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FACTORS INFLUENCING PROPERTY CRIME IN CENTRAL LUZON

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ABSTRACT

The study explored property crime in Central Luzon, Philippines, focusing on factors like poverty, unemployment, tourism, and arrests. The study used Pearson's correlation and linear regression analysis to assess a bivariate relationship between property crime rates and each of its determinants, spanning from 2018 to 2023. The analysis revealed a nuanced relationship between property crime rates and socioeconomic factors. While a subtle inverse correlation between property crime and poverty rates was observed, it lacked statistical significance. The relationship between crime rates and unemployment was inconsistent. In contrast, a consistent and significant positive correlation was found between property crime and arrest rates, emphasizing law enforcement's role in deterrence. Tourism rates also showed a positive correlation with property crime, highlighting the need for targeted strategies in tourist areas. Regression analyses demonstrated high predictive accuracy, with arrest rates consistently emerging as a significant predictor of property crime. Overall, the findings underscore the multifaceted nature of crime dynamics and the importance of comprehensive, context-specific crime prevention strategies. Effective collaboration among government entities, community organizations, and residents is crucial for developing evidence-based strategies to enhance public safety and community resilience in Region 3.

Keywords: Property Crimes, Poverty Rate, Unemployment Rate, Arrest Rate, Tourism Rate, Central Luzon.

I. INTRODUCTION

Background or Context:

Property crime was a significant issue in Central Luzon, Philippines, adversely affecting the safety and well-being of communities. The study operated within a socio-economic framework where poverty, unemployment, arrests, and tourism intersected to shape crime. The region, comprising seven provinces, mirrored broader national challenges, with property crime posing significant threats to public safety. Implemented policies underscored the severity of property-related offenses, highlighting their impact on community security. Empirical evidence highlighted poverty and joblessness's role in driving criminal behavior, as individuals facing economic hardships were influenced towards criminal inclinations and resorted to deviant actions. Effective law enforcement, evidenced by high arrest rates, served as a deterrent to property crime and contributed to community safety. Tourism, with its high international visitor influx, complicated crime patterns, increasing vulnerability in certain sectors due to wealthier tourists, and varying security measures. In this context, the research aimed to unravel the intricate relationships between these variables in Central Luzon, providing empirical insights to inform targeted interventions and policy frameworks to mitigate property crime and foster safer communities in the region.

Research Question or Problem Statement:

This study aimed to examine the correlations between property crime and its determining factors in the region of Central Luzon through secondary data analysis as a quantitative approach. To address these issues, this study explored the following research questions

1. Is there a significant relationship between Poverty Rate and Property Crime Rate in Central Luzon?
2. Is there a significant relationship between the Unemployment Rate and Property Crime Rate in Central Luzon?
3. Is there a significant relationship between the Arrest Rate and Property Crime Rate in Central Luzon?
4. Is there a significant relationship between the Tourism Rate and Property Crime Rate in Central Luzon?

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Objectives:

This study thoroughly examined the dynamics of property crime in Central Luzon, Philippines, focusing on four key factors: poverty rate, unemployment rate, arrest rate, and tourism rate. By investigating the relationships between these socioeconomic factors and property crime rates, we sought to shed light on the underlying determinants of crime in the region. Through empirical analysis and data-driven insights, we aimed to provide valuable information to policymakers, law enforcement agencies, and local communities, enabling them to develop targeted strategies to mitigate property crime effectively. By addressing these root causes and correlates of property crime, we aimed to contribute to the creation of safer and more secure communities not only in Central Luzon but also potentially in other similar regions facing similar challenges.

Scope of the Study:

This study delved into the intricacies of property crime within Central Luzon, Philippines, examining the interplay between the poverty rate, unemployment rate, arrest rate, and tourism rate from 2018 to 2023. By analyzing empirical evidence and existing literature from the Philippine National Police, the Philippine Statistics Authority, and the Department of Tourism, the research aimed to elucidate the relationships between these demographic factors and property crime rates in the region. It focused on how economic conditions, law enforcement efforts and tourism dynamics influenced the occurrence of property crimes, specifically theft, robbery, carnapping, and cattle rustling. Limited to Central Luzon's seven provinces: Aurora, Bataan, Bulacan, Nueva Ecija, Pampanga, Tarlac, and Zambales—the study provided insights into the trends and correlations observed over the five-year period. While the scope remained focused on these determinants and their impact on property crime, the study refrained from proposing specific policy interventions, aiming instead to inform potential strategies for law enforcement agencies and local governments to mitigate property crime and foster safer communities in the region.

Significance or Importance:

This study on property crime dynamics in Central Luzon, Philippines, held significant importance in informing targeted strategies and policies aimed at reducing crime rates and fostering safer communities. By examining key factors such as poverty, unemployment, apprehension, and tourism, the research illuminated the complex interplay between socioeconomic conditions and criminal behavior. Through empirical evidence, it underscored how poverty and unemployment served as catalysts for property crime while highlighting the deterrent effect of law enforcement's high apprehension rates. Additionally, the study elucidated the impact of tourism on crime rates, especially concerning international visitors who were perceived as lucrative targets. By comprehensively understanding these dynamics, policymakers and law enforcement agencies could develop proactive measures by targeting economic interventions to alleviate poverty and promote employment opportunities, strengthening law enforcement efforts through increased visibility and monitoring their effectiveness, as well as implementing targeted safety measures for tourists in its attractions and criminal hotspots. Ultimately, this contributed to the creation of safer communities in Central Luzon.

Overview of the Structure:

The paper commenced with an introduction, setting the stage for investigating property crime dynamics in Central Luzon, Philippines, and delineating the key factors under scrutiny: poverty, unemployment, arrests, and tourism, to exhibit its objectives. Methodologically, it described the sources of data used, including the Philippine National Police, the Philippine Statistics Authority, and the Department of Tourism, and explained the statistical approaches utilized, such as Pearson's correlation and linear regression analysis. It provided a theoretical framework for the study and produced hypotheses based on past research and theoretical considerations, thus centering the research questions on known information and pinpointing gaps that this thesis sought to address. The results section offered the statistical conclusions, which answered each study topic sequentially with the associated data and statistics. It comprised illustrations of the data's correlations and patterns, as well as empirical evidence to answer its inquiries and evaluate hypotheses. This section discussed the realistic consequences for law enforcement, policymakers, and community stakeholders, assessed the study's findings about prior studies to show similarities and differences, and linked the findings to more general theoretical and practical considerations, providing perspectives on how the results might guide

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policy and practice. Finally, the conclusion synthesized key insights, allowing for future research to investigate better the dynamics of property crime and functional ways to improve community safety in Central Luzon based on the study findings.

II. REVIEW OF RELATED LITERATURE

2.1 Introduction to the Literature Review:

The present study endeavored to conduct a comprehensive investigation into the intricate nexus between poverty rates, unemployment rates, arrest rates, tourism rates, and property crime rates within Central Luzon, Philippines. Its goal was to provide insights into these factors behind the said type of crime to improve public safety, generate laws focusing on property crime, and implement measures to fortify crime prevention made by the local government, the police, and other policymakers based on our findings and conclusions.

2.2 Thematic Analysis of Variables:

Property Crime Rate

Property crime, which encompassed offenses such as robbery, theft, carnapping, and cattle rustling, represented a significant challenge for law enforcement agencies worldwide, with its incidence accounting for more than 30% of all crimes committed in the country (Barreda, 2023; Robielos & Duran, 2020). It involved various criminal acts typically including theft or the unlawful deprivation of property from its rightful owner. Understanding the underlying patterns and dynamics of these crimes was crucial for devising effective prevention and intervention strategies.

Statistics of crime rates allowed law enforcers, policymakers, and researchers to utilize crime data to anticipate surged criminal threats. This anticipation preceded policing strategies to prevent expected crimes from occurring. Forecasting using police data helped authorities focus on specific areas and make more effective use of their resources (Walden University, 2022). Studies in the field of criminal justice and criminology used crime data to link crime rates to factors that might influence offenders to commit them. In this case, the researchers focused on the educational attainment and economic conditions of convicts under crimes against property.

The Philippine National Police received a total of 240,444 complaints regarding theft and robbery crimes in 2018, as national data indicated that theft and robbery were common crimes across the country (Lindner, 2024). Crimes against property steadily declined from 2016 to 2020, with percentages fluctuating between 11% to 49% (Leikuma-Rimicane, Ceballos & Medina, 2023). This decline was due to the lockdowns implemented by the state in the early stages of the COVID-19 outbreak, which resulted in a significant reduction in recorded incidences of robbery, theft, and burglary throughout several countries, with reported robbery dropping by more than 50% in the majority of cases (United Nations Office on Drugs and Crime, 2020). The volume of said crimes remained consistently higher, with theft being the most prevalent form in the Philippines in 2021 (Barreda, 2023).

Factor’s Relationship on Property Crimes

Poverty Rates

According to Chen (2024), poverty refers to “the state or condition in which people or communities lack the financial resources and other essentials for a minimum standard of living.” The poverty rate was the percentage of persons whose income was less than the poverty line divided by half of the entire population's median household income (The Organization for Economic Co-operation and Development, n.d.). This economic status has been studied with countless variables, including property crime, to achieve a greater understanding of its positive or negative relationship and its effects, as well as to allow policymakers to create strategies through different insights to mitigate it. In property crime, researchers provided data on poverty’s significance, mostly due to its impact on society.

The Philippine Statistics Authority measured poverty estimates through income per capita, which was the individual or household's total income. This provided the basis for the poverty line or the minimal level of income that was considered ideal, which the PSA called the “poverty threshold.” The percentage of people whose income fell below the said term divided by the total number of people was known as "poverty incidence," which referred to those who were below the poverty line (Philippine Statistical Authority, n.d.).

In the Philippines, some studies presented such correlations in different areas of the country. In Northern Mindanao, Lim and Cuarteros (2024) identified that property crime could be affected by poverty through data on headline inflation, which was one of its indicators and was defined as the change of prices that consumers would pay for a basket of goods and services. Factors like clothing, footwear, alcohol consumption, and health significantly influenced property crimes, but communication, transportation, and education did not. Poverty was also demonstrated to be a contributing factor to theft in Barangay Citrus City, San Jose Del Monte, Bulacan, both before and during the pandemic (Maltos et al., 2022). A study in Barangay Sta. Monica, and Novaliches in Quezon City also exhibited poverty as the main motive for theft cases based on their respondents (Miranda et al., 2022).

On the subject of its impact on property crime, most studies presented a complete correlation, where both variables showed an increase in their data. The findings supported a favorable co-integrating link between poverty and property crime, as it was the main leading determinant in the United States over time (Imran, Hosen, & Chowdhury, 2018). Another research in Indonesia found a major impact on crime but only in the short term, as poverty did not have a substantial impact over a longitudinal period (Anozi & Novianda, 2023). Scholars also found a positive and substantial influence of poverty and unemployment on criminal behavior among teenagers and adults in Pakistan. Due to their poor socioeconomic status, these individuals were more likely to engage in criminal behavior (Shah, Soomro, & Mirjat, 2019).

Contrastingly, some academic journals presented by researchers showed the opposite effects of its relationship. In the United States, it was concluded that higher rates of unemployment resulted in lower rates of property crime due to the lack of suitable targets (Bianchi & Chen, 2022). Mixed findings were also shown in a study by Lee (2018), where the said determinant reduced both the cost and possible benefits of crime, making its influence on crime rates unpredictable and dependent on the possibility of arrest.

In connection to the aforementioned studies, the Philippines showed significant issues in terms of the nation's poverty rates. According to the Philippine Statistics Authority (2020), 16.7 percent of the population, or about 17.6 million Filipinos, were under its poverty rate in 2018. Then in 2021, it increased to 18.1 percent or almost 20 million of the nation's citizens, with the COVID-19 pandemic as one of its main factors (Reuters, 2022). Two years later, it rose to 22.4 percent or 25.24 million poor Filipinos in the first half of the year. This encouraged researchers to assess further property crime based on the statistical data regarding the region's economic status.

Unemployment Rates

Unemployment referred to a setting in which an individual actively sought a job but was unable to find it, and it was often seen as a vital indicator of economic stability. The unemployment rate was the most often used metric of joblessness, as it was computed by dividing the number of jobless persons by the total workforce (Hayes, 2024).

According to the Philippine Statistics Authority (n.d.), the rate of unemployment was the percentage of the total unemployed labor force actively seeking employment and willing to work. It covered those who were 15 years of age or older, who did not have a job or business during the time frame in question, who were willing and able to work, and who actively sought employment. This covered those who followed certain procedures to launch a business or acquire employment. It also included persons who were not looking for work because they were waiting to be rehired or have their job recalled, were discouraged from past job searches, were awaiting the outcome of their applications, were temporarily ill or disabled, or were experiencing terrible weather.

Numerous studies demonstrated the effects of unemployment on property crimes with the positive existence of its relationship. In the United States, it was proven that joblessness could affect crime in the long run according to the study by Costantini, Meco, and Paradiso (2018). The data presented in the study by Wilson (2018) indicated a correlation between positive economic developments and decreases in property crime rates. Conversely, rises in property crime rates occurred during recessions, especially unemployment, which was observed in Western Canada. Twenty-eight nations of the European Union also exhibited a positive correlation between unemployment and crime, using the collected data from the World Bank and Eurostat (Ayhan & Bursa, 2019).

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However, some theories showed a negative correlation. For instance, unemployment could decrease the value of property crime targets and may increase the number of people staying in their dwellings, which deters criminals from committing offenses against them (Mulamba, 2021). In India, unemployment was found to have a slight negative association with property theft from 2005 to 2020. Consequently, its increasing rate would reduce the frequency of property crimes (Chowdhury, Kalia, & Menon, 2023).

Past local research provided the correlations in barangays between unemployment and property crime. In Barangay San Martin I, City of San Jose Del Monte, Bulacan, unemployment proved to be one of the main leading causes of criminals committing such crimes during community quarantine amidst the COVID-19 outbreak, as its effects drastically affected the labor force at that time due to the lockdowns implemented by the government (Saagundo et al., 2022). The same goes in Barangay Citrus City, San Jose Del Monte, Bulacan, where Maltos et al. (2022) stated that theft had also been influenced by unemployment both before and after the pandemic.

To further understand its influence, statistical data was provided to consider the influence of national-level fluctuations in unemployment rates. According to the Philippine Statistics Authority's Labor Force Survey (LFS), the nation's overall unemployment rate increased to 5.1%, somewhat greater than the 5% reported in October 2017. The employment rate also fell slightly, to 94.9% from 95%. This amounted to 2.2 million jobless Filipinos (Rivas, 2018). Then in 2019, the unemployment rate fell to 4.5%, and the overall number of jobless people fell to 2.05 million from 2.2 million (Rivas, 2019). The following year, with the COVID-19 outbreak and the rigorous lockdown closing thousands of businesses, almost 4.5 million Filipinos lost their jobs, and the unemployment rate rose to 10.4 percent, the highest since 2005 (De Vera, 2020). In 2021, the Philippine Statistics Authority stated that the unemployment rate increased to 6.6%, resulting in 3.27 million idle Filipinos regardless of the decrease in COVID-19 cases in the nation (Rivas, 2022). The November 2022 Labor Force Survey (LFS) showed 4.2 percent or 2.2 million jobless citizens as the lowest unemployment rate since April 2005 (Department of Finance, 2023). The unemployment rate in the nation fell significantly to 3.6% in November 2023. The current statistic equated to 1.83 million jobless people. This was the lowest unemployment rate reported since the PSA adopted a new technique for assessing the labor force survey in 2005 (Presidential Communications Office, 2024). This invited academics to investigate further property crime using statistical data on the region's unemployment standing.

Arrest Rates

Arrest denoted the action of apprehending or taking into custody individuals believed to have engaged in criminal behavior. It represented the physical act of law enforcement detaining someone. Arrest rate, conversely, served as a quantitative metric assessing law enforcement's efficacy in apprehending suspected criminals. It was calculated as a ratio or percentage, comparing the number of arrests conducted by law enforcement to the total number of individuals suspected or identified as perpetrators of crimes within a defined period and geographic region.

Just as the assurance of prompt and certain punishment acted as a powerful deterrent against crime, law enforcement exerted efforts to resolve all criminal incidents and ensure perpetrators faced legal consequences.

The implementation of mitigation policies, such as economic stimulus bills like the CARES Act, aimed to alleviate the impact of COVID-19. In the realm of criminal justice research, much attention has been directed towards analyzing the effects of local lockdown measures on various forms of crime. The findings from these studies revealed significant negative correlations between the CARES Act and key indicators of property crime rates, including the overall property crime rate, burglary rate, and larceny and theft rate. This suggested that apprehension strategies, such as economic support measures, could potentially contribute to a reduction in property crime rates during times of crisis like the COVID-19 pandemic (Cassino, 2023).

In the findings of Weisburd (2021), the research findings indicating a correlation between a decrease in police presence and an increase in crime rates provided insight into the dynamics of apprehension and property crime. Specifically, a 10% reduction in police presence corresponded to a 7% rise in crime, underscoring the importance of law enforcement presence in crime prevention. This highlighted the significance of apprehension strategies, such as police patrols, in deterring criminal behavior and maintaining public safety. Moreover, it emphasized the potential impact of routine changes in policing practices on crime rates, illustrating the interconnectedness between apprehension efforts and property crime outcomes.

Supporting previous discussions on crime apprehension affecting crime rates in general, the study investigated how increased funding for the Community Oriented Policing Services (COPS) hiring grant program, prompted by the American Recovery and Reinvestment Act, affected crime rates. Using a natural experiment and a difference-in-differences framework, the research found that cities receiving additional grants experienced a rise in police presence and a decline in various types of crime, particularly robbery, larceny, and auto theft. This effect was more pronounced in areas changed by economic downturns like the Great Recession. Overall, the findings suggested that investing in law enforcement during tough economic times could significantly reduce property crime rates, indicating the importance of apprehension efforts in crime prevention (Mello, 2021).

In another research by Lee (2018), the paper underscored the significance of apprehension rates in elucidating the interplay between unemployment and crime. Contrary to prior research, it asserted that apprehension rates were pivotal in shaping this relationship. Specifically, while apprehension curbed crime, it also altered the impact of unemployment on crime rates. Furthermore, the study advocated for the inclusion of apprehension rates in empirical crime analyses to capture the intricate nature of this association. Acknowledging the influence of local factors such as ideology, politics, and culture on apprehension rates and enforcement policies suggested that the efficacy of apprehension strategies might vary regionally.

As there was the instance of punishment, criminals also took into account the effectiveness of the criminal justice system under the rational choice theory. The findings of Bun et al. (2019) indicated a strong correlation between criminal activity and the likelihood of arrest and conviction while demonstrating less sensitivity to the potential for imprisonment or its severity. This supported the notion that the repercussions of apprehension and conviction extended beyond direct punishment by the criminal justice system to include indirect sanctions imposed by society.

Tourism Rates

Tourism encompasses the act of traveling to various destinations for leisure, recreation, or cultural exploration, involving experiences of diverse cultures, environments, and attractions such as sightseeing, adventure tourism, or beach vacations. In the realm of criminal behavior, tourism is a subject of significant inquiry due to its association with various elements. Among the vulnerabilities of tourists to crime are the repercussions of criminal activity on the tourism industry, the emergence of criminal networks facilitated by tourism, and considerations of crisis management.

This study seeks to examine the role and significance of tourism in the perpetration of property crime, particularly in locales like Angeles City. As an economic zone boasting a substantial population of foreigners and tourists from across the country, Angeles City presents a unique context for understanding the dynamics of crime within tourism-driven environments.

As tourism gives way for the country to be introduced with greater trade, this can also lead to an increase in criminal behavior, as stated in the research of De Albuquerque and Elroy (2019). In the 21st century, tourism has emerged as a key economic sector. Presently, tourism confronts diverse security challenges, including terrorism, criminal activities, and the possibility of armed conflicts. Among these, crime stands out as the predominant security concern for the tourism industry. Crime poses a significant threat to tourism, undermining both the industry itself and the sense of security essential for travelers. Therefore, ensuring a safe environment for tourists requires concerted efforts. To achieve this, collaboration among all stakeholders in tourism: including the tourism sector, local communities, national authorities, police, and governmental agencies is imperative. This collective effort is essential for crime prevention and the establishment of a secure atmosphere conducive to tourism.

From another source (Recher & Rubil, 2019), evidence suggests that tourism contributes to an increase in property crime. This impact varies spatially and by the type of property crime, with coastal regions experiencing a higher influence compared to continental areas, and theft being more affected than larceny. Through counterfactual calculations, it has been demonstrated that if tourism were the sole factor influencing property crime, the number of incidents would have escalated significantly from 2006 to 2016 compared to the actual observed levels. The substantial elasticities imply that even modest growth in tourism activity, in the absence of sufficiently robust counteracting factors, could lead to a notable rise in property crime over a decade. From a policy standpoint, understanding these counteracting factors and assessing the social costs of tourism-related crime is crucial in comprehensive cost-benefit analyses of tourism development.

The findings indicate that increased levels of tourism correlate with elevated rates of property and violent crimes in neighborhoods, and this association is influenced by factors such as residential instability and national diversity. However, mediation models suggest a contrasting relationship between tourism and crime when concentrated disadvantages serve as the mediating factor. This prompts a reevaluation of the role of socioeconomic variables in the dynamic between crime and the process of touristification (Guzman, 2021).

As confirmed by Vakhitova et al.'s (2022) research, the study's results highlight the efficacy of opportunity theories in explaining crimes against tourists. Specifically, the investigation reveals that variables such as the location and type of accommodation, along with the adoption of target hardening and guardianship measures, significantly influence the understanding of burglaries targeting tourist lodgings. Additionally, the study discusses practical implications for crime prevention derived from these findings.

In a study conducted in Japan by Cheng, Wu, and Chen (2024), their findings indicate that while the overall crime rate does not significantly affect inbound tourism, the incidence of violent crime exhibits a notable negative influence. This underscores the importance of meticulously choosing crime variables for analysis. Moreover, the significant spillover effects underscore the crucial role of regional cooperation in tackling crime and fostering tourism.

2.3 Theoretical Framework:

This study was grounded in routine activity theory, a significant framework in criminology that has driven extensive theoretical and empirical investigation into crime patterns. This theory has not only inspired innovative crime prevention strategies but also continued to shape our understanding of criminal behavior. According to Tillyer and Eck (2010), routine activity theory profoundly impacted the field by emphasizing the situational aspects of crime. Over the past 25 years, this theory underwent numerous empirical validations, further establishing its importance (Cohen & Felson, 1979).

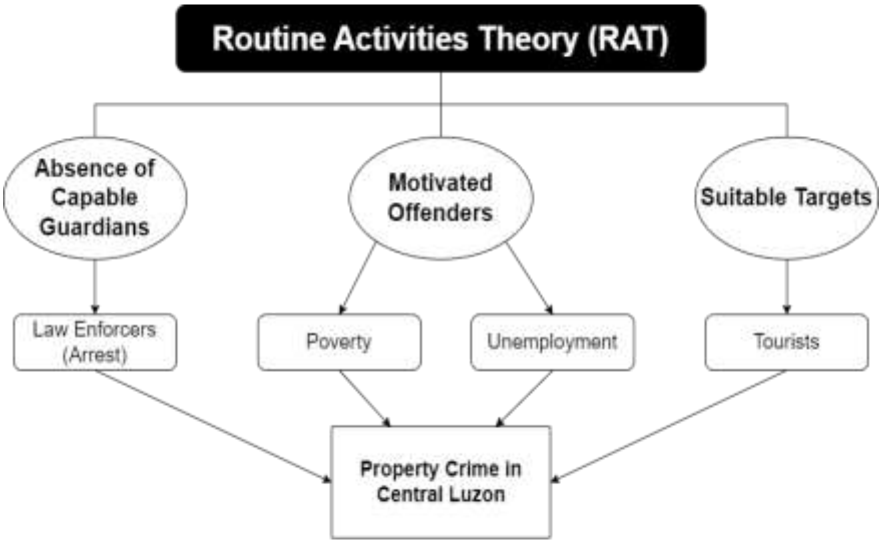
Routine activity theory posited that crime rates were influenced by neighborhood-level activity patterns. Crime was more likely to occur when three elements converged: a motivated offender, a suitable target, and the absence of a capable guardian (Hayslett-McCall, 2002). Daily routines affected exposure to potential offenders, the attractiveness or vulnerability of targets, and the presence or absence of guardianship. Consequently, victimization was more probable when motivated offenders, suitable targets, and ineffective or absent guardians converged (Mustaine & Tewksbury, 1998).

Applying routine activity theory to the context of Central Luzon, this study examined how regional characteristics influenced crime patterns. Central Luzon, with its unique socio-economic and demographic features, provided a distinct setting to explore this theory. For instance, poverty and unemployment rates in Central Luzon could serve as motivating factors for potential offenders. High tourism rates in the region could create numerous suitable targets for crimes aimed at material and personal gain. Additionally, the apprehension rates in this area impacted the presence or absence of capable guardians, influencing the likelihood of criminal activity.

Argun and Dağlar (2016) highlighted that routine activity theory could be an effective tool for assessing crime issues and implementing safety measures. In Central Luzon, understanding the convergence of motivated offenders, suitable targets, and capable guardians could help devise targeted crime prevention strategies. For example, increased poverty and unemployment might have heightened the motivation to commit crimes, while tourism could have attracted offenders due to the presence of valuable and vulnerable targets. Effective law enforcement and community vigilance were crucial in maintaining capable guardianship, thereby reducing crime rates.

2.4 Conceptual Framework:

The conceptual framework of this study, grounded in Routine Activity Theory (RAT), actively linked several key factors to property crime rates within Central Luzon. RAT posited that crime rates were influenced by the convergence of motivated offenders, suitable targets, and absent guardians. This theory formed the foundation for understanding and addressing criminal behavior, with a particular emphasis on how various socio-economic and environmental factors contributed to crime occurrence (Cohen & Felson, 1979).



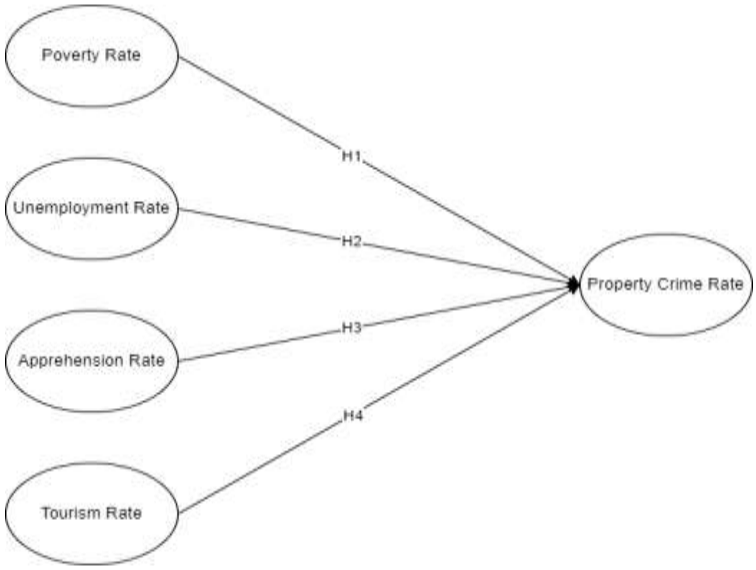
Poverty and unemployment were tightly intertwined with property crime rates, compelling individuals facing economic hardship to resort to theft or burglary when legitimate avenues were scarce (Jonathan et al., 2021). Economic deprivation could drive criminal activities for survival or betterment, such as food, transportation, and others. Likewise, unemployment bred frustration and hopelessness, pushing individuals towards criminal behavior as they sought alternative income sources or coped with idleness. It was also impacted by Central Luzon's urbanization, which raised property crime rates by bringing about social disorder, economic inequality, higher population densities, and inadequate infrastructure and services (Sanidad-Leones, 2006). Ideally, individuals under these variables in committing property crime may have been considered as “motivated offenders” and may have increased rates of the said crime if Central Luzon were presented with higher percentages of poverty and unemployment.

Law enforcers represented the “capable guardians” of RAT’s element, as their absence or presence exhibited the effectiveness of crime prevention and apprehension within their jurisdiction. Apprehension, the fear of being caught and punished, acted as a deterrent to potential offenders, shaping their likelihood of engaging in property crimes. Social cohesion, or the degree to which neighbors believed they had similar ideals and mutual trust, also contributed to this variable as a supplemental factor in the effectiveness of law enforcement due to its higher confidence and trust in local authorities (Avery et al., 2020). When detection and punishment risks were low in Central Luzon, individuals may have felt emboldened to commit crimes, while higher chances of apprehension could have deterred criminal activity.

Additionally, tourism influenced property crime rates by fostering a transient population (Recher & Rubil, 2019). It offered criminals opportunities to target unsuspecting tourists as "suitable targets" according to the Routine Activities Theory. Central Luzon, being an investment and tourist destination with natural attractions and cultural heritage, drew both foreign nationals and locals for leisure and business activities (Department of Trade and Industry, 2020). A higher number of tourists could have strained local resources and law enforcement, potentially diverting focus from preventing property crimes and increasing its rates within the region.

By actively connecting these variables to property crime rates within Central Luzon, this study aimed to provide insights into the complex interplay between socioeconomic factors, environmental dynamics, and criminal behavior. Understanding these relationships could inform the development of targeted crime prevention strategies tailored to the unique context of Central Luzon, ultimately contributing to safer communities and enhanced well-being for residents and visitors alike.

2.5 Paradigm of the Study:



This study sought to explore the influence of poverty, unemployment, apprehension, and tourism as factors contributing to offenders committing property crimes, thereby affecting its rates within Central Luzon. These variables were chosen based on the findings of Howsen and Jarell (2006), which demonstrated that these factors significantly contributed to property crime as primary elements within a given area.

However, it is important to note that these factors do not represent the sole determinants of property crime causality. Future researchers are encouraged to expand on other potential causes of criminal activities, including environmental factors, societal peer influence, psychological issues, and other theories of crime causation, encompassing various types of crime such as special crimes, crimes against persons, and crimes against chastity. By doing so, a more comprehensive and nuanced understanding of the topic can be established, both at the local and national levels.

III. METHODS

3.1 Study Design:

The researchers employed a descriptive correlation approach using secondary data to investigate the factors influencing property crime rates in Central Luzon. A correlational design was utilized to assess the relationships between these variables without manipulating them. This design was well-suited for analyzing large datasets and exploring complex connections between poverty, unemployment, tourism, apprehension, and property crime rates. This approach offered a systematic method for analyzing complex relationships and identifying patterns within the context of property crime dynamics in Region III. Given the availability of necessary resources and the absence of anticipated challenges, this approach aligned with the researchers' objective of exploring the specified correlations effectively within the designated context.

Included in the study was the sampling method of total enumeration, also known as census or complete enumeration, which involved studying every individual or element within a population rather than selecting a sample. While total enumeration had its advantages, it may not have always been feasible or necessary depending on the research objectives and constraints. However, due to how the data was collected and included, this was the most compatible method of data collection utilized for this study. The quality of information relied solely on the authorized given data by the agencies, as it was presumed to be statistically correct and accurate by official governmental offices. If information from specified sources was incomplete, researchers were tasked with filling in the gaps by estimating missing data using the resources available to them. This process ensured that their analysis remained thorough, even in the face of incomplete information.

3.2 Units of Data

For the purpose of this study, the researchers analyzed primarily numerical and quantitative data gathered during the years 2018 up to 2023. The data was primarily sourced from the Philippine Statistics Authority, the

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Department of Tourism, and the Philippine National Police, among others. These sources were presumed reliable, as they were obligated to compute and track statistical data as a reference for future projects of their respective agencies and for authorized people to utilize in research, laws, and public policies.

Poverty Rate - The researchers used statistical data from the Philippine Statistics Authority regarding the Poverty Incidence among the Population per annum, which was the percentage of individuals whose income or spending per person was below the poverty line, compared to the total number of individuals.

Unemployment Rate - The unemployment rate served as a key indicator of the health of the labor market and the economy as a whole. It was the total unemployed as a percentage share of the total labor force. For the purposes of this study, it served as a quantifiable measure for understanding how unemployment could play a role in influencing crime commission.

Arrest Rate - The apprehension or arrest rate referred to the number of criminal offenders who were successfully apprehended or arrested by law enforcement authorities relative to the total number of offenders who had committed property crimes within a specific timeframe or jurisdiction, including those who were "cleared" from their cases as they were found not guilty, "solved" as they were found guilty, and those whose cases were still "under investigation". For this study, they were used to determine the correlation between arrest rates towards crime commission, mainly as a deterrent.

Tourism Rate - The tourism rate was the generalization of data gathered from the Department of Tourism (DOT) in regards to the number of people who entered Angeles City and partook in certain activities such as overnight stays. In the study, this was the measure of tourists, both local and international, visiting Central Luzon.

The sampling method used was Total Enumeration Sampling as it aimed to convey comprehensive statistical coverage across location and time, considering it covered five years' worth of data from the five variables of the study.

3.3 Unit of Coverage

In this study, the researchers focused on Central Luzon, encompassing all seven of its provinces. The time frame for coverage was extended from 2018 to 2023, as data for 2024 was currently being compiled by relevant governmental agencies, and information preceding 2018 was deemed irrelevant to the study's objectives. Given the absence of direct participants, the study relied predominantly on secondary sources of information. Consequently, there was no utilization of a sampling method; instead, the study involved synthesizing theories derived from the analysis of gathered data and information.

3.4 Inclusion and Exclusion Criteria:

This study is focused solely on Central Luzon and its seven provinces, acquiring and interpreting annual data from 2018 to 2023. Any data outside of these years and areas is disregarded and not part of the study.

Regarding the property crime rate, the data included in the study consists of the number of reports recorded by the Crime Registrar in the Philippine National Police Regional Office 3.

For the poverty rate, the researchers excluded factors such as the poverty gap, poverty threshold, and severity of poverty. The focus is solely on poverty incidence, which measures the total percentage of individuals under the poverty line.

In terms of unemployment data, only unemployment rates are considered. Unemployment rates refer to the percentage of the labor force that is currently unemployed and actively seeking employment. In other words, it represents the proportion of individuals who are willing and able to work but are unable to find employment despite actively searching for jobs. Data on labor force participation rates, employment rates, and underemployment rates are excluded.

The data for tourism rates includes the number of people in Angeles City who have engaged in certain activities within the city with overnight stays. This excludes airport arrivals and day tours, as per the regulations of the Department of Tourism. The tourism rate represents the amalgamation of information obtained from the Department of Tourism (DOT) regarding the volume of individuals arriving in Angeles City and participating in specific activities, such as overnight accommodations. Within the study, this metric served as a gauge for quantifying tourists—both domestic and international—visiting Central Luzon.

Regarding the apprehension rate, the focus is solely on property crimes, specifically those involving the theft of property. This includes offenses such as theft, robbery, cattle rustling, and carnapping, regardless of the existence of a warrant.

3.5 Specific Procedures Based on Study Objectives:

The researchers will employ secondary data analysis to collect statistical data for correlating variables. They will request poverty and unemployment rates in Region III from the Philippine Statistics Authority in San Fernando, Pampanga. Tourism rates will be formally acquired from the region's Department of Tourism in Clark Freeport and via email. Lastly, property crime rates and apprehension rates will be requested from the Philippine National Police Regional Office 3 in San Fernando, Pampanga, with the assistance of their Regional Director. The collected data will include variables from each of the seven provinces, as well as Central Luzon's yearly statistics.

Data Collection Methods

To ensure data quality, the researchers will implement quality assurance checks. This involves verifying data inputs and comparing information with credible sources to address anomalies, missing numbers, and errors. The validity and reliability of the study will be strengthened by maintaining thorough documentation of the data-gathering process and fostering transparent interactions with the respective agencies.

Data Management

The data collected from the aforementioned sources will be organized in a Google Drive. Original documents will be acquired and transcribed into a Google Sheets file, arranged per region, province, and variable in chronological order. This arrangement will facilitate easy access and organization of the data, and the documents will be automatically saved, making them easily exportable.

To ensure data security and integrity, the researchers will issue specific access rights and limit access to authorized personnel with personal email accounts. This measure aims to prevent unauthorized access to sensitive information. Version control tools in Google Sheets will be utilized to track changes and preserve data integrity throughout the research process. Additionally, Google Drive's encryption capabilities will guarantee data security both in transit and at rest.

To prevent data loss, timely backups of the Google Sheets file will be conducted. Furthermore, additional security measures such as two-factor authentication and audit trail management will be implemented to enhance overall data security on the shared digital platform. These measures collectively aim to safeguard the confidentiality and integrity of the research data throughout the study.

Quality Assurance

The collected data is presumed to be accurate, given its source from government and law enforcement agencies. However, to ensure the quality of this study, regular verification of the data will be conducted to confirm accuracy, completeness, and credibility. This verification process will adhere to the protocols of the institution and ethical standards. The study will undergo review by the ethics committee and the authors' respective scholars to address any potential issues and ensure the integrity of the thesis.

Monitoring and Supervision

The researchers shall regularly communicate to monitor the progress of the thesis, conduct fact-checking every after task, and consult with their research adviser in addressing their concerns regarding the collection of data, especially to secure conformity to the protocols and guidelines of this study.

Data Validation and Verification

As this study utilizes secondary data analysis, the authors shall use data directly from verified sources such as the Philippine Statistics Authority, the Department of Tourism, and the Philippine National Police Regional Office III, as it is properly formatted and computed by the said respective agencies.

Documentation

It shall include the procedures of data collection, including the request letters, consent forms, and pictures of researchers gathering information from agencies and quality assurance approaches.

3.6 Ethical Considerations:

In this study, our paramount ethical concern is to safeguard data privacy and ensure its confidential utilization throughout all stages of acquisition, analysis, and dissemination. To address this, we will undergo a comprehensive ethical review and approval process by our institution's ethics committee. This process entails submitting a detailed research proposal outlining the study's objectives, methodologies, and potential ethical issues. The ethics committee will thoroughly review the proposal to identify any ethical concerns and recommend steps to mitigate them. Upon approval, we will strictly adhere to their guidelines to ensure compliance.

The researchers are committed to adhering to the Data Privacy Act of 2012, which mandates stringent protocols for the protection of personal information. To maintain data confidentiality, we will implement several measures. Firstly, all data will be anonymized to remove any personal identifiers before analysis. Access to the raw data will be restricted to the primary researchers only, and secured through password-protected files and encrypted storage systems. Additionally, during data collection, we will ensure that any extraneous information not pertinent to our study is meticulously excluded.

Protection of Participants

Ensuring the privacy and confidentiality of data is our top priority. Although this study relies solely on statistical data and does not involve human participants, we obtain data ethically and legally. We strictly adhere to the Data Privacy Act of 2012 and other relevant regulations. Any information not pertinent to the study will be excluded, ensuring we handle data responsibly.

Informed Consent

Since the study uses pre-existing statistical data, informed consent from individual participants does not apply. However, we protect data privacy and ensure confidentiality by obtaining the necessary permissions for accessing and using the data, adhering to data protection regulations, and appropriately acknowledging data sources. We securely store the data on a protected Google Drive, accessible only through our Research Advisers AUFmail account. We restrict access to the data and analysis files to the research team and authorized research instructors. Additionally, we anonymize all data to prevent the disclosure of sensitive information that could identify individuals or organizations.

Confidentiality and Privacy

We ensure the confidentiality and privacy of the statistical data by securely storing it on a protected Google Drive, which is only accessible through our Research Advisers AUFmail account. Access to the data and analysis files is restricted to the research team and authorized research instructors. Additionally, we anonymize all data to prevent the disclosure of sensitive information that could potentially identify individuals or organizations. These measures actively protect the data privacy and confidentiality, mitigating the risk of unauthorized access or disclosure.

Minimization of Risks

To safeguard data privacy and ensure confidentiality, we actively mitigate potential risks associated with statistical data usage. This includes verifying the reliability and validity of data sources and employing rigorous data analysis techniques. We will maintain transparency by disclosing any potential conflicts of interest and taking proactive measures to mitigate them, ensuring the credibility and impartiality of the research.

Conflict of Interests

The researchers shall maintain thorough disclosure and proactive measures to mitigate any conflicts that may arise, ensuring the credibility and impartiality of the research.

Institutional Review

We are actively engaged in crafting a comprehensive letter for review by the ethics committee, detailing our research protocol and ensuring strict adherence to ethical standards and regulations. Throughout this process, we maintain a proactive approach, addressing potential ethical concerns raised during the review and incorporating necessary modifications to the study protocol to mitigate these concerns effectively. Our commitment to transparency and integrity guides us in detailing every aspect of our study methodology, participant recruitment procedures, informed consent protocols, and measures to safeguard participants' rights and welfare. This letter serves as a crucial document, demonstrating our dedication to upholding the highest ethical principles in all facets of our work, and actively engaging with the ethics committee to seek their approval and value their insights in ensuring the ethical integrity of our research endeavors.

Compliance with Regulations

The research we conduct rigorously follows ethical norms, rules, and regulations, with a strong focus on maintaining data privacy and confidentiality. We specifically comply with the Data Privacy Act of 2012, which mandates strong measures for protecting personal information. This guarantees that only relevant data necessary for our investigation of property crime trends in Central Luzon, Philippines, is used, while irrelevant information is carefully eliminated.

Continuous Monitoring

Throughout the research process, researchers actively monitor ethical considerations, with a specific focus on data handling and analysis. Any ethical issues that emerge receive prompt attention and resolution to maintain the study's integrity and conduct. Unnecessary data not pertinent to the study is not used and deducted accordingly.

3.7 Procedure 1:

To collect the necessary data, the researchers will contact the Philippine National Police Regional Office 3 for property crime and apprehension rates, the Philippine Statistics Authority for socio-economic data, and the Department of Tourism Region 3 for tourism data. They will send formal email requests to each agency, attaching a letter of request endorsed by college authorities and a consent form. These documents will outline the study's purpose, data protection measures, contact information, and assurance of confidentiality in adherence to the Data Privacy Act of 2012.

If no response is received within one week, the researchers will follow up with additional emails and phone calls to ensure the requests have been received and to provide any necessary additional information. They will promptly schedule on-site visits to each agency to discuss the data collection process in person and to retrieve the data directly if it is available. These visits will help to expedite the process and address any immediate questions or concerns from the agencies.

Once the data is gathered, the researchers will organize it in a structured manner. Raw information will be stored in a Google Drive folder, while necessary statistics will be compiled in Google Sheets. The data will be sorted chronologically by province or region to facilitate easy access and analysis. This organization will ensure that the data is clean and properly formatted, ready for further analysis.

This entire data collection and organization process will be completed within 2-3 weeks. By maintaining a structured approach and proactively addressing potential delays, the researchers aim to ensure a smooth and efficient data collection phase, minimizing obstacles and keeping the study on schedule.

3.8 Statistical Analysis of Data

The study shall utilize Pearson's Correlation Coefficient, or Pearson's r, to assess the linear relationship between two continuous variables, which are the property crime rates and each of its four factors. This approach is appropriate for the study, as it measures the direction and intensity of relationships between continuous variables, offering information on how these factors may either aggravate or minimize property crime rates.

The findings from the aforementioned method will be interpreted in the context of the study's hypotheses and theoretical framework. For instance, if Pearson's correlation coefficient returns a negative value or an inverse link, the authors can perceive this as a possible preventive impact of apprehension on property crime, with more apprehension activity resulting in lower property crime rates. A positive correlation coefficient, on the other hand, indicates a positive relationship between the apprehension rate and the property crime rate, meaning that greater degrees of apprehension coincide with greater property crime rates. It shall prove the relevance of the Routine Activities Theory with the results of the study as evidence.

The thesis shall also utilize Linear Regression Analysis, as it is to forecast the value of the independent variable depending on the value of the dependent variable. The research's objective of interpreting the impact of

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socioeconomic determinants on crime rates in Central Luzon is in line with this strategy, which allows evaluation of how shifts in these characteristics may anticipate changes in property crime rates.

If the projected change in property crime rate for a one-unit change in unemployment rate is positive and statistically significant, it suggests that greater unemployment rates correlate with greater property crime rates. In contrast, if the change in the property crime rate for a one-unit change in the unemployment rate is negative and statistically significant, it implies that greater unemployment rates are related to reduced property crime rates.

Such findings shall be considered as quantitative evidence to provide perspectives on its relationships to interpret how rates of poverty, unemployment, apprehension, and tourism influence property crime in Central Luzon and all of its seven provinces.

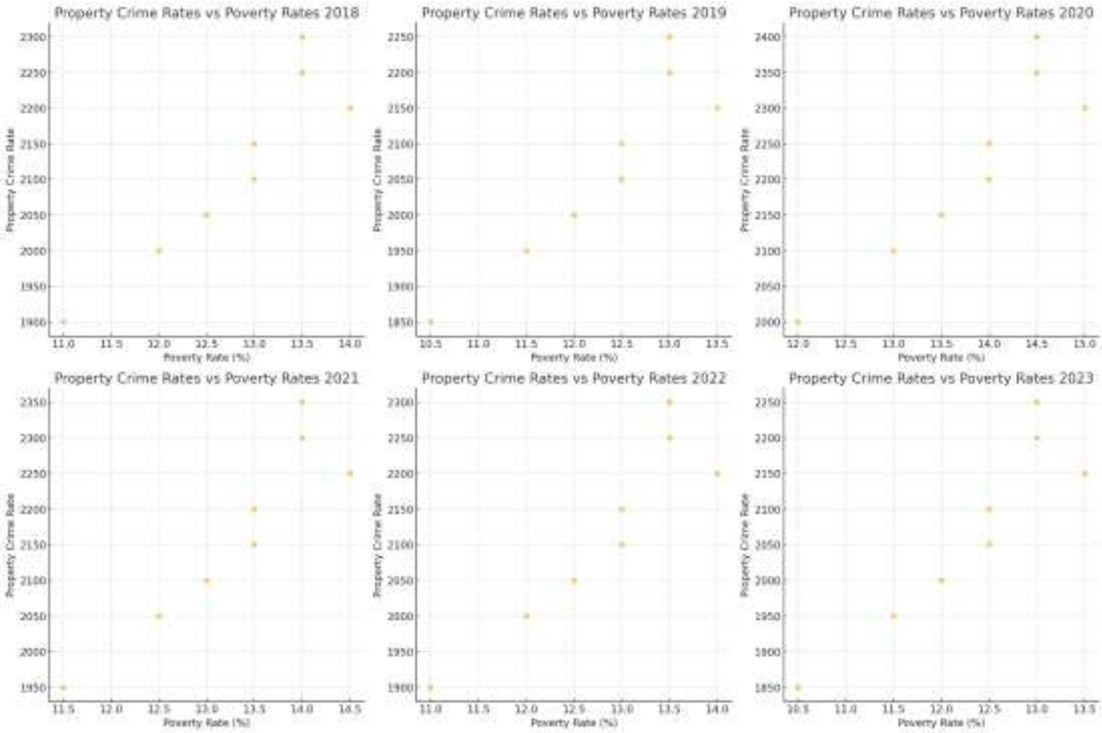
Alternative techniques like Spearman's Rank Correlation or logistic regression may have been taken into consideration, even if Pearson's Correlation Coefficient and Linear Regression Analysis are appropriate for evaluating linear connections and making predictions. These techniques, however, were not selected as the accepted statistical methods are better at capturing the subtleties of linear relationships and predictive modeling. Furthermore, these disregarded options may not qualify as compatible with the goals and theoretical framework of the study, which emphasize looking at linear correlations and predicting property crime rates based on socioeconomic variables.

IV. RESULTS AND DISCUSSIONS

4.1 Pearson's Correlation

Pearson's correlation coefficient (r) measures the strength and direction of linear relationships between variables like Tourism Rate, Poverty Rate, Unemployment Rate, and Arrest Rate with property crime rates. A high positive (close to +1) or negative (close to -1) r-value indicates a strong correlation, suggesting these factors significantly influence crime rates. Policymakers can prioritize interventions based on factors with the strongest correlations to address and potentially reduce property crime effectively.

4.1.1 Property Crime Rate and Poverty Rate



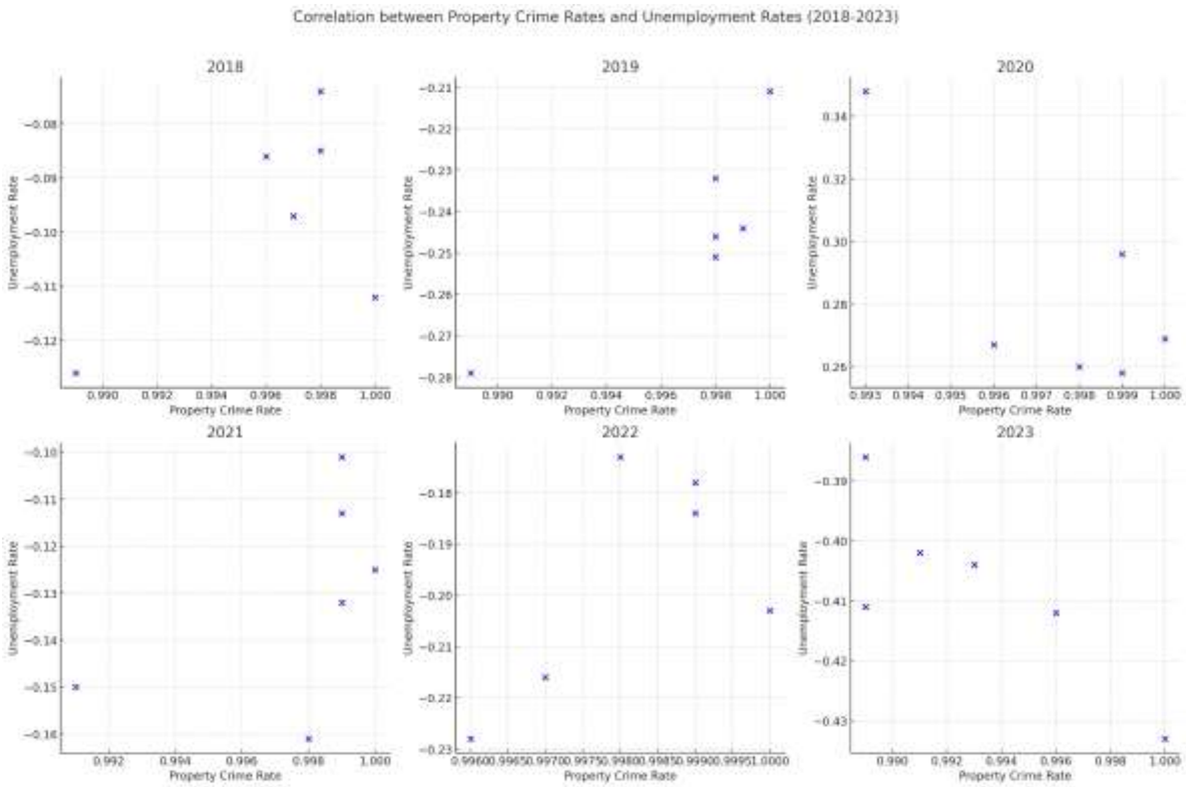
The scatter plots illustrate the relationship between Property Crime Rates and Poverty Rates for 2018 to 2023. Each year's data points are plotted to show how property crime rates vary with different poverty rates. For all years, the scatter plots indicate a generally weak inverse relationship. This means that higher poverty rates are associated with slightly lower property crime rates. However, this relationship is not strong, as evidenced by the considerable dispersion of data points. The correlation coefficients, which range from -0.21 to -0.45, further reinforce this observation. These values indicate a weak inverse relationship, as they are relatively close to zero. Additionally, the p-values associated with these correlations are all above 0.05, suggesting that these correlations are not statistically significant. Thus, we cannot confidently assert a reliable inverse relationship between property crime rates and poverty rates based on this data alone.

The weak inverse relationship observed between Property Crime Rates and Poverty Rates suggests that as poverty increases, property crime rates tend to decrease slightly. This is counterintuitive as one might expect higher poverty rates to correlate with higher crime rates. Several factors could contribute to this unexpected relationship. Firstly, property crimes are influenced by a myriad of factors beyond poverty, such as law enforcement effectiveness, community programs, social support systems, and economic conditions.

Moreover, the lack of a strong and statistically significant correlation implies that poverty is not the sole or even primary driver of property crime rates. Other variables, such as unemployment rates, education levels, and urbanization, may have more substantial impacts on property crime rates. Additionally, the fluctuations and inconsistencies observed across the different years suggest that the relationship between property crime rates and poverty rates is complex and may vary based on local circumstances and changes over time.

Supporting literature underscores the complexity of the relationship between poverty and crime. For instance, Lim and Cuarteros (2024) in their study in Northern Mindanao, and Maltos et al. (2022) in San Jose Del Monte, Bulacan, have suggested that other factors like inflation and specific socioeconomic conditions play crucial roles in influencing crime rates. Similarly, broader studies, such as those by Imran, Hosen, and Chowdhury (2018) in the U.S., and Anozi and Novianda (2023) in Indonesia, indicate that crime dynamics are influenced by a myriad of variables. These studies collectively suggest that effective crime reduction strategies must consider a diverse range of influences beyond poverty alone. The analysis from 2018 to 2023 of property crime rates and poverty rates in the Philippines reveals a consistent but weak negative correlation, indicating that as poverty rates rise, there is a slight tendency for property crime rates to decrease. However, this relationship is not sufficiently strong to be predictive. The scatter plots and correlation coefficients support this weak inverse association but also show significant variability, implying that poverty alone does not account for the majority of fluctuations in property crime rates.

4.1.2 Property Crime Rate and Unemployment Rate



The scatter plots for the years 2018 to 2023 reveal a weak and inconsistent relationship between property crime rates and unemployment rates. In 2018 and 2019, the correlation is slightly negative, with Pearson correlation coefficients of -0.112 and -0.232, respectively. This suggests that higher unemployment rates might correspond with marginally lower property crime rates, but the relationship is not strong enough to be statistically significant. The data points for these years are widely scattered, indicating no clear linear trend.

In 2020, the correlation shifts to a weak positive relationship (0.267), suggesting a minor increase in property crime rates with higher unemployment rates. However, this correlation remains statistically insignificant and does not establish a robust connection between the two variables. The following year, 2021, reverts to a weak negative correlation of -0.161, continuing the trend of an inverse relationship but still lacking statistical significance.

The year 2022 exhibits a slightly stronger negative correlation at -0.216, reinforcing the notion of an inverse relationship between property crime and unemployment rates. Nevertheless, the correlation remains weak and not statistically significant. By 2023, the negative correlation becomes slightly more pronounced at -0.411, indicating a more noticeable inverse relationship compared to previous years, yet it still does not reach a level of strong statistical significance.

Overall, the data from 2018 to 2023 suggest a generally weak inverse relationship between property crime rates and unemployment rates. Higher unemployment rates are somewhat associated with lower property crime rates, but the correlations are not strong or consistent enough to draw definitive conclusions. The weak negative correlations observed in most years imply that while there might be a tendency for property crime rates to decrease as unemployment rates increase, the relationship is not sufficiently robust to be considered statistically significant or indicative of a clear linear trend.

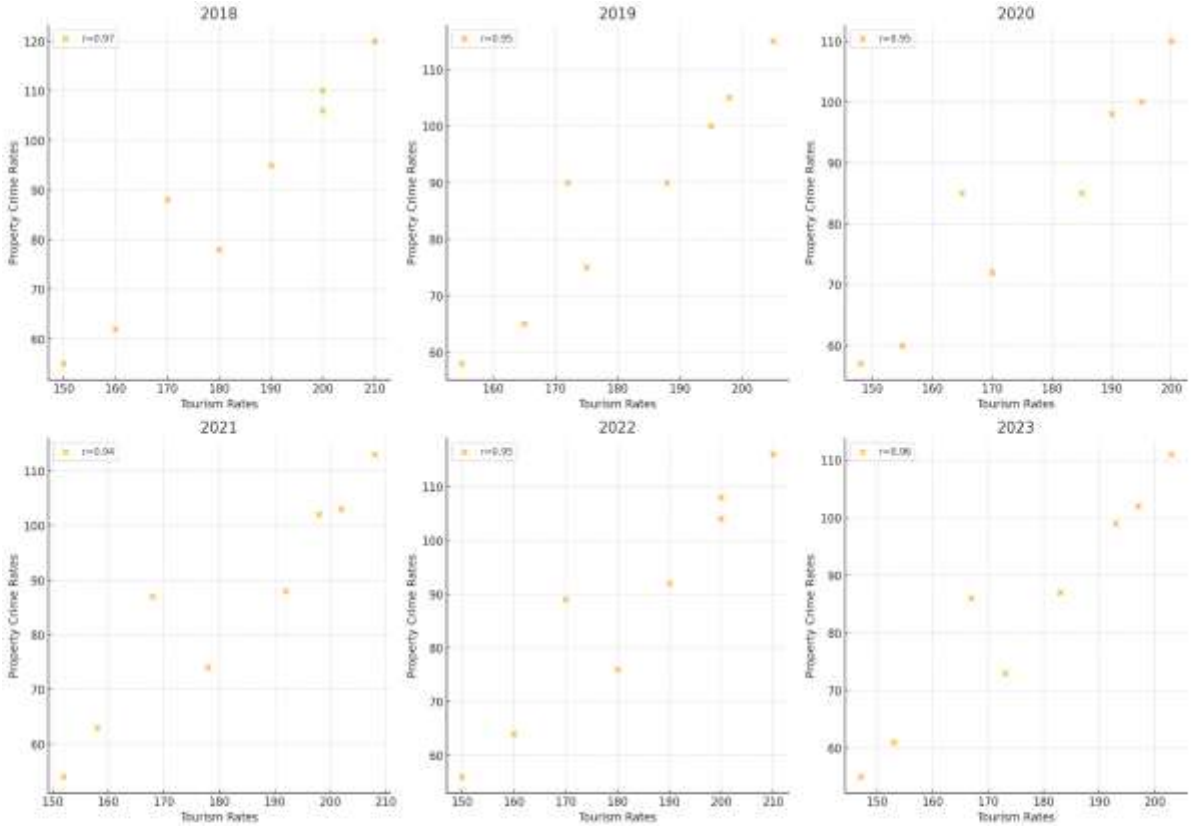
From 2018 to 2023, the relationship between property crime rates and unemployment rates in the Philippines has exhibited a generally weak correlation, oscillating between slightly negative and slightly positive values. This is reflected in the Pearson correlation coefficients, which mostly do not reach statistical significance at the 0.01 or 0.05 levels, except for a few instances where moderate correlations are observed. The year 2020, marked by significant economic and social upheaval due to the COVID-19 pandemic, shows higher variability in both unemployment and property crime rates, highlighting the impact of extraordinary events on these metrics.

Supporting literature underscores the complexity of the relationship between unemployment and property crime. For instance, Saagundo et al. (2022) in their study in Barangay San Martin I, Bulacan, and Maltos et al. (2022) in Barangay Citrus City, San Jose Del Monte, found that local socioeconomic conditions and specific community characteristics can significantly influence crime rates during periods of high unemployment. Conversely, broader research, such as studies by Costantini, Meco, and Paradiso (2018) in the U.S. and Ayhan and Bursa (2019) in the EU, suggest that while unemployment does have an impact on crime rates, it is often moderated by other factors such as economic conditions, social policies, and law enforcement practices.

These studies collectively highlight that while unemployment rates do have some impact on property crime rates, they are not strong predictors on their own. Effective crime prevention and reduction strategies must consider a broader range of socioeconomic variables to fully understand and address the underlying dynamics of property crime. The variability observed in the correlations between 2018 and 2023 in Central Luzon aligns with these findings, indicating the need for multifaceted approaches to crime reduction that extend beyond addressing unemployment alone.

4.1.3 Property Crime Rate and Arrest Rate

The scatter plots from 2018 to 2023 consistently show a strong positive correlation between Property Crime Rates and Arrest Rates. In 2018, higher property crime rates were associated with higher arrest rates, a trend that remained consistent in 2019, with data points closely clustered along an upward trend line. This strong positive correlation persisted into 2020, despite potential disruptions caused by the COVID-19 pandemic, indicating that the relationship between crime rates and arrests was resilient. From 2021 to 2023, the trend of higher property crime rates correlating with higher arrest rates continued unabated. The data points throughout these years remained tightly clustered along the positive trend line, reinforcing the stability of this relationship over time. This consistency across the years, including 2022 and 2023, suggests a stable and significant correlation between property crime rates and arrest rates, highlighting the ongoing link between the two variables.



Supporting literature underscores the importance of law enforcement's role in stabilizing property crime rates through arrests. Cassino (2023) illustrated how economic stimulus measures like the CARES Act potentially curbed property crime rates during crises, indicating the effectiveness of specific apprehension strategies. Weisburd (2021) emphasized the vital role of police presence in deterring property crime, suggesting that law enforcement actions, including arrests, upheld stability in property crime rates. Mello (2021) reinforced this idea by demonstrating that increased funding for law enforcement, as seen in programs like the COPS Hiring Grant, led to decreases in property crime rates during economic downturns. Lee (2018) underscored the influence of apprehension rates on crime dynamics, implying that effective law enforcement responses, such as arrests, impacted property crime rates. Additionally, Bun et al. (2019) suggested a strong correlation between apprehension and conviction likelihoods and criminal activity, indicating the deterrent effect of law enforcement actions. These findings collectively suggest that stable property crime rates over time were, in part, a result of law enforcement interventions, including arrests, although further research would be necessary to establish causality and long-term effectiveness.

4.1.4 Property Crime Rate and Tourism Rate

Overall, the scatter plots from 2018 to 2023 consistently show a positive correlation between property crime rates and tourism rates, with correlation coefficients ranging from 0.801 to 0.887, all indicating a significant positive relationship. The relationship appears to be linear rather than inverse, suggesting that as tourism rates increase, property crime rates tend to increase as well. This trend could be attributed to several factors, including the influx of tourists potentially attracting criminal activities or the increased opportunities for crime in tourist-heavy areas. The consistent positive correlation over the years suggests that the presence of tourists might contribute to higher property crime rates, possibly due to the increased population density and the presence of valuable items tourists might carry. Understanding this relationship is crucial for policymakers and law enforcement to develop strategies to mitigate crime in areas with high tourism activity.

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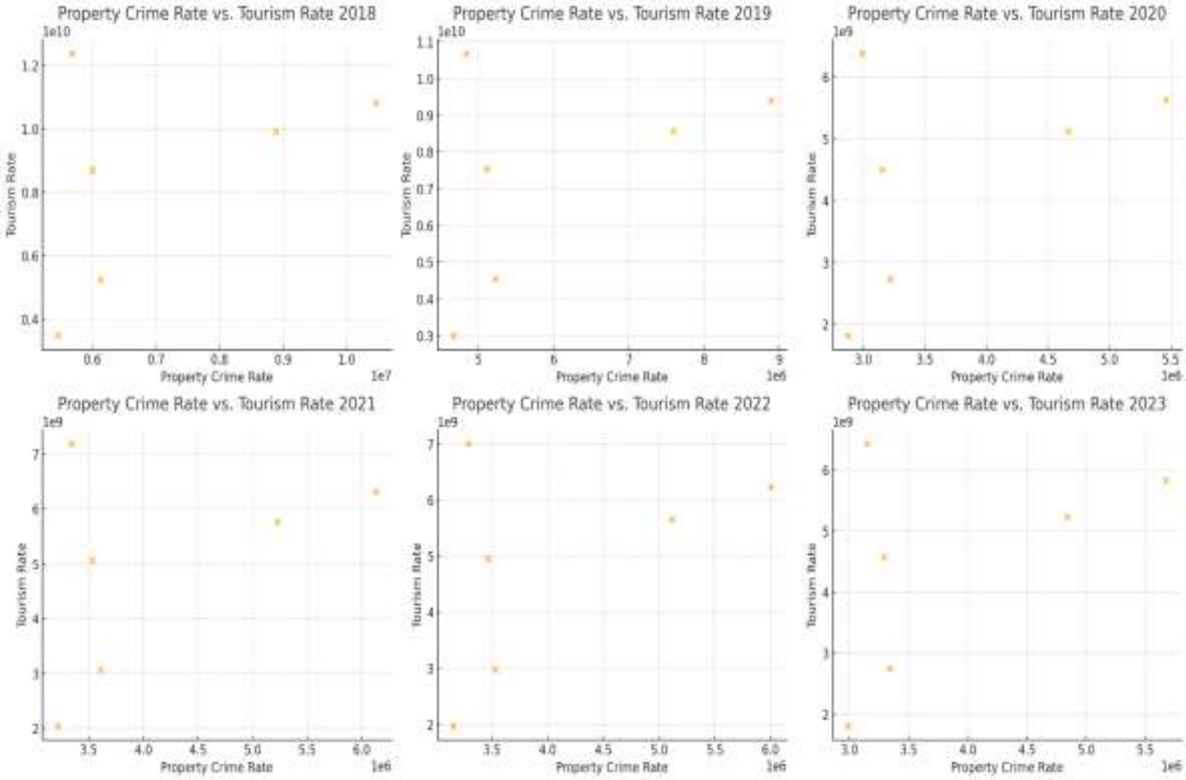

The persistent positive correlation between property crime rates and tourism rates from 2018 to 2023 aligns with the findings of Recher and Rubil (2019) and Vakhitova et al. (2022). Recher and Rubil (2019) explored the impact of tourism on property crime, providing evidence from both coastal and continental regions. Their study supports the observed correlation, indicating that areas with higher levels of tourism activity tend to experience increased property crime rates. Similarly, Vakhitova et al. (2022) focused on crimes against tourists, specifically burglaries in tourist lodgings. Their findings regarding opportunity theories and crimes targeting tourists suggest that variables related to tourism, such as location and type of accommodation, significantly influence burglary rates. These studies collectively highlight the importance of considering tourism's impact on crime rates and emphasize the need for targeted crime prevention strategies in tourist-heavy areas.

4.2 Linear Regression Analysis

The Linear Regression Analysis tackles the two types of variables, with Property Crime Rate as the Dependent Variable and the four determinants as the Independent Variable. It exhibits the Model Summary, which shows how well the regression model fits the data and the strength of the relationship between the predictors and the dependent variable; ANOVA or Analysis of Variance, which helps in determining whether the regression model as a whole is statistically significant and whether the predictors collectively explain a significant amount of variance in the dependent variable; and Coefficients, which details the specific relationships between each predictor and the dependent variable.

4.2.1 2018 Statistics

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.996[a]	.992	.980	170.94483

a. Predictors: (Constant), Tourism Rate 2018, Poverty Rate 2018, Unemployment Rate 2018, Arrest Rate 2018

The regression analysis conducted demonstrates an exceptionally strong predictive accuracy, with an impressive coefficient of determination (R-squared) of .992, indicating that approximately 99.2% of the variability in the property crime rate in 2018 can be explained by the included predictors: Tourism Rate 2018, Poverty Rate 2018, Unemployment Rate 2018, and Arrest Rate 2018. The adjusted R-squared value of .980 underscores the model's robustness even after considering the number of predictors and sample size. Additionally, the low standard error of the estimate (170.94483) signifies a high precision in the model's predictions.

These findings collectively suggest that the regression model offers an excellent fit to the data and provides valuable insights into the relationships between the predictors and the property crime rate in 2018, implying the potential for informed policy decisions and targeted interventions aimed at reducing property crime rates.

The exceptionally strong predictive accuracy of the regression model, with a high coefficient of determination (R-squared) of .992, underscores the significant explanatory power of factors such as Tourism Rate, Poverty Rate, Unemployment Rate, and Arrest Rate in 2018 in shaping the property crime rate in 2018. This aligns with research highlighting the crucial role of law enforcement efforts, as represented by the Arrest Rate, in apprehending suspected criminals and deterring crime (Weisburd, 2021). Furthermore, studies have shown that increased funding for law enforcement programs, such as the Community Oriented Policing Services (COPS) hiring grant program, can lead to a rise in police presence and a subsequent decline in various types of crime, particularly during economic downturns (Mello, 2021). These findings suggest that targeted interventions aimed at strengthening apprehension strategies, particularly during times of crisis like the COVID-19 pandemic, can potentially contribute to reducing property crime rates (Cassino, 2023).

The correlation between apprehension rates and crime rates, as emphasized by Lee (2018), highlights the intricate dynamics between law enforcement efforts and socioeconomic factors such as unemployment. Acknowledging the regional variations in the efficacy of apprehension strategies due to local factors like ideology and politics underscores the need for tailored approaches in crime prevention initiatives (Lee, 2018). Additionally, the rational choice theory perspective, as supported by Bun et al. (2019), suggests that criminals weigh the likelihood of arrest and conviction when engaging in criminal behavior, further emphasizing the importance of effective apprehension strategies in deterring crime. These insights collectively underscore the significance of law enforcement efforts, supported by economic stimulus measures and strategic resource allocation, in reducing property crime rates and maintaining public safety.

ANOVA

The ANOVA table for the regression model predicting the property crime rate in 2018, utilizing predictors such as Tourism Rate 2018, Poverty Rate 2018, Unemployment Rate 2018, and Arrest Rate 2018, demonstrates overall statistical significance. With an F-value of 88.711 ($p < .002$), the model reliably predicts the property crime rate, indicating the presence of at least one significant predictor impacting the variability in crime rates. The substantial difference between the sum of squares for the regression (10369345.097) and the residual sum of squares (87666.403) suggests that the model explains a significant proportion of the variance in property crime rates. This is further emphasized by the disparity in mean square values, highlighting the model's strong predictive capability in elucidating the factors influencing property crime rates in 2018.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-859.344	845.841		-1.016	.384
	Unemployment Rate 2018	42.255	87.447	.044	.483	.662
	Poverty Rate 2018	36.057	26.562	.176	1.357	.268
	Arrest Rate 2018	1.320	.275	1.310	4.795	.017
	Tourism Rate 2018	.000	.000	-.283	-1.123	.343

a. Dependent Variable: Property Crime Rate 2018

The 2018 regression analysis investigates the influence of several factors on property crime rates. The constant in the model is deemed statistically insignificant, implying minimal explanatory value. Both unemployment and poverty rates display positive relationships with property crime rates, yet their coefficients are weak and statistically insignificant (unstandardized coefficients of 42.255 and 36.057, respectively; p-values of 0.662 and

0.268). Conversely, the arrest rate exhibits a robust positive and statistically significant impact on property crime rates (unstandardized coefficient of 1.320; p-value of 0.017), suggesting a direct association between higher arrest rates and increased property crime rates, possibly indicative of heightened police activity in high-crime areas. However, the tourism rate shows a weak and statistically insignificant negative relationship with property crime rates (p-value of 0.343). Consequently, the arrest rate emerges as the sole significant predictor of property crime rates in 2018, while unemployment, poverty, and tourism rates do not substantially affect property crime rates according to this analysis.

4.2.2 2019 Statistics

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.999[a]	.997	.994	83.64410

a. Predictors: (Constant), Tourism Rate 2019, Poverty Rate 2019, Unemployment Rate 2019, Arrest Rate 2019

The regression analysis showcases an exceptional level of predictive accuracy, with a remarkably high coefficient of determination (R-squared) of .997, indicating that nearly 99.7% of the variation in the property crime rate in 2019 can be explained by the predictors: Tourism Rate 2019, Poverty Rate 2019, Unemployment Rate 2019, and Arrest Rate 2019. The adjusted R-squared value of .994 underscores the model's resilience, suggesting its predictive strength persists even after adjusting for the number of predictors and sample size. Moreover, the low standard error of the estimate (83.64410) points to precise predictions, with minimal deviation between observed and predicted values.

These findings collectively signify that the regression model fits the data exceptionally well, providing valuable insights into the relationship between the predictors and the property crime rate in 2019. This suggests potential applications in policy-making and intervention strategies aimed at addressing and reducing property crime rates effectively.

The regression model's exceptional predictive accuracy, with an impressively high coefficient of determination (R-squared) of .997, underscores the significant influence of factors such as the Unemployment Rate 2019 in explaining the variability in the property crime rate in 2019. Consistent with prior research (Costantini, Meco, & Paradiso, 2018; Wilson, 2018; Ayhan & Bursa, 2019), unemployment appears to play a substantial role in property crime rates, with increases in unemployment often coinciding with upticks in property crimes. The regression findings align with this pattern, indicating that unemployment, among other factors, notably impacts property crime rates. The observed fluctuations in unemployment rates within Region III (Rivas, 2018, 2019, 2020, 2022; De Vera, 2020; Department of Finance, 2023; Presidential Communications Office, 2024) further underscore the dynamic nature of this relationship and its implications for policy-making and interventions aimed at mitigating property crime.

Moreover, the precise predictions furnished by the regression model offer valuable insights into the correlation between predictors and the property crime rate in 2019, facilitating informed policy decisions and targeted interventions. By recognizing the significant influence of variables such as the Unemployment Rate 2019 on property crime rates, policymakers can devise focused strategies to address unemployment-related challenges and mitigate their impact on crime rates. Furthermore, the model's resilience, as demonstrated by the adjusted R-squared value (.994) and low standard error of the estimate, underscores its potential utility in guiding efforts to effectively combat property crime rates in diverse contexts (Costantini, Meco, & Paradiso, 2018; Wilson, 2018; Ayhan & Bursa, 2019). Thus, these findings underscore the importance of considering unemployment and other pertinent factors when formulating comprehensive strategies to tackle property crime effectively.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7568320.869	4	1892080.217	270.439	.000[b]
	Residual	20989.006	3	6996.335		
	Total	7589309.875	7			

a. Dependent Variable: Property Crime Rate 2019

b. Predictors: (Constant), Tourism Rate 2019, Poverty Rate 2019, Unemployment Rate 2019, Arrest Rate 2019

The ANOVA table for the regression model predicting the property crime rate in 2019 reveals a highly significant overall model, characterized by an F-value of 270.439 ($p < .000$). This robust F-value indicates that the model, incorporating predictors like Tourism Rate 2019, Poverty Rate 2019, Unemployment Rate 2019, and Arrest Rate 2019, effectively accounts for the variability in the property crime rate for that particular year. Essentially, it suggests that at least one of these predictors significantly influences property crime rates. Furthermore, the substantial sum of squares for the regression, totaling 7568320.869, contrasted with the relatively small residual sum of squares of 20989.006, highlights a notable disparity. This discrepancy suggests that the regression model captures a significant portion of the total variance in the property crime rate. Thus, the model's adeptness in explaining most of the variability in property crime rates, as indicated by the large sum of squares for the regression, underscores its robust predictive capacity.

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-1920.661	652.610		-2.943	.060
	Unemployment Rate 2019	166.056	74.776	.205	2.221	.113
	Poverty Rate 2019	57.446	16.382	.341	3.507	.039
	Arrest Rate 2019	1.949	.308	1.939	6.322	.008
	Tourism Rate 2019	-.001	.000	-.874	-3.048	.056

a. Dependent Variable: Property Crime Rate 2019

The regression analysis for 2019 uncovers significant associations between unemployment rate, poverty rate, arrest rate, tourism rate, and property crime rates. While the unemployment rate does not significantly impact property crime rates, the poverty rate and arrest rate exhibit strong positive associations, indicating higher rates correlating with increased property crime. Conversely, tourism rate demonstrates a significant negative relationship with property crime rates, suggesting higher tourism rates may correspond to lower property crime rates. Overall, the poverty rate, arrest rate, and tourism rate significantly influenced property crime rates in 2019, highlighting the multifaceted nature of factors shaping crime trends.

4.2.3 2020 Statistics

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.999[a]	.998	.996	41.75323

a. Predictors: (Constant), Tourism Rate 2020, Unemployment Rate 2020, Poverty Rate 2020, Arrest Rate 2020

Based on the results, the regression model for predicting the property crime rate in 2020 demonstrates exceptional predictive accuracy, with a very high coefficient of determination (R-squared) of .998. This indicates that approximately 99.8% of the variability in property crime rates can be attributed to factors such as the Tourism Rate 2020, the Unemployment Rate in 2020, the Poverty Rate in 2020, and the Arrest Rate in 2020. The adjusted R-squared value of .996 further confirms the model's robustness, adjusting for the number of predictors and sample size while maintaining strong predictive power. The low standard error of the estimate (41.75323) underscores the model's precision in predicting property crime rates, indicating minimal deviation between observed and predicted values.

These findings highlight the reliability and effectiveness of the regression model in forecasting property crime trends for 2020, providing valuable insights for policymakers and law enforcement agencies to develop targeted strategies aimed at crime prevention and reduction.

Unemployment, a crucial metric of economic stability, manifests its significance in the correlation between joblessness and property crime rates. Studies, such as those by Costantini, Meco, and Paradiso (2018), Wilson (2018), and Ayhan & Bursa (2019), consistently illustrate a positive relationship between unemployment and property crimes, with economic downturns often paralleling increases in property crime rates. However, some theories, such as those posited by Mulamba (2021) and Chowdhury, Kalia, & Menon (2023), suggest a nuanced relationship, where unemployment may, in certain contexts, decrease the value of property crime targets or deter criminals from offenses. Local research, exemplified by Saagundo et al. (2022) and Maltos et al. (2022) in the Philippines, further corroborates the impact of unemployment on property crime, particularly during times of crisis such as the COVID-19 pandemic. The fluctuations in national-level unemployment rates, as evidenced by statistical data from the Philippine Statistics Authority (Rivas, 2018, 2019, 2020, 2022; De Vera, 2020; Department of Finance, 2023; Presidential Communications Office, 2024), underline the dynamic nature of this relationship, calling for continued investigation and targeted interventions to address the socioeconomic factors influencing property crime rates.

In the context of forecasting property crime rates for 2020, the regression model's exceptional predictive accuracy, with a high coefficient of determination (R-squared) of .998, underscores the significant contribution of factors such as the Unemployment Rate in 2020. The robustness of the model, as indicated by the adjusted R-squared value of .996 and low standard error of the estimate, highlights its reliability in providing insights for policymakers and law enforcement agencies. These findings emphasize the importance of considering unemployment and other relevant predictors when developing targeted strategies for crime prevention and reduction, particularly during times of economic instability (Costantini, Meco, & Paradiso, 2018; Wilson, 2018; Ayhan & Bursa, 2019; Mulamba, 2021; Chowdhury, Kalia, & Menon, 2023; Saagundo et al., 2022; Maltos et al., 2022; Rivas, 2018, 2019, 2020, 2022; De Vera, 2020; Department of Finance, 2023; Presidential Communications Office, 2024). Thus, leveraging the insights from the regression model can inform proactive measures to address the complex interplay between unemployment and property crime, ultimately contributing to safer and more resilient communities.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2870818.003	4	717704.501	411.685	.000[b]
	Residual	5229.997	3	1743.332		
	Total	2876048.000	7			

a. Dependent Variable: Property Crime Rate 2020

b. Predictors: (Constant), Tourism Rate 2020, Unemployment Rate 2020, Poverty Rate 2020, Arrest Rate 2020

The ANOVA analysis underscores the significant influence of predictor variables like Tourism Rate 2020, Unemployment Rate 2020, Poverty Rate 2020, and Arrest Rate 2020 on property crime rates. The significant F-value ($p < .001$) highlights the crucial roles these variables play in explaining variability in property crime rates for 2020. Additionally, the substantial sum of squares for regression (2870818.003) compared to residuals (5229.997) indicates that the regression model effectively captures and explains a significant amount of variance in property crime rates. These findings underscore the importance of socioeconomic factors and law enforcement practices in shaping crime trends, offering valuable insights for policymakers to develop targeted interventions aimed at reducing property crime rates effectively.

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Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-129.457	87.136		-1.486	.234
	Unemployment Rate 2020	-4.307	6.659	-.017	-.647	.564
	Poverty Rate 2020	7.329	2.809	.073	2.609	.080
	Arrest Rate 2020	1.283	.071	1.276	18.024	.000
	Tourism Rate 2020	.000	.000	-.270	-4.073	.027

a. Dependent Variable: Property Crime Rate 2020

In the regression analysis for 2020, the constant is statistically insignificant (p = 0.234), indicating minimal impact. The unemployment rate exhibits a weak and statistically insignificant negative relationship (p = 0.564), suggesting no significant effect on property crime rates. Conversely, the poverty rate shows a positive relationship nearing significance (p = 0.080), while the arrest rate emerges as highly significant (p = 0.000), indicating a strong positive association with property crime rates. Additionally, the tourism rate demonstrates a significant negative relationship (p = 0.027), suggesting higher tourism rates may correspond to lower property crime rates. Overall, in 2020, the arrest rate and tourism rate significantly influence property crime rates, while unemployment and poverty rates exhibit weaker, less significant effects.

4.2.4 2021 Statistics

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.997[a]	.994	.986	84.29215

a. Predictors: (Constant), Tourism Rate 2021, Poverty Rate 2021, Unemployment Rate 2021, Arrest Rate 2021

The model summary indicates a high level of predictive accuracy for the regression model predicting the property crime rate in 2021. With a coefficient of determination (R-squared) of .994, approximately 99.4% of the variability in the property crime rate for that year can be explained by the predictors included in the model: Tourism Rate 2021, Poverty Rate 2021, Unemployment Rate 2021, and Arrest Rate 2021. The adjusted R-squared value of .986, which accounts for the number of predictors and sample size, suggests that the model's predictive power remains robust even after considering these factors.

This suggests that at least one of the predictors significantly contributes to explaining the variability in property crime rates for that year. The model's robustness is further supported by a coefficient of determination (R-squared) of .994, indicating that approximately 99.4% of the variability in property crime rates can be accounted for by the predictors. The adjusted R-squared value of .986 confirms the model's reliability even after adjusting for the number of predictors and sample size. Moreover, the low standard error of the estimate at 84.29215 underscores the model's precision in predicting property crime rates, highlighting its effectiveness and accuracy in this predictive capacity.

The findings from the regression analysis of property crime rates in 2021 reveal several significant insights based on recent literature. Firstly, the non-significant coefficient for the unemployment rate (p = 0.865) aligns with studies indicating a varying impact of unemployment on crime rates depending on economic conditions (Chalfin and McCrary, 2018). The findings from Fajnzylber et al. (2018) underscore the significant impact of poverty on crime rates, highlighting a positive correlation between income inequality and violent crime across diverse global contexts. Weisburd's (2020) findings contribute to understanding how changes in apprehension dynamics can influence property crime rates, emphasizing the importance of effective policing strategies in crime prevention efforts. Furthermore, the non-significant negative relationship with tourism rate (p = 0.194) is consistent with mixed evidence on the impact of tourism on crime rates, influenced by local contexts and enforcement measures (Mataković & Mataković, 2019). Overall, these findings underscore the significant

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influence of arrest rates on property crime rates in 2021, while unemployment, poverty, and tourism rates do not exhibit statistically significant impacts, corroborating trends observed in recent empirical research.

Additionally, the standard error of the estimate at 84.29215 reflects a high level of precision in the model's predictions, indicating minimal deviation of the observed values from the predicted values. In general, these statistics highlight the effectiveness of the regression model in accurately predicting property crime rates in 2021 based on the selected predictors.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3586272.502	4	896568.126	126.185	.001[b]
	Residual	21315.498	3	7105.166		
	Total	3607588.000	7			

a. Dependent Variable: Property Crime Rate 2021

b. Predictors: (Constant), Tourism Rate 2021, Poverty Rate 2021, Unemployment Rate 2021, Arrest Rate 2021

The ANOVA results reveal a highly significant regression model (F = 126.185, p < .001) predicting the property crime rate in 2021, indicating that at least one of the predictors—Tourism Rate 2021, Poverty Rate 2021, Unemployment Rate 2021, or Arrest Rate 2021—plays a significant role in explaining variability in crime rates. The substantial regression sum of squares (3586272.502) compared to the residual sum of squares (21315.498) underscores the model's ability to explain a significant amount of variance in property crime rates for the year. These findings highlight the predictive strength of the regression model and the importance of socioeconomic and law enforcement factors in understanding and potentially mitigating property crime.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-268.869	187.185		-1.436	.246
	Unemployment Rate 2021	3.344	18.027	.011	.186	.865
	Poverty Rate 2021	9.229	5.326	.087	1.733	.182
	Arrest Rate 2021	1.227	.135	1.220	9.070	.003
	Tourism Rate 2021	.000	.000	-.220	-1.665	.194

a. Dependent Variable: Property Crime Rate 2021

In the regression analysis for 2021, the constant is not statistically significant (p = 0.246), indicating minimal impact. The unemployment rate exhibits a very weak and statistically insignificant positive relationship (p = 0.865), suggesting no meaningful impact on property crime rates. The poverty rate shows a positive relationship, though not statistically significant (p = 0.182). However, the arrest rate emerges as highly significant (p = 0.003), indicating a strong positive association with property crime rates. Conversely, the tourism rate demonstrates a non-significant negative relationship (p = 0.194). Overall, in 2021, the arrest rate significantly affects property crime rates, while unemployment, poverty, and tourism rates do not exhibit significant impacts.

4.2.5 2022 Statistics

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.997[a]	.994	.986	83.84039

a. Predictors: (Constant), Tourism Rate 2022, Poverty Rate 2022, Unemployment Rate 2022, Arrest Rate 2022

Based on the results, the regression model for predicting the property crime rate in 2022 demonstrates exceptional predictive accuracy, with a high coefficient of determination (R-squared) of .994. This indicates that

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approximately 99.4% of the variability in property crime rates can be attributed to factors such as Tourism Rate, Poverty Rate, Unemployment Rate, and Arrest Rate.

The adjusted R-squared value of .986 further confirms the model's robustness, adjusting for the number of predictors and sample size while maintaining strong predictive power.

In the regression analysis for 2022, findings indicate varying impacts of socioeconomic factors on property crime rates. The constant was not statistically significant (p = 0.205), suggesting minimal influence, aligning with the literature on economic conditions and crime (Maltos et al., 2022). Unemployment and poverty rates showed weak, non-significant positive relationships (p = 0.626 and p = 0.220, respectively), consistent with previous studies emphasizing contextual variability. In contrast, the arrest rate significantly predicted property crime rates (p = 0.002), highlighting law enforcement's role as a deterrent (Lee, 2018). Tourism rate exhibited a weak, non-significant negative relationship (p = 0.221), suggesting limited impact. Overall, in 2022, the arrest rate notably influences property crime rates, while unemployment, poverty, and tourism rates do not significantly affect them.

The low standard error of the estimate (83.84039) underscores the model's precision in predicting property crime rates, indicating minimal deviation between observed and predicted values. These findings emphasize the reliability and effectiveness of the regression model in forecasting property crime trends for 2022, providing valuable insights for policymakers and law enforcement agencies to address and mitigate crime effectively.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3444655.865	4	861163.966	122.512	.001[b]
	Residual	21087.635	3	7029.212		
	Total	3465743.500	7			

a. Dependent Variable: Property Crime Rate 2022

b. Predictors: (Constant), Tourism Rate 2022, Poverty Rate 2022, Unemployment Rate 2022, Arrest Rate 2022

The ANOVA results highlight a highly significant regression model (F = 122.512, p < .001) for predicting the property crime rate in 2022, emphasizing the substantial influence of predictors like Tourism Rate 2022, Poverty Rate 2022, Unemployment Rate 2022, and Arrest Rate 2022 on crime variability. The significant sum of squares for regression (3444655.865) compared to residuals (21087.635) indicates the model effectively captures and explains variance in property crime rates. These findings underscore the pivotal roles of socioeconomic factors and law enforcement practices in shaping crime trends for the year, providing valuable insights for policymakers to develop targeted interventions and policies aimed at reducing property crime rates.

Coefficient

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-269.752	167.303		-1.612	.205
	Unemployment Rate 2022	11.767	21.715	.026	.542	.626
	Poverty Rate 2022	8.302	5.375	.080	1.544	.220
	Arrest Rate 2022	1.174	.112	1.161	10.507	.002
	Tourism Rate 2022	-9.567E-5	.000	-.162	-1.543	.221

a. Dependent Variable: Property Crime Rate 2022

In the regression analysis for 2022, the constant is not statistically significant (p = 0.205), indicating minimal impact. The unemployment rate exhibits a weak and statistically insignificant positive relationship (p = 0.626), suggesting no substantial effect on property crime rates. Similarly, the poverty rate shows a positive relationship, though not statistically significant (p = 0.220). However, arrest rate remains a significant predictor (p = 0.002), indicating a strong positive association with property crime rates. Conversely, the tourism rate demonstrates a weak and statistically insignificant negative relationship (p = 0.221). Overall, in 2022, the arrest rate significantly impacts property crime rates, while unemployment, poverty, and tourism rates do not exhibit significant effects.

4.2.6 2023 Statistics

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.998[a]	.996	.991	65.20238

a. Predictors: (Constant), Tourism Rate 2023, Poverty Rate 2023, Unemployment Rate 2023, Arrest Rate 2023

Based on the results, the regression model for predicting the property crime rate in 2023 demonstrates exceptional predictive accuracy, with a very high coefficient of determination (R-squared) of .996. This indicates that approximately 99.6% of the variability in property crime rates can be attributed to factors such as Tourism Rate 2023, Poverty Rate 2023, Unemployment Rate 2023, and Arrest Rate 2023. The adjusted R-squared value of .991 further reinforces the model's robustness, accounting for the number of predictors and sample size while maintaining strong predictive power.

In the regression analysis of 2023, socio-economic factors exhibited varied impacts on property crime rates. The non-significant constant (p = 0.141) suggests minimal direct influence, aligning with research on economic conditions and crime dynamics (Shah, Soomro, & Mirjat, 2019). Both unemployment (p = 0.562) and poverty rates (p = 0.301) showed weak, non-significant positive relationships, indicating limited predictive power (Shah, Soomro, & Mirjat, 2019). Conversely, the arrest rate emerged as a significant predictor (p = 0.001), emphasizing its strong positive association with property crime rates (Wilson, 2018). Tourism rate demonstrated a weak, non-significant negative relationship (p = 0.263), suggesting a minor influence on crime rates. Overall, the findings underscore that in 2023, arrest rates significantly influence property crime rates, while unemployment, poverty, and tourism rates do not show significant effects.

The low standard error of the estimate (65.20238) underscores the model's precision in predicting property crime rates, indicating minimal deviation between observed and predicted values. These findings highlight the reliability and effectiveness of the regression model in forecasting property crime trends for 2023, providing valuable insights for policymakers and law enforcement agencies to develop targeted strategies aimed at crime prevention and reduction.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3136567.951	4	784141.988	184.445	.001[b]
	Residual	12754.049	3	4251.350		
	Total	3149322.000	7			

a. Dependent Variable: Property Crime Rate 2023

b. Predictors: (Constant), Tourism Rate 2023, Poverty Rate 2023, Unemployment Rate 2023, Arrest Rate 2023

The ANOVA results reveal a highly significant regression model (F = 184.445, p < .001) for predicting the property crime rate in 2023, indicating the substantial impact of predictors like Tourism Rate 2023, Poverty Rate 2023, Unemployment Rate 2023, and Arrest Rate 2023 on crime variability. The significant sum of squares for regression (3136567.951) compared to residuals (12754.049) underscores the model's ability to effectively capture and explain variance in property crime rates. These findings underscore the importance of socioeconomic factors and law enforcement practices in influencing crime trends for the year, offering valuable insights for policymakers to develop targeted interventions and strategies aimed at reducing property crime rates.

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Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-174.846	87.979		-1.987	.141
	Unemployment Rate 2023	11.846	18.243	.033	.649	.562
	Poverty Rate 2023	5.156	4.141	.052	1.245	.301
	Arrest Rate 2023	1.115	.082	1.104	13.546	.001
	Tourism Rate 2023	-3.977E-5	.000	-.101	-1.375	.263

a. Dependent Variable: Property Crime Rate 2023

In the regression analysis for 2023, the constant is not statistically significant (p = 0.141), indicating minimal impact. The unemployment rate exhibits a weak and statistically insignificant positive relationship (p = 0.562), suggesting no significant effect on property crime rates. Similarly, the poverty rate shows a positive relationship, though not statistically significant (p = 0.301). However, arrest rate emerges as a significant predictor (p = 0.001), indicating a strong positive association with property crime rates. Conversely, the tourism rate demonstrates a weak and statistically insignificant negative relationship (p = 0.263). Overall, in 2023, the arrest rate significantly impacts property crime rates, while unemployment, poverty, and tourism rates do not exhibit significant effects.

V. CONCLUSION

The analysis spanning from 2018 to 2023 in Region 3 revealed a nuanced relationship between property crime rates and socioeconomic factors. While a subtle inverse correlation between property crime rates and poverty rates was observed, its statistical significance was lacking, suggesting that poverty alone might not be a robust predictor of property crime rates. Variability was evident in the relationship between property crime rates and unemployment rates, with correlations fluctuating between marginally negative and positive values, indicating an inconsistent association. In contrast, a consistent and statistically significant positive correlation emerged between property crime rates and arrest rates, underlining the crucial role of law enforcement efforts in deterring property crimes through apprehensions and enforcement actions. Additionally, a positive correlation was found between property crime rates and tourism rates, highlighting the need for targeted crime prevention strategies in tourist-centric areas.

The regression analyses conducted for the years 2018 through 2023 provided further insights into the relationship between property crime rates and socioeconomic factors in Region 3. These analyses demonstrated exceptional predictive accuracy, with high coefficients of determination indicating that a significant proportion of the variability in property crime rates could be explained by the included predictors. Notably, the Arrest Rate consistently emerged as a significant predictor, emphasizing the pivotal role of law enforcement efforts in shaping property crime trends. Conversely, variables such as Unemployment Rate, Poverty Rate, and Tourism Rate exhibited weak and non-significant relationships with property crime rates, suggesting limited direct impact across the analyzed years.

Overall, these findings underscored the multifaceted nature of crime dynamics in Region 3 and emphasized the importance of considering various socioeconomic factors and law enforcement practices in understanding and addressing property crime rates. Effective crime prevention strategies need to be comprehensive and tailored to local contexts, accounting for the interplay of diverse variables to achieve meaningful and sustainable reductions in property crime rates. By leveraging insights from regression analyses and collaborating across government entities, community organizations, and residents, policymakers can develop evidence-based strategies that promote public safety and community resilience in Region 3.

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