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RESEARCH ARTICLE

REGIONAL VARIATIONS IN CRIME ACROSS THE US STATES

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Abstract

The economics of crime encompasses a broad framework, highlighting the impact of unemployment, poverty, and inequality on criminal behavior. Addressing these issues requires a comprehensive approach that considers not only individuals' rational choices but also systemic factors contributing to inequality and their potential impact on crime rates. Effective solutions necessitate a thorough understanding of these interrelated factors to enhance social well-being and create environments that mitigate the conditions fostering criminal behavior. This study employs the Spatial Durbin Model (SDM) to examine spatial variations in property crime across US states in 2022. Findings indicate that GDP, minimum wage, and the demographic composition of the prison population significantly influence property crime and are, in turn, shaped by socioeconomic conditions in neighboring states.
Keywords: Crime, Spatial Analysis, Regional Economics, Spatial Durbin Model, Unemployment
JEL classification: J01, J1, J6, K13

1. Introduction

Crime is a significant issue that requires careful examination. Since Becker (1968), numerous scholars have attempted to explore its complexities, each contributing new insights to the literature. The investigation of crime and its relationship with different parameters reveals a complicated interplay between economic, social, and individual factors. The search for solutions aims to include a complete understanding of these interconnected phenomena to foster social well-being and create environments that mitigate the conditions encouraging to criminal behavior. The literature on the economics of crime, focusing on the determinants of crime, is vast. Several studies explore the relationship between crime and macroeconomic and institutional variables such as unemployment, unemployment benefits, education and income inequality. A strong link between unemployment and crime has been widely documented. Jawadi et al. (2021) established a robust connection between unemployment and crime, focusing on both violent and non-violent crimes by using a time-varying VAR model. They find that significant positive effects of unemployment shocks on crime rates. Schleimer et al. (2022) explore the association between unemployment and violent crime during the COVID-19 pandemic in the US between

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2018-2020. They observe that increases in unemployment are correlated with higher firearm violence and homicide rates. Juárez et al. (2022) examine the relationship between youth bulges, unemployment, and violent crime in Mexico from 1997 to 2010. The study suggests high youth unemployment in the low-education strata correlates with increased violent crime rates and large cohorts of young men may facilitate the recruitment of criminal organizations.

Another crucial component is the link between income inequality, education and crime. Sugiharti et al. (2023) examine the relationship between income inequality, poverty, and crime rates across 34 Indonesian provinces. The findings indicate that higher income levels and wider income inequality correlate with higher crime rates. Non-food expenditure significantly affects crime rates more than food expenditure and the Gini ratio. The research suggests leveraging education and investment to minimize crime rates in Indonesia. According to van de Weijer et al. (2024), the causal effects of educational attainment on criminal offending using a discordant sibling design and data from the Netherlands. Their research emphasizes that higher education may reduce the risk of delinquency and crime. There are also some studies focus on institutional factors like unemployment insurance benefits to understand crime patterns. NoghaniBehambari and Maden (2021) explore how unemployment insurance (UI) benefits effect crime rates in the US. They conclude that one standard deviation increase in UI benefits correlates with reduced property and violent crime rates. In another study by Britto et al. (2022), the role of unemployment benefits is observed to increase the crime probability by 23% for displaced workers, particularly among young and low-tenure individuals in Brazil. Unemployment benefits offset the potential crime increases, but the effects vanish after benefit expiration.

Research on the economics of crime examines both the linear and spatial dimensions. The seminal study of Andresen (2006) investigates the spatial aspect of criminal activity in Vancouver using social disorganization and routine activity theories. The author compares crime counts and rates with residential and ambient populations as denominators and finds strong support for the routine activity theory and the use of ambient populations in crime rate calculations. Another spatial study by Quick et al. (2018) examine spatial crime patterns using Bayesian multivariate spatial models for burglary, robbery, vehicle, and violent crimes in Greater London. They identify shared components that explain the correlations between crime types and their underlying crime-general patterns. In their study, ToppiReddy et al. (2018) address crime prediction using advanced systems and machine-learning algorithms to improve crime analytics and community protection by employing visualization techniques to analyze crime data and reveal patterns and trends for law enforcement . Leiva et al. (2020) analyze the relationship between immigration and crime in Chile from 2005 to 2015 using a dynamic Spatial Durbin Model (SDM). Their study reveals a negative relationship between immigrants and crime for one of the eight crime types analyzed.

I believe this study contributes to the literature in two key ways. First, it extends beyond a single set of variables by incorporating socioeconomic, institutional, and demographic factors that may impact property crime. Second, it reexamines the determinants of property crime from a spatial perspective across the US states using cross-sectional data for 2022, a period that allows for post-pandemic analysis. By applying Spatial Durbin Model (SDM), it explores both the direct and spillover effects. The purpose of this study is to spatially explore the regional variations in crime in the US. By revisiting the determinants of crime, such as unemployment rate, educational attainment, GDP growth, minimum wage rate, and prison population based on gender and race, SDM is employed. The results suggest that the GDP, minimum wage, and demographic composition of the prison population have a significant impact on property crime. Additionally, findings confirm that determinants of property crime are also influenced by neighboring states.

The remainder of this paper is organized as follows. Section 2 presents the data and empirical methodology, along with stylized facts. Section 3 presents the empirical results of the study. Finally, Section 4 concludes the study.

2. Data and Empirical Strategy

This study aims to spatially and empirically investigate regional variations in crime across US states. This study uses property crime rates at the state level, and the data is compiled from the Federal Bureau of Investigation (FBI). The study period is 2022, including 45 states [1] in the US. Crime is affected by many factors such as unemployment, education, gender, age, and poverty. Reduced unemployment results in a decreased opportunity cost for persons to engage in criminal activities (Becker, 1968; Melick, 2003). Moreover, higher education is expected to reduce crime rates, as it results in a more trained workforce and increased pay (Lochner and Moretti, 2004; Lochner, 2010). Gender and age influence criminal behavior, with males exhibiting a higher propensity for criminal activity (Wilson and Hernstein, 1985). Poverty, associated with inadequate nutrition and living conditions, is also correlated with criminal activity (Philips 1991). Rapid socioeconomic changes, and crime prevention are crucial elements that contribute to an increase in crime rates (Quetelet, 1835). Economic inequality, which impacts the living standards of both rich and poor individuals, increases the probability of criminal engagement (Merton, 1938; Shaw and McKay, 1942; Becker, 1968). Rapid socioeconomic changes such as industrialization and urbanization generate increased opportunities for criminal activity, as individuals are often resistant to adopting new norms and values (Tsushima, 1996). Crime prevention requires moderating the risk factors associated with individuals, including the financial implications of punishment and the effectiveness of public policy (Becker 1968). By comprehending these factors, society can more effectively tackle and avoid crime. Therefore, we incorporate determinants of crime such as (high school) educational attainment, GDP growth rate, unemployment rate, hourly minimum wage, and prison population based on gender and race, and include them in the model (Zavodny 2000; Elsby et al. 2013; Altonji et al. 2016; Fanfani 2023). Data for the control variables are obtained from the Bureau of Labor Statistics (BLS) and the National Center for Education Statistics.

1 Alaska, Connecticut, Delaware, Hawaii, Rhode Island, and Vermont are not included in the analyses due to data availability. District of Columbia is included.

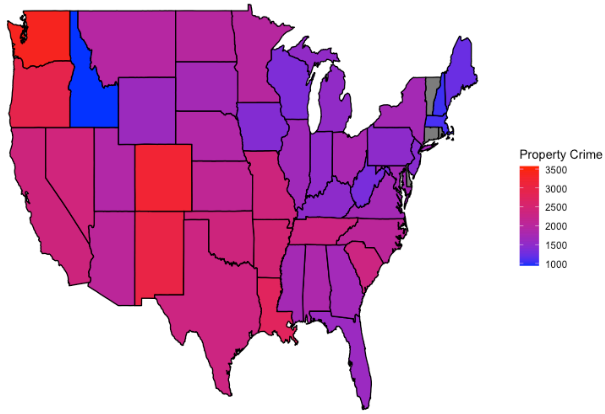

Figure 1. Property Crime Rate in the US (per 100,000)

Source: FBI, Author's own calculation.

Figure 1 presents maps of property crime for 2022, demonstrating how different regions spatially experience changes in property crime rates. In Washington, Oregon, Colorado, New Mexico, and Louisiana, we observe higher levels of property crimes that may reflect higher population density, inequality, urbanization, and more opportunities, that is, theft. The high levels of substance use in these states also reflect higher crime rates. As we move to states such as Idaho, New Hampshire, and Massachusetts, we observe lower crime rates that may be due to low population density and greater economic stability, reducing opportunities for property crime.

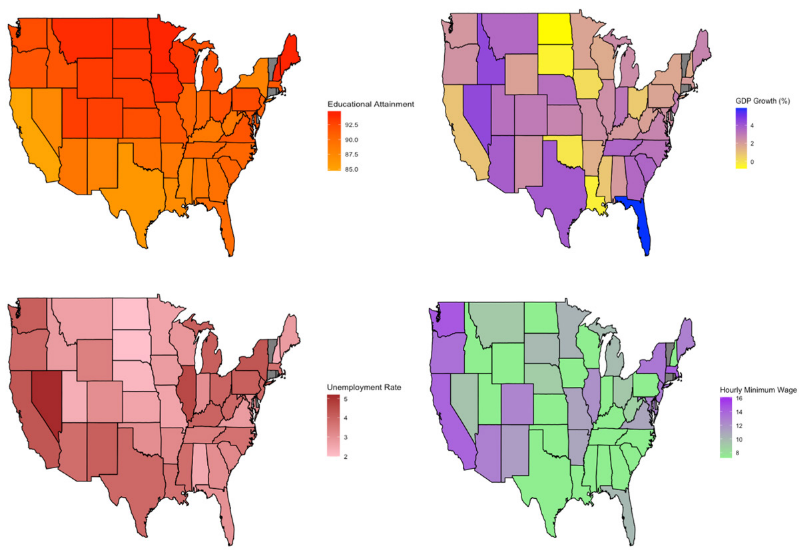

Figure 2. Economic and Labor Market Indicators

Source: Bureau of Labor Statistics (BLS), National Center for Education Statistics, Author's own calculation.

Figure 2 represents the socioeconomic factors in the US States in 2022. The map on the top left presents high school educational attainment, and Northern States such as Minnesota, North Dakota, New England have the highest level, while we see lower rates for the southern states. The map on the top right shows the GDP growth rate across states, and we observe that some of the Midwest states show higher GDP along with Florida, while yellow shaded states indicate lower GDP growth. Regarding the unemployment rate, a higher unemployment rate appears in the Midwest and Southern states such as Nevada, while the Northern states reflect a lower unemployment rate. Finally, the map on the bottom right represents the hourly minimum wage across states, and higher wage levels are seen in West and Northeastern states, such as California and Washington. This reflects the differences in state policies and cost of living adjustments.

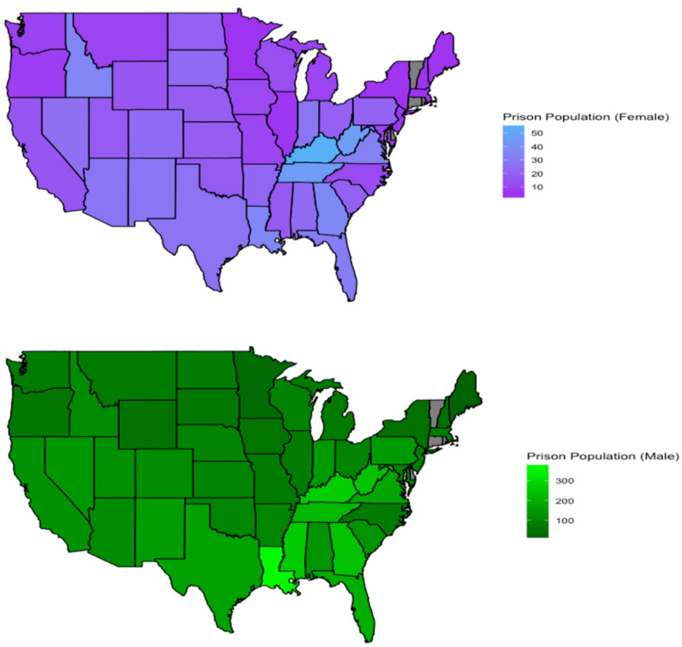

Figure 3. Prison Population Based on Gender

Source: Annual Survey of Jails, Author's own calculation.

The prison population for men and women is higher in states such as Kentucky, Tennessee, Idaho, West Virginia, Georgia, and Louisiana as depicted in Figure 3. Strict criminal justice policies, high drug use rates, and economic conditions reflect the higher prison population in these states. Additionally, Louisiana has a very large private prison industry in the US However, overall, the prison population is six times higher for men, revealing the importance of the gender aspect of the criminal justice system.

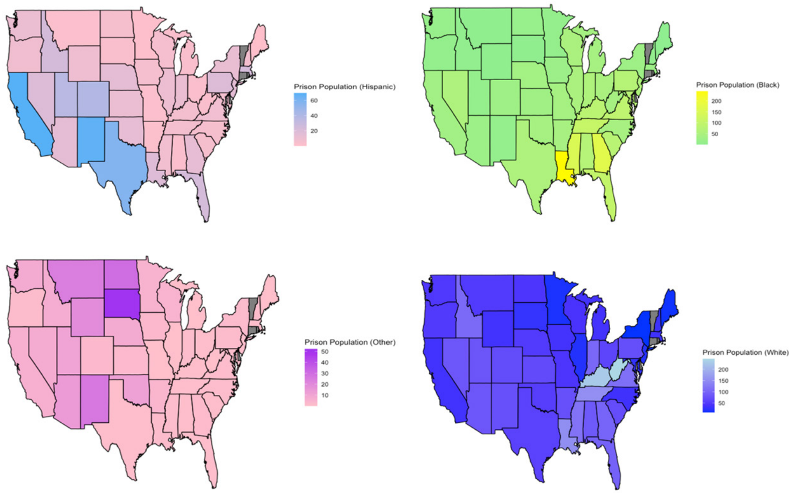

Figure 4: Prison Population Based on Race

Source: Annual Survey of Jails, Author's own calculation.

The prison population based on race showed different outcomes across states, as shown in Figure 4. The Hispanic prison population is mostly higher in Southern Western states (California, New Mexico, Texas), which are neighbors of Mexico. When we look at the black individuals' prison population, we see that Louisiana and Georgia have the highest rates, which could be explained by the high number of private prisons in these states. The prison population for white individuals is mostly higher in Kentucky and West Virginia, while the rate is higher for others in the Northern states.

The Spatial Durbin Model (SDM) extends the Spatial Lag Model (SLM) by including spatial lags of the independent variables. This allows the model to capture both direct effects (the impact of independent variables on the dependent variable within a region) and spillover effects (the impact of independent variables from neighboring regions).

The general form of SDM is:

$$y = \rho W_y + X\beta + WX\theta + \varepsilon$$

where y is the N×1 vector of the dependent variable property crime, p is the spatial autoregressive parameter, capturing the dependence of y on neighboring values through the spatial weight matrix W. W_y is the spatially lagged dependent variable, which introduces spatial feedback effects and $WX\theta$ is the spatially lagged control variables. X is the N×K matrix of control variables. And ε is the error term.

3. Results

To scrutinize the spatial dependence of crime rates across US states, we employ spatial models, including the Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model

(SDM). These models are selected to account for potential spatial autocorrelation in the data, ensuring robust estimation. We first estimate the SLM, which incorporates spatial dependence in the dependent variable by including a spatially lagged term. Next, we run the SEM, which accounts for spatial dependence in the error term. Finally, we estimate the SDM, which extends the SLM by including spatially lagged explanatory variables. One must consider two key criteria when determining the most appropriate model. The first criterion is the Akaike Information Criterion (AIC), in which a lower AIC value indicates a better model fit [2]. Second is Moran's I test of residuals. Moran's I [3] is to assess whether spatial autocorrelation remains in the residuals after model estimation. Given that SDM had the lowest AIC and shows no significant spatial autocorrelation in the residuals, we selected it as the preferred model for our analysis. SDM not only provides a better fit, but also effectively accounts for spatial spillover effects by incorporating both spatially lagged dependent and independent variables.

Table 1 presents the results of the spatial models of property crimes. The Spatial Durbin Model (SDM), which includes spatially lagged independent variables to capture both direct and spillover effects, indicates significant spatial dependence (p = 0.073293). Unlike the Spatial Lag Model (SLM), SDM accounts for these dependencies and provides a more comprehensive analysis. Among the key determinants of property crime, GDP growth is statistically significant with a negative coefficient, aligning with the general expectation that better economic conditions reduce economically motivated crimes. This may stem from improved job prospects and stronger social cohesion. The coefficient of minimum wage indicates a positive and significant relationship with property crime, which may be explained by adjustments in the labor market, since minimum wage is determined at the federal level. This may reflect an adjustment period in which businesses reduce employment opportunities, or a cost-of-living effect.

Regarding demographic variables, a negative coefficient for the male prison population suggests that higher incarceration rates are associated with lower property crime, consistent with deterrence or incapacitation effects. The prison populations of Black, Hispanic, and White are positively associated with property crime, whereas the prison populations of other individuals show no significant relationship with property crime.

Table 1. Spatial Durbin Model (SDM) Estimates

	Property Crime
Educational Attainment	0.031
	(0.025)
Unemployment Rate	-0.009
	(0.022)

2 AIC for the SLM is – 47.48917, SEM is – 49.82004, and finally SDM is – 57.76281. Therefore, SDM is a better fit, and results are reported for SDM. Results for SLM and SEM are available upon request.

3 Additionally, we conducted Moran's I test on the residuals to evaluate the presence of spatial dependence. The test results indicated no significant spatial autocorrelation in all models (for SLM p = 0.2965, for SEM p= 0.5295 and for SDM p= 0.4485 residuals).

GDP growth	-0.038*
	(0.019)
Log_minimum wage	0.031*
	(0.017)
Prison Population (male)	-0.802*
	(0.386)
Prison Population (female)	-0.059
	(0.063)
Prison Population (white)	0.471*
	(0.259)
Prison Population (black)	0.568**
	(0.264)
Prison Population (Hispanic)	0.248**
	(0.096)
Prison Population (other)	0.079
	(0.056)
L.Educational Attainment	-0.053
	(0.048)
L.Unemployment Rate	-0.013
	(0.049)
L. GDP growth	-0.095**
	(0.040)
L.log_minimum wage	-0.072
	(0.063)
L. Prison Population (male)	-2.625*
	(1.351)
L. Prison Population (female)	-0.090
	(0.219)
L. Prison Population (white)	1.537*
	(0.904)
L. Prison Population (black)	1.772*
	(0.925)
L. Prison Population (Hispanic)	0.748**
	(0.325)
L. Prison Population (other)	0.208
	(0.168)
Intercept	3.015***
	(0.657)
Rho	0.073
Moran's I	-0.011
Log-Likelihood	51.881
AIC	-57.763
LM	0.081332

Note: ***p < 0.01; **p < 0.05; *p < 0.1. L refers to the lagged value. Author's own calculation.

To measure spillover effects, we examine the statistically significant lagged independent variables, as they exhibit cross-state influences on property crime. These spillover effects would allow us to distinguish the direct and indirect impacts. By measuring these influences, one can understand how economic and social circumstances in one state would spread across state borders that shape crime dynamics beyond local factors. A positive coefficient reveals that higher values in neighboring states are linked with an increase in the property crime in the local region, highlighting spillover effect. On the other hand, a negative coefficient shows that higher values in neighbor states stand for a decrease in the local property crime rate, reflecting a deterrent spillover effect. Specifically, lagged GDP growth indicates that higher GDP in neighboring states is associated with local crime rates, potentially due to improved economic opportunities. Regarding the prison population, the findings suggest that higher male incarceration in neighboring states reduces property crime. However, higher incarceration rates among different racial groups in neighboring states are linked to increased property crimes, possibly due to economic distress spillovers or migration patterns. Gunadi (2021) analyzes the pace at which 11 million illegal immigrants in the US have become part of the institutional system, as well as the impact of their presence on crime rates. The rate of institutionalization is higher among younger newcomers. Stuart and Taylor (2021) investigate the influence of social connectivity on crime rates in the US cities between 1970 and 2009. The findings indicate that higher levels of social connectedness have a substantial effect in lowering crime rates, especially among teenagers and young adults engaged in gang – and drug-related behaviors. Furthermore, demographic structures in neighboring states play a crucial role in shaping local crime dynamics. These findings highlight the importance of considering regional interactions, economic opportunities, and disparities in law enforcement when analyzing crime patterns.

4. Conclusion

This study aims to empirically investigate regional variations in crime across the US states. We used cross-sectional data for the US states for the year 2022. Literature on the economics of crime indicates that various factors affect crime rates in a society (Becker, 1968; Freeman, 1999; Melick, 2003; Imrohoroglu et al., 2006). Consequently, we empirically investigate this issue by conducting spatial analysis. Our approach moves beyond the standardization of crime determinants and introduces a novel methodological framework that incorporates neighborhood effects to analyze the factors influencing crime. SDM provides the most comprehensive understanding of spatial crime dynamics by capturing both direct and spillover effects. The results underscore the significance of GDP, minimum wage, and demographic composition in explaining crime patterns, while also emphasizing the role of neighboring states' socioeconomic and institutional conditions on local crime rates. Finally, our results reveal that crime is not merely a local phenomenon but is strongly influenced by the socioeconomic and demographic conditions of neighboring states.

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