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Spatial Spillover Effects of Upper Secondary Education on Drug Trafficking in Riau Province, Indonesia: A Spatial Econometric Analysis

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Abstract
This study examines the economic, social, and demographic factors that influence illicit drug trafficking in Riau Province, considering the spatial interactions between regions. Increased regional connectivity facilitates the movement of people, goods, and information, which impacts drug trafficking through direct and spillover effects. Using spatial modelling across 12 districts/cities from 2013 to 2022, we applied the SAR, SAC, SDM, and SLX models. The SLX model provided the best fit, based on an AIC value of 1188.154 and a BIC value of 1227.179. The findings show that unemployment directly increases drug trafficking, while poverty reduces it. In addition, high school education levels show a spillover effect on drug crime in the surrounding areas. The results emphasise the need for a coordinated and cross-regional approach to drug prevention, focusing on education, job creation, and inter-regional law enforcement cooperation.
Keywords: Drug Trafficking; Spatial Interaction; Spillover Effect; Spatial Modelling; Riau Province.
JEL Classification Code: A21; C01; C21; E26

1. INTRODUCTION

Globalisation has promoted economic and social integration between countries by easing borders, advancing information technology, and facilitating free trade agreements. On the one hand, this process increases the flow of capital, goods, and labour; on the other hand, it also facilitates the development of the underground economy, which is economic activity not recorded in the official statistical system (Bashlakova & Bashlakov, 2021). Among the various forms of illegal activities, illicit drug trafficking stands out as a serious threat due to its economic value on par with precious commodities and the complexity of its distribution network (Boivin, 2014).

According to Faal (2003), the underground economy is divided into legal activities, such as informal jobs that support daily life, and illegal activities, including drug smuggling. In Indonesia, data from the UN Office (2023) notes that the country ranks third highest in Southeast Asia for amphetamine-type stimulants (ATS) seizures, with a total of 8,637.7kg of methamphetamine seized throughout 2022. However, the seizure trend decreased in 2022 compared to 2019 (17,928.3 kg) and 2021 (11,743.5 kg) (UN Office, 2023).

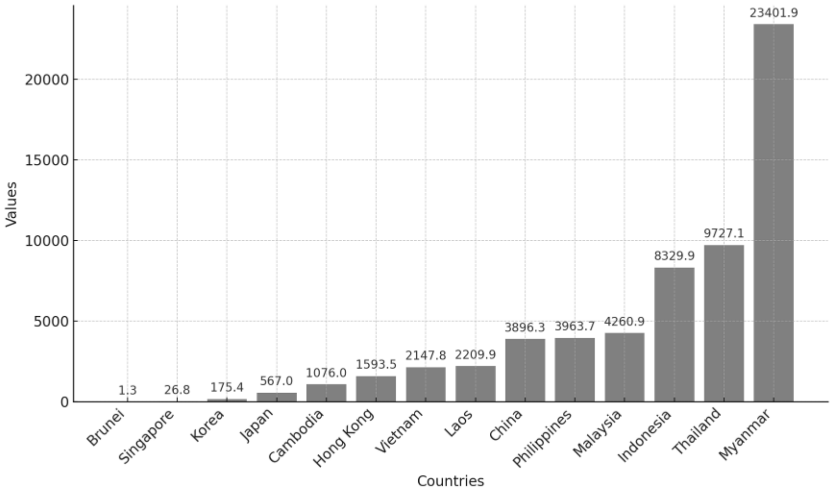

Figure 1. Drug Seizures in the East Asia-Southeast Asia Region
Source: Author's own work

Figure 1 above shows that despite a decrease in the number of methamphetamine seizures in Indonesia in 2022, total seizures remain at a high level, the third highest since 2017. This indicates that the supply of methamphetamine in Indonesia is still enormous.

Legal arrangements related to narcotics in Indonesia are contained in Law No. 35 of 2009 on Narcotics and Law No. 36 of 2009 on Health. In the Health Law, Article 102 prohibits the misuse of narcotics, while Article 103 requires the fulfilment of standards in the production, storage, distribution, and use of narcotics. Law No. 35/2009 classifies narcotics into three classes based on their dependence potential and uses:

1. Class I: Not used in therapy, only for research, and has a very high potential to cause dependence (for example: cannabis, cocaine, opium).
2. Class II: May be used on a limited basis in therapy and research, with a high potential for dependence (eg, morphine, levorphanol).
3. Class III: Used widely in medicine and research, with mild potential for dependence (eg, buprenorphine, ethylmorphine).

In addition, this law also regulates drug precursors, which are substances or chemicals used in the process of making drugs, such as ephedrine and acetone. At the international level, the regulation of drug trafficking is regulated in the United Nations Single Convention on Narcotic Drugs 1961, which affirms that narcotics may only be used for medical and scientific purposes, and criminalises their illegal trade. The distribution of narcotics, as part of the illicit trafficking chain, is one of the main criminal offences regulated in Law No. 35/2009 and is the most common form of offence in Indonesia (Novia, 2022).

The rise of illicit drug trafficking in Indonesia cannot be separated from the impact of global trade, which has made Indonesia no longer just a transit country but has transformed into one of the leading destinations for illegal narcotics trade (Herindrasti, 2018; Suhartanto, 2023). One province in Indonesia that stands out in this context is Riau Province, with its strategic location in the western region of Indonesia and its direct border with Malaysia, making it a crucial entry point for cross-border smuggling networks, as shown in Figure 2 below.

Figure 2. Map of Drug Smuggling Routes by Sea
Source: Puslitdatin BNN (2022)

Figure 2 above illustrates the drug route through the Malacca Strait, where drugs enter Aceh, North Sumatra and Riau. Indonesia's transformation from a transit country to a final destination for drug trafficking is driven by high domestic demand and a network of unofficial ports that are difficult to monitor. Research by Herindrasti (2018) and Suhartanto (2023) shows that drug market penetration is expanding in urban centres and peripheral areas. The sea route map of Puslitdatin BNN (2022) illustrates how Riau's coastal waters, particularly those around Dumai City and Bengkalis Regency, have become the primary corridor for drug smuggling, utilising fishing fleets and small speedboats to evade authorities' patrols.
At the local level, Riau Province reported an increase in drug trafficking offences, from 833 cases in 2014 to more than 2,500 cases in 2023 (Riau Regional Police, 2024). Methamphetamine and ecstasy dominated the evidence seized, with fluctuations in quantity reflecting the syndicates' dynamic distribution strategies. The highest spike in methamphetamine was recorded in 2018-2021, especially in the Bengkalis, Dumai and Pekanbaru Police areas (Riau Regional Police, 2024).

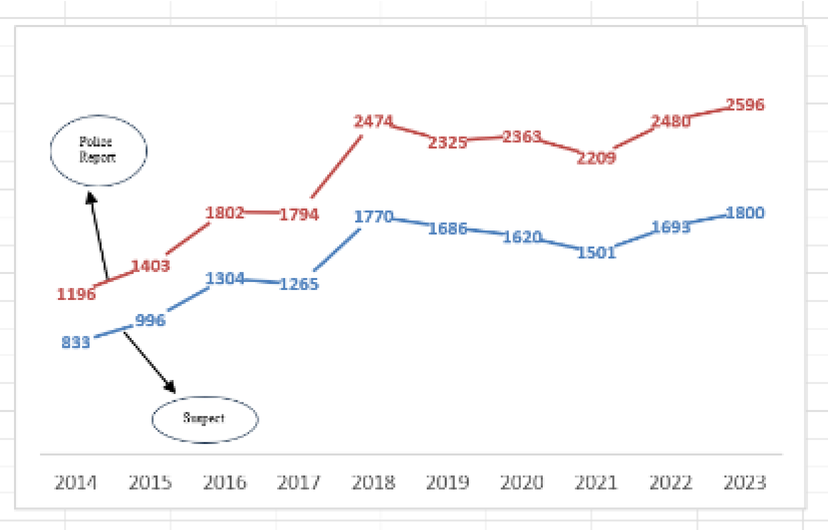

Figure 3. Drug Disclosure of Riau Regional Police
Source: Riau Regional Police (2024)

Figure 3 above shows that the number of police reports in the Riau Police region experienced a significant upward trend from 2014 to 2023, although it declined in 2022. The number of suspects also increased, but with a more stable trend. This indicates an increase in recorded criminal activity, accompanied by a rise in prosecution by the authorities.
The increase in the number of police reports and suspects is consistent with the pattern of drug trafficking in the region, as reflected in the evidence seized during the period. The most dominant types of drugs are crystal methamphetamine and ecstasy, with the amount showing fluctuations as a reflection of the dynamic distribution strategies of the syndicates. The highest spike in methamphetamine evidence was recorded between 2018 and 2021, particularly in the Bengkalis, Dumai, and Pekanbaru Police areas (Riau Regional Police, 2024).

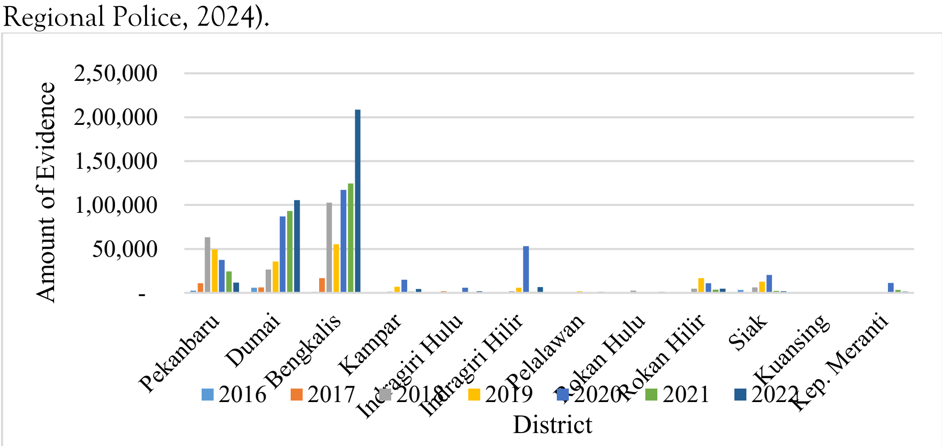

Figure 4. Evidence of Methamphetamine Drugs Evidence of Methamphetamine Drugs
Source: Riau Regional Police (2024)

Figure 4 above shows that methamphetamine seizures in the Riau region between 2016 and 2021 varied between regions. Pekanbaru experienced a spike in 2018, while Dumai and Bengkalis showed a significant upward trend until 2021. Other regions, such as Kampar, Inhu, Inhil, and Siak, experienced unstable fluctuations, while Kuansing and Meranti showed relatively minor changes. This reflects the different dynamics of methamphetamine trafficking in each region.

In addition to crystal methamphetamine, ecstasy is also one of the most common drugs found in law enforcement operations in Riau Province. Although the volume is not as large as methamphetamine, the distribution pattern of ecstasy shows a similar trend, which is concentrated in strategic areas close to international shipping lanes and centres of economic activity. The following graph presents the amount of ecstasy evidence seized from 2016 to 2022 across 12 districts and cities in the Riau Regional Police jurisdiction.

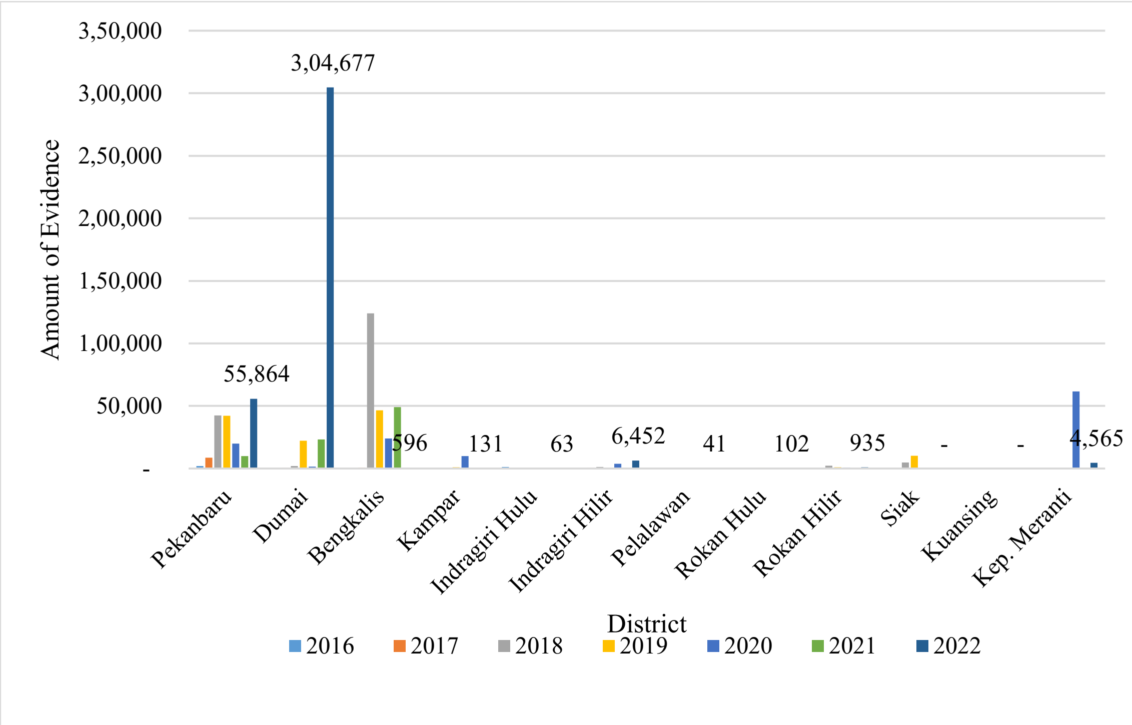

Figure 5. Evidence of Ecstasy-type Narcotics Evidence of Ecstasy-type Drugs
Source: Riau Regional Police (2024)

Figure 5 above shows that ecstasy seizure data in the jurisdiction of Riau Police shows a fluctuating trend, but still shows a strong concentration pattern in certain areas. The three central regions that dominate the number of ecstasy seizures are Dumai City, Bengkalis Regency, and Pekanbaru City. The highest overall seizure peak occurred in Dumai City in 2022, with a total of 304,677 grains of ecstasy, a sharp spike compared to previous years. This figure is striking compared to other regions and shows that Dumai City is not only a significant route for methamphetamine but also plays a major role in ecstasy trafficking. Previously, Bengkalis recorded a significant spike in 2018 with 124,001 grains seized, and Pekanbaru in 2018 and 2019 also recorded high numbers (more than 42,000 grains each).

The high number of narcotics secured by the Riau Regional Police and its ranks shows that drug trafficking in the region is still a serious problem. This trend not only reflects the breadth of the drug distribution network but also the involvement of various community groups in the illegal activity. Regarding education, most suspects were high school graduates (SMA/SMK), with 1,462 people. This number is much higher than other groups and reflects the vulnerability of the post-secondary productive age group to drug abuse and trafficking. Secondary school graduates (645 people) and primary school graduates (536 people) came next. This indicates a considerable involvement of individuals with low educational backgrounds, who may have limited access to information, stable employment, or adequate social support systems. As for higher education, only 53 suspects were recorded, which may reflect the positive influence of higher education in raising legal and social awareness of the dangers of drugs.

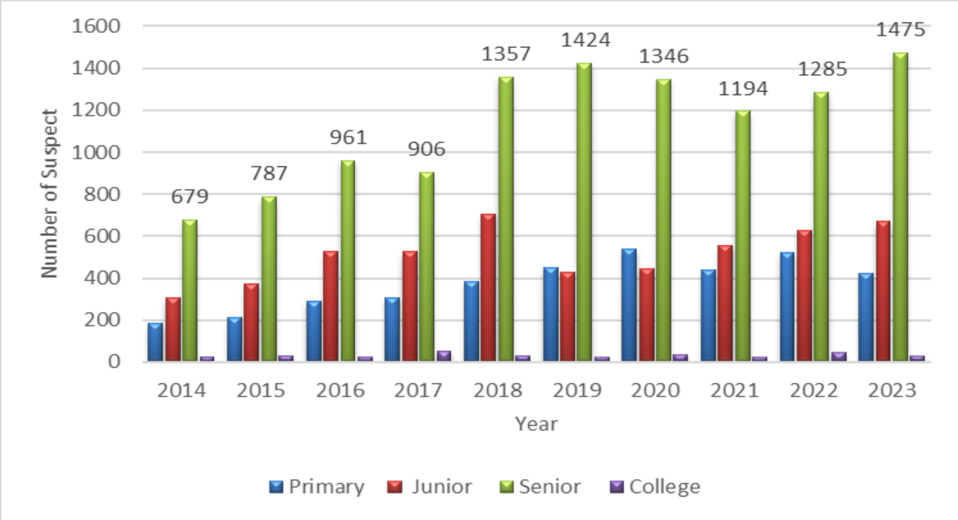

Figure 6. Drug Suspect Trends by Education
Source: Riau Regional Police (2024)

Figure 6 above shows that the secondary education level (Senior) has a significant contribution to the number of suspects in drug trafficking cases in Riau Province. The group with senior secondary education (SMA/SMK) has consistently dominated the number of suspects over the past decade, with a trend of increasing numbers from year to year. This trend is further reinforced when examined in terms of occupation. Three occupational categories consistently dominate the number of suspects: Entrepreneur, Unemployed, and Private Employee. The Entrepreneur group had the highest number of suspects in each year of observation, with the trend increasing significantly from 372 people in 2014 to 953 people in 2022. A sharp spike was seen starting in 2016 and continued to increase until the end of the period. This shows that self-employed individuals are the group most involved in the criminal offences referred to in this graph.

The Unemployed group has the second highest number of suspects, also showing an increasing trend from 157 in 2014 to 577 in 2022. This may reflect the link between unemployment status and involvement in criminal activity. Next in line is the Private Employee group, with the number of suspects also relatively high and increasing from year to year, although not as fast as the previous two groups. Meanwhile, occupational groups such as Labourers, Farmers, and Undergraduates showed a relatively stable number of suspects from year to year, but still lower than the three main groups. Civil Servant and Student groups showed the lowest numbers throughout the period, with relatively small and stable numbers of suspects. This may reflect tighter surveillance or more limited access to illegal activities for these two groups.

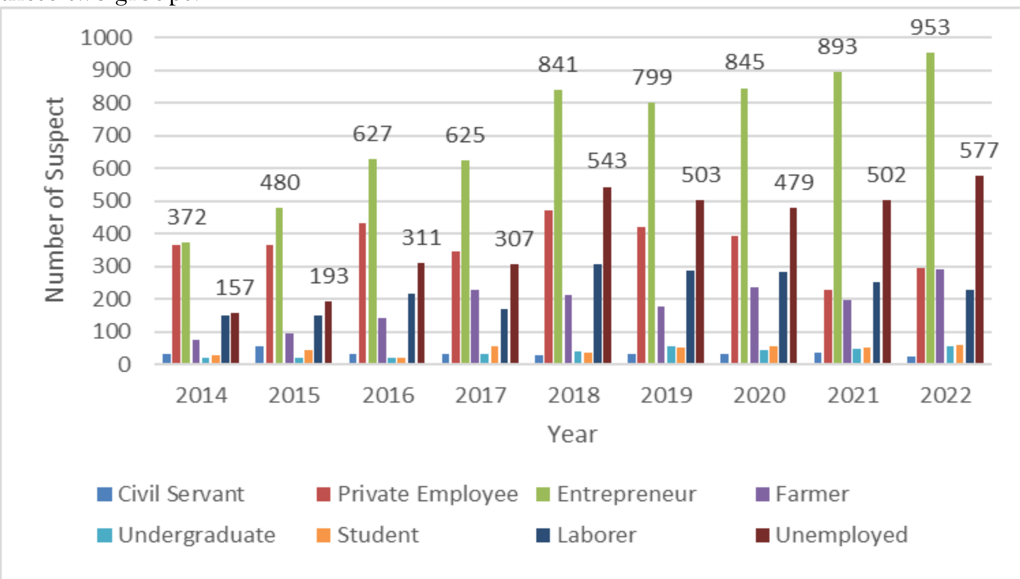

Figure 7. Drug Suspect Trends by Occupation
Source: Riau Regional Police (2024)

The above findings shows in Figure 7 align with the results of previous studies, which explain that poverty and a lack of employment opportunities often lead individuals to initiate alternative sources of income (Murialti & Hadi, 2023; Rahmawati et al., 2021). Low economic status, family breakdown, and urbanisation are important factors that increase crime (Entorf & Spengler, 2000). Community welfare and alleviation of poverty problems can significantly reduce crime rates in a region or country (Fulu et al., 2013; Hu et al., 2024; Jewkes et al., 2013; Sánchez, 2021). The influence of several educational, demographic, and economic variables explains the differences in crime between regions, concluding that socio-economic indicators are essential for understanding crime (Blackmore, 2003; Cracolici & Uberti, 2009; Entorf & Spengler, 2000; Feher, 2020; Hazra & Cui, 2018). Akçomak & Weel (2009) investigated the correlation between social capital and crime, aiming to elucidate the spatial heterogeneity of crime and explore the extent to which crime rates can be associated with levels of social capital.

While there is extensive literature on the relationship between income inequality and crime (Anser et al., 2020; Clément & Piaser, 2021; Enamorado et al., 2016; Li et al., 2019; McDaniel et al., 2021; Song et al., 2020), some of it is implicitly or indirectly related to education (Ades & Mishra, 2021; Hjalmarsson & Lochner, 2012; Lochner & Moretti, 2004). Other seemingly relevant literature focuses on the relationship between crime, unemployment, economic growth, poverty and the proportion of the male population aged 15-34 years (Adri et al., 2019; Akay, 2022; Basrowi et al., 2018; Bothos & Thomopoulos, 2016; Igbinedion & Ebomoyi, 2017; Jawadi et al., 2021; Khan et al., 2015; Lambe & Craig, 2017; Matthews et al., 2023; Nikolaos & Alexandros, 2009; Nugroho et al., 2015; Purnamawati & Yuniarta, 2021; Romero et al., 2020; Sukirno, 2015; Zhou et al., 2023). The Author considers that there is a significant research gap related to understanding how economic, social and demographic factors such as income inequality, unemployment, economic growth, poverty rate, education level, and the proportion of the male population aged 15-34 years old affect crime in a region, but no one has conducted a specific crime study such as drug trafficking crime, especially at the level of smaller administrative areas such as districts/cities within a province. This is because most previous studies have used large administrative units of analysis, either at the provincial or state level. Secondly, in the spatial context, there is also an emerging research gap in understanding how geographic location affects the distribution and accessibility of drug markets (Masot et al., 2020; Okpa et al., 2021). While some research has begun to move in this direction (Abdel-Bar et al., 2021; Gavrilova et al., 2019), there is still room to explore further how the presence or absence of stable employment in an area affects drug demand and trafficking. The varying spatial conditions that contribute to the movement of drugs in the region are an aspect that warrants further research.

This research contributes to a comprehensive understanding of the rise of illicit drug trafficking in Riau Province from an economic, social and demographic perspective, as well as its spatial impacts. Additionally, this research contributes to the development and refinement of existing theories by adapting them to a new, more specific context. The urgency of this research stems from the scarcity of academic studies that thoroughly discuss this phenomenon, resulting in a significant research gap in the literature. This increasingly complex phenomenon, coupled with the limitations of previous research, is the primary reason the author analyses the influence of economic, social, and demographic factors on drug trafficking crime in Riau Province through a spatial approach.

This study explores which factors among income inequality, unemployment, economic growth, poverty rate, education level and proportion of male population aged 15-34 years contribute to drug trafficking crime in a province. The data analysis in this study integrates insights from field research and existing literature studies, interprets secondary data, and draws relevant conclusions. The results of this study revealed that unemployment, poverty and senior secondary education level contribute significantly to drug trafficking crime rates in Riau Province. Spatial patterns were identified in the distribution of these crimes, where inter-regional linkages create a spillover effect that amplifies the dynamics of crime in neighbouring areas.

2. LITERATURE REVIEW

2.1 Economic Theory of Crime and Rational Choice

The economic theory of Crime and Rational Choice Theory both view crime as the result of individuals' rational decisions that weigh the benefits and risks. In this framework, crimes such as drug trafficking, which are transnational, organised, and of high economic value, become a rational choice for some people because of the significant returns despite the high risks (Nurhadiyanto, 2010; Boivin, 2014). Rational

Choice Theory emphasises that offenders consciously assess the expected gain, risk of being caught, level of punishment, as well as available opportunities before acting (Daukere et al., 2023). Thus, crime emerges from rational calculations of economic incentives and opportunity structures.

Further development of this rationality framework was undertaken by Cornish and Clarke (1986) through Rational Choice Theory, which emphasises that criminal behaviour is the result of a conscious and planned decision-making process. Individuals are viewed as rational agents who have goals, evaluate information, and consider opportunities, obstacles, and consequences before taking action. Criminals consciously assess the expected benefits, the risk of being caught, the level of punishment, and the available opportunities. Three key concepts in this theory—rationality, decision-making, and choice—suggest that social deviance is not a manifestation of a pathological condition, but rather part of normal, contextualised human behaviour. As such, offenders are viewed as autonomous, conscious individuals, responsible for their choices (Bennett, 1986).

2.2Spatial Economy in the Context of Drug Trafficking Crime

Drug trafficking crime has an essential and complex spatial dimension. This aspect has garnered the attention of various disciplines, including criminology, economics, and sociology (Martin, 2015; Roman et al., 2017; Sari & Rahman, 2021). Various studies have highlighted how location affects drug crime patterns, as well as how local conditions and spatial strategies impact the dynamics of drug trafficking (Berawi et al., 2018; Martin et al., 2016; Mohammadi et al., 2016).

Geographically, neighbouring regions tend to share similar characteristics. This principle is known in regional economics as Tobler's Law (1970), which states that ‘everything is related, but what is close is more closely related than what is far away’. This reflects spatial dependence, a phenomenon also observed in studies on crime (Cracolici & Uberti, 2009). Kawachi et al. (1999) also confirmed that crime is strongly related to spatial issues and the accompanying socioeconomic parameters. Unfortunately, in practice, spatial analysis is often overlooked in inter-regional economic development studies, despite crime distribution also exhibiting clear geographical patterns (Nugroho et al., 2015).

The phenomenon of spatial clusters indicates that areas with similar socioeconomic characteristics, such as low income or high crime rates, tend to cluster together. This suggests the existence of inter-regional influences that form spatial dependency patterns (Anselin, 1992). Various analytical approaches have been used to understand this dynamic. The ‘Spatial Configuration of Homicide Crime’ (SCHC) model, for example, is used to analyse homicide cases based on the location of the perpetrator, victim, incident, and body disposal (Kim et al., 2013). For other crimes, such as robbery and theft, the Moran autocorrelation method is employed, while for rape cases, spatial scanning statistics serve as an effective geographic surveillance tool (Amin et al., 2015; Sim & Miller, 2016). In a broader approach, exploratory spatial data analysis (ESDA) is used to identify micro- and macro-territorial characteristics of criminal events (Cracolici & Uberti, 2009), as well as to inform 3D and 4D spatial modelling (Wolff & Asche, 2009). Increasingly, researchers are also interested in examining the simultaneous time and space dimensions of crime patterns, including differences between days of the week (Andresen & Malleson, 2015).

In the context of drug trafficking crime, the relationship between illegal activity and space is two-way: criminal activity leaves a spatial footprint, while being influenced by the characteristics of the territory. Drug trafficking as a form of organised crime has transnational implications and is often run by highly systematic criminal networks (Andriani & Firzani, 2023). The choice of drug distribution location is generally influenced by the stability of the surrounding area, the quality of the physical environment, and favourable socioeconomic conditions. Factors such as problematic home ownership, poor housing conditions, malfunctioning streetlights, or high population mobility are indicators of a high risk of drug activity (Aschner & Montero, 2021). However, locations with good physical conditions, such as bars, schools, and car parks, can also be strategic targets due to their proximity to vulnerable populations.

In some cases, the link between geographic location and organised drug crime is evident, such as in border areas. In many countries, border areas have become centres of concentration for drug trafficking due to their geographical advantages that favour smuggling activities (Simmons et al., 2018). For example, the border between the United States and Mexico is a major route for drug distribution to the US market (Gavrilova et al., 2019; Rodríguez, 2022). Aschner & Montero's (2021) research, ‘Architectures, Spaces, and Territories Of Illicit Drug Trafficking In Colombia And Mexico’, shows how physical spaces in Colombia and Mexico play a role in supporting drug production and distribution activities. In both countries, the cultivation of illicit crops such as cocaine and opium is concentrated in certain areas that are physically difficult to reach, conflict-ridden, poor, and lack state presence. Drug processing laboratories are also temporary and scattered in strategic locations. At the distribution stage, criminal organisations exhibit careful spatial strategies, including route diversification and evasion tactics. This suggests that each stage in the drug trafficking chain involves the utilisation of spatial and social elements, ranging from natural resources to local protection networks (Andriani & Firzani, 2023). In addition to border areas, large ports are also key nodes in the illegal trade. Organised crime takes advantage of port infrastructure and connectivity to smuggle a variety of illegal goods, including drugs, weapons, artwork and even people (Coscioni et al., 2019; Simmons et al., 2018). In the spatial economy, such illicit markets are strategically managed by criminal groups who carefully select distribution locations to reach consumers (Robinson et al., 2019; Simmons et al., 2018).

Spatial analysis offers a powerful tool to examine the influence of economic, social and demographic factors on drug trafficking crime in Riau Province by considering both spatial dependence and spillover effects. Spillover effects refer to the impact or influence that an activity, policy or event in one region has on other neighbouring regions. According to Elhorst (2014), an indicator or explanatory variable can have two effects: one is a direct effect on the observed region, and the other is a spillover or indirect effect on other regions. In the context of drug trafficking crime, the spillover effect refers to the situation where the crime rate in a region can be influenced by variables studied in neighbouring regions. For example, an increase in poverty in one district can increase/decrease drug trafficking crime not only in neighbouring districts/cities.

Spatial Dependence refers to the interconnectedness or interdependence of spatial units (e.g. districts/cities) based on geographical proximity. In the context of drug trafficking crime, spatial dependence means that the level of crime in one area is influenced by the level of crime in neighbouring areas. Spatial dependence can occur due to interconnected factors that influence drug crime, such as population mobility, transport infrastructure, or law enforcement policies. Analysing spatial dependence can help identify spatial patterns of drug crime and determine the extent to which neighbouring areas influence a particular area.

2.3The Relationship between Income Inequality and Drug Trafficking Crime and Its Spatial Effects

Elevated levels of inequality may give rise to social unrest, weakened communal bonds, industrial action, increased crime rates, and a diminished trust in governmental policies, as public apathy towards institutional effectiveness intensifies. Fajnzylber et al. (2002) in their study reinforce this concern, finding evidence that income inequality is a significant factor behind the rise of violent crime. In line with these findings, Schargrodsky & Freira (2023) also found a significant positive relationship between income inequality and crime in Latin America and the Caribbean. In the context of North America, income inequality is responsible for approximately fifty percent of the disparity in homicide rates observed between states in the United States and provinces in Canada (McDaniel et al., 2021). Enamorado et al. (2016) also mentioned the rise of drug trafficking in Mexico due to income distribution factors that do not match employment.

This finding is reinforced by Clément and Piaser (2021), who use a 2SLS model to show a strong positive linear relationship between urban income inequality and the fear of crime. Likewise, Anser et al. (2020), in their research, showed that income inequality contributes to an increase in crime rates, especially violent crime. Another study by Li et al. (2019) examined the relationship between the two in China and found that income polarisation, which encompasses social clustering and mobility, has a positive and significant correlation with crime rates. Similar findings were made by Hazra (2020) in India using the Random Effects Model (REM). The same results were also found by McDaniel et al. (2021), who showed inequality is correlated with various social problems, including shorter life expectancy, poor mental and physical health, drug and alcohol problems, low social mobility, and increased violence and crime.

Several studies by Becker (1968), Hakim (2007), and Igbinedion & Ebomoyi (2017) have shown that increasing income to reduce disparities in income can negatively affect the level of property crime. The same results are also found in the research of Garidzirai (2021), Shikida et al. (2019), Sugiharti et al. (2023), and Anser et al. (2020), which demonstrate a causal relationship and a direct effect of the Gini ratio on crime. The same results were also found by McDaniel et al. (2021), who showed that inequality correlates with various social problems, including shorter life expectancy, poor mental and physical health, drug and alcohol problems, low social mobility, and increased violence and crime. Enamorado et al. (2016) attributed the rise of drug trafficking in Mexico to income distribution factors that do not match employment. On the other side of the effect of vast income inequality in society, there is a tendency

to turn to illegal activities to find additional income. As found in Malaysia, a study conducted by Harry (2021) shows that most of the women sentenced to death on drug trafficking charges in Malaysia come from developing countries in the southern region of the world, and many of them work in low-level, low-paid, and unofficial jobs. From a review of their cases, it was found that most of the women travelled across international borders and were paid to deliver goods. The one-off payments they receive are a form of 'fast money' and are usually used to meet immediate financial needs. Communities with high income inequality tend to have higher prevalence rates of drug use. Inequality creates social conditions that push individuals into drug use as a response to dissatisfaction and economic injustice (Friedman et al., 2016). Based on the above research, the Author proposes the following hypothesis:
H1: Income inequality has a positive and significant effect on drug trafficking crime in regencies/municipalities within Riau Province, and has a spatial effect on the level of drug trafficking crime in neighbouring regencies/municipalities within Riau Province.

2.4The Relationship of Unemployment to Drug Trafficking, Crime and Its Spatial Effects

A growing body of literature examines the influence of socio-economic factors on organised crime (Arlyapova & Ponomareva, 2021; Moeller & Sandberg, 2015). Several scholars have linked socio-economic conditions to the development of organised crime. Areas with high unemployment tend to be more vulnerable to organised crime recruitment. Increased employment opportunities may deter potential offenders from committing crimes (Akay, 2022; Zhou et al., 2023). Even Zhou et al. (2023) found that unemployment triggers criminal events in different areas of the city that vary spatially. This statement is reinforced by Jawadi et al. (2021), a study involving 22 European countries found that an increase in unemployment is significantly associated with an increase in violence, including homicide.

Several studies have highlighted the positive relationship between unemployment and crime rates in various countries. Buonanno (2006) found that unemployment has a significant impact on crime in Italy, particularly in the Southern Regions. Igbinedion and Ebomoyi (2017) confirmed a positive correlation between unemployment, inflation, and crime in Nigeria, while Yaacoub (2015) concluded that decreasing unemployment contributes to a reduction in crime. In Latin America, Romero et al. (2020) showed that unemployment and police effectiveness affect economic crimes such as robbery and drug trafficking in Chile. Using the GWR model, Andresen et al. (2021) found that the relationship between unemployment and crime is spatially heterogeneous in Vancouver, Canada.

Several studies have highlighted the positive correlation between unemployment and crime rates in various countries. A notable meta-analysis by Chiricos (1987) of 63 studies revealed that the relationship between unemployment and crime is conditional and influenced by various factors, including the type of crime and the level of data aggregation. Chiricos identified that property crime, which is often influenced by economic need, has a stronger and more consistent relationship with unemployment than violent crime. The study also noted that the U-C relationship is more likely to be significant at the sub-national level, such as a city or regency, which is relevant to this study that examined the smaller administrative region of Riau Province. This is in line with the findings in this article that unemployment at the district or city level may directly contribute to higher crime rates, including drug trafficking.

A study in the Latin American region by Villavicencio and Molina in Romero et al. (2020) also found that unemployment and the effectiveness of police performance have an impact on economic crime, including robbery and drug trafficking in Chile. Furthermore, Arkes (2011) and Chalmers & Ritter (2011) explain the complexity of the relationship between unemployment, recession, and drug use. They point out that interventions designed to reduce drug use should consider both economic and psychological factors, given that unstable labour market conditions can increase individuals' vulnerability to drug abuse.

Based on the above research, the authors propose the following hypothesis:
H2: Unemployment has a positive and significant effect on drug trafficking crime in Riau Province, and an increased crime rate in an area has a spatial effect by affecting the crime rate in neighbouring areas within the scope of districts/cities in Riau Province.

2.5The Relationship of Economic Growth to Drug Trafficking, Crime and Its Spatial Effects

A growing economy with an increasing Gross Domestic Product (GDP) tends to reduce crime as the opportunity cost for individuals to engage in illegal activities increases. This provides more opportunities for employment, education, and broader economic access, thus promoting social stability. Several studies show that the relationship between economic growth and crime varies across countries. Khan et al. (2015) found that economic growth affected crime rates in Pakistan from 1972 to 2011, while Nikolaos and

Alexandros (2009) revealed that economic depression increased crime in Greece, whereas prosperity decreased it. In the United States, Levitt (2004) noted that rapid economic growth in certain areas increases crime rates due to the increased profit potential of criminal activity. Similarly, Gull et al. (2020) found that a 1% increase in GDP per capita in South Asia resulted in a 5.087% increase in crime. In addition, Reyes et al. (2016) highlighted that higher purchasing power in wealthy regions increases the demand for drugs, making them a significant market for narcotics trafficking. However, other studies show different results. Silvia & Ikhsan (2021) and Garidzirai (2021) assert that stable economic growth can reduce crime, as in Indonesia and Gauteng, South Africa. This difference in results reflects that the relationship between economic growth and crime is complex and influenced by contextual factors in each region.

Based on the above research, the Author proposes the following hypothesis:

H3: Economic growth has a negative and significant effect on drug trafficking crime in Riau Province, as well as spatial effects that affect crime rates in neighbouring regions within Riau Province.

2.6The Relationship of Poverty Level to Drug Trafficking Crime and Its Spatial Effects

It has long been believed that social problems are caused by material deprivation or poverty present in the neighbourhood (Hadiprayitno, 2017; Waly et al., 2021). Historically, numerous periods of unrest, crime, and social uprisings have been linked to hunger and poverty (Fulu et al., 2013; Mesa et al., 2021; Thompson et al., 2020). The wider the poverty gap (as a measure of poverty) and the severity index, the higher the level of deprivation among the poor, which in turn results in increased crime (Sugiharti et al., 2023).

Low income causes people to take 'shortcuts' to fulfil their daily needs. One of the most common criminal activities caused by poverty is being involved in drug trafficking. Positive results were found in a study conducted by Cheteni et al. (2018) that there is a relationship between drug-related crime and poverty in South Africa. Although this relationship is not a direct causation, poverty factors have a significant contribution to drug-related crime rates. Matthews et al. (2023) said in their research that the poorer and higher the crime rate in an area, the more likely it is to receive drug parcel shipments.

Dalberis (2015) studied the relationship between poverty and crime rates in Latin American countries. The results show that poverty significantly affects crime rates in Colombia, Brazil, Uruguay and El Salvador. Furthermore, Sugiharti et al. (2023) assert that poverty exhibits a significant association with crime rates, indicating that extreme poverty is positively correlated with criminal activity. Among the four poverty indicators examined, the average poverty gap and the poverty severity index exert the most substantial influence on crime rates. Likewise, Putra et al. (2020) concluded that poverty has a significant impact on the crime rate in Indonesia.

Based on the above research, the Author proposes the following hypothesis:

H4: Poverty level has a positive and significant effect on drug trafficking crime in Riau Province, and has a spatial effect on crime rates in neighbouring regions within Riau Province.

2.7The Relationship of Educational Completion Level to Drug Trafficking Crime and Its Spatial Effects

Educational attainment is expected to reduce criminal behaviour by opening up opportunities for legitimate employment. Grover (2008) noted that college graduates earn almost twice as much as high school graduates, earning almost 1.5 times more than those who did not complete their education. Numerous studies have demonstrated that a person's education can significantly influence their likelihood of committing a crime. Research conducted by Hjalmarsson and Lochner (2012) at Queen Mary University of London and the University of Western Ontario found that individuals with higher levels of education have lower crime rates. This study reveals that higher levels of education are associated with a lower risk of involvement in crimes such as theft, violence, and property crimes. This opinion is corroborated by research by Lochner & Moretti (2004) in the United States and Buonanno & Leonida (2009) in the Italian region, which found that increasing education levels have a negative relationship with crime rates (Jonck et al., 2015; Machin et al., 2010; Saraswati & Agustina, 2020).

Based on the above research, the authors propose the following hypothesis:

H5: Level of educational completion has a negative and significant effect on drug trafficking crime in Riau Province, and has a spatial effect on crime rates in neighbouring areas within Riau Province.

2.8The Relationship of the Male Population Aged 15-34 to Drug Trafficking Crime

As explained by South & Messner (2000), key demographic characteristics such as age, gender, and race are the most powerful individual-level risk factors for crime and victimisation. Elements of gender and age have a close correlation with crime rates, where young males tend to be more dominant in criminal activity (Adri et al., 2019). The 'Not in Education, Employment, or Training' (NEET) phenomenon exacerbates the situation, especially in the United Kingdom, with 83% of men and 63% of women in this group neither working nor intending to work (Chris, 2008). Studies by Entorf and Spengler (2000) and Gould et al. (2002) demonstrate that youth unemployment increases the likelihood of involvement in crime, particularly for those without relevant skills. The MAPPI FHUI study revealed that in Jakarta, 89.1% of criminal offenders were male, with the 15-24 age range dominating theft cases (38.4%), while those aged 25-34 were more involved in extortion and threats (Kompas.com, 2017).

From a demographic perspective, property crime is more often committed by the 15-24-year-old age group who have the physical strength for criminal acts (Nugroho et al., 2015). Hajdari & Hajdari (2020) and Shikida et al. (2019) confirmed that drug offences are dominated by men aged 18-48 years, with 70.1% of offenders coming from the 18-33 age group. Youth involvement in crime is often driven by the promise of luxury and social status, despite the risk of punishment and loss of respect (Rosa et al., 2023). These findings corroborate that age and economic conditions are crucial in driving individuals into criminal activity.

Economic pressures often fuel young men's involvement in crime, driven by the desire for instant social status and a lack of access to education and decent work (Rosa et al., 2023). Therefore, the age range of 15-34 years is seen as the most crucial phase in the formation of potential risks towards involvement in criminal activities, including drug crime.

Based on the above research, the authors propose the following hypothesis:

H6: The male population aged 15-34 years has a positive and significant effect on drug trafficking crime in Riau Province, as well as spatial effects that affect crime rates in neighbouring areas within Riau Province.

2.9This Study's Position in Related Literature

Unlike most previous spatial studies, which use provincial or state-level units of analysis, this study explicitly examines drug trafficking crime at the district or city level within a province. This more micro unit of analysis allows for a more rigorous and locally policy-relevant spatial analysis. In addition, the focus of this study is specifically on drug trafficking crime as a specific form of the underground economy, which has tended to be analysed in aggregate under the general crime category.

This study also provides evidence of a significant spillover effect of the completion rate of senior secondary education on drug trafficking crime in neighbouring areas. This finding has not been explored in previous literature. Using the Spatial Lag of X (SLX) model and the Queen contiguity spatial weighting matrix, this study can identify the inter-regional indirect effects of exogenous variables more precisely than conventional spatial models such as SAR, SAC, or SDM. Thus, this study makes significant theoretical and empirical contributions to the development of the spatial econometrics literature on drug crime, supporting the formulation of place-based policies that are more adaptive to local dynamics.

3. METHODOLOGY

This research employed a quantitative approach. This study utilised annual data from 12 districts and cities in Riau Province for the period 2014-2023. Based on research into drug trafficking crime, the variables influencing the crime include the Gini ratio, unemployment rate, economic growth, poverty rate, education level, and the proportion of the male population aged 15-34 years. Annual data for 12 regions between 2013 and 2024 were obtained from the Central Bureau of Statistics of Riau Province, district/city BPS, and the Riau Regional Police for drug crime disclosure cases. In the study, drug trafficking crime was the dependent variable. The Gini ratio, unemployment rate, economic growth, poverty rate, education level, and proportion of the male population aged 15-34 years in each region were used as explanatory variables. The variables used, along with their descriptions, are presented in Table 1.

Table 1. Operational Variables

Variable	Indicators	Measurement Unit	Data Source
Illicit Drug Trafficking (PGN)	Number of police reports (case disclosures) on drug-related crimes by District/City Police	Case	Riau Regional Police
Gini Ratio (Gini)	Gini ratio level of the population in the regency/city	Percentage	BPS-Statistics Riau

Unemployment (Unemploy)	Open unemployment rate in the regency/city	Percentage	BPS-Statistics Riau
Economic Growth (Growth)	Regional gross domestic product growth rate measured at constant prices in the regency/city	Percentage	BPS-Statistics Riau
Poverty Rate (Poverty)	The proportion of the poor population in the regency/city	Percentage	BPS-Statistics Riau
Education Level (Educ)	The proportion of the population with upper secondary school certificates/equivalent in the regency/city	Percentage	BPS-Statistics Riau
The proportion of the Male Population Aged 15–34 (Male)	Male residents aged 15 to 34 in the regency/city	Percentage	BPS-Statistics Riau

Sources: Author's own work

Table 1 above illustrates that the narrative explains how the analysis utilises several key operational variables to measure Drug Trafficking (PGN), specifically the number of drug cases reported in Riau. Other variables include the Gini Coefficient (a measure of income inequality), unemployment rate, economic growth, poverty rate, education level (high school graduates or equivalent), and the proportion of males aged 15-34 years. Data on drug cases were sourced from the Riau Police, while socio-economic data came from the BPS Riau.

The analysis was conducted by applying two regression analyses consisting of classical panel regression (Ordinary Least Square) which includes Multicollinearity Test, Moran's I Test on Residuals, and Lagrange Multiplier Test and performing spatial panel regression, including; Exploratory Spatial Data Analysis (ESDA), spatial dependency test, determination of spatial panel data models considered based on research objectives, namely SAR (Spatial Autoregressive Model), SAC (Spatial Autoregressive Combined), SDM (Spatial Durbin Model), and SLX (Spatial Lag of X).

3.1Research Design

This research examines the relationship between economic, social, and demographic factors and drug trafficking crime rates in Riau Province, and how the spatial pattern of crime is analysed to support more effective policy formulation. The economic, social, and demographic factors studied include income inequality, unemployment rate, economic growth rate, poverty rate, education level, and the proportion of the male population aged 15 to 34 years. As shown in the figure 8 below.

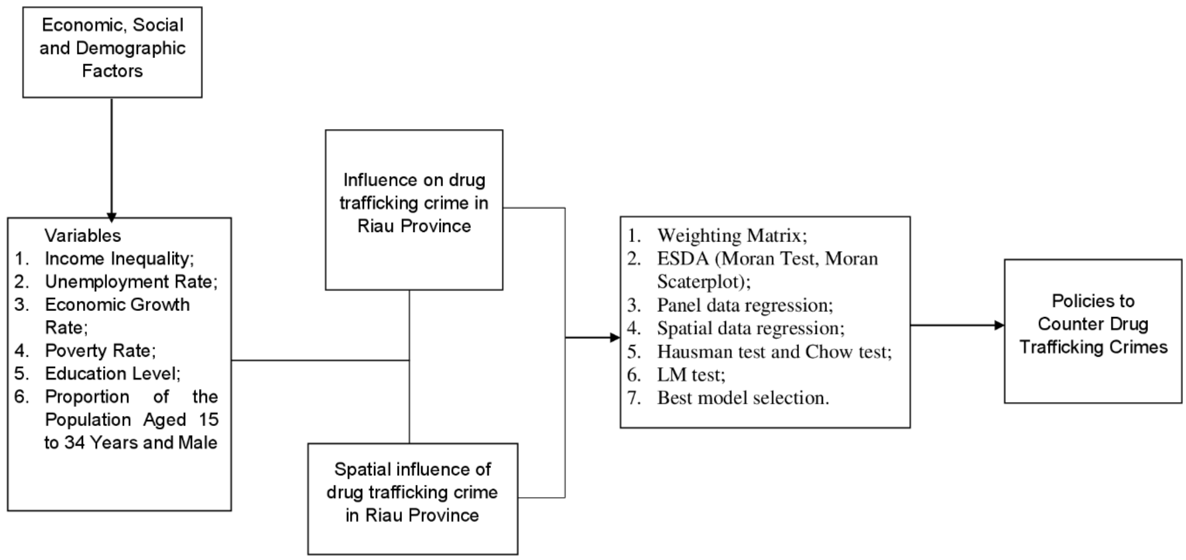

Figure 8. Research Design

Sources: Author's own work

Figure 8 above shows that this research examines the spatial aspects of drug trafficking crime using various analytical methods. Starting with the formation of a spatial weighting matrix (W) to identify inter-regional linkages, the study then applied Spatial Data Exploration (ESDA) through the Moran Test and Moran Scatterplot to detect spatial patterns of crime. In addition, panel and spatial data regression analyses were employed to investigate the relationship between economic, social, and demographic variables and regional crime rates. The Hausman and Chow tests were used to identify the most appropriate regression model. In contrast, the Lagrange Multiplier (LM) test was used to verify the presence of spatial dependence in the model. Through this methodological approach, the study was able to ascertain the predominant factors influencing drug trafficking and the regional disparities in crime. The findings of this analysis are anticipated to serve as a foundational reference for the development of more effective policy interventions aimed at combating illicit drug trafficking in Riau Province, with due consideration given to economic, social, and demographic aspects, as well as the spatial dynamics of criminal activity.

3.2Moran's I Spatial Autocorrelation Test

Proposed by Australian statistician Patrick Alfred Pierce Moran in 1950. It is considered the best method for testing spatial autocorrelation. There are two types of Moran's I, each with a distinct function. The global Moran's I is used to determine whether variables are spatially clustered, while the local Moran's I is used to identify the specific clusters into which the variables are clustered. There are four types of clusters: high-high clusters (HH), low-low clusters (LL), high-low clusters (HL), and low-high clusters (LH). Cluster identification is based on the coefficients of the indicators.

3.3Panel Data Spatial Econometric Model

Spatial econometrics is an estimation tool used to complement the estimation of Moran's I index or the Geary coefficient. With spatial econometrics, regional relationships are not only limited to the grouping of variables with similar values, but also to how regional relationships can influence or explain the causality between two or more variables. Spatial econometrics is a step or effort to improve estimation. If it turns out that there is a spatial correlation between observed variables, then estimation using ordinary OLS will be biased. Researchers tend to reject the null hypothesis, declaring it incorrect when it is true, a phenomenon often referred to as a Type I error.

There are three types of interaction effects in spatial econometrics: endogenous interaction effects between dependent variables (Y), exogenous interaction effects between independent variables (X), and interaction effects between residuals or error terms. The first step in utilising spatial econometrics is to test the urgency of its use. In other words, it is necessary to test whether the standard OLS model needs to be upgraded to a model with spatial variables. This is based on the idea that the value of observations in an observation unit can be related or correlated with the value of observations in other areas, but not necessarily to the extent that it requires special modelling (Masniaritta, 2019).

3.3.1 Spatial Autoregressive Model (SAR)

The Spatial Autoregressive (SAR) model constitutes a linear regression framework wherein spatial correlation is present within the dependent variable. This model integrates autoregressive components with conventional regression analysis, specifically when the parameter $\rho \neq 0$ and $\lambda = 0$. The structure of the spatial autoregressive model is represented as follows:

$$y = \rho Wy + X\beta + \mu$$

The symbol ρ denotes the spatial autoregressive coefficient (also referred to as the spatial lag parameter), while W represents the spatial weight matrix. Accordingly, the SAR specification for drug trafficking-related crime in Riau Province is formulated as follows:

$$PGN_{ijt} = \rho WPGN_{ijt} + \beta_1 Gini_{ijt} + \beta_2 Unemploy_{ijt} + \beta_3 Growth_{ijt} + \beta_4 Poverty_{ijt} + \beta_5 Educ_{ijt} + \beta_6 Male_{ijt} + \mu_{ijt} \quad (1)$$

P is the spatial autoregressive coefficient (spatial lag parameter), and W is the spatial weight matrix. Therefore, the SAR equation for drug trafficking crime in Riau Province is as follows:

$$PGN_{ijt} = \rho WPGN_{ijt} + \beta_1 Gini_{ijt} + \beta_2 Unemploy_{ijt} + \beta_3 Growth_{ijt} + \beta_4 Poverty_{ijt} + \beta_5 Educ_{ijt} + \beta_6 Male_{ijt} + \mu_{ijt} \quad (2)$$

3.3.2 Spatial Autoregressive Combined (SAC)

The SAR model in this study aims to analyse the spillover effect of drug trafficking crime in a district/city to other districts/cities/neighbours in Riau Province by focusing on estimating the spatial lag coefficient parameter (ρ), which shows how much influence drug trafficking crime in a region has on drug trafficking crime in the surrounding area (Wy) (Masniaritta, 2019).

The Spatial Autoregressive Combined (SAC) model is a linear regression framework characterised by the presence of spatial correlation within the error terms. The SAC model is applicable when either $\lambda \neq 0$ or $\rho \neq 0$, indicating spatial dependence in both the dependent variable and the error (residual) component (Karim et al., 2020).

Then, the equation can be expressed as follows:

$$y = \rho Wy + X\beta + \mu, \mu = \lambda W\mu + \varepsilon \quad (3)$$

The parameter λ represents the spatial autocorrelation coefficient associated with the error term, while W denotes the spatial weighting matrix. Therefore, the SAC equation for drug trafficking crime in Riau Province is as follows:

$$PGN_{ijt} = \rho WPGN_{ijt} + \beta_1 Gini_{ijt} + \beta_2 Unemploy_{ijt} + \beta_3 Growth_{ijt} + \beta_4 Poverty_{ijt} + \beta_5 Educ_{ijt} + \beta_6 Male_{ijt} + \mu_{ijt}, \mu = \lambda W\mu + \varepsilon \quad (4)$$

3.3.3 Spatial Durbin Model (SDM)

The Spatial Durbin Model (SDM) represents the third type of spatial regression model that has been developed. It constitutes a specific extension of the SAR model, incorporating lagged effects of the independent variables (X), thereby allowing for an expanded formulation of the fundamental spatial regression framework (Karim et al., 2020):

$$y = \rho Wy + X\beta + \theta WX + \varepsilon \quad (5)$$

In this context, the parameter ρ denotes the spatial autoregressive coefficient (also referred to as the spatial lag parameter), θ captures the spatial autocorrelation associated with the independent variables, and W signifies the spatial weight matrix. Thus, the HR equation for drug trafficking crime in Riau Province is as follows:

$$PGN_{ijt} = \rho WPGN_{ijt} + \beta_1 Gini_{ijt} + \beta_2 Unemploy_{ijt} + \beta_3 Growth_{ijt} + \beta_4 Poverty_{ijt} + \beta_5 Educ_{ijt} + \beta_6 Male_{ijt} + \theta_1 WGini_{ijt} + \theta_2 WUnemploy_{ijt} + \theta_3 WGrowth_{ijt} + \theta_4 WPoverty_{ijt} + \theta_5 WEduc_{ijt} + \theta_6 Male_{ijt} + \varepsilon \quad (6)$$

The SDM model was designed to account for the spatial dependence between both the independent variable (X) and the dependent variable (y). It is a spatial model that considers the correlation between the dependent and independent variables across different observation locations (Duque, 2009; Elhorst, 2014). When $\rho \neq 0$, $\theta \neq 0$, and $\lambda \neq 0$, the Spatial Durbin Model (SDM) equation is expressed as shown in equation (6).

3.3.4 Spatial Lag of X Model (SLX)

Duque (2009) defines a spatial model that considers the effects of spatial dependence on the independent variable while ignoring the spatial effects on the dependent variable. The error construct can be referred to as Spatial Lag of X (SLX), so the SLX model equation is as follows:

$$y = X\beta + \theta WX + \mu \quad (7)$$

The SLX model can occur if the value of $\rho=0$ and $\lambda=0$ while $\theta\neq0$, then the SLX model for drug trafficking crime in Riau Province is as follows:

$$PGN_{ijt} = \beta_1 Gini_{ijt} + \beta_2 Unemploy_{ijt} + \beta_3 Growth_{ijt} + \beta_4 Poverty_{ijt} + \beta_5 Educ_{ijt} + \beta_6 Male_{ijt} + \theta_1 WGini_{ijt} + \theta_2 WUnemploy_{ijt} + \theta_3 WGrowth_{ijt} + \theta_4 WPoverty_{ijt} + \theta_5 WEduc_{ijt} + \theta_6 Male_{ijt} + \varepsilon \quad (8)$$

4. FINDINGS

4.1Non-Spatial Initial Test

OLS Model

To understand the influence of economic, social and demographic factors on drug trafficking crime, particularly between regions, an initial estimation using the Ordinary Least Squares (OLS) model was conducted. This model aims to identify variables that significantly influence drug trafficking crime before considering the possibility of spatial linkages between regions. The results of the independent variable estimation are presented in Table 2 below.

Table 2. Estimation Results of the OLS Model on Drug Trafficking Crime

Variable	Coefficient (Estimate)	Std. Error	t-Statistic	p-value
(Intercept)	152.625	59.374	2.571	0.0115*
Gini Ratio	-494.285	170.978	-2.891	0.0046**
Unemployment	4.988	2.510	1.987	0.0494*
Economic Growth	-0.261	1.922	-0.136	0.8920
Poverty	-3.399	0.959	-3.544	0.0006***
Education	3.915	0.702	5.580	<0.0001***
Male 15-34	0.071	0.129	0.551	0.5826

Sources: Author's own work

Based on the results of the Ordinary Least Squares (OLS) model estimation in Table 2, it was found that several independent variables have a significant influence on drug trafficking crime in Riau Province.

Gini ratio, unemployment, poverty, and education show statistically significant coefficients, with varying levels of significance. Gini ratio and poverty have negative coefficients, while unemployment and education show positive effects. On the other hand, economic growth and the proportion of males aged 15-34 years showed no significant influence on the number of offenders.

Multicollinearity Test

To ensure there is no interference in the estimation of regression coefficients, multicollinearity between independent variables was tested using the Variance Inflation Factor (VIF). The VIF value indicates the level of linear correlation between an independent variable and other independent variables in the model. A high VIF value (generally greater than 10) indicates the potential for serious multicollinearity. The VIF test results are presented in the following table.

Table 3. VIF Values of Independent Variables

Independent Variables	VIF	Independent Variables	VIF
Gini Ratio	1.701716	Poverty	1.856883
Unemployment	1.563870	Education	1.505409
Economic Growth	1.194429	Men aged 15-34	1.075766

Sources: Author's own work

Based on the table 3 above, it is known that all VIF values obtained are far below the critical threshold, indicating that there are no indications of serious multicollinearity in the model. Thus, all independent variables are considered suitable for use in regression estimation without the need for further exclusion or modification.

Moran's I Test on Residuals

Next, to evaluate the presence of spatial effects in the OLS model, Moran's I test was conducted on the residuals. This test aims to detect systematic spatial patterns in the error term, which, if significant, indicates the need for a spatial model approach. The test was conducted using a randomisation approach with a spatial weight matrix between regions. The test results are presented in the following table.

Table 4. Results of Moran's I Test on OLS Model Residuals

```
Moran's I test under randomisation.

data:  residuals_model
weights: w2

Moran I statistic standard deviate = 7.696, p-value = 1.404e-14
alternative hypothesis: two-sided
sample estimates:
Moran I statistic,      Expectation        Variance
  0.475326911      -0.008403361      0.003950764
```

Sources: Author's own work

The results in table 4 show a Moran's I value of 0.4753, indicating positive spatial autocorrelation in the model residuals. This means that areas with high residuals tend to be close to other areas with high residuals, and vice versa. The very small p-value (1.404e-14) indicates that this finding is highly significant, even far below the 1% threshold. In addition, the standard deviation (Z-score) value of 7.696 indicates a substantial deviation from the expected value of zero, so the null hypothesis stating that there is no spatial autocorrelation can be rejected. Overall, these results confirm that the OLS model does not adequately capture the spatial structure in the data, and a spatial model approach is needed to address the identified spatial dependence.

Lagrange Multiplier Test

After finding spatial autocorrelation in the OLS model residuals through Moran's I test, the next step is to perform a Lagrange Multiplier (LM Test) to identify the most relevant form of spatial dependence. This test includes LM Error and LM Lag, as well as their robust versions, Robust Error and Robust Lag, to determine whether the dependence occurs in the error, the lag of the dependent variable, or both simultaneously. The results of the LM test form the basis for selecting the appropriate spatial model. A summary of the test results is presented in the following table 5.

Table 5. Lagrange Multiplier Test (LM Test) Results

Test Type	Statistical Values	df	p-value	Interpretation

LM Error (RSerr)	54.736	1	1.378e-13***	There is spatial dependence in the error.
LM Lag (RSlag)	46.265	1	1.033e-11***	There is spatial dependence in the lag of the dependent variable.
Robust Error (adjRSerr)	9.119	1	0.0025**	The error remains significant after controlling for lag.
Robust Lag (adjRSlag)	0.648	1	0.4208	The lag is not significant after controlling for error.
SARMA	55.384	2	9.406e-13***	There is combined spatial dependence (lag and error), but the error is dominant.

Sources: Author's own work

4.2Spatial Modelling of Illegal Drug Trafficking in Riau Province

Exploratory Spatial Data Analysis (ESDA)

This concept measures the spatial autocorrelation of variables with themselves across space. Bekti (2012) explains that Moran's test tests spatial dependence or autocorrelation between observations or locations. Moran's I use a spatial contiguity matrix to evaluate the relationship between attribute values at a location and those at neighbouring locations. This process involves the covariance (how two variables change together) of attribute values and a spatial weight matrix, which yields standardised values from -1 to 1 (Lin, 2023). Suppose there are dependencies between locations on various characteristics of drug trafficking crime and the factors that cause drug trafficking crime. In that case, it indicates that the characteristics between districts/cities in Riau Province are interrelated. Characteristics in a district or city will affect or be affected by characteristics in nearby districts. The formula for calculating spatial autocorrelation using the Moran Index is as follows (Yasin et al., 2020):

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (1)$$

where x_i Is the value of the x variable in region i, x_j Is the value of the x variable in region j, then W_{ij} is described as the spatial weight matrix for regions i and j, and $\bar{x}$ Is the average of the x variable. Spatial autocorrelation can be identified by looking at the Moran's I Index test results. The spatial autocorrelation test statistic can be explained as follows:

$$Z_{count} = \frac{I - E(I)}{\sqrt{var(I)}} \quad (2)$$

Where Var(I) is the variance of Moran's I, E(I) is the expected value of Moran's I. Hypothesis testing is as follows: $H_0 : I = 0$ (no spatial autocorrelation between regions) and $H_1 : I \neq 0$ (spatial autocorrelation exists). The decision H_0 is rejected if $| Z_{count} | > Z_{\alpha/2}$.

The values of Moran's I Index fall within the range -1 < I < 1. A significantly positive Moran's I Index indicates the presence of spatial autocorrelation, characterised by similar regional characteristics. In contrast, a negative and significant Moran's I Index suggests spatial autocorrelation with dissimilar regional characteristics. If Moran's I Index equals 0, it signifies the absence of spatial autocorrelation between regions.

In this study, the global Moran's Index (Moran's I) is employed to examine the presence of the drug trafficking crime agglomeration phenomenon, as Moran's I reflects the spatial dependence coefficient between regions based on the variables utilised, with values ranging from -1 to 1. This article investigates spatial dependence to analyse the factors influencing drug trafficking crime across 12 districts/cities within a single province.

Moran's index of illicit drug trafficking crime in districts and municipalities in Riau Province was calculated using Queen contiguity spatial weights. The results of Moran's I statistics are in Table 2 below.

Table 6. Moran's I Index

No	Variable	I	ZI	p-value
1	Illicit Drug Trafficking	0.5180	8.4800	0e+00
2	Gini Ratio	0.4639	7.6286	0e+00
3	Unemployment	0.4596	7.5413	0e+00
4	Economic Growth	0.2189	3.6720	2e-04
5	Poverty	0.6037	10.1458	0e+00
6	Education	0.6190	10.1062	0e+00
7	Male Population Aged 15–34	0.2468	4.4877	0e+00

Source: Author's own work

Table 6 shows that the global Moran's I value of the index is positive and significant. Therefore, it can be concluded that drug trafficking crimes in Riau Province have strong spatial dependence. However, before obtaining accurate estimation results for spatial panel data, panel data regression model selection can be done through Chow, Hausman, and LM tests. In this study, the Chow test, also known as the F-statistic test, is used to determine whether the appropriate model is the Pooled Least Squares or the Fixed Effects Model (FEM), by paying attention to the p-value of the Chi-Square test or the probability value (p-value) of the F-test (Armin, 2020). This step is essential as it is required to determine the appropriate spatial model.

Spatial Dependency Test

Before obtaining accurate estimation results for spatial panel data, panel data regression models can be selected through Chow tests, Hausman tests, and LM tests. Next, the significance test results will be explained, including t-tests (partial testing) and F-tests (simultaneous testing). In this study, the Chow test, also known as the F-statistic test, is used to determine whether the appropriate model is the Pooled Least Squares model or the Fixed Effects Model (FEM), considering the Chi-Square p-value or the probability value (p-value) of the F-test (Armin, 2020).

Table 7. Basic Hypotheses in Chow, Hausman, and Lagrange Multiplier Tests in Selecting Spatial Panel Regression Models

Chow Test	Hausman Test	Lagrange Multiplier Test
H_0: CEM	H_0: REM	H_0: CEM
H_1 :FEM	H_1 : FEM	H_1 : REM
Reject H_0 if $\rho < \alpha$	Reject H_0 if $\rho < \alpha$	Reject H_0 if $\rho < \alpha$

Source: Author's own work

Table 7 above presents the results of the panel regression model selection test using the Chow, Hausman, and Lagrange Multiplier tests. Each test is used to determine the best model among the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). Model selection is based on the significance of the test statistic value, where the null hypothesis is rejected if the ρ value is smaller than α, indicating that the alternative model is more appropriate.

Table 8. Output Results of Chow Test, Hausman Test and LM Test

Test	Test Statistics	df	p-value	Decision
Chow Test	11.977	12	4.062e-14	Fixed Effect Model
Hausman Test	χ^2 = 2.9495	6	0.8152	Random Effect Model
LM Error (spatial)	LM= 5.4071	1	0.02005	Indikasi spasial pada error (signifikan)
LM Lag (spatial)	LM= 12.905	1	0.0003277	Indikasi spasial pada lag (sangat signifikan)

Source: Author's own work

Based on the test results presented in Table 8, the panel regression model selection process began with the Chow test, which compared the Common Effect Model (CEM) and the Fixed Effect Model (FEM). The F-statistic value of 11.977 with a p-value of 4.062e-14 indicates that the null hypothesis (CEM) was significantly rejected. Thus, there are statistically significant individual effects between entities (e.g., between regions or years), making the FEM more appropriate than the CEM. Next, the Hausman test was used to determine whether the Random Effect Model (REM) or FEM was more appropriate. The results showed a chi-square (χ^2) statistic value of 2.9495 with a p-value of 0.8152, indicating that the null hypothesis cannot be rejected. Therefore, the REM is considered more efficient because there is no significant correlation between individual effects and independent variables. The test statistics obtained to test the hypotheses set for the selection of SAR, SAC, SDM, and SLX models under the assumption of random effects are provided.

Spatial Econometric Models

As a first step in spatial analysis, it is essential to describe the distribution patterns of illegal drug trafficking cases across various districts and cities. This visualisation provides an initial overview of case concentrations and the potential for significant spatial clusters. Darker colours represent higher case numbers, while lighter colours indicate lower case numbers. The spatial distribution pattern of drug trafficking crime cases in Riau Province from 2013 to 2022 is shown in the figure 9 below.

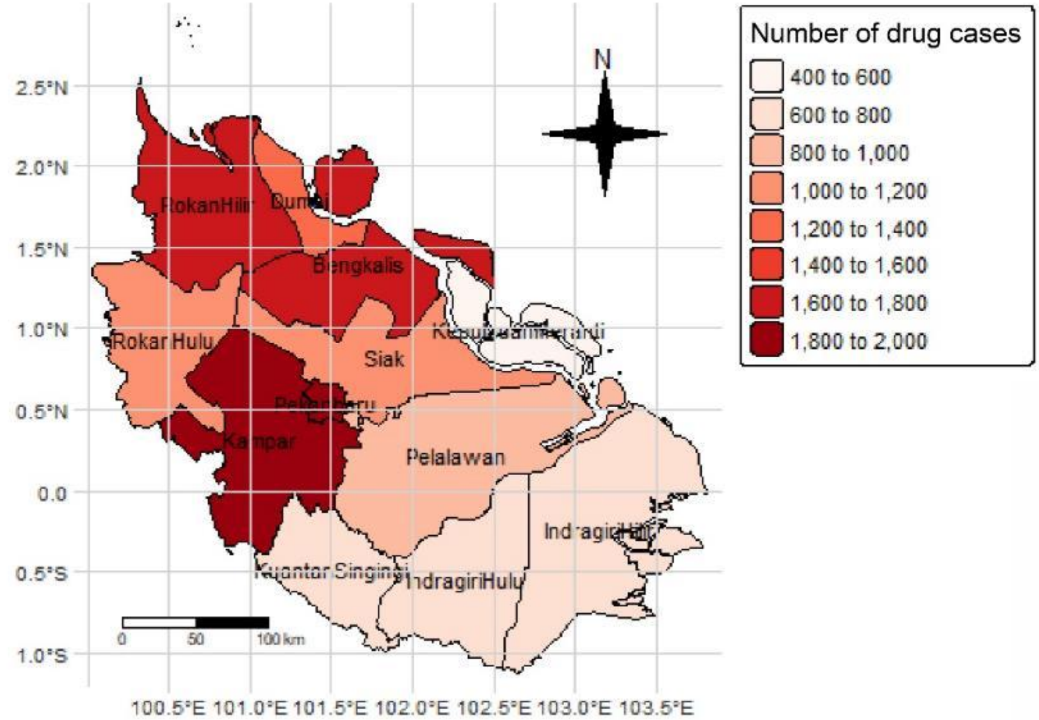

Figure 9. Clustering of Drug Case Distribution, 2013-2022
Source: Author's own work

As shown in Figure 9 above, there is a high concentration of cases in the central and northwestern regions of Riau Province, particularly in the city of Pekanbaru and Kampar District. As the provincial capital with high levels of urbanisation and population mobility, Pekanbaru has become a primary destination for illicit drug trafficking. At the same time, Kampar, as a buffer zone and interprovincial transportation corridor, has also been significantly affected. Additionally, there are secondary clusters with high case numbers in Bengkalis, Dumai, and Rokan Hilir. These areas possess strategic characteristics, such as being situated along transportation routes or having direct access to the sea, which can facilitate the entry of drug distribution networks across regions or even national borders.

Meanwhile, areas with moderate case intensity, such as Rokan Hulu, Siak and Pelalawan Regencies, show the possibility of spillover effects from neighbouring areas that are crime centres. As for areas with relatively low case numbers, such as Kuantan Singingi, Indragiri Hulu, Indragiri Hilir, and the Meranti Islands, these are generally rural areas with more limited connectivity.

Following the evaluation of the optimal spatial panel model and an assessment of the clustering of illicit drug trafficking in Riau Province, this study determined that the Random Effects Model (REM) constitutes the most appropriate spatial panel specification for estimating drug trafficking-related crime. Furthermore, the models estimated include the SAR (Spatial Autoregressive Model), SAC (Spatial Autoregressive Combined), SDM (Spatial Durbin Model), and SLX (Spatial Lag of X) models. The corresponding results of the analysis are presented in Table 9.

Table 9. Spatial Model of Illegal Drug Trafficking Crime

Parameter	Model Random Effect			
	SAR	**SAC**	**SDM**	**SLX**
Direct Effect				
Intercept	-1.709090 (0.98022)	-32.493151 (0.62258)	58.797387 (0.426820)	82.047340 (0.271655)
Gini	-130.173983 (0.35562)	-73.618642 (0.58033)	-172.592136 (0.202512)	-130.602980 (0.413982)
Unemploy	3.422059 (0.1082)	3.473897 (0.05335)	3.853208 (0.097627)	**7.056945** **(0.007199**)**

Growth	1.695856 (0.25342)	1.373771 (0.25526)	0.659088 (0.700783)	0.208101 (0.917836)
Poverty	-2.716850 (0.10011)	-1.997462 (0.23855)	-1.340782 (0.439113)	**-3.341167 (0.029777*)**
Educ	**3.910114 (3.659e-05***)**	**3.356441 (4.894e-05 ***)**	**3.097381 (0.002881 **)**	1.739241 (0.119620)
Male	0.065619 (0.50310)	0.028791 (0.74549)	-0.041430 (0.672713)	0.022712 (0.836738)
Indirect/Spillover Effect				
Gini_1			**-94.755490 (0.048378*)**	**-103.491678 (0.011093*)**
Unemploy_1			-0.742306 (0.556493)	0.106241 (0.926591)
Growth_1			-0.943287 (0.326907)	0.297271 (0.695412)
Povert_1			0.820432 (0.380298)	-0.177678 (0.820509)
Educ_1			**1.907768 (1.085e-06 ***)**	**1.291154 (0.000203***)**
Male_1			-0.085915 (0.133344)	-0.028461 (0.620506)
Phi (ρ)	1.38914 (0.0395*)	1.57002 (0.05196)	1.13020 (0.06922)	
Lamda (λ)	0.078313 (0.0003792***)	0.128883 (5.116e-06 ***)	-0.12331 (0.02956 *)	
R-Squared	-	-	-	0.46274
Theta		-0.10902 (0.06451)	0.14830 (1.881e-07 ***)	
Chi sq	-	-	-	0.544

Significance code: $p < 0.1$; ** Significance code: $p < 0.05$; *** Significance code: $p < 0.01$
Source: Author's own work

Based on the spatial econometric model in Table 9, the results show that the Spatial Lag of X (SLX) model has the smallest Akaike and Bayesian information criteria values of 1208.823 and 1247.848, respectively, which means that the Spatial Lag of X (SLX) econometric model is more suitable than other spatial econometric models. As shown in Table 10 below.

Table 10. Best Model Selection

Model	AIC	BIC
Spatial Autoregressive Model (SAR)	1350.667	1372.967
Spatial Autoregressive Combined (SAC)	1422.263	1461.288
Spatial Durbin Model (SDM)	1418.925	1441.225
Spatial Lag of X (SLX)	1208.823	1247.848

Source: Author's own work

The results of the Spatial Lag of X (SLX) model estimation using the Random Effects approach indicate that the socio-economic characteristics of a region and its surrounding areas play a significant role in influencing the level of drug trafficking crime in Riau Province. This model is based on balanced panel data from 12 districts/cities over a 10-year period, with an Adjusted R-squared value of 46.27% and a statistically significant Chi-square value ($\chi^2 = 92.1569$, $p < 0.0001$), indicating that the model adequately explains the variation in drug-related crime across the region. Directly, the unemployment rate in a region has a positive and significant effect on drug-related crime. Additionally, poverty also has a significant but negative effect ($\beta = -3.341$; $p = 0.030$), which may indicate that poor areas have limited access to drug

networks or underreporting. On the other hand, some variables, such as the Gini coefficient, education, economic growth, and the number of young men, do not show direct significance.
However, when considering the spillover effects of neighbouring regions, it was found that the inequality of neighbouring regions (Gini Ratio_1) has a significant negative impact on local drug crime rates (β = -103.49; p = 0.011), while the average education level in the surrounding region (Education_1) has a positive and highly significant effect (β = 1.291; $p < 0.001$). This indicates that drug crime can spread or be distributed across regions through spatial connections, either through the mobility of perpetrators or through inter-regional social networks.

5. DISCUSSION

First, unemployment has a positive and significant effect (β = 7.06, p = 0.007), indicating that a 1% increase in the unemployment rate in a region can lead to approximately 7 additional cases of drug-related crime. Unemployment can increase crime because individuals without formal employment will seek alternative sources of income, including informal and even illegal work. In addition, high unemployment can increase social frustration, which also contributes to criminal behaviour. This also indicates a strong correlation between an individual's economic circumstances and their propensity to engage in criminal activity. This also reveals a strong correlation between an individual's economic condition and their tendency to engage in criminal activity. Apart from the illegal employment aspect, high drug trafficking also occurs due to demand from consumers, such as those affected by layoffs or job-related stress. Research shows that illicit drug use tends to increase during times of recession, mainly due to the increased psychological stress experienced by individuals who lose their jobs. Priatna (2010) concluded that unemployment has a significant impact on an area's crime rate. Several studies that show similar things explain that the inability to find work can make people vulnerable to illegal activities or substance abuse as a way of surviving or coping with economic stress and neighbourhoods with high unemployment rates have a greater risk of increased drug use and distribution, especially in times of recession or economic uncertainty (Anser et al., 2020; Buonanno, 2006; Li et al., 2019; Putra et al., 2020; Troha et al., 2023).
Second, poverty has a significant adverse effect on the rate of drug trafficking (β = -3.34, p = 0.0298). Statistically, this means that every 1 per cent increase in the poverty rate in a region tends to reduce the number of drug-related crimes by 3.34 cases. From a social environment perspective, when poor communities dominate an area, the likelihood of drug trafficking decreases. This is due to the lack of economic incentives available in the area, as well as the reduction in potential targets that are attractive to criminals. Gunawan et al. (2020) show that income levels and economic conditions greatly influence heroin consumption. In economically constrained situations, drug consumption tends to decrease due to low purchasing power, while in more prosperous economic conditions, consumption increases.
Additionally, drug dealers typically target individuals with sufficient financial capacity to engage in buy-sell transactions. Therefore, in areas experiencing extreme poverty, infrastructure limitations and low purchasing power among the population can act as constraints on the development of the drug market (Oliveira et al., 2015). The finding that an increase in poverty reduces the crime rate was found by Afrian (2022). The results of this study are relevant to research from Arizona State University, revealing that adolescents from wealthy families have a higher risk of using drugs than adolescents from middle or lower classes. Key factors include academic pressure, social expectations and easy access to drugs such as Adderall, Ritalin or cocaine, which are often more expensive. The study noted that addiction rates among young adults from the upper class are two to three times the national average in that age group (Cestone & Oneonta, 2019; Patrick et al., 2012). Likewise, Metz & Burdina (2018) found that the relatively poorest block groups committed fewer property crimes than their neighbours.
Meanwhile, drug distribution patterns also show that it is more likely to be accepted in wealthier neighbourhoods, and of course, these areas will become target markets for drug trafficking. As found by Morgan & Mall (2019), Ratcliffe & McCord (2007), and Vilalta (2010), the use of online drug markets is higher in urban areas than in rural communities. This is due to the ease of access to services. Similarly, Rosa et al. (2023) found that average formal sector income has a positive relationship with the level of drug trafficking, indicating that cities with higher income levels are more attractive for economically motivated crime.
Third, the indirect influence on the independent variables in this model affects the existence and magnitude of spillover effects between regions in Riau Province. The Gini_1 ratio has a significant negative influence (β = -103.49, p = 0.011). This indicates that the higher the income inequality in a

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region, the lower the drug crime rate in neighbouring regions. In other words, high income inequality in neighbouring regions can create a spillover effect that suppresses drug market activity in the central region (the observed region), as an unequal economic environment lowers the purchasing power of the majority of the population, thereby limiting access to and demand for drugs and making them economically unattractive to illegal drug trafficking networks. In line with these findings, Enamorado et al. (2014) also found that an increase in income inequality resulted in more than four additional drug-related deaths and more than three additional total homicides during the 2005–2010 period.

Furthermore, we also found that the Education variable in the surrounding area (Educ_1) has a positive and highly significant effect on the number of drug-related crimes in a region, with a coefficient value of $\beta = 1.291$ and a p-value < 0.001. This finding indicates that regions surrounded by areas with an average education level of senior high school tend to experience an increase in drug-related crimes. Statistically, this means that every one-unit increase in the average education level in the surrounding area is associated with an increase of approximately 1.29 drug-related crimes in the central area (under observation). Substantively, this result may seem paradoxical, as education is generally associated with a decrease in crime rates. However, in a spatial context, higher education in surrounding areas may reflect high population mobility, the development of social networks, and ease of inter-regional access. This has the potential to open up space for the expansion of drug trafficking networks into neighbouring areas with more vulnerable social or economic conditions. In other words, central areas surrounded by regions with high school education levels may be affected by cross-border activities that facilitate drug distribution, whether through dealers, users, or crime network logistics. According to Becker (1968), the decision to commit a crime is the result of a rational calculation of the benefits and losses.9

There are several theoretical reasons why education may impact crime. Existing literature highlights at least three main channels through which education can influence criminal participation: income effects, forbearance or risk aversion, and time availability (Machin et al., 2012). First, income effects correlate with education, reducing crime by increasing the returns to legitimate employment and/or increasing the opportunity costs of illegal behaviour (Hjalmarsson, 2008; Lochner & Moretti, 2004). Second, education can change a person's perspective, for example, making them more patient or cautious when taking risks (Lochner & Moretti, 2004).

Hjalmarsson & Lochner (2012) state that human capital is the sum of knowledge, skills, experience and social qualities that contribute to a person's ability to perform work in a way that generates economic value. Education is a crucial element in preventing offenders from engaging in criminal activities. Education aims to educate young people and enhance their ability to return to legitimate employment rather than resorting to crime. As education increases, some types of property crime decrease, but other types of white-collar crime may increase, such as fraud, bankruptcy, and tax evasion (Lochner & Moretti, 2004). Education helps reduce crime rates, child labour and terrorism through poverty reduction (Hjalmarsson & Lochner, 2012).

This counterintuitive relationship can be attributed to cross-border crime: the education level of high school graduates in one jurisdiction affects crime rates in other jurisdictions. According to Trisnawati et al. (2019), the percentage of high school dropouts has a spatially significant influence on inter-provincial crime rates in Indonesia. Likewise, Barros et al. (2020) in Brazil demonstrate that economic and educational factors influence crime rates in various regions, although the impact varies. In the Northern region, increased educational and economic standards were associated with increased crime (homicide) rates. This may be due to the expansion of agricultural areas, which, while promoting socio-economic development, also fuelled land use conflicts and illegal activities. In contrast, improved economic and educational standards contributed to lower crime rates in the Southeast, South, and Central-West regions. This can be explained by rising opportunity costs, such as higher salaries in the formal sector, which reduce individuals' incentives to engage in illegal activities.

Cross-regional crimes fuelled by education tend to be more challenging to detect, identify and track. In some cases, they move to the city because it has enormous appeal, both to those living in the countryside and the surrounding small towns, in the form of wider employment opportunities (Trisnawati et al., 2019). In such a situation, inter-administrative collaboration becomes crucial. Instead of simply addressing the impacts, a more effective solution would be to tackle high school graduates in their areas of origin to eradicate the root causes of crime.

Addressing drug trafficking crime requires a collaborative approach involving local government, law enforcement officials and civil society so that policies are aligned with social and economic development goals. The findings also confirm that strain and rational choice theories can be powerful analytical frameworks for understanding this phenomenon. The managerial implications of this study emphasise the importance of incorporating spatial perspectives in policy planning to create more effective and evidence-based intervention strategies to curb drug trafficking in Riau Province.

6. CONCLUSION

In this study, we aimed to determine the most suitable model specification for measuring the influence of economic, social, and demographic factors, including the Gini ratio, unemployment rate, economic growth, poverty rate, education level, and proportion of the male population aged 15-34 years, on drug trafficking crime in Riau Province. Based on the estimation results, the SLX mixture model is the best spatial model because it has the smallest AIC and BIC values. The results of the SLX model indicate that an increase in the unemployment rate in a district or city in Riau Province will lead to an increase in drug trafficking crime in the region. In addition, the poverty level variable has a significant direct effect on reducing illicit drug trafficking in the region.

In this study, the model estimation results indicate that there is no spatial interaction between districts/cities in Riau Province, as evidenced by the endogenous interaction effect between dependent variables or spatial lag (Wy), which suggests that crimes do not influence drug trafficking crimes in a district/city in neighbouring districts/cities. This finding shows the existence of a new economic geography theory, which states that an area is related to other areas. Still, neighbouring areas will be more connected than those far apart (Tobler, 1970), which is not observed in the case of drug trafficking crime in Riau Province.

Although there is no endogenous interaction effect on the dependent variable in this study, the model estimation results indicate a spillover effect in the model of illicit drug trafficking crime in Riau Province, specifically in the variable of senior secondary education completion level. The level of upper secondary education exhibits a significant spillover effect on drug trafficking crime in districts and cities in Riau Province. It can be inferred that the variable level of secondary education completion among the population of neighbouring regencies/municipalities in Riau Province indirectly influences drug trafficking crime in regencies/municipalities in Riau Province.

Based on the findings above, several policy implications can be drawn. First, illegal drug abuse knows no boundaries in terms of social background or life status. Everyone, from the general public to students, civil servants, public officials, and members of the police or military, has the potential to be involved or affected. This situation requires local governments and related agencies to initiate programmes that are responsive to the specific needs of drug users who choose to report themselves. Such programmes may include providing employment opportunities, affordable medical rehabilitation services, social and sports activities, as well as moral and spiritual guidance, as part of a recovery strategy that encourages them to contribute positively and responsibly to society. Additionally, educational campaigns about the dangers of drugs—both to individual health, family harmony, and social stability—need to be promoted through cross-sectoral collaboration to enhance public awareness and resilience against the threat of narcotics.

Second, local governments need to reduce income inequality by strengthening unemployment reduction programmes, especially in areas with high unemployment rates, as part of efforts to mitigate migration and reduce drug trafficking crimes. The most minor government units (RT/RW level) actively check the identities of migrants. Community participation in maintaining security is also necessary to control phenomena within their environment. Creating job opportunities and skill training programmes for vulnerable communities can be part of a long-term solution. Additionally, local governments should collaborate with educational institutions and industries to create more job opportunities for youth in Riau. They should also provide financial support and guidance for young people who wish to start their businesses, including access to business capital.

Furthermore, although high poverty rates are associated with a decrease in drug trafficking crimes, local governments still need to develop effective and targeted social assistance programmes to help low-income families escape the cycle of poverty. Additionally, there is a need for local economic empowerment focused on enhancing the skills and capacity of communities to start small and medium-sized businesses. Furthermore, encouraging investment in areas with high poverty rates through tax incentives or streamlined licensing processes is necessary to create new job opportunities that can absorb local labour. This policy is essential to ensure that poverty alleviation efforts do not create opportunities for drug trafficking networks. Additionally, there is a need for enhanced surveillance by law enforcement agencies, including the Indonesian National Police and the National Narcotics Agency, in areas with low poverty levels.

Third, the implementation of a decentralised government system has consequences for the expansion of the substance, process, and context of educational development. In this context, the implementation of education policies at the regional level requires the presence of relevant and contextually appropriate management models, in line with the social, cultural, and local characteristics of each region. In regions with unique resource potentials that have become integral to the local community's economic activities, an education approach tailored to regional potential will be more effective in addressing local needs. Such an approach not only has the potential to improve human resource quality through strengthening creativity and innovation in managing local production outcomes but can also enhance regional competitiveness. Furthermore, the alignment between educational content and the socio-economic reality of the community is seen as capable of increasing community participation in the educational process, given the relevance between learning and their daily livelihoods. In addition, local governments need to increase scholarships for marginalised groups to continue their education in higher education, with the hope of increasing employment opportunities in the formal sector in the future.

This study has several limitations: it utilises secondary data for 2014-2023, so it cannot capture the long-term impact of drug trafficking policy interventions implemented within a specific period. Therefore, further research can be used with a broader temporal coverage. Secondly, this study has not included migration, regulation, and law enforcement effectiveness factors, such as the intensity of law enforcement operations, sentences for perpetrators (such as TPPU), and the effectiveness of drug user rehabilitation programs. Therefore, further research can accommodate these variables in analysing the spatial influence of illicit drug trafficking.

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Authors Name		Contributions
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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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