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Analysis of the Influence of Economic, Social, and Demographic Factors on Narcotics Trafficking Crime in Riau Province Using a Spatial Approach

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Abstract
This study examines the spatial determinants of narcotics crime across 12 districts and cities in Riau Province, Indonesia, by integrating socio-economic and demographic factors into a spatial econometric framework. The increase in narcotics-related offenses, along with regional disparities in economic conditions and law enforcement capacity, highlights the need to explore how local characteristics and spatial interdependencies contribute to crime distribution. Using panel data from 2014 to 2023 and applying the Spatial Lag of X (SLX) model with random effects, this study investigates the direct and spillover effects of unemployment, poverty, income inequality, education level, economic growth, and youth male population on narcotics crime rates. The results reveal that unemployment has a significant positive effect on narcotics crime, indicating that individuals in economically vulnerable areas are more likely to engage in illegal activities. Education level shows a strong spatial spillover effect, suggesting that improvements in educational attainment in one district can reduce crime in neighboring regions. Interestingly, poverty is negatively associated with narcotics crime, possibly due to limited market viability and enforcement presence in extremely poor areas. Income inequality and male youth population were not statistically significant, although they remain theoretically relevant. The presence of strong spatial autocorrelation, confirmed through Moran's I and Lagrange Multiplier tests, validates the use of spatial panel regression models. This research contributes to spatial criminology in Indonesia by highlighting the regional interconnectedness of socio-economic factors and narcotics crime. It suggests that anti-narcotics policies must be coordinated at the provincial level, integrating employment programs, education reform, and inter-district cooperation. The study recommends future research to incorporate institutional quality, law enforcement capacity, and micro-level spatial data for more nuanced policy formulation.

Keywords: Spatial Econometrics, Narcotics Crime, Socioeconomic Factors, Unemployment, Education, Spatial Spillover, Regional Inequality, Riau Province, Panel Data, Spatial Lag Model

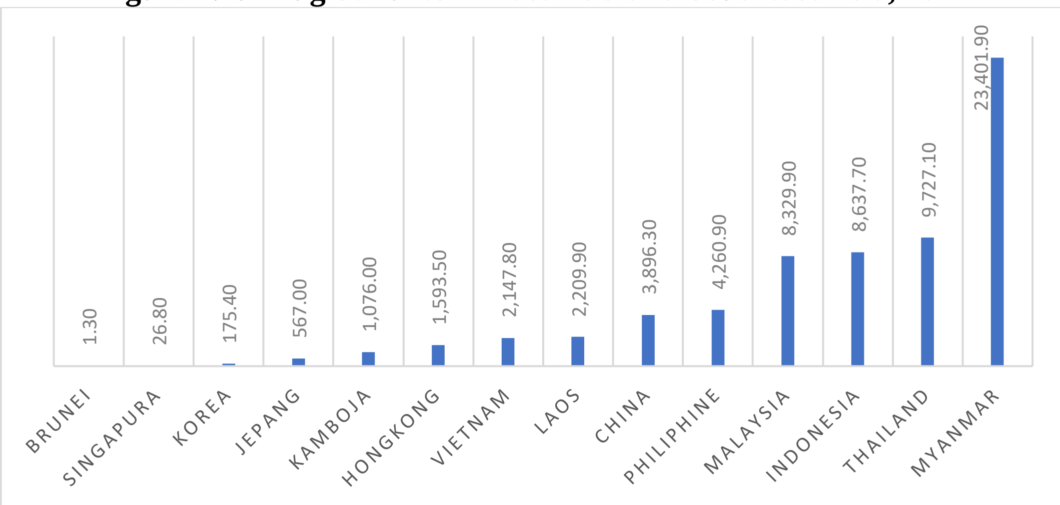
1. Introduction

Globalization has transformed economic and social landscapes, fostering interconnectedness through technological advancements, relaxed border policies, and global trade integration (Amalia Siti et al., 2020). While these changes have spurred economic growth and cultural exchange, they have also facilitated the rise of underground economies, which operate outside formal regulatory frameworks. These clandestine activities, including illicit drug trafficking, undermine national economies by reducing tax revenues, distorting economic indicators, and fueling social instability (Hoinaru et al., 2020). Illicit drug trafficking, a transnational crime, poses significant challenges to public safety, health, and economic development, with far-reaching consequences for communities worldwide. In Indonesia, particularly in Riau Province, the interplay of geographic, economic, social, and demographic factors creates a unique environment that exacerbates the prevalence of drug-related crimes, necessitating a comprehensive analysis to inform effective policy interventions.

The underground economy, as defined by Smith (1994, as cited in Faal, 2003), includes both legal and illegal activities that evade official GDP calculations. Illicit drug trafficking falls wzed by its violation of legalnorms and operation within the "black economy" (Feige, 1990, as cited in Amalia Siti et al., 2020). Globally, the illicit drug trade generates approximately US$400 billion annually, accounting for 8% of total global trade (Sandi Awet, 2016). The profitability of this trade is evident in the varying wholesale prices of narcotics: for example, a kilogram of heroin costs US$2,089 in Pakistan, US$53,333 in the United States, and up to US$142,857 for high-quality heroin in Indonesia (UNODC, 2023). These high profit margins drive sophisticated trafficking networks that exploit weaknesses in border controls and leverage advanced organizational structures to operate across borders (Reichel & Albanese, 2013).

In Indonesia, the drug trafficking landscape has shifted dramatically, with the country evolving from a transit hub to a primary destination for narcotics (Lusia Sinta Herindrasti, 2018). This trend is particularly pronounced in Riau Province, strategically located in Sumatra along the Malacca Strait, a critical maritime route bordering Malaysia. The United Nations Office on Drugs and Crime (UNODC, 2023) reports that Indonesia ranks third globally in the seizure of amphetamine-type stimulants (ATS), with 8,637.7 kilograms of methamphetamine confiscated in 2022, as illustrated in **Figure 1.1**(UNODC, 2023).

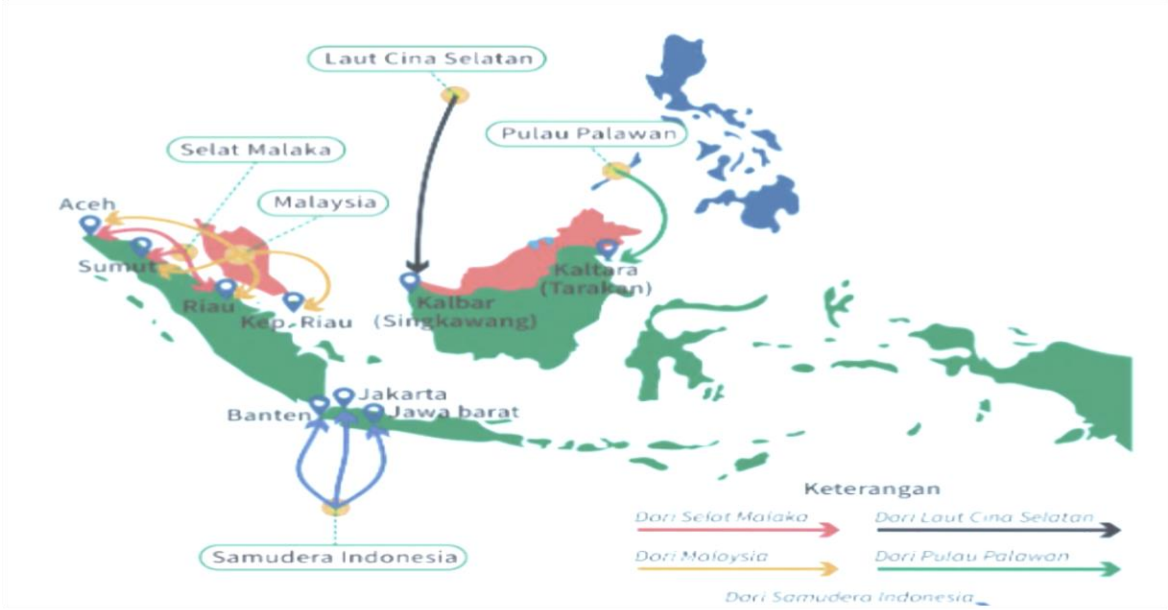
Figure 1.1: Drug Seizures in East Asia and Southeast Asia, 2022



Source: (UNODC, 2023).

This figure highlights the significant volume of ATS seizures in Indonesia compared to other Southeast Asian countries, underscoring the country's growing role in the global drug trade. Within Riau, the National Narcotics Agency (BNN) documented 1,910 drug-related cases in 2022, making it the second-highest in Sumatra after North Sumatra (BNN, 2022). Riau's extensive coastline and proximity to international waters facilitate smuggling, as depicted in **Figure 1.2** which maps key entry points through the Malacca Strait and Indian Ocean (Puslitdatin BNN, 2022).

Figure 1.2: Maritime Drug Smuggling Routes in Riau Province

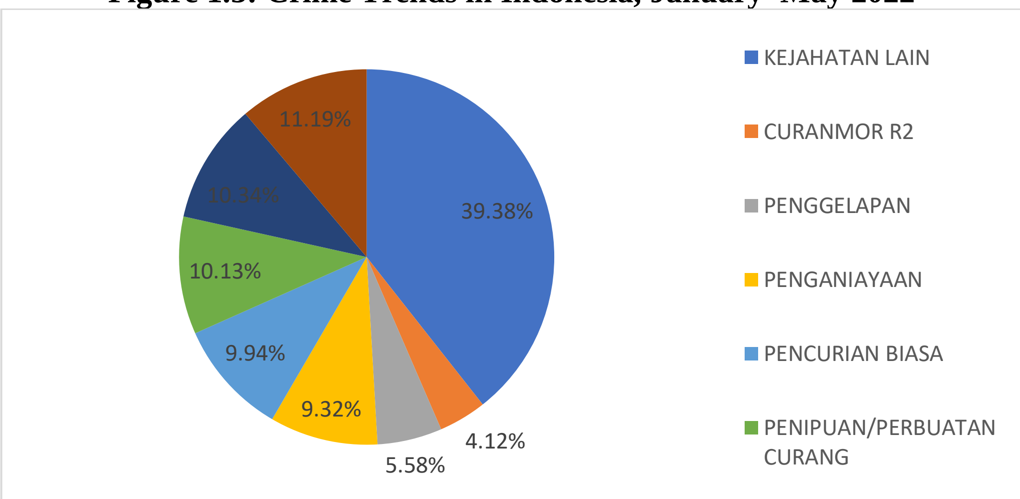


Source: (Puslitdatin BNN, 2022)

This figure illustrates the maritime pathways exploited by traffickers, highlighting Riau's coastal regencies, such as Bengkalis and Dumai, as critical nodes in the drug trade.

The socio-economic impacts of drug trafficking are profound, encompassing economic losses, social disruption, and public health challenges. The high cost of sustaining drug addiction often leads users to commit secondary crimes, such as theft and robbery, to finance their habits (Goode, 1999, as cited in Puslitdatin BNN, 2022). Globally, the economic burden is significant: in England and Wales, drug-related crime costs between £10.1 billion and £17.4 billion annually (Godfrey et al., 2002). In the United States, Washington State reported a US$5.21 billion economic loss from drug and alcohol abuse in 2005, a 105% increase from 1996 (Wickizer, 2007). In Texas, substance abuse led to US$26 billion in economic losses in 2000, with healthcare costs alone amounting to US$791 million (Liu, 2003, as cited in BNN, 2014). In Indonesia, drug-related crimes rank as the second-highest after theft, with 15,459 cases reported nationwide in the first half of 2022, as shown in **Figure 1.3** (Pusiknas Polri, 2022).

Figure 1.3: Crime Trends in Indonesia, January–May 2022

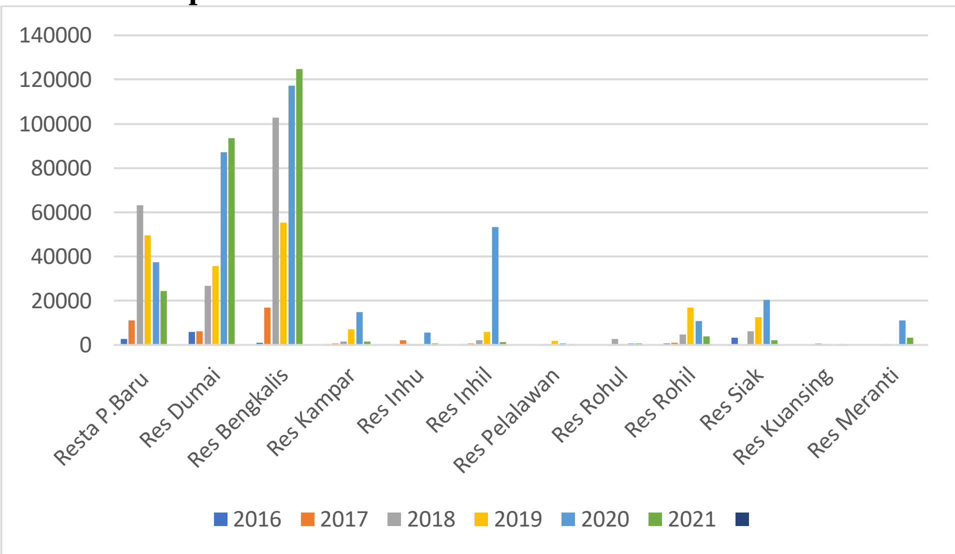


Source: National Police Education Center data processed by researchers

This diagram illustrates the prominence of drug crimes within Indonesia's broader crime landscape, emphasizing the need for targeted interventions.

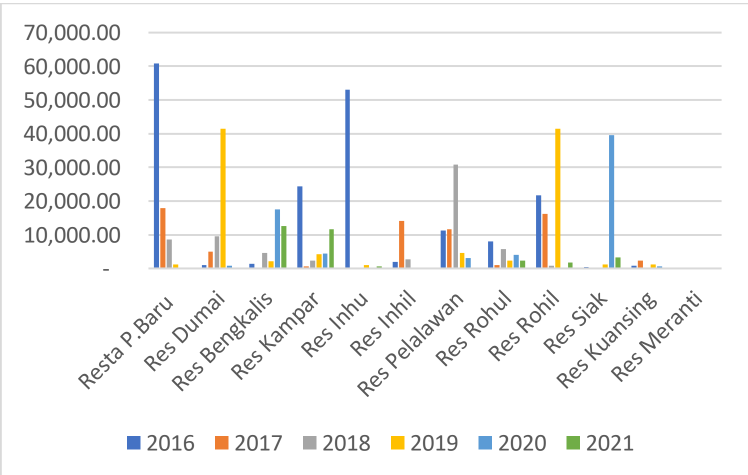
Riau Province's unique socio-economic and geographic characteristics make it particularly vulnerable to drug trafficking. Spanning 87,023.66 km², Riau is Sumatra's second-largest province and one of Indonesia's wealthiest, driven by its oil, gas, and palm oil industries (BPS RI, 2023). However, economic prosperity is unevenly distributed, with income inequality, unemployment, and poverty creating conditions conducive to underground economies (Murialti & Hadi, 2023). The province is divided into resource-rich inland areas, dominated by palm oil plantations, and coastal regions that serve as gateways for international trade and smuggling (Hendraparya, 2016). Coastal regencies like Bengkalis and Dumai are hotspots for methamphetamine and ecstasy trafficking, as evidenced by **Fgure 1.4,** which shows a sharp increase in methamphetamine seizures in Bengkalis from 1,023.71 grams in 2016 to 124,705.90 grams in 2021 (Ditresnarkoba Polda Riau, 2024). In contrast, inland areas report higher cannabis seizures, as depicted in **Figure 1.5**, highlighting the spatial variation in drug types across the province (Ditresnarkoba Polda Riau, 2024).

Figure 1.4: Methamphetamine Seizures from Criminal Activities in Riau Province,



Source: (Riau Police Narcotics Investigation Directorate, 2024)

Figure 1.5: Cannabis Seizures from Criminal Activities in Riau Province



Source: (Riau Police Narcotics Investigation Directorate, 2024)

Economic factors significantly influence drug trafficking in Riau. Unemployment and poverty drive individuals toward illegal activities as a means of economic survival (Rahman et al., 2021). **Table 1.1** provides a detailed breakdown of suspects' occupational and educational backgrounds, revealing the prevalence of low-skill and unstable employment among offenders. Income inequality further exacerbates these issues, creating social tensions that fuel criminal behavior (Hazra & Cui, 2018). However, Riau's economic growth, driven by its resource-based economy, may have a dual effect: while it can reduce poverty, it may also attract criminal networks seeking to exploit economic opportunities (Cornwell & Trumbull, 1994, as cited in Eide et al., 2006).

The Riau Police, through the Directorate of Drug Investigation, revealed that drug crimes in 2022 were committed mainly by people who work as self-employed, namely 1,020 suspects (37.83%), 639 suspects were unemployed (23.70%), 301 suspects worked as farmers (11.16%) and 324 suspects were private workers (12.02%), as shown in **Table 1.1**(Ditresnarkoba Polda Riau, 2022). Social factors, particularly education, play a crucial role in shaping drug trafficking patterns. Lower educational attainment is associated with higher involvement in underground economies, as individuals with limited skills are more likely to engage in illegal activities (Atkinson, 1988, as cited in Amalia Siti et al., 2020). Moreover,let us consider the educational aspect. In that case, the suspects are dominated by high school graduates of 54.23% or 1,462 people, junior high school graduates of 23.92% or 645 people, elementary school graduates of 536 people or around 19.88% and university graduates of 53 suspects (1.97%) (See **Table 1.1**).

Table 1.1: Profile of Drug Crime Suspects by Occupation and Education in Riau Province, 2022

NO	KESATUAN	JUMLAH LP	JUMLAH TSK	PENDIDIKAN				PEKERJAAN									
				SD	SLTP	SLTA	PT	PNS	TNI	POL	SWT	WST	TANI	MHS	PLJ	BR	PNG
1	DIT RES NARKOBA	122	216	14	18	177	7	0	0	4	31	67	9	6	10	27	62
2	RESTA P. BARU	171	273	0	23	248	2	1	0	1	47	47	3	5	6	24	139
3	RES DUMAI	110	158	19	26	110	3	0	0	0	19	35	13	2	0	36	53
4	RES BENGKALIS	200	346	19	157	170	0	4	0	0	43	100	33	0	0	43	123
5	RES KAMPAR	291	392	109	115	159	9	0	0	0	57	218	18	27	13	13	46
6	RES INHU	80	115	42	30	41	2	2	0	0	15	52	18	1	7	6	14
7	RES INHIL	96	157	39	33	76	9	4	1	0	12	87	11	2	1	9	30
8	RES PELALAWAN	134	177	82	47	46	2	0	0	0	29	66	58	0	1	3	20
9	RES ROHUL	146	197	68	65	56	8	1	0	0	10	95	47	1	6	15	22
10	RES ROHIL	187	280	50	18	211	1	2	0	1	17	114	48	0	2	40	56
11	RES SIAK	131	175	53	54	67	1	0	0	0	38	37	19	2	7	23	49
12	RES KUANSING	73	92	13	35	41	3	0	0	0	6	38	20	0	13	4	11
13	RES KEP MERANTI	74	118	28	24	60	6	2	0	5	0	64	4	15	2	12	14
JUMLAH		1815	2696	536	645	1462	53	16	1	11	324	1020	301	61	68	255	639
				2696				2696									

Sumber : Ditresnarkoba Polda Riau 2022

NOTES: LP (Police Report), TSK (Suspect), SD (Elementary School), SLTP (Junior High School), SLTA (Senior High School), PT (Higher Education), PNS (Civil Servant), TNI (Indonesian National Army), POL (Police), SWT (Private Sector), WST (Self-employed), TANI (Farmer), MHS (University Student), PLJ (Student), BR (Laborer), PNG (Unemployed), RES (District), DIT (Directorate), KEP (Islands).

Demographic factors, particularly gender and age, are also critical drivers of drug trafficking. In Riau, males dominate drug-related crimes, with 2,520 male suspects compared to 176 female suspects in 2022, as shown in **Table 1.2**(Ditresnarkoba Polda Riau, 2022).

Table 1.2: Profile of Drug Crime Suspects by Gender and Age in Riau Province, 2022

NO	KESATUAN	JUMLAH LP	JUMLAH TSK	WARGA NEGARA				USIA				
				WNI		WNA		<15	16-18	19-24	25-29	>30
				LK	PR	LK	PR					
1	DIT RES NARKOBA	122	216	197	19	0	0	0	1	45	62	108
2	RESTA P. BARU	171	273	243	30	0	0	0	3	67	59	144
3	RES DUMAI	110	158	144	14	0	0	0	2	33	29	94
4	RES BENGKALIS	200	346	326	20	0	0	1	13	65	65	202
5	RES KAMPAR	291	392	367	25	0	0	0	14	66	90	222
6	RES INHU	80	115	103	12	0	0	0	4	17	29	65
7	RES INHIL	96	157	153	4	0	0	1	3	18	25	110
8	RES PELALAWAN	134	177	169	8	0	0	0	1	28	38	110
9	RES ROHUL	146	197	189	8	0	0	1	25	38	67	66
10	RES ROHIL	187	280	268	12	0	0	0	6	38	43	193
11	RES SIAK	131	175	163	12	0	0	0	5	35	37	98
12	RES KUANSING	73	92	89	3	0	0	0	6	14	20	52
13	RES KEP MERANTI	74	118	109	9	0	0	0	19	22	19	58
JUMLAH		**1815**	**2696**	**2520**	**176**	**0**	**0**	**3**	**102**	**486**	**583**	**1522**
				2696				**2696**				

Sumber : Ditresnarkoba Polda Riau 2022

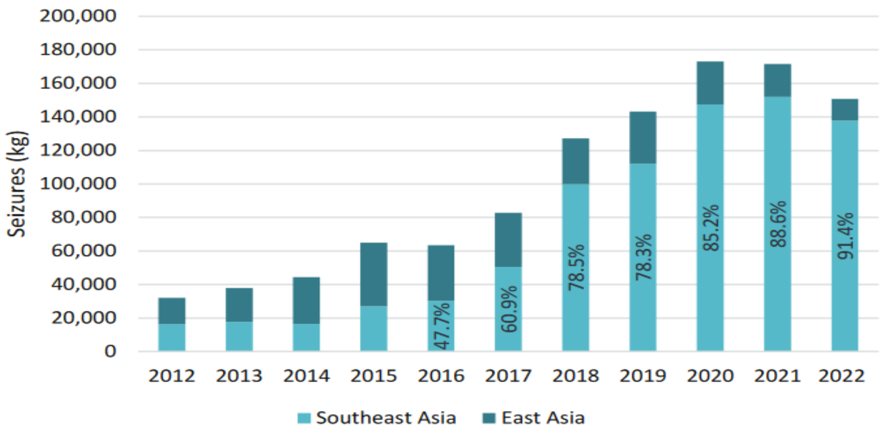
NOTE:LP (Police Report), TSK (Suspect), WNA (Foreign Citizens), LK (Male), PR (Female), USIA (Age), RES (District), DIT (Directorate), KEP (Islands), WARGA NEGARA (Citizens), RESTA (Police Resort)

Table 1.2 highlights the significant gender disparity and the concentration of suspects in the 25–29 and over-30 age groups, with 583 and 1,522 suspects, respectively. This aligns with Rational Choice Theory, which suggests that males are more likely to engage in criminal activities due to lower perceived risks and higher expected rewards (Antonaccio et al., 2010). Young males aged 15–34 are particularly vulnerable, as criminal networks target this demographic for recruitment due to their economic vulnerability and risk-taking behavior (Neiss et al., 2019).

The spatial dimension of drug trafficking in Riau offers a critical lens for understanding its distribution and dynamics. Coastal areas report higher seizures of methamphetamine and ecstasy, while inland areas are more associated with cannabis, as illustrated in **Graph 1.4** and **Graph 1.5** (Ditresnarkoba Polda Riau, 2024). These graphs underscore the geographic variation in drug types, with coastal proximity to international borders driving the influx of synthetic drugs. Spatial econometric models, such as the Spatial Durbin Model (SDM) and Spatial Autoregressive Model (SAR), can uncover interdependencies between neighboring regencies/cities, revealing how socio-economic conditions in one area influence drug trafficking in adjacent regions (Anselin, 1992). Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things," underpins this approach (Tobler, 1970).

The regional context further highlights Riau's significance in the global drug trade. The Southeast Asian region, particularly the Golden Triangle (northern Thailand, western Laos, and eastern Myanmar), is a major hub for heroin and methamphetamine production, with 137.8 tons of methamphetamine seized in 2022, as shown in **Graph 1.10** (UNODC, 2023).

Figure 1.6: Trends in Drug Seizures in East Asia and Southeast Asia, 2012–2022



Source:(United Nations Office on Drugs and Crime, 2023)

This graph illustrates the escalating drug trafficking activity in the region, with Indonesia playing a pivotal role. Riau's strategic location along global trade routes and its large population make it a prime target for trafficking syndicates (Pamungkas, 2017).

Existing research on underground economies and crime has often focused on general crime categories, such as property crimes or homicide, rather than specific issues like drug trafficking (Entorf & Spengler, 2000; Hazra & Cui, 2018). While spatial analyses have been applied to crime in Western contexts (Cracolici & Uberti, 2009), their use in Southeast Asia, particularly Indonesia, remains limited. Recent studies, such as Aschner and Montero (2021), highlight the role of geographic features in facilitating drug trafficking in Colombia and Mexico, suggesting the potential for similar analyses in Riau. Okpa et al. (2021) emphasize socio-economic deprivation as a driver of drug trafficking in developing countries, a finding relevant to Riau's challenges.

This study addresses these gaps by examining the combined influence of income inequality, unemployment, economic growth, poverty, education, and the proportion of young males on drug trafficking in Riau, with a focus on spatial interdependencies across its 12 regencies/cities. The research questions are: (1) Do economic, social, and demographic factors influence the prevalence of illicit drug trafficking crimes in Riau Province? (2) How do spatial characteristics affect the distribution and dynamics of these crimes? The study uses secondary data from the Central Bureau of Statistics (BPS) Riau, Riau Provincial Police (Polda Riau), and the National Narcotics Agency (BNN), analyzed through spatial econometric models.

The novelty of this study lies in its integrated approach, combining economic, social, and demographic factors within a spatial framework to analyze drug trafficking in Riau. Unlike prior studies that address general crime or focus solely on economic factors, this research targets explicitly illicit drug trafficking, a pressing issue in Indonesia. The use of spatial econometric models, such as SDM and SAR, is innovative in the Indonesian context, where such methods are rarely applied to criminology. By examining spatial spillovers, the study reveals how socio-economic conditions in one regency/city influence neighboring areas, offering a nuanced understanding of regional dynamics. This approach builds on theoretical frameworks like Rational Choice Theory and Tobler's First Law of Geography, adapting them to a Southeast Asian context (Antonaccio et al., 2010; Tobler, 1970). The findings will provide policymakers with actionable insights, enabling targeted interventions such as economic development programs, educational reforms, and enhanced coastal security to address the root causes of drug trafficking in Riau.

2. Literature Review and Hypothesis Development

2.1.The Underground Economy and Illicit Drug Trafficking

The underground economy encompasses a range of economic activities that evade official oversight, thereby escaping inclusion in national accounts such as gross domestic product (GDP). Smith (1994, as cited in Faal, 2003) defines the underground economy as comprising both legal and illegal activities that are unreported or unrecorded in official statistics. Illegal activities, such as illicit drug trafficking, fall within the "illegal economy," often referred to as the "black economy" due to their violation of legal norms (Feige, 1990, as cited in Amalia Siti et al., 2020). Schneider et al. (2002) categorize underground economic activities into illegal, unreported, unrecorded, and informal economies, with drug trafficking being a prominent example of the illegal economy. Globally, the illicit drug trade is estimated to generate US$400 billion annually, constituting approximately 8% of total global trade (Sandi Awet, 2016). The profitability of this trade is driven by significant price disparities; for instance, a kilogram of heroin costs US$2,089 in Pakistan, US$53,333 in the United States, and up to US$142,857 in Indonesia (UNODC, 2023). This economic incentive fuels sophisticated trafficking networks that exploit vulnerabilities in border controls and leverage advanced organizational structures (Reichel & Albanese, 2013).

In Indonesia, drug trafficking has transitioned from a transit hub to a primary destination, with Riau Province playing a pivotal role due to its strategic location along the Malacca Strait (**Figure 1.2)** (Puslitdatin BNN, 2022). This figure illustrates the maritime pathways through the Malacca Strait and Indian Ocean, highlighting coastal regencies like Bengkalis and Dumai as key entry points for narcotics. The economic implications of drug trafficking are substantial, as it reduces tax revenues, distorts economic indicators, and fosters secondary crimes such as theft and robbery, which are often committed by addicts to finance their habits (Goode, 1999, as cited in Puslitdatin BNN, 2022). Globally, the economic burden is significant: in England and Wales, drug-related crime costs between £10.1 billion and £17.4 billion annually (Godfrey et al., 2002), while in the United States, Washington State reported a US$5.21 billion loss from substance abuse in 2005 (Wickizer, 2007). In Indonesia, drug-related crimes rank second after theft, with 15,459 cases reported nationwide in the first half of 2022 (**Figure 1.3**) (Pusiknas Polri, 2022). This diagram underscores the prominence of drug crimes within Indonesia's crime landscape, emphasizing their economic and social impact.

Rational Choice Theory provides a theoretical lens for understanding drug trafficking as a rational economic activity, where individuals weigh the high financial rewards against the risks of legal consequences (Antonaccio et al., 2010). In Riau, the underground economy is amplified by economic disparities, particularly in coastal areas where smuggling routes facilitate high-profit drug trafficking (**Figure 1.1**) (Puslitdatin BNN, 2022). The economic incentives and opportunities created by the underground economy drive the hypothesis that socio-economic factors significantly influence drug trafficking prevalence.

Hypothesis 1: The underground economy, through its economic incentives and opportunities, positively affects the prevalence of illicit drug trafficking in Riau Province.

2.2. Economic Determinants of Drug Trafficking

Economic factors, including income inequality, unemployment, economic growth, and poverty, are critical drivers of criminal behavior, particularly drug trafficking. Income inequality, often measured by the Gini coefficient, creates social tensions and economic desperation, incentivizing individuals to engage in illegal activities to bridge the wealth gap (Hazra & Cui, 2018). In Riau, significant income disparities exist due to the concentration of wealth in resource-based industries such as oil and palm oil, which contrasts with widespread poverty in certain regencies (BPS RI, 2023). Unemployment further exacerbates these dynamics, prompting individuals to turn to underground economies as a means of survival (Rahman et al., 2021). In Riau, 23.70% of drug crime suspects in 2022 were unemployed, and 37.83% were self-employed in precarious conditions, as shown in **Table 1.1)** (Ditresnarkoba Polda Riau, 2022). This table highlights the economic vulnerability of suspects, with many engaged in low-skill or unstable employment.

Economic growth, measured by regional GDP growth rates, can have an ambiguous effect on drug trafficking. While growth may reduce poverty and provide legitimate employment opportunities, it can also attract criminal networks seeking to exploit economic prosperity (Cornwell & Trumbull, 1994, as cited in Eide et al., 2006). In Riau, the resource-driven economy has led to significant growth, but coastal areas like Bengkalis have seen a surge in methamphetamine seizures, as evidenced by **Graph 1.4**, which shows an increase from 1,023.71 grams in 2016 to 124,705.90 grams in 2021 (Ditresnarkoba Polda Riau, 2024). Poverty, closely linked to unemployment, creates economic desperation that incentivizes participation in high-profit illegal activities (Murialti & Hadi, 2023). The interplay of these economic factors suggests that they significantly influence drug trafficking in Riau, particularly in economically disadvantaged areas.

Hypothesis 2: Income inequality positively affects the prevalence of illicit drug trafficking in Riau Province.

Hypothesis 3: Unemployment positively affects the prevalence of illicit drug trafficking in Riau Province.

Hypothesis 4: Economic growth negatively affects the prevalence of illicit drug trafficking in Riau Province.

Hypothesis 5: Poverty positively affects the prevalence of illicit drug trafficking in Riau Province.

2.3.Social Determinants of Drug Trafficking

Social factors, particularly education, play a crucial role in shaping criminal behavior by influencing access to legitimate opportunities and awareness of legal consequences. Lower educational attainment is associated with higher involvement in underground economies, as individuals with limited skills face barriers to formal employment (Atkinson, 1988, as cited in Amalia Siti et al., 2020). In Riau, 54.23% of drug crime suspects in 2022 were high school graduates, while only 1.97% had tertiary education, as detailed in **Table 1.1** (Ditresnarkoba Polda Riau, 2022). This table underscores the protective role of education, suggesting that higher educational attainment reduces the likelihood of engaging in drug trafficking by providing pathways to legitimate livelihoods (Okpa et al., 2021). Education also fosters critical thinking and awareness of the risks associated with illegal activities, further deterring participation in the underground economy. In Riau, disparities in educational access between urban and rural areas exacerbate the vulnerability of less-educated populations to criminal recruitment.

Hypothesis 6: Education level negatively affects the prevalence of illicit drug trafficking in Riau Province.

2.4.Demographic Determinants of Drug Trafficking

Demographic characteristics, particularly gender and age, are significant determinants of drug trafficking involvement. Rational Choice Theory suggests that males are more likely to engage in criminal activities due to lower perceived risks and higher expected rewards (Antonaccio et al., 2010). In Riau, males dominate drug-related crimes, with 2,520 male suspects compared to 176 female suspects in 2022, as shown in **Table 1.3** (Ditresnarkoba Polda Riau, 2022). This table also highlights the overrepresentation of young males aged 15–34, with 583 suspects aged 25–29 and 1,522 aged over 30. Neiss et al. (2019) argue that young males are prime targets for recruitment by criminal networks due to their economic vulnerability and propensity for risk-taking behavior. In Riau, the significant presence of young males in urban and coastal areas, driven by labor migration to resource-based industries, amplifies their exposure to drug trafficking networks (Hendraparya, 2016).

Hypothesis 7: The proportion of males aged 15–34 positively affects the prevalence of illicit drug trafficking in Riau Province.

Spatial Analysis of Drug Trafficking

Spatial analysis provides a critical framework for understanding the geographic distribution and interdependencies of drug trafficking activities. Tobler's First Law of Geography posits that "everything is related to everything else, but near things are more related than distant things," emphasizing the role of spatial proximity in shaping crime patterns (Tobler, 1970). Cracolici and Uberti (2009) demonstrate spatial clustering in property crimes across Italian provinces, using spatial econometric models to reveal how socio-economic conditions in one area influence neighboring regions. Similarly, Aschner and Montero (2021) highlight the role of geographic features, such as borders and ports, in facilitating drug trafficking in Colombia and Mexico. In Riau, coastal regencies like Bengkalis and Dumai report higher seizures of methamphetamine and ecstasy, while inland areas are more associated with cannabis, as shown in **Graph 1.4** and **Graph 1.5** (Ditresnarkoba Polda Riau, 2024). These graphs illustrate the spatial variation in drug types, with coastal proximity to smuggling routes driving synthetic drug trafficking (**Figure 1.1**) (Puslitdatin BNN, 2022).

Spatial econometric models, such as the Spatial Durbin Model (SDM) and Spatial Autoregressive Model (SAR), offer robust tools for analyzing these interdependencies (Anselin, 1992). These models account for spatial spillovers, where socio-economic conditions in one regency influence drug trafficking in adjacent areas. For example, high unemployment or poverty in one regency may drive trafficking activities that spill over into neighboring regions, amplifying the regional impact. The application of spatial analysis to drug trafficking in Southeast Asia, particularly Indonesia, is limited, with most studies focusing on Western contexts (Cracolici & Uberti, 2009). However, Masot et al. (2020) underscore the potential of spatial models to identify high-risk areas and inform targeted interventions, a methodology applicable to Riau's diverse geographic and socio-economic landscape.

Hypothesis 8: Spatial interdependencies exist between regencies/cities in Riau Province, influencing the prevalence of illicit drug trafficking.

Research Gaps and Theoretical Synthesis

The literature reveals significant gaps in understanding the specific dynamics of illicit drug trafficking in Indonesia, particularly in Riau Province. While studies like Entorf and Spengler (2000) and Hazra and Cui (2018) explore socio-economic determinants of general crime, few focus on drug trafficking as a distinct phenomenon. Moreover, spatial analysis, widely applied in Western contexts (Cracolici & Uberti, 2009), is underexplored in Southeast Asia, where geographic and socio-economic factors create unique challenges (Aschner & Montero, 2021). The integration of economic, social, and demographic factors within a spatial framework is also limited, with few studies examining their combined influence on drug trafficking (Okpa et al., 2021).

This study synthesizes Rational Choice Theory and Tobler's First Law of Geography to provide a comprehensive framework for analyzing drug trafficking in Riau. Rational Choice Theory explains individual motivations for engaging in drug trafficking based on economic incentives and perceived risks (Antonaccio et al., 2010), while Tobler's First Law highlights the spatial interdependencies that shape regional crime patterns (Tobler, 1970). By integrating these frameworks, the study addresses the identified gaps, offering a nuanced understanding of the economic, social, demographic, and spatial drivers of drug trafficking in Riau Province.

3. Methodology

3.1.Research Design

A quantitative, cross-sectional design is adopted to investigate the relationships between economic, social, and demographic factors and drug trafficking in Riau Province for 2022. This design facilitates the analysis of multiple variables and their spatial effects at a single point in time (Creswell & Creswell, 2018). Spatial econometric models, specifically the Spatial Durbin Model (SDM) and Spatial Autoregressive Model (SAR), are employed to capture spatial spillovers, aligning with Tobler's First Law of Geography (Tobler, 1970; Anselin, 1992). Visualizations such as **Figure 1.2: Maritime Drug Smuggling Routes in Riau Province** highlight coastal smuggling pathways, underscoring the spatial context (Puslitdatin BNN, 2022).

3.2.Data Sources

Secondary data are sourced from:

1. **Central Bureau of Statistics (BPS) Riau**: Provides data on income inequality, unemployment, economic growth, poverty, education level, and the proportion of males aged 15–34 for 2022 (BPS RI, 2023).
2. **Riau Provincial Police (Polda Riau)**: Supplies drug crime data, including case counts and seizure volumes (**Table 1.1**, **Table 1.2**, **Figure 1.4**, **Figure 1.5**) (Ditresnarkoba Polda Riau, 2022, 2024).
3. **National Narcotics Agency (BNN)**: Offers data on trafficking trends and smuggling routes (**Figure 1.1**, **Figure 1.2**) (Puslitdatin BNN, 2022; UNODC, 2023).
4. **Indonesian National Police**: Provides regional crime trends (**Figure 1.3: Crime Trends in Indonesia, January–May 2022**) (Pusiknas Polri, 2022).

3.3.Operationalisation of Variables

Variables are operationalized as shown in **Table 4.1: Operationalization of Variables**, ensuring measurable indicators for hypothesis testing.

Table 3.1: Operationalization of Variables

Variable	Definition	Measurement	Data Source
Dependent Variable			
Prevalence of Illicit Drug Trafficking	Number of drug-related crime cases in 2022	Number of cases (count)	BNN, Polda Riau (2022)
Independent Variables			
Income Inequality	Disparity in income distribution	Gini coefficient (0–1)	BPS Riau (2023)
Unemployment	Proportion of labor force without employment	Unemployment rate (%)	BPS Riau (2023)
Economic Growth	Annual growth in regional economic output	Regional GDP growth rate (%)	BPS Riau (2023)

Poverty	Proportion of population below the poverty line	Poverty rate (%)	BPS Riau (2023)
Education Level	Average educational attainment	Average years of schooling or % with tertiary education	BPS Riau (2023)
Proportion of Males Aged 15–34	Percentage of males aged 15–34	Percentage (%)	BPS Riau (2023)
Spatial Effects	Interdependencies based on geographic proximity	Spatial weight matrix (shared borders or distance)	Generated using GIS software

3.4.Analytical Procedure

The study employs spatial econometric models, specifically the Spatial Durbin Model (SDM) and Spatial Autoregressive Model (SAR), to test the hypotheses, capturing direct and spatial spillover effects of economic, social, and demographic factors on drug trafficking. The SDM is specified as:

$$\mathbf{Y=\rho WY+X\beta+WX\theta+\epsilon}$$

Where:

- (Y): Number of drug-related cases (dependent variable)
- (WY): Spatially lagged dependent variable
- (X): Matrix of independent variables (income inequality, unemployment, economic growth, poverty, education level, proportion of males aged 15–34)
- (WX): Spatially lagged independent variables
- (ρ): Spatial autoregressive coefficient
- (β,θ): Coefficient vectors for direct and spillover effects
- (ϵ): Error term, assumed to be normally distributed with zero mean and constant variance

The SAR model, a restricted version, excludes spatially lagged independent variables:

$$\mathbf{Y = \rho WY + X\beta + \epsilon}$$

The spatial weight matrix (W) is constructed using a queen contiguity criterion (shared borders) or inverse distance, row-standardised to ensure sums equal one, following established spatial econometric practices (LeSage & Pace, 2009). Models are estimated using maximum likelihood estimation (MLE) in R (e.g., spdep package) or GeoDa, with diagnostic tests to ensure model appropriateness and robustness (Anselin, 1992).

4. RESULTS

This chapter presents the findings from the spatial econometric analysis on the impact of economic, social, and demographic factors on narcotics trafficking crimes across 12 districts and cities in Riau Province. The results were generated using multiple spatial panel models to account for spatial dependence, and diagnostic tests and model performance criteria guided the final model selection.

4.1.Spatial Autocorrelation Analysis

To examine whether narcotics crime and its associated socio-economic indicators are spatially clustered across Riau Province, Moran's I Index was applied. The results are summarized in Table 4.1.

Table 4.1. Global Moran's I Index for Key Variables

Variable	Moran's I	Z-Score	p-value
Narcotics Crime Rate	0.2652	4.0377	0.0001
Gini Index (Income Inequality)	0.1407	2.2074	0.0273
Unemployment Rate	0.3818	5.7596	0.0000
Economic Growth	0.2493	3.8143	0.0001
Poverty Rate	-0.0056	0.0425	0.9661
Education Level	0.2664	4.0556	0.0001
Male Youth Population (15–34 yrs)	0.2677	4.2128	0.0000

The results reveal that the spatial distribution of narcotics crime and most explanatory variables—such as unemployment, education, and the male youth population—are significantly clustered across neighboring regions. The highest Moran's I was observed in unemployment (0.3818), followed by education and crime rate, indicating that areas with similar socio-economic profiles tend to share similar crime patterns. Poverty did not exhibit significant clustering, suggesting a more random distribution. These results confirm the appropriateness of spatial regression models.

4.2 Model Selection and Diagnostic Testing

Before estimating spatial models, a series of diagnostic tests were conducted to determine the most suitable panel model specification (Table 4.2).

Table 4.2. Model Selection Tests (Chow and Hausman)

Test	Statistic	p-value	Preferred Model
Chow F-test (PLS vs FEM)	3.55	< 0.05	Fixed Effects
Hausman Test (FEM vs REM)	3.7241	0.714	Random Effects

The Chow test result favors the Fixed Effects model over Pooled OLS, indicating that unobserved heterogeneity among regions exists. However, the Hausman test fails to reject the null hypothesis, suggesting that the Random Effects model is more efficient and consistent. Therefore, all subsequent spatial panel models are estimated using the Random Effects specification.

Table 4.3. Lagrange Multiplier (LM) Tests for Spatial Dependence

Test	LM Statistic	p-value
LM (Spatial Lag)	13.155	0.00029
LM (Spatial Error)	3.3759	0.06616

The Lagrange Multiplier tests in Table 4.3 show strong evidence of spatial lag dependence, as indicated by a significant LM-Lag statistic ($p < 0.001$). In contrast, the LM-Error test is not significant. This suggests that the narcotics crime rate in a district is influenced by similar socio-economic conditions in neighboring districts. Therefore, spatial panel models that incorporate spatial lag effects, such as the SAR, SDM, and SLX models, are appropriate.

4.3 Spatial Regression Model Estimation

Table 4.4. Spatial Autoregressive (SAR) Model – Random Effects

Variable	Coefficient	p-value
Gini Index	-117.70	0.3810
Unemployment Rate	3.22	0.1082
Economic Growth	0.96	0.5224
Poverty Rate	-1.88	0.2517
Education Level	**4.04**	**0.00001**
Youth Male Population	-313.91	0.2652

Among all variables in the SAR model, only education level has a statistically significant and positive effect on narcotics crime (Table 4.4). This counterintuitive finding may suggest that more educated populations also include more sophisticated networks of distribution or reflect urbanization effects. Other variables such as inequality, unemployment, and poverty did not have significant direct effects in this model.

Table 4.5. Spatial Durbin Model (SDM) – Random Effects

Variable	Direct Effect	p-value	Spillover Effect	p-value
Education Level	**2.25**	**0.025**	**2.30**	**0.000**
Others	NS	NS	NS	NS

The SDM model captures both direct and spatial spillover effects as shown in Table 4.5. Education level remains significant in both dimensions, suggesting that not only does education influence narcotics crime locally, but its effect also spills over to adjacent districts. No other variable demonstrates significant effects, limiting the interpretive power of this model compared to SLX.

Table 4.6. Spatial Lag of X (SLX) Model – Random Effects (Best Fit)

Variable	Direct Effect	p-value	W*X (Spillover)	p-value
Intercept	129.40	0.123		
Gini Index	15.72	0.914	-10.41	0.863
Unemployment Rate	**5.41**	**0.019**	-0.33	0.764
Economic Growth	-0.66	0.732	-0.69	0.412
Poverty Rate	**-3.50**	**0.013**	-0.65	0.606

Education Level	1.17	0.286	**1.83**	**0.000**
Youth Male Population (15–34)	-374.69	0.231	-210.89	0.090
Model Fit Metrics	**Value**			
R-squared	**0.511**			
AIC	1188.15			
BIC	1227.18			
Spatial Coefficient θ	0.619			

Table 4.6 showsthat the SLX model provides the most robust insights into the determinants of narcotics crime. Unemployment rate is positively associated with crime, confirming that joblessness drives individuals toward illegal activity. Poverty, however, shows an adverse effect, suggesting complex interactions such as underreporting or limited access to illegal networks in impoverished areas. Education level is highly significant as a spatial spillover variable, indicating that educational attainment in surrounding districts has a measurable influence on local crime patterns. The SLX model also has the highest R-squared (0.511) and lowest AIC/BIC, validating it as the best model.

4.6 Robustness and Model Validation

To ensure the robustness of the empirical findings, several diagnostic and specification tests were conducted. These tests evaluated the suitability of panel data models, the presence of spatial dependence, and the consistency of estimates across alternative spatial specifications. The aim was to validate the reliability of the selected model and rule out estimation bias due to model mis-specification.

Table 4.7. Robustness and Diagnostic Tests Summary

Test/Method	Purpose	Test Statistic	p-value	Decision
Chow Test (F-Test)	Pooled OLS vs Fixed Effects	F = 3.55	< 0.05	Fixed Effects better than Pooled OLS
Hausman Test	Fixed vs Random Effects	$\chi^2 = 3.72$	0.714	Random Effects model preferred
Moran's I	Spatial autocorrelation (global)	Multiple (e.g., 0.26)	< 0.01	Significant spatial clustering found
LM-Lag Test	Spatial lag dependence	13.155	0.00029	Significant – spatial lag model appropriate
LM-Error Test	Spatial error dependence	3.3759	0.066	Not significant – spatial error not dominant
Robust LM-Lag Test	Controls for both error and lag	Significant	–	Spatial lag effect remains significant
Model Comparison (SAR, SDM, SLX)	Tests estimation consistency across spatial specifications	AIC, R², Significance	–	SLX chosen for better fit and interpretability

The **Chow test** confirmed that the Fixed Effects Model (FEM) was superior to the Pooled Least Squares (PLS), indicating that heterogeneity across districts was statistically significant

and should not be ignored. However, the Hausman test failed to reject the null hypothesis, implying that the Random Effects Model (REM) is more efficient and consistent under the assumptions of the dataset. This justified the use of random effects in all spatial regressions.
To validate the presence of spatial dependence—a key assumption for spatial econometric modelsthe Moran's I test revealed significant global spatial autocorrelation for the dependent variable (narcotics crime rate) and several independent variables (e.g., unemployment, education), with all p-values < 0.05. This provided initial evidence of spatial clustering and motivated the use of spatial panel models.
Further robustness was confirmed through the Lagrange Multiplier (LM) tests**.** The LM-Lag test was highly significant (p = 0.00029), indicating that spatial lag dependence is present and must be modeled explicitly. In contrast, the LM-Error test was not significant, suggesting that spatial dependence is better captured through spatial lag rather than error correlation. The Robust LM-Lag test remained significant even after controlling for possible spatial error, confirming the appropriateness of using spatial lag models such as SAR**,** SDM**, or** SLX**.**
Finally, results were estimated using multiple spatial models (SAR, SAC, SDM, and SLX). The SLX model with random effects provided the best performance, with the highest explanatory power ($R^2 = 0.511$), the lowest AIC and BIC, and the clearest identification of both direct and spillover effects. The consistency of key variable effects across models, especially the significance of unemployment and spatial spillovers of education, demonstrates the robustness of the findings**.**

4.7 DISCUSSION

4.7.1. Unemployment and Narcotics Crime: An Economic Escape Mechanism

The finding that unemployment has a significant positive direct effect on narcotics crime is consistent with numerous studies emphasizing the role of economic distress in facilitating criminal behavior. Unemployment reduces individuals' opportunity costs of engaging in illegal activities, especially drug trafficking, which is often seen as a "profitable substitute" when legitimate income-generating options are unavailable.
This supports the Opportunity Theory (Cloward & Ohlin, 1960), which states that when access to legitimate means of success is blocked, individuals may turn to illegitimate channels, especially in urban and peri-urban areas with visible inequality. In the context of Riau, where industrial job growth is uneven and concentrated in capital cities like Pekanbaru, unemployed youth in smaller districts may feel excluded from economic participation, making them more vulnerable to criminal networks.
This aligns with Murialti and Hadi (2023), who reported that nearly 62% of drug-related offenders in Riau were either unemployed or self-employed, indicating an informal economy overlap with narcotics distribution. Similar patterns are seen in West Java and North Sumatra, where narcotics networks often exploit unemployed youth for logistics and street-level distribution.
Internationally, Edmark (2005) in Sweden and Fougere et al. (2009**)** in France demonstrated that youth and long-term unemployment are particularly associated with drug-related crimes. These findings reinforce the importance of targeted employment programs, job guarantees, and skill-building initiatives to disrupt the economic appeal of illicit activity.

4.7.2 Education as a Double-Edged Sword: Spatial Spillover but Local Inertia

A particularly nuanced finding is the insignificant direct effect of education on local narcotics crime, contrasted with a significant positive spillover effect from neighboring districts. This suggests that while education within a district may not be sufficient to reduce drug crime, education in adjacent areas exerts a meaningful influence, potentially through knowledge diffusion, social modeling, or enhanced community surveillance.

This phenomenon can be explained by Social Disorganization Theory (Shaw & McKay, 1942), which holds that communities with strong educational institutions and civic engagement can resist criminal infiltration. These effects often spill over into adjacent regions, especially where administrative borders are porous but cultural and economic ties are strong.

This also aligns with Buonanno and Leonida (2009) who demonstrated that regional education levels in Italy had cross-border effects on crime rates. In Indonesia, Setianto and Triharjono (2022) argued that education is one of the few "preventive investments" with long-term dividends in social stability and crime deterrence.

However, the insignificance of local education may stem from qualitative issues in educational delivery. As noted by the Ministry of Education and Culture (2022), many rural schools in Riau suffer from high dropout rates, outdated curricula, and limited career linkage, diluting education's deterrent effect. Moreover, drug networks may exploit educated individuals for higher-level coordination roles, as observed in Jakarta, Surabaya, and Pekanbaru, where university students were arrested for digital drug transactions.

Thus, education must be holistic, inclusive, and practically oriented, and efforts to raise educational attainment must be pursued collaboratively across districts to harness the regional spillover benefits.

4.7.3 Poverty and Crime: The Hidden Paradox

The finding of a significant negative association between poverty and narcotics crime contradicts many conventional assumptions. However, this paradox has been observed in other developing regions and can be attributed to limited market viability and weaker institutional capacity in extremely poor districts.

This result supports the argument by Cheteni et al. (2018) that extremely poor communities may be structurally excluded from organized drug markets due to lack of purchasing power, weaker transportation networks, and minimal digital penetration. In Riau, remote regencies such as Kepulauan Meranti and Indragiri Hulu report lower narcotics cases not necessarily because crime is lower, but because detection, reporting, and enforcement are underdeveloped.

Furthermore, Murialti and Hadi (2023) observed that poverty-stricken areas often lack BNN (National Narcotics Agency) branch offices, limiting surveillance and reducing crime visibility. In these cases, the dark figure of crime—the gap between reported and actual crimeis likely substantial.

Poverty may also redirect criminal motivation. In severely impoverished zones, individuals prioritize survival, often through subsistence or informal work, leaving little room for high-risk engagement in structured narcotics markets. This aligns with Routine Activity Theory (Cohen & Felson, 1979), which emphasizes the convergence of motivated offenders, suitable targets, and a lack of capable guardianshipconditions that may be absent in remote, impoverished settings.

Therefore, anti-poverty strategies should be pursued not only for economic equity but also to enhance institutional presence and social infrastructure, enabling better detection and prevention.

4.7.4 Income Inequality: Statistically Neutral but Structurally Relevant

Although income inequality (Gini index) was not statistically significant in the model, its theoretical and policy relevance remains. Inequality has long been associated with crime through mechanisms of relative deprivation, resentment, and social fragmentation.

In this study, the lack of significance may reflect a narrow range of Gini variation across districts or overshadowing by more proximal factors like unemployment. However, inequality still shapes the broader social context in which narcotics crime emerges, particularly in urban corridors where wealth contrast is highly visible.

Studies by Hazra and Cui (2018) and Bourguignon (2000) emphasize that inequality can have delayed or indirect effects on crime, often mediated through governance quality and urban planning. In Indonesia, Sudibyo (2020) found that inequality became a strong crime predictor only when coupled with weak institutional trust.

In Riau, inequality is spatially evident in districts with high natural resource rents but low redistribution. While it may not be statistically visible in this model, its role as a structural backdrop to social tension and criminal opportunity should not be ignored.

4.7.5 Male Youth Population: A Latent Risk Factor

Although not statistically significant, the male youth population (ages 15–34) shows a positive and near-significant spatial spillover effect, suggesting it remains a latent risk factor for narcotics crime. This demographic is often at the heart of drug supply chains due to greater risk appetite, mobility, and peer influence.

This aligns with general strain theory (Agnew, 1992), which posits that youth experiencing failure, marginalization, or social stress are more prone to deviant behavior. In regions with inadequate education or employment channels, youth may become both consumers and distributors of drugs, as seen in arrest data from West Sumatra, South Kalimantan, and South Sulawesi.

The spatial spillover pattern likely reflects youth mobility across district lines, as younger populations commute for work, education, or recreation. In this regard, youth-centric interventions must be coordinated regionally, targeting schools, social media channels, and youth organizations.

4.7.6 Spatial Dependence: Policy Must Cross Borders

The significance of spatial dependence in narcotics crime across Riau confirms the hypothesis that crime is not confined by administrative boundaries. This aligns with Tobler’s First Law of Geography and findings by Cracolici and Uberti (2009) and Graif et al. (2021) that crime "spills over" into neighboring areas when left uncoordinated.

This has deep policy implications. First, it suggests that district-specific interventions are insufficient. Second, it emphasizes the importance of data sharing, inter-district law enforcement cooperation, and coordinated development strategies. Third, it validates the application of spatial econometric models in criminology, which can more accurately capture indirect effects and optimize policy targeting.

In practice, provincial governments must institutionalize spatial governance mechanisms such as joint patrols, shared youth centers, integrated social services, and coordinated education-employment pipelines. Only by understanding the interwoven spatial fabric of crime can policymakers move from containment to prevention.

5. Conclusion, Limitations, and Implications

This study investigated the determinants of narcotics crime across districts in Riau Province using spatial econometric models, particularly the Spatial Lag of X (SLX) model with random effects. The analysis confirmed that unemployment significantly increases narcotics crime at the district level, while education has a notable spillover effect across neighboring regions. Poverty showed a negative association, likely due to underreporting and limited drug market access in extremely poor areas. Although income inequality and the male youth population were not statistically significant, their theoretical relevance remains important. The presence of strong spatial autocorrelation in both dependent and independent variables validates the use of spatial models, highlighting that narcotics crime is not isolated within administrative borders but influenced by broader regional dynamics. However, this study is not without limitations. The analysis relied on secondary data, which may be subject to inconsistencies in crime reporting and differences in enforcement capacity across districts. Furthermore, the model focused on structural socio-economic factors and did not include institutional or cultural variables, such as policing intensity, drug policy variation, or local governance quality, which may also shape narcotics-related outcomes. Additionally, the use of district-level data may mask intra-regional heterogeneity and micro-level dynamics. Despite these limitations, the study provides important policy insights. Crime prevention strategies must extend beyond reactive law enforcement to include proactive interventions in employment generation and educational reform. Spatial spillover findings suggest that anti-narcotics programs must be coordinated regionally rather than implemented in isolation. Furthermore, integrating spatial analysis into policy planning will allow for more accurate identification of hotspots and more efficient resource allocation. Future research should consider mixed-methods approaches, incorporating qualitative insights and more granular spatial units to enrich understanding and information.

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Disclosure of Interest

The authors report no potential competing interests

Data Availability Statement

The datasets used in this study comprise secondary data sourced from the Riau Regional Police website and datasets provided by the BPS Riau Province. To gain access to the data, interested parties can contact the corresponding Author at aditya_rezas@student.ub.ac.id

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