of Offenders with Domestic Violence Rearrests	Average Number of Domestic Violence Rearrests	Proportion of Offenders who Specialized	Proportion of Offenders who Escalated
Johnson	114.65	108.12	0.69	0.41	0.63	0.03	0.19
Knox	33.05	28.82	1.00	0.50	1.00	0.00	0.17
Laclede	51.83	47.68	0.58	0.19	0.23	0.02	0.13
Lafayette	78.58	74.86	0.61	0.22	0.32	0.02	0.11
Lawrence	114.38	106.79	0.75	0.36	0.53	0.03	0.14
Lewis	105.87	104.72	0.56	0.19	0.27	0.04	0.08
Lincoln	113.53	104.23	0.71	0.38	0.60	0.02	0.09
Linn	77.51	75.13	0.76	0.39	0.73	0.02	0.24
Livingston	90.12	86.19	0.74	0.39	0.66	0.01	0.25
Macon	132.50	130.6	0.74	0.22	0.32	0.02	0.06
Madison	122.26	117.45	0.69	0.33	0.37	0.02	0.02
Maries	66.07	62.20	0.81	0.35	0.54	0.00	0.12
Marion	126.54	119.34	0.75	0.34	0.53	0.02	0.14
McDonald	103.40	100.05	0.62	0.26	0.39	0.01	0.12
Mercer	66.44	56.92	0.48	0.20	0.24	0.00	0.00
Miller	40.04	39.08	0.51	0.11	0.12	0.00	0.02
Mississippi	178.87	165.10	0.79	0.43	0.71	0.00	0.15
Moniteau	40.76	38.54	0.70	0.33	0.52	0.03	0.24
Monroe	34.39	33.75	0.50	0.40	0.85	0.05	0.29
Montgomery	95.83	92.86	0.64	0.21	0.46	0.00	0.07
Morgan	91.20	85.99	0.69	0.29	0.36	0.03	0.16
New Madrid	105.92	103.67	0.70	0.28	0.41	0.02	0.13
Newton	143.90	138.91	0.64	0.31	0.51	0.01	0.07
Nodaway	22.37	21.10	0.75	0.13	0.25	0.00	0.00
Oregon	54.14	47.04	0.54	0.11	0.20	0.00	0.07

Appendix C: Domestic Violence Charge Rate, Domestic Violence Arrest Rate, and Recidivism Outcomes by County Cont.

County	Domestic Violence Charge Rate (2000-2016)	Domestic Violence Arrest Rate (2000-2016)	Proportion of Offenders who recidivated	Proportion of Offenders with Domestic Violence Rearrests	Average Number of Domestic Violence Rearrests	Proportion of Offenders who Specialized	Proportion of Offenders who Escalated
Osage	26.11	24.82	0.78	0.44	0.44	0.11	0.33
Ozark	60.08	55.78	0.59	0.24	0.32	0.00	0.13
Pemiscot	126.17	112.51	0.70	0.13	0.15	0.00	0.03
Perry	55.65	51.65	0.91	0.49	0.67	0.02	0.29
Pettis	121.67	118.30	0.72	0.37	0.61	0.02	0.15
Phelps	142.18	134.45	0.75	0.36	0.63	0.02	0.17
Pike	145.08	141.90	0.70	0.28	0.4	0.00	0.11
Platte	27.93	27.75	0.51	0.19	0.27	0.03	0.1
Polk	179.91	175.16	0.72	0.36	0.66	0.03	0.17
Pulaski	83.61	80.35	0.53	0.21	0.31	0.01	0.09
Putnam	54.09	52.88	0.42	0.04	0.04	0.00	0.00
Ralls	22.62	21.47	0.90	0.60	0.60	0.10	0.33
Randolph	128.77	117.23	0.78	0.41	0.73	0.02	0.21
Ray	73.04	65.35	0.48	0.23	0.34	0.00	0.06
Reynolds	35.53	33.77	0.36	0.18	0.18	0.00	0.00
Ripley	119.55	112.78	0.68	0.32	0.43	0.00	0.10
Saline	102.28	98.23	0.57	0.25	0.32	0.02	0.14
Schuyler	37.75	35.10	0.60	0.20	0.20	0.10	0.10
Scotland	33.88	29.07	0.50	0.14	0.29	0.00	0.14
Scott	449.94	429.54	0.76	0.44	0.83	0.01	0.18
Shannon	43.81	42.40	0.77	0.23	0.23	0.00	0.12
Shelby	30.50	28.68	0.73	0.20	0.20	0.00	0.14
St. Charles	117.40	112.88	0.65	0.32	0.53	0.01	0.13
St. Clair	55.38	55.38	0.63	0.26	0.30	0.04	0.05
St. Francois	103.45	95.80	0.68	0.32	0.47	0.02	0.18

Appendix C: Domestic Violence Charge Rate, Domestic Violence Arrest Rate, and Recidivism Outcomes by County Cont.

County	Domestic Violence Charge Rate (2000-2016)	Domestic Violence Arrest Rate (2000-2016)	Proportion of Offenders who recidivated	Proportion of Offenders with Domestic Violence Rearrests	Average Number of Domestic Violence Rearrests	Proportion of Offenders who Specialized	Proportion of Offenders who Escalated
St. Louis	117.72	112.15	0.65	0.32	0.51	0.02	0.14
St. Louis City	407.66	286.61	0.78	0.44	0.82	0.01	0.20
Ste. Genevieve	171.69	165.83	0.63	0.36	0.58	0.02	0.17
Stoddard	75.77	74.19	0.61	0.23	0.29	0.02	0.08
Stone	131.72	125.51	0.66	0.33	0.53	0.02	0.14
Sullivan	44.46	41.81	0.78	0.44	0.61	0.00	0.12
Taney	158.54	150.73	0.63	0.30	0.44	0.03	0.13
Texas	26.96	26.05	0.66	0.30	0.48	0.07	0.18
Vernon	137.13	125.73	0.74	0.31	0.45	0.02	0.13
Warren	121.95	115.22	0.75	0.38	0.71	0.02	0.16
Washington	114.39	106.79	0.64	0.30	0.49	0.01	0.13
Wayne	13.19	13.19	0.33	0.17	0.17	0.00	0.20
Webster	126.91	120.73	0.68	0.30	0.49	0.02	0.14
Worth	24.45	21.72	0.57	0.14	0.29	0.00	0.00
Wright	94.10	91.56	0.70	0.38	0.54	0.00	0.18

Appendix D: County-level Correlation Matrix

		1	2	3	4	5	6	7	8
1.	Domestic violence charge rate								
2.	Domestic violence arrest rate	.991**							
3.	Any Recidivism	.229*	.213*						
4.	Domestic Violence recidivism	.299**	.278**	.730**					
5.	Number of Domestic Violence Rearrests	.360**	.333**	.619**	.902**				
6.	Specialization	-.057	-.056	.117	.308**	.160			
7.	Escalation	.089	.068	.443**	.718**	.682**	.304**		
8.	Log population	.316**	.343**	.110	.154	.171	-.039	.135	
9.	Ln violent crime rate (No Aggravated)	.665**	.638**	.145	.124	.194*	-.096	.065	.435**
10.	Property crime rate	.684**	.639**	.225*	.225*	.301**	-.048	.086	.346**
11.	Percentage of population 20-54	.239*	.256**	.126	.160	.186*	-.072	.188*	.672**
12.	Disadvantage Index	.163	.175	.029	-.102	-.083	-.273**	-.244**	.003
13.	Percentage Minority	.152	.168	.058	.001	-.020	-.171	-.019	.566**
14.	Ln arrest rate for drug sales and distribution	.429**	.414**	.226*	.142	.153	-.159	.110	.182
15.	Ln arrest rate for cocaine and opium possession	.272**	.263**	.150	.208*	.193*	-.168	.196*	.169
16.	Arrest rate for marijuana possession	.089	.078	.023	-.056	-.072	-.160	.036	.263**
17.	Ln arrest rate for synthetic possession	.300**	.314**	-.065	-.100	-.043	-.166	-.003	.091
18.	Ln arrest rate for other possession	.415**	.391**	.051	.009	.084	-.089	-.019	.275**
19.	Ln arrest rate for Drunkenness	.282**	.268**	.091	-.008	-.018	-.087	-.138	.001
20.	Arrest rate for DUI	.536**	.506**	.070	.055	.069	-.025	.015	.236**

*p = .05; **p = .01

Appendix D: County-level Correlation Matrix Cont.

		9	10	11	12	13	14	15	16
1.	Domestic violence charge rate								
2.	Domestic violence arrest rate								
3.	Any Recidivism								
4.	Domestic Violence recidivism								
5.	Number of Domestic Violence Rearrests								
6.	Specialization								
7.	Escalation								
8.	Log population								
9.	Ln violent crime rate (No Aggravated)								
10.	Property crime rate	.828**							
11.	Percentage of population 20-54	.334**	.197*						
12.	Disadvantage Index	.261**	.141	-.132					
13.	Percentage Minority	.311**	.173	.494**	.446**				
14.	Ln arrest rate for drug sales and distribution	.411**	.409**	.101	.393**	.229*			
15.	Ln arrest rate for cocaine and opium possession	.260**	.325**	.269**	-.075	.150	.409**		
16.	Arrest rate for marijuana possession	.308**	.268**	.173	.151	.231*	.297**	.341**	
17.	Ln arrest rate for synthetic possession	.158	.209*	-.047	.283**	-.009	.512**	.106	.337**
18.	Ln arrest rate for other possession	.464**	.571**	.132	.115	.103	.464**	.299**	.345**
19.	Ln arrest rate for Drunkenness	.149	.193*	.024	.084	.003	.195*	.069	-.062
20.	Arrest rate for DUI	.555**	.602**	.185*	.020	.116	.329**	.366**	.275**

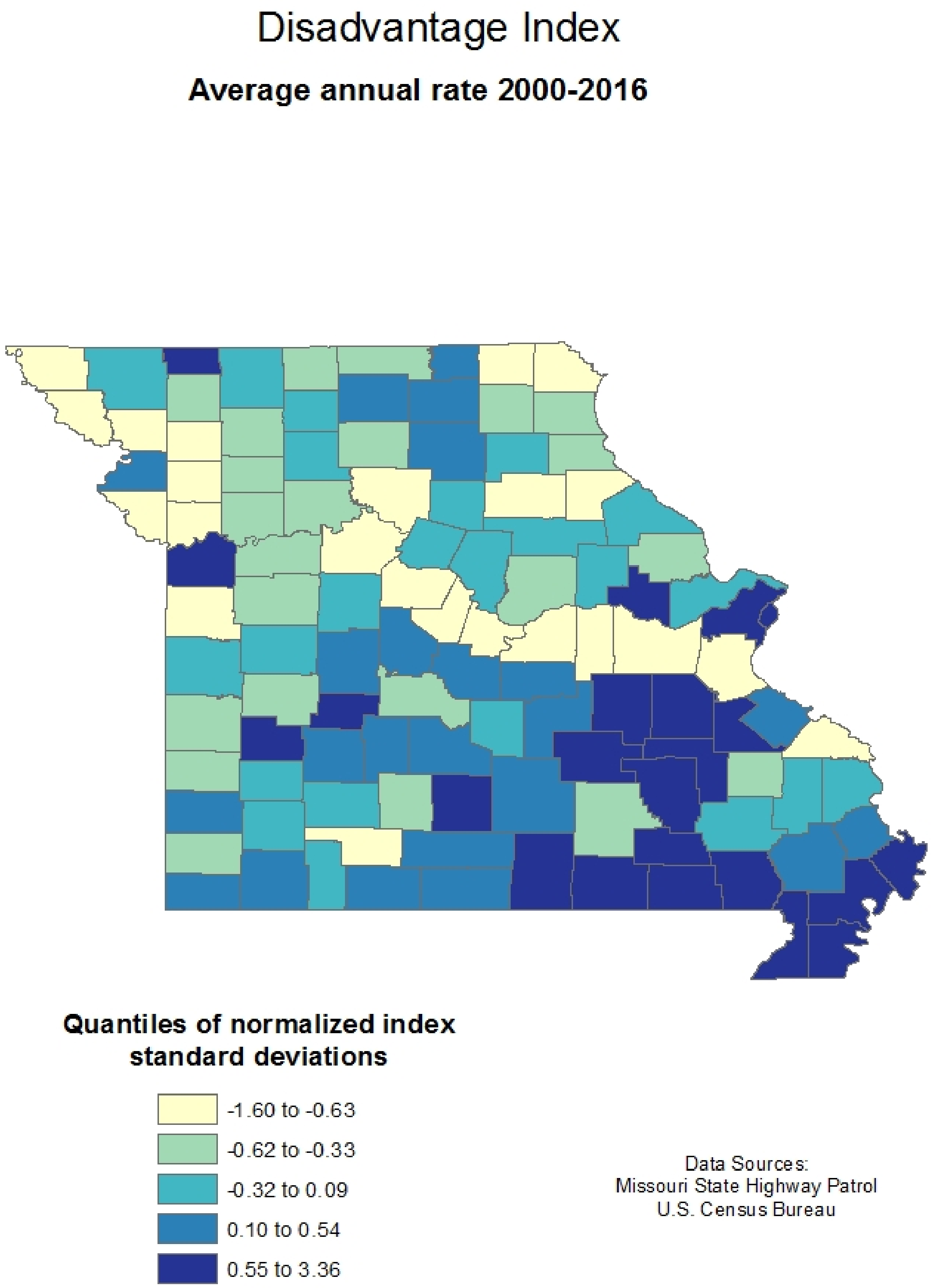
*p = .05; **p = .01

Appendix D: County-level Correlation Matrix Cont.

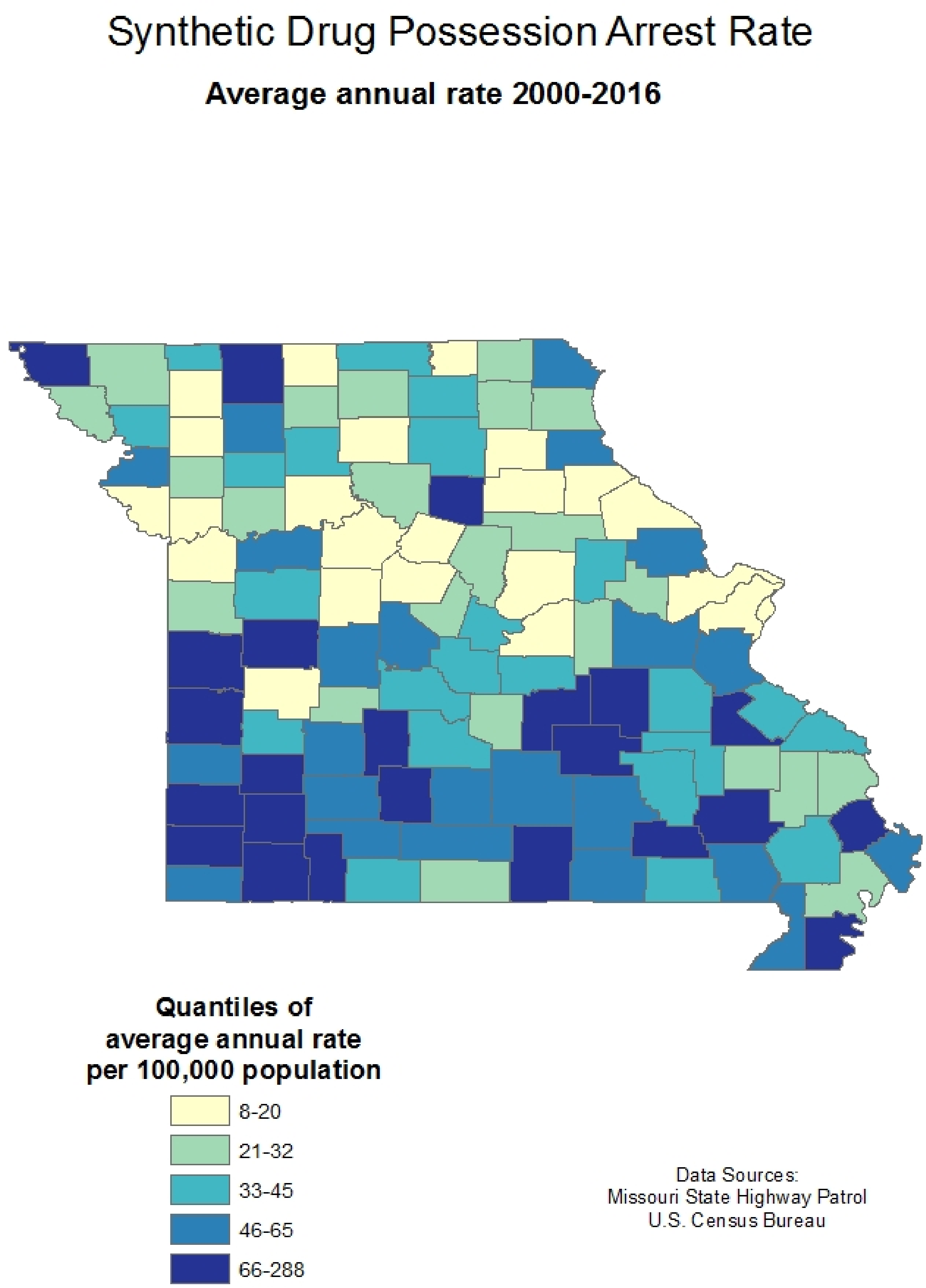
		17	18	19
1.	Domestic violence charge rate			
2.	Domestic violence arrest rate			
3.	Any Recidivism			
4.	Domestic Violence recidivism			
5.	Number of Domestic Violence Rearrests			
6.	Specialization			
7.	Escalation			
8.	Log population			
9.	Ln violent crime rate (No Aggravated)			
10.	Property crime rate			
11.	Percentage of population 20-54			
12.	Disadvantage Index			
13.	Percentage Minority			
14.	Ln arrest rate for drug sales and distribution			
15.	Ln arrest rate for cocaine and opium possession			
16.	Arrest rate for marijuana possession			
17.	Ln arrest rate for synthetic possession			
18.	Ln arrest rate for other possession	.354**		
19.	Ln arrest rate for Drunkenness	.253**	.185*	
20.	Arrest rate for DUI	.257**	.415**	.191**

*p = .05; **p = .01

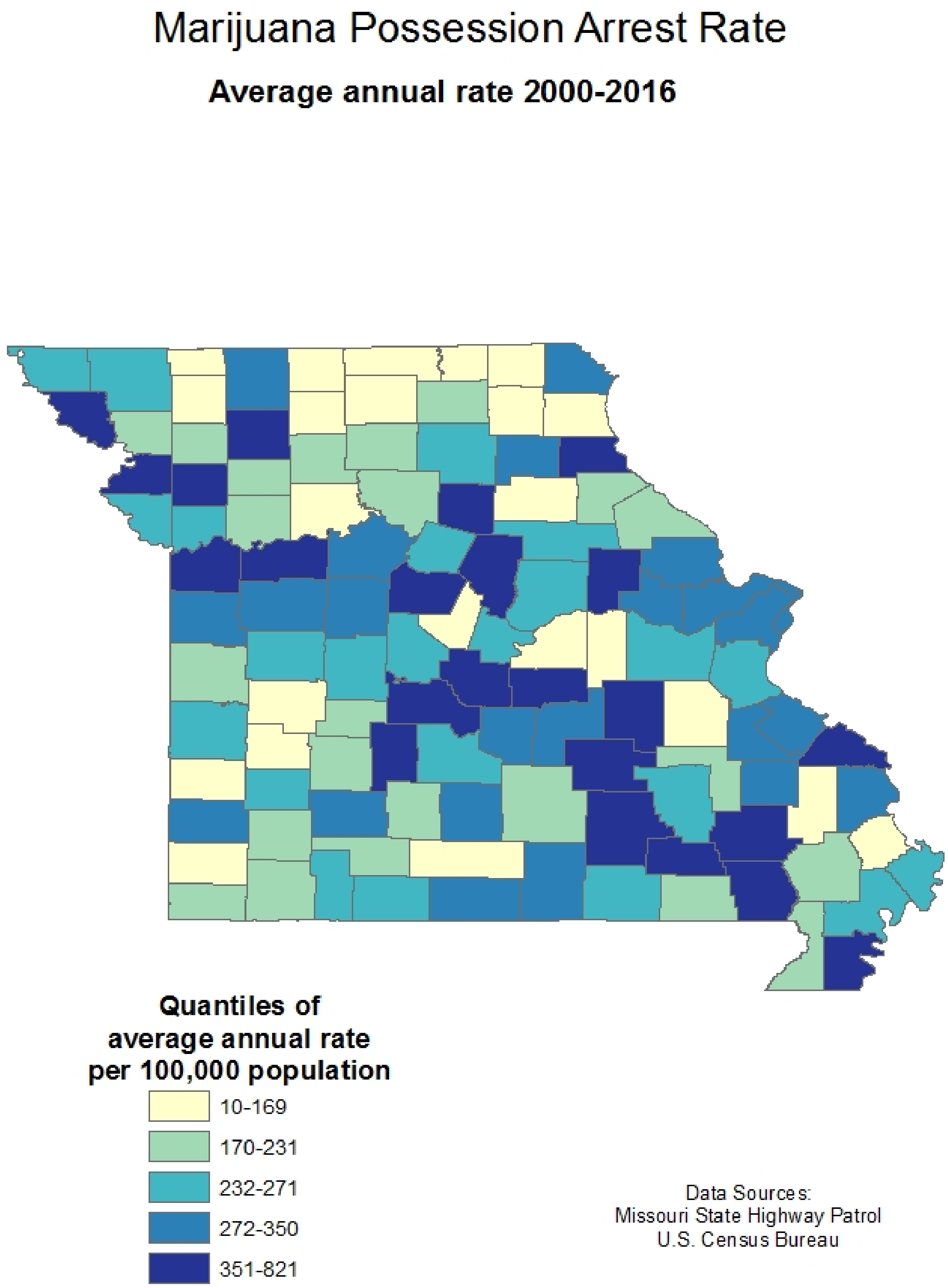
APPENDIX E: Univariate Map – Disadvantage Index



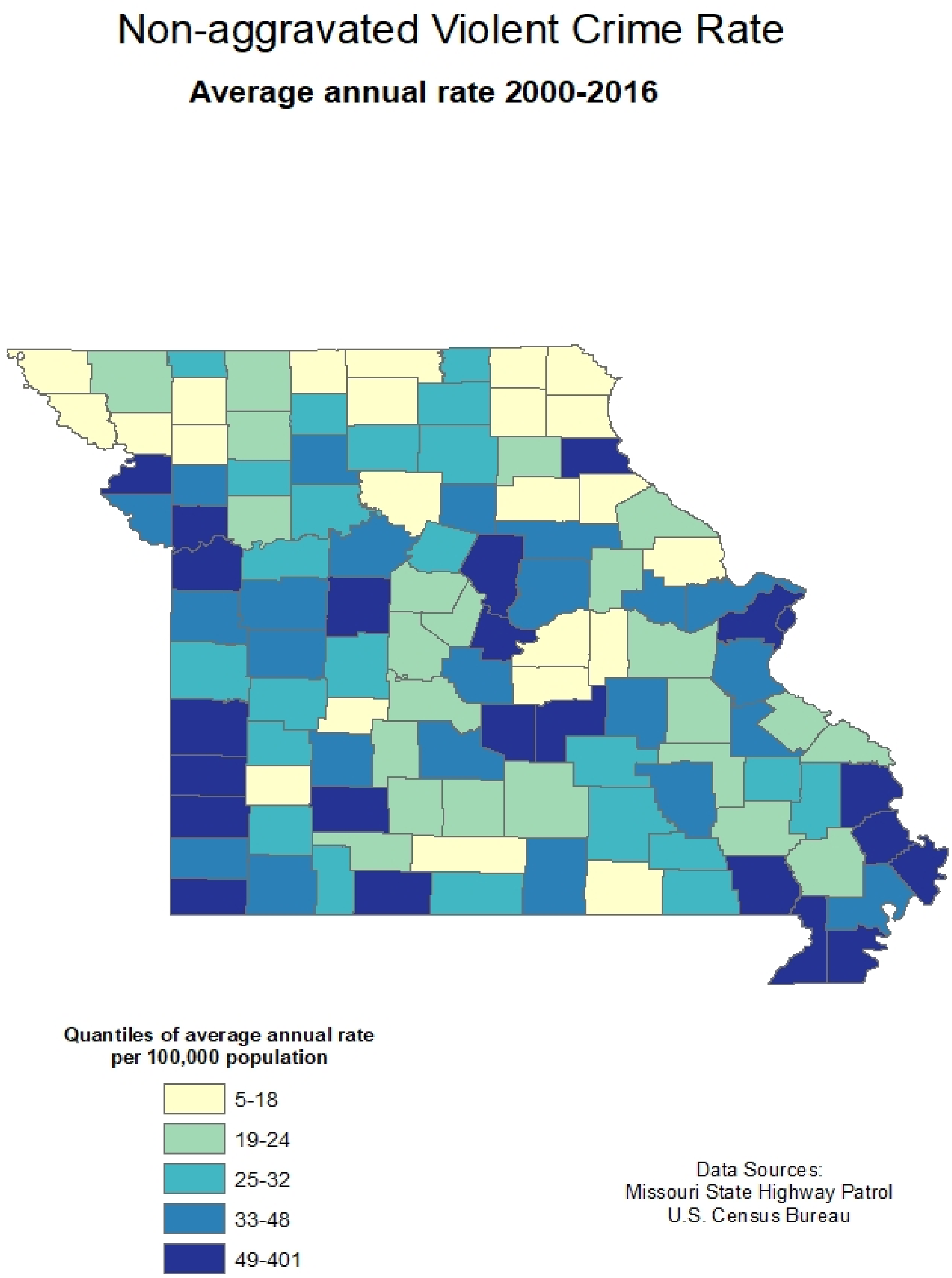
APPENDIX F: Univariate Map – Synthetic Drug Possession Arrest Rate



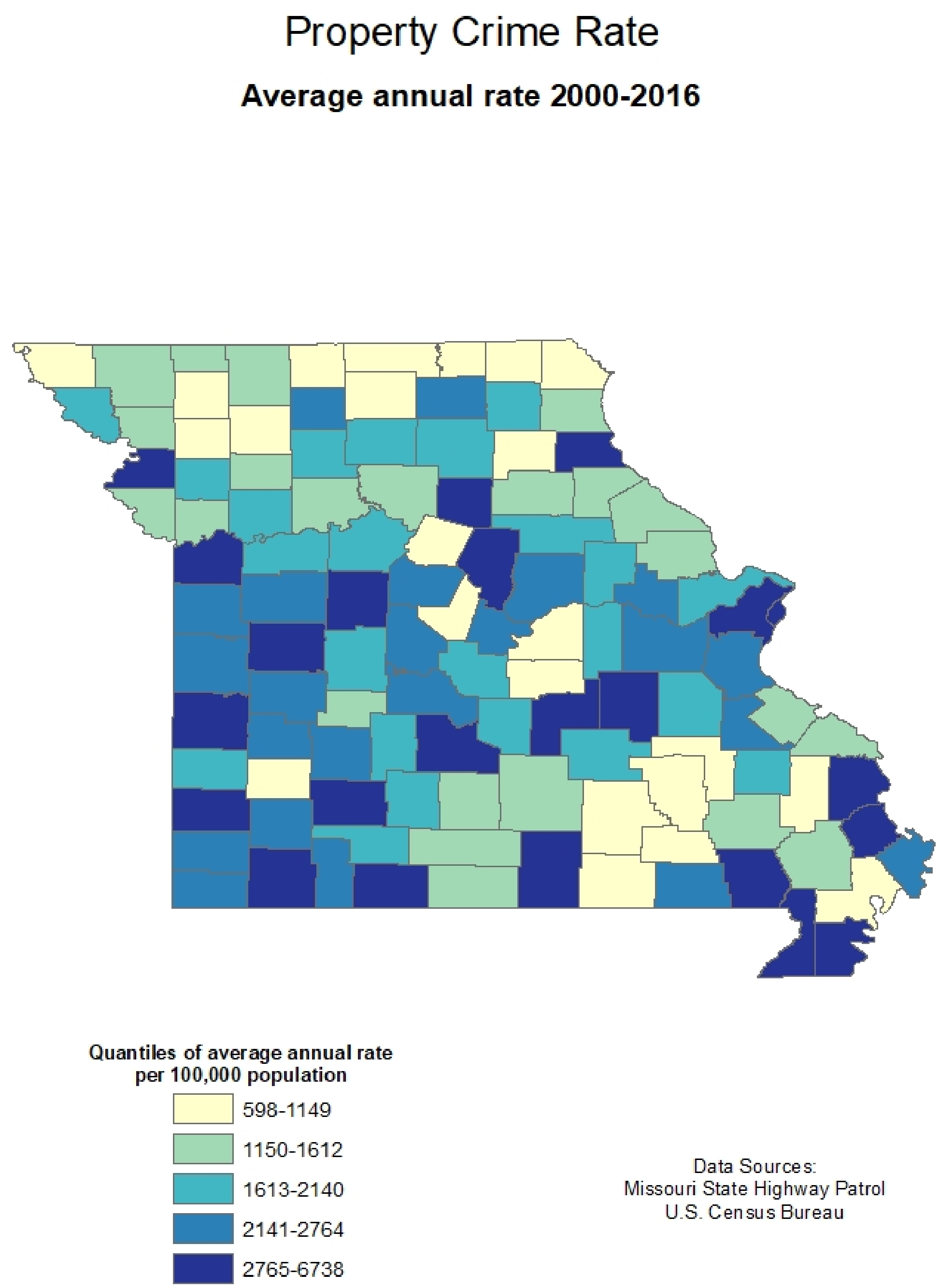
APPENDIX G: Univariate Map – Marijuana Possession Arrest Rate



APPENDIX H: Univariate Map – No Aggravated Assault Violent Crime Rate



APPENDIX I: Univariate Map – Property Crime Rate



APPENDIX J: Univariate Map – Drug Sales and Distribution Arrest Rate