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What Determines Crime: Prosperity or Poverty?

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Abstract:

Purpose: *The purpose of this study was to identify the socioeconomic determinants of crime on a local scale. Three research questions were asked. (1) Do prosperity or poverty indicators better determine crime? (2) Which socioeconomic variables are most strongly correlated with crime? (3) Which types of crimes are most influenced by socioeconomic variables?*
Design/Methodology/Approach: *The research area was Szczecin in Poland (population of approximately 400,000). The dependent variables included six crime types reported in 2017, and the independent variables included three indicators of poverty and three indicators of prosperity. The dataset was analyzed using linear regression and random forest approaches to further investigate the statistical characteristics of variables, obtaining the following answers to our research questions obtained.*
Findings: *(1) The variables of poverty determine the occurrence of crime more than those related to prosperity. (2) The variables of poverty related to low income, including population assisted by the Municipal Family Assistance Center per 1,000 persons and unemployment per 1,000 persons have the strongest influence on crime. (3) Drug crimes per 1,000 persons are the most strongly influenced by socioeconomic variables, while theft of property per 1,000 persons revealed no impact.*
Practical Implications: *The study highlights the strong influence of poverty, particularly unemployment, on crime rates and suggests limited impact of prosperity on crime prevention.*
Originality/Value: *The article presents the results of own desk research. The issue presented has not previously been addressed in discussions published internationally.*

Keywords: *Crime, prosperity, poverty, linear regression, random forest.*

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1. Introduction

The intricate relationship between economic growth, social inequality, and public security forms a complex backdrop against which the phenomenon of crime unfolds. While regional economic prosperity is conventionally linked with enhancements in public security through the reduction of unemployment, poverty, and social disparities, paradoxical evidence from Latin America suggests otherwise, challenging the notion that social equality invariably leads to diminished crime rates.

This counterintuitive outcome invites a reevaluation of established theories, including Aristotle's assertion that poverty is the progenitor of crime and Merton's strain/anomie theory, which posits crime as a response to the frustrations borne out of economic inequity.

The scenario in Latin America, marked by a surge in crime amidst economic prosperity, underscores the multifaceted nature of crime, influenced not just by economic factors but also by law enforcement efficacy, societal values, and the availability of illegal opportunities. This study delves into the nuanced interplay between prosperity and poverty indicators and their impact on crime rates.

2. Literature Review

Regional economic growth and prosperity combined with state legitimacy, which promote unemployment reduction, poverty minimization, and reduction of social inequalities, are generally expected to increase the level of public security. Paradoxically, prosperity can contribute to the deterioration of public safety, as occurred in Latin America (Bergman, 2018). This outcome contradicts the claim that reducing social inequality leads to less crime and greater public safety (Albahli *et al.*, 2021), countering Aristotle’s assertion that “poverty is the parent of crime” (To Have and Have Not, 2014).

The strain/anomie theory developed by Merton (Merton, 1938) assumes that crimes are committed by individuals who are frustrated by the unequal distribution of economic resources in society, which motivates those with less economic resources to commit criminal acts.

Economic prosperity combined with weak law enforcement is considered to be factors that contribute to increased criminal activity. Beginning in 1990, Latin American countries experienced economic growth, which resulted in increased consumption, rising purchases of goods (i.e., cars, computers, mobile phones), and expansion in the production and trade of various drugs (Bergman, 2018).

Prosperity intensified the demand for various goods, some of which were procured through theft and other illegal activities that took place in the secondary market (Bergman, 2018). Along with increased societal wealth and consumption, the largest rise in number of crimes was recorded in such crimes as homicides, robberies, kidnapping, the sale of illegal substances, car thefts, abductions, and human trafficking (Caldeira, 2001; Carrillo, 2009; Dudley, 2012). Crime is a highly lucrative business for perpetrators who usually recruit young people from poverty as street soldiers (Briceño-León, 2012; Misse, 2006).

Crime has an extremely strong impact on socioeconomic indicators, and the cause and effect relationship occurs in a cycle in which socioeconomic indicators such as unemployment and GDP per capita increase the number of crimes committed. A criminal is less likely to look for work and secure legitimate work after being convicted of a crime, which contributes to increased unemployment and more crime (Chalfin *et al.,* 2019).

The increased crime rate is also influenced by such socioeconomic indicators as income group, race, age group, family structure (Messner and Sampson, 1991), poverty and income inequality (Armin and Idris, 2020), education (Tseloni, 2007), apartment size, the proportion of unemployed to employed individuals (Raphael and Winter-Ebmer, 2001), unemployment rates (Mittal *et al.,* 2019; Raphael and Winter-Ebmer, 2001) and the proportion of police to residents (Alsaqabi *et al.,* 2019).

An insufficient number of jobs raise unemployment. Some unemployed people will look for opportunities to obtain livelihoods via illegal sources in order to meet their life needs (Hardianto, 2009). Khan et al. claimed that an individual's earning potential is considerably reduced, and individuals are often compelled by such circumstances to engage in criminal behavior (Khan *et al.,* 2015).

A noteworthy discussion has emerged in the media. While it may be assumed that criminals are likely to be poor, it is essential to distinguish this perspective from the assumption that the poor are likely to be criminals. This claim is offensive to the poor and has not been supported by the data. Criminals are not always poor, as some press reports suggest; for instance, "Today's Britain: where the poor are forced to steal... a system where the hungry go to jail" (Chakrabortty, 2014), "The law exists to clamp down on the misdemeanors of the poor" (Jones, 2014), and "Poverty 'pushing young into crime'" (Poverty "Pushing Young into Crime," 1993).

According to a study conducted in the UK (Public Perceptions of Crime in England and Wales - Bulletin Tables - Office for National Statistics, 2017), compared with those receiving high incomes (above £50,000) people with low incomes (below £10,000) experience a much higher level of fear of crime, with the highest concerns regarding car theft (384%), racial attack (332%), having things stolen from a car (322%), robbery (296%), being attacked (295%), burglary (249%), and being raped (241%).

Many studies have demonstrated that the poor are more likely to be victims of crime than the general population (Gordon and Pantazis, 1997; Larsson, 2006; Mawby and Walklate, 1994; Nilsson and Estrada, 2003; Smith and Jarjoura, 1989). Conversely, Cohen and Felson (Cohen and Felson, 1979) investigated why, during the golden age of economic prosperity (no unemployment, no conflict and segregation, and increased prosperity of the general population) between 1945 and 1975, crime rates increased in all Western countries. They claimed that increased prosperity raises the number of social interactions, including interactions with possible criminals, and there is also the issue of ensuring the security of accumulated property.

According to rational choice theory, analyses of the factors correlated with the occurrence of crime assumes that the criminal is a rational actor who, faced with a criminal opportunity, makes a decision to commit an act, considering the associated costs and benefits (Cornish and Clarke, 2016). Digital predictions of human behavior applying machine learning (ML) have become extremely popular. Resulting data have indicated that the predictions obtained are equal to or better for many types of criminal events than clinical prediction methods (Grove *et al.,* 2000; Lin *et al.,* 2020).

Data mining and ML are algorithms used to explore the spatial patterns of crime, predict the potential occurrence of events, and identify factors conducive to crime using linear regression or Bayesian models (Babakura *et al.,* 2014; Zhao and Tang, 2017). ML applies various statistical techniques (Duwe and Kim, 2017; Tollenaar and van der Heijden, 2013) such as random forest (RF) (Alves *et al.,* 2018), K-nearest neighbor (Sivaranjani *et al.,* 2016; Tayal *et al.,* 2015), decision tree (Ahishakiye *et al.,* 2017; Nasridinov *et al.,* 2013), artificial neural networks (Memon and Mehboob, 2003), and support vector machine (Kianmehr and Alhajj, 2008) algorithms.

Crime is unevenly distributed in space, with some areas experiencing higher crime rates than others. The primary reason that crime accumulates in certain areas is that the areas are inhabited by people with specific social problems that weaken institutions, which causes social bonds and control to decrease, with no social norms to cease deviant behavior in such areas (Hagan, 1994; Shaw and McKay, 1969; Tseloni, 2000; Wikström, 1998; Wilson, 1987).

Other theories have argued that certain subcultures contribute to the occurrence of crime in certain areas (Agnew, 1999; Hoffmann, 2002).

Crime significantly affects society, diminishing quality of life and straining state finances. In recent decades, Poland has seen a notable decrease in crime rates, attributed largely to socio-economic improvements, including lower unemployment and economic growth. Between 1999 and 2022, crime rates fell alongside improvements in crime detection. Significant reductions were observed in burglaries and homicides, with the latter halving and detection rates reaching over 99% in 2022.

Road safety improved despite more vehicles, with decreases in traffic offenses and fatalities. However, car thefts dropped by nearly 90%. Conversely, computer fraud and cybercrime have risen with technological advancement, while economic and drug-related crimes show significant fluctuation, indicating not all crime categories follow a downward trend (Statista Research Department, n.d.).

This study applied the RF method to determine the significance of three variables for prosperity and three variables for poverty for predicting the crime rate examining six crime types in particular areas of police beats in the city of Szczecin (Poland).

The study was conducted using data sets from 2017 for 94 police beats to investigate correlations with fights and battery, drug crimes, theft of property, apartment break-ins, car-related crimes, and property damage, and disposable income (PLN), consumption expenses (PLN), and share of green areas as measures of prosperity, and the number of people seeking aid from the Municipal Family Assistance Center, unemployment, and population density per sq km as measures of poverty.

The purpose of this study was to identify the socioeconomic determinants of crime on a local scale using ML techniques to analyze crime data. We argue that different socioeconomic variables generate different types of crime, asking research questions. (1) Do prosperity or poverty indicators better determine crime? (2) Which socioeconomic variables are most strongly correlated with crime? (3) Which types of crimes are most influenced by socioeconomic variables?

3. Study Area and Data

The study focuses on Szczecin, a city in northwest Poland by the Odra River, near the Polish-German border, with 403,883 people registered in Szczecin in 2017 and covering around 300 km². Szczecin's landscape includes about 78 km² of forests, 70 km² of water, and 45 km² of urban areas. Post-1989, Poland witnessed rapid changes in its economic, political, and social systems, leading to significant economic growth but also challenges such as industrial decline and increased unemployment, potentially influencing crime rates.

Despite these changes, Szczecin's crime rate, with 34 incidents per 1000 people in 2010, is moderate compared to other large Polish cities. This makes it an ideal location for studying urban crime due to its representative crime rate, diverse urban and natural environments.

Our study expands the growing body of literature that has statistically analyzed crime as a socioeconomic problem that affects quality of life (Bogomolov *et al.*, 2014; Kim *et al.*, 2019). We address the problem of crime and its relationship with several factors of poverty and prosperity applying different statistical methods.

In the process of data collection for this research, a secondary analysis approach was employed. The study utilized formal data repositories as its primary source of information. The data for this study were provided by: Szczecin City Police Headquarter, Szczecin City Hall, Municipal Family Support Center in Szczecin, Poviat Employment Office in Szczecin. The study also incorporated data obtained from the Topographic Geodatabase for the City of Szczecin.

We assumed that crime is neither systematic nor entirely random, first analyzing the dataset with simple linear regression. In statistics, this approach is used to determine the relationship between a scalar response (dependent variable) and one or more explanatory variables (independent variables).

Six crime types, including fights and battery (778), drug crimes (794), thefts of property (3,751), apartment break-ins (151), car-related crimes (544), and property damage (730) reported in the city of Szczecin in 2017 were analyzed and set against various factors of wellbeing, poverty, and prosperity. The data used for the analysis are available at: (Sypion, 2023).

Maps depicting the spatial distribution of crime in Szczecin for the year 2017 were created using the cartogram method, aligned with police beats for all analyzed crime types (Figure 1). The classification of crimes into five classes was performed using the natural breaks (Jenks) method. It is observed that various crime types exhibit distinct concentrations in specific areas.

Fights and battery are predominantly concentrated in two central police beats. Drug crimes show a significant presence in the city center, as well as in the commercial district and in an extensive district characterized by multi-family housing. Thefts of property is primarily concentrated in three police districts—two within the city center and one expansive district also dominated by multi-family residences.

Apartment break-ins are notably prevalent in the northern part of the city, within areas composed of multi-family and single-family homes. Car-related crimes have a higher occurrence in the city center and in a northern district recognized for multi-family housing.

Lastly, property damage is most concentrated in a police district to the south of the city center, spanning the multi-family residential area and another central district.

4. Methodology

The study subjected the relationships between variables to linear regression analysis using the scikit-learn and seaborn Python libraries, excluding outlier samples by quantile (limiting 0.25, 0.75 percentiles) with the library pandas and data structure. The use of outlier elimination in linear regression at quantile levels of 0.25 and 0.75, was intended to remove potentially erroneous samples, i.e., those that are significantly different from the rest of the dataset.

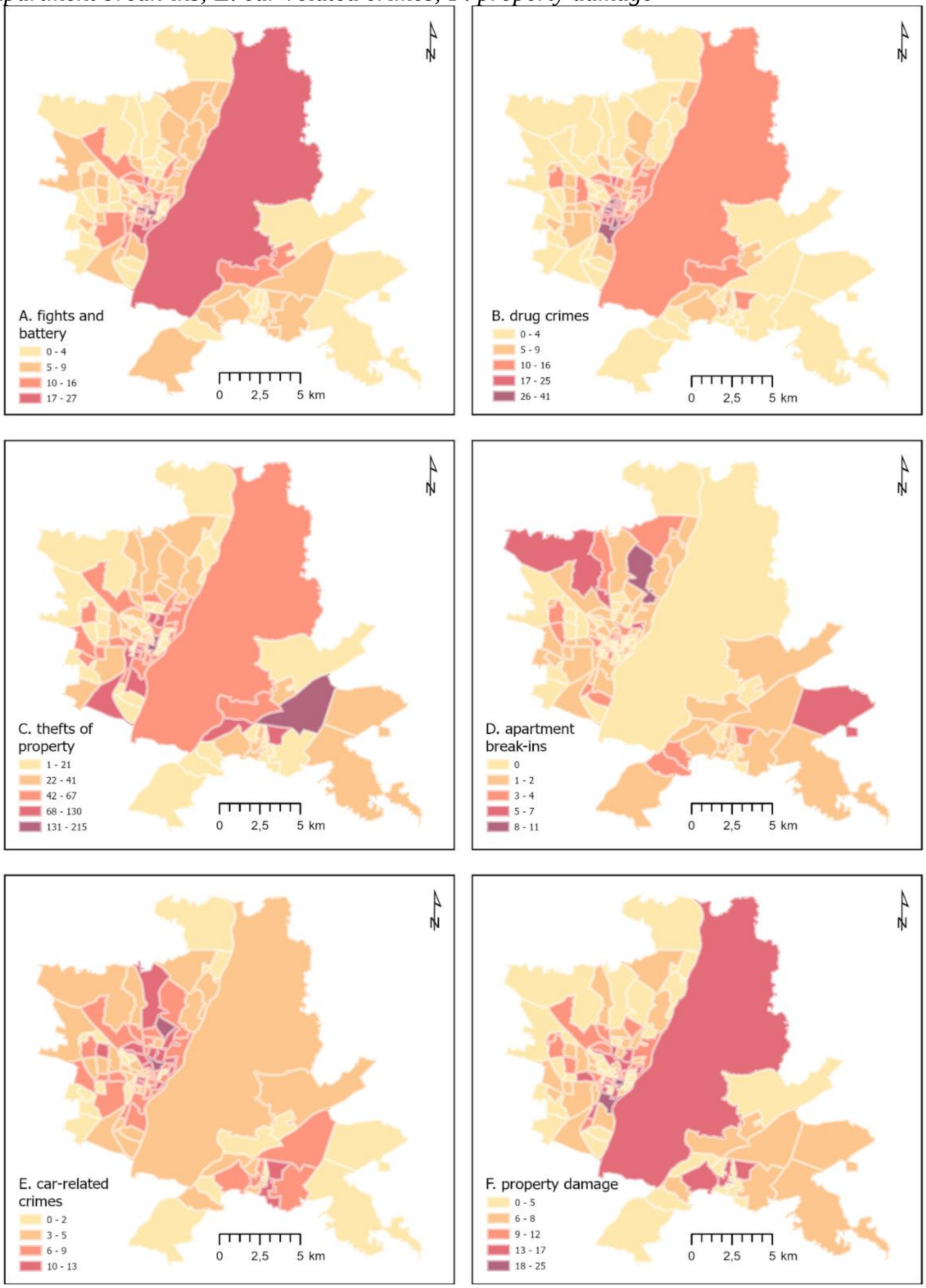
Different outliner elimination threshold values has been tested. A regression analysis based on quantiles of 0.25 and 0.75 has proved to be less sensitive to extreme outliers than an analysis based such as 0.1 and 0.9 or 0,2 and 0,8 levels. We also applied regression analysis to identify the independent variables that were most strongly correlated with the dependent variable and explore the forms of these relationships.

We applied a simple linear regression model to elicit an accurate description of how an input affected the output. This approach predicts a variable (A; target variable) as a linear function of another variable (B; input variable/features), given m training examples of the form (A1, B1), (A2, B2), …, (An, Bn) (Awal *et al.,* 2016; Bodare *et al.,* 2019).

To confirm the results of linear regression the study employed more sophisticated data mining techniques to reveal the status of crime more accurately. We have used machine learning methodology as a method that its robust to outliers and noise in the output values. Data mining focuses on modeling and knowledge discovery for prediction, rather than purely descriptive purposes (Świecka, Terefenko, and Paprotny, 2021; Yu *et al.,* 2011).

We used it to investigate the data, revealing useful information and relevant conclusions. We also applied an approach based on the multivariate Random Forest (RF) data mining method using an ensemble of regression and classifier trees (Świecka, Terefenko, Wiśniewski, *et al.,* 2021), employing readily available ML in Statistica software to develop a learning model to incorporate the features identified.

***Figure 1**. Spatial distribution of crimes in Szczecin police beats in 2017 according to the following types of crimes: A. fights and battery; B. drug crimes; C. theft of property; D. apartment break-ins; E. car-related crimes; F. property damage*



***Source:** Own study.*

The RF approach has an important advantage over other statistical methods as it can represent nonlinear dependencies; therefore, no assumptions are required regarding data distribution or the dependency structure in contrast to other regression models, particularly linear ones. Finally, we used RF to compute the uncertainty ranges of the model's predictions, which is not possible with most cluster analysis or multivariate regression methods.

We classified the data using a standard ML RF algorithm that recursively subdivided the data space of predictors into smaller and smaller regions. The algorithm made further delineations by searching all possible categories and

5. Results

5.1 Statistical Characteristic of Variables

To correctly interpret the correlation coefficients reflecting the influence of the explanatory variables (prosperity and poverty) on the dependent variables (types of crime), their standard statistical characteristics were performed. Mean, Minimum (to detect crime types and influence variables present in all police beats), Coefficient of variation in %, Skewness coefficient, Kurtosis, Type of kurtosis, and occurrence and significance of extreme outliers were calculated.

Values of variables outside the range of "mean plus/minus two standard deviation" were considered extreme outliers. In a normal distribution, 95% of the data fall within this range. It may be different in other distributions, but it was assumed that this is a moderate criterion (Table 1).

Table 1. *Statistical characteristics of variables.*

Variables	Mean	Median	(Mean - Median) / Median	Minimum	Coefficient of variation in %	Skewness coefficient	Kurtosis	Kurtosis - 3	Type of kurtosis	Extreme outliers	
										Num-ber	in % of data set
Fights and battery per 1000 persons	2,51	1,63	0,54	0,00	133,99	0,79	11,30	8,30	Lepto-curtic	4	4,30
Drug crimes per 1000 persons	2,48	1,32	0,88	0,00	112,35	1,25	5,07	2,07	Lepto-curtic	2	2,15
Theft of property per 1000 persons	11,87	6,97	0,70	1,40	146,80	0,84	22,26	19,26	leptoc urtic	2	2,15
Property damage per	2,12	1,80	0,18	0,00	86,22	0,53	17,15	14,15	Lepto-curtic	2	2,15

1000 persons											
Apartment burglary per 1000 persons	0,38	0,33	0,16	0,00	101,17	0,42	1,17	-1,83	Platy-curtic	0	0,00
Car crimes per 1000 persons	1,55	1,10	0,41	0,00	86,97	1,00	9,03	6,03	Leptoc-urtic	2	2,15
Disposable income (PLN) per 1 person	1,98	1,97	0,00	1,83	170,30	0,26	1,44	-1,56	Platy-curtic	0	0,00
Consumption expences per 1 person	1,28	1,28	0,00	1,14	4,79	-0,28	0,17	-2,83	Platy-curtic	0	0,00
Share of green areas in %	35,06	29,63	0,18	0,00	74,09	0,63	-0,96	-3,96	Platy-curtic	0	0,00
Population assisted by the Municipal Family Assistance Center per 1000 persons	27,02	20,51	0,32	4,17	112,05	0,64	29,82	26,82	Lepto-curtic	2	2,15
Unemployed per 1000 persons	14,79	11,74	0,26	0,00	72,01	0,86	6,06	3,06	Meso-curtic	3	3,23
Population density per sq km	9,06	5,77	0,57	0,01	98,87	0,05	1,22	-1,78	Platy-curtic	1	1,08

Source: *Own study.*

The "Minimum" indicator shows variables that are not present in all police beats. These include all types of crime except "Theft of property per 1000 persons". It is therefore a type of crime occurring throughout the city. A similar spatial concentration is shown by most variables of influence, with the exception “Share of green areas in % in the police beat and “Unemployed per 1000 persons”, which is obvious given the nature of these variables related to the inhabitants of individual police beats.

“Coefficient of variation in %” is a standardized measure of dispersion of a distribution. This measure varies strongly from 3 to 147. The type of crime "Theft of property per 1000 persons" shows the extremely high level if this coefficient, und namely 147. This indicates a significant spatial variation of this type of crime in police beats. The following three crime types show a "Coefficient of variation in %" above the overall average (83): "Fights and battery per 1000 persons", "Drug crimes per 1000 persons", “Apartment burglary per 1000 persons”, and two influence variations: “Population assisted by the Municipal Family Assistance Center per 1000 persons”, “Population density per sq km”. For these types of crime, the indicators are significantly spatially differentiated in police beats.

On the other hand, the following two types of crime show variation at an average level, which indicates a moderate variation in their spatial distribution: "Property damage per 1000 persons", "Car crimes per 1000 persons", and two influence variations: "Share of green areas in %", " Population density per sq km. Two influence variations of prosperity show extremely low differentiation: “Disposable income (PLN 1000) per 1 person”, “Consumption expenses (PLN 1000) per 1 person”.

In general, the “Coefficient of variation in %” of crime types are much higher (average 105) than the analogous indicators for influence variables. This means a certain limitation of the explanatory power of influence variables, which is reflected in the correlation indicators. However, this is not an unambiguous relationship.

“Skewness coefficient” is a measure of the asymmetry of the distribution of a variable about its mean. The skewness value can be positive, zero, negative, or undefined. For a unimodal distribution, negative skew commonly indicates that the tail is on the left side of the distribution, and positive skew indicates that the tail is on the right. This applies to all variables except "Consumption expenses (1000 PLN) per 1 person". Such a distribution means a significant variation of police beats with values above the mean.

“Kurtosis” and “Excess kurtosis” (the value of kurtosis minus 3) describe a particular aspect of a distribution of variable and namely the "tailedness". Number of “extreme outliers” and their “percentage in data set” are indicators verifying the type of kurtosis determined based on the “kurtosis” and “excess kurtosis” values.

None of the analysed variables has a mesokurtic distribution. This also means that they are different from the normal distribution. Most variables describing the level of crime have a leptokurtic distribution with the relatively low number of extreme outliers from 2 to 4. The exception is the variable "Apartment breakings per 1,000 persons", which is characterized by a platykurtic distribution with as many as 7 extreme outliers.

However, among the variables describing prosperity vs. poverty, the platykurtic distribution dominates, with more numerous extreme outliers, from 2 to 6. Only two variables: "Population assisted by the Municipal Family Assistance Center per 1,000 persons", and Unemployment per 1,000 persons" have a leptokurtic distribution with 2 or 4 extreme outliers. This means which means differences in spatial distribution directly showing the level of poverty.

The occurrence of numerous extreme outliers, that is in platykurtic variables, mainly describing the level of prosperity or poverty, slightly lowers the calculated coefficients of their correlation with the leptokurtic variables, mainly describing the level of crime.

However, this reduction in correlation coefficients is not significant, as the highest percentage of extreme outliers in the data set only for three variables exceeds the theoretical 5%: one explained "Apartment burglary per 1000 persons" (7,53%), and two explanatory variables: "Disposable income (PLN 1000) per 1 person" (5,38), and "Population density per sq km" (6,45).

5.2 Influence of Variables on the Types of Crime

The measure of influence was a correlation coefficient ranging from 0 to 1, where a coefficient above 0.7 was assumed to indicate a strong influence, and a coefficient below 0.4 indicated no influence of the variable.

Theft of property was committed most often. The mean for analyzed police beats is up to 11.87 per 1,000 persons, representing about five times more than the next in terms of quantity, including fights and battery, drug crimes, and property damage.

This type of crime was characterized by the strongest differentiation among the variables analyzed and a significant deviation from the normal distribution, indicating uneven distribution throughout the city; however, significant differences in intensity were evident between individual police beats. The coefficient of variation is 147% and the skewness coefficient is 0.84.

The type of kurtosis is leptokurtic, indicating that there are compact deviations from the mean that are equally numerous, positive and negative, and include few extreme outliers. This means that police beats with both a higher and lower number of thefts of property were minimal.

The calculations obtained from RF regression trees resulted in estimates of predictor significance and hit rates for each model. The model could only correctly predict 49% of the theft of property cases, which was very low in this study. For a better fit and a higher significance coefficient for the model, the explanatory variables should have a similar distribution, which is unlikely.

Based on the RF analysis, none of the prosperity or poverty variables exhibited a strong influence on the theft of property level or distribution. Their impact was moderate and statistically insignificant. The prosperity variable of consumption expenses (PLN) (0.35) and the poverty variable of unemployment (0.29) showed no influence (below 0.4).

Our analysis of the significant coefficients (Table 2) revealed some tendencies. Theft of property decreased slightly as the variables population density per sq km and share of green areas increased. This indicates that such measures of prosperity and poverty did not generate this type of crime, a conclusion that was not obvious and requires further research.

In summary, no grounds were revealed to discern whether theft of property is determined by prosperity or poverty. We also confirmed the results obtained with ML tools applying linear regression analysis (Fig. 2), observing minimal positive correlations with population density per sq km and share of green areas and a negative correlation with population assisted by the Municipal Family Assistance Center, which were extremely weak and insignificant.

Table 2. *Random forest significance coefficients for theft of property per 1,000 persons.*

Variables	Significance coefficient
Population density per sq km	0.598975
Share of green areas in percentage	0.571211
Disposable income (PLN) per one person	0.466610
Population assisted by the Municipal Family Assistance Center per 1,000 persons	0.424702
Consumption expenses (PLN) per one person	**0.351211**
Unemployment per 1,000 persons	**0.287951**

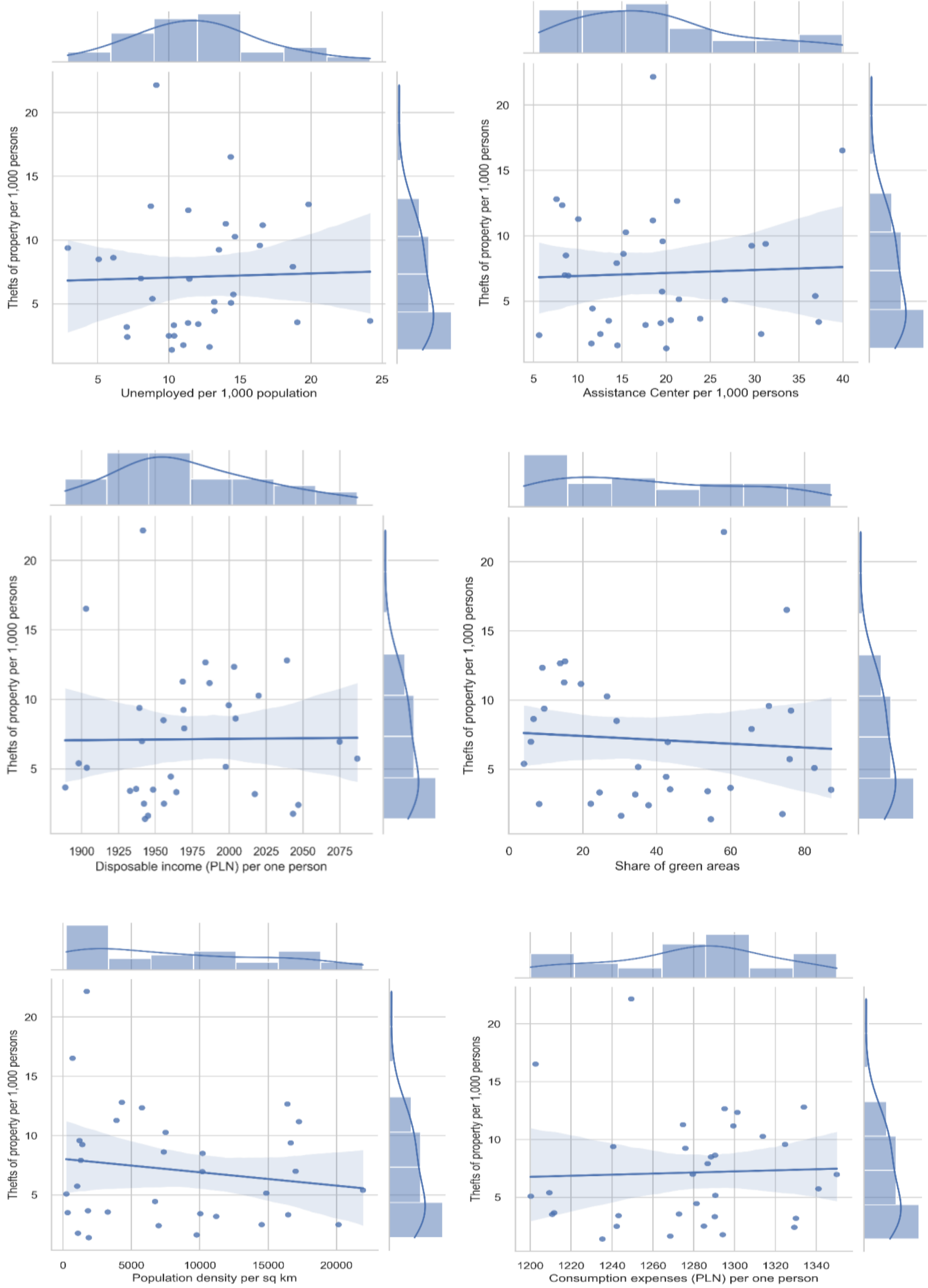
Note: *Significance coefficients above 0.7 (below 0.4) indicate a variable's strong influence (no influence).*
Source: *Own study.*

Fights and battery were committed quite often on average. The mean for analyzed police beats is 2.51 per 1,000 persons, which was similar to most other types of analyzed crimes; however, some areas were free of fights and battery.

The occurrence of fights and battery was characterized by strong differentiation among the variables analyzed and a significant deviation from the normal distribution, indicating that it is unevenly distributed throughout the city; however, some differences in intensity were evident between individual police beats.

The coefficient of variation is equal to 134% and the skewness coefficient to 0.79. The type of kurtosis is almost mesokurtic, which is strongly similar to a normal distribution, without outliers. Furthermore, the RF model correctly predicted 58%, which is moderate in this study.

Figure 2. *Regression analysis between the independent variable theft of property and six dependent prosperity and poverty variables.*



Source: *Own study.*

Unemployment (0.78) and population assisted by the Municipal Family Assistance Center (0.72) had a strong influence on the level and distribution of fights and battery. Table 3 demonstrates that an increase in each of these variables led to a rapid rise in fights and battery. We also confirmed the results using linear regression analysis (Figure 3). All other prosperity and poverty variables revealed similar (ca 0.45), but statistically insignificant, effects.

It can be argued that areas of poverty characterized by high unemployment and high number of beneficiaries of social assistance determine fights and battery.

Table 3. *Random forest significance coefficients for fights and battery per 1,000 persons.*

Variables	Significance coefficient
Unemployment per 1,000 persons	**0.782456**
Population assisted by the Municipal Family Assistance Center per 1,000 persons	**0.716077**
Disposable income (PLN) per one person	0.464612
Consumption expenses (PLN) per one person	0.465026
Population density per sq km	0.454389
Share of green areas in percentage	0.413361

Note: *Significance coefficients above 0.7 (below 0.4) indicate a variable's strong influence (no influence).*
Source: *Own study.*

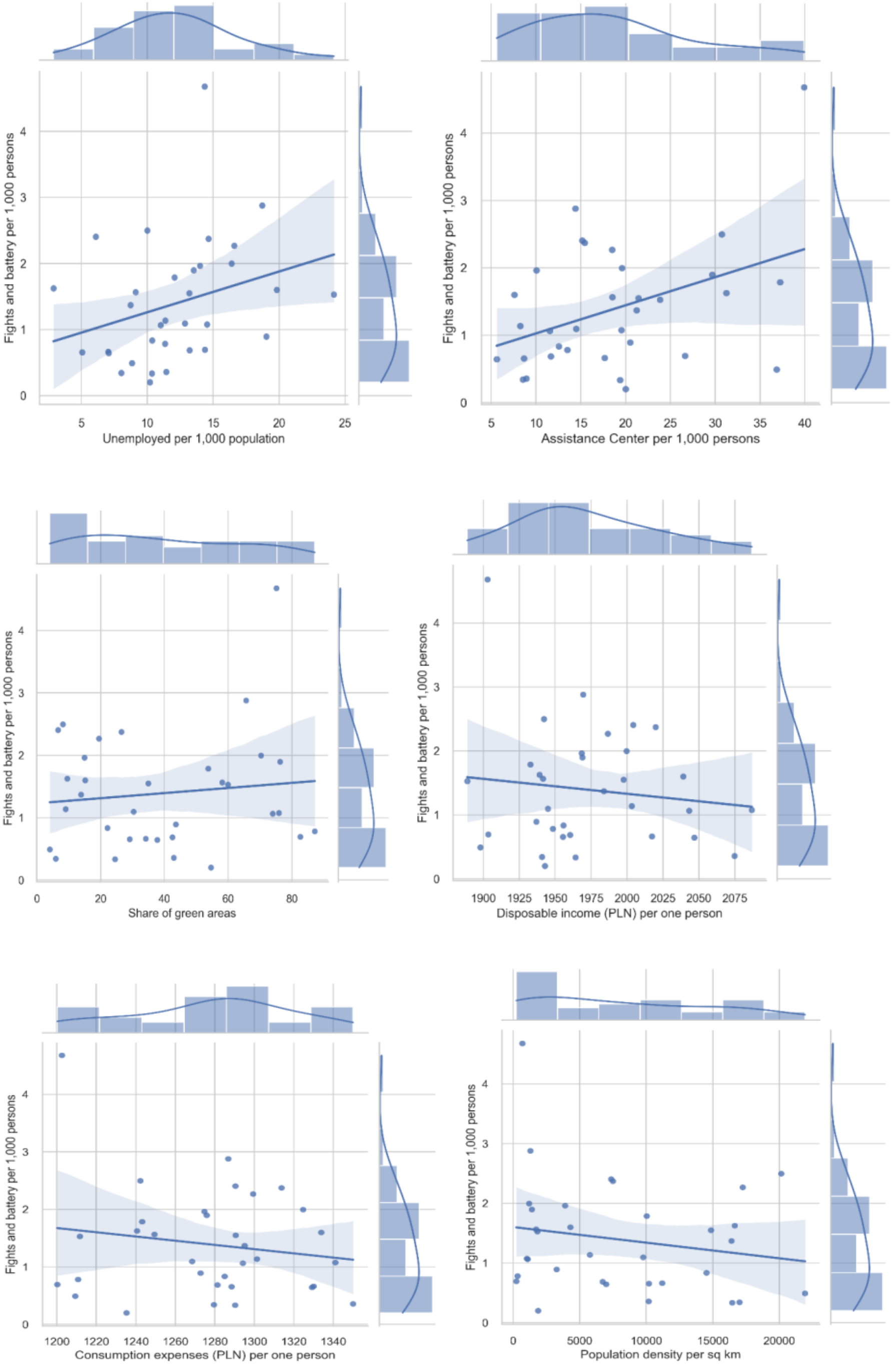
Drug crimes were found to be committed often on average. The mean for analyzed police beats was 2.48 per 1,000 persons, which is similar to most other types of crimes; however, some areas were free of drug crimes.

Drug crimes are characterized by strong differentiation among the analyzed variables and a significant deviation from the normal distribution, indicating that it was unevenly distributed throughout the city. The coefficient of variation is 112% and the skewness coefficient is 1.25.

This means that this type of crime had a strong spatial concentration. The type of kurtosis is almost mesokurtic, which is strongly similar to a normal distribution, without outliers. The RF model reached the highest hit rate of 71%, which was the most significant in this study.

Three variables exhibited a strong influence on the level and distribution of drug crimes, which included poverty measures of unemployment (0.77) and population assisted by the Municipal Family Assistance Center (0.8) and the prosperity measure of consumption expenses (PLN) (0.78).

Figure 3. *Regression analysis between the independent variable fights and battery and six dependent prosperity and poverty variables.*



Source: *Own study.*

Notably, Table 4 shows that an increase in the number of unemployed and increased consumption was connected with a decrease in drug crimes. In contrast, an increase in the number of beneficiaries of social assistance leads to an increase in drug crimes. All other prosperity and poverty variables exhibited relatively similar (ca 0.65) statistically insignificant effects.

According to linear regression analysis (Figure 4) among the poverty and prosperity variables, the assistance center and consumption expenses were the most strongly correlated determinants with the highest positive and negative correlations, respectively. It can be argued that areas of poverty characterized by high unemployment, a high number of social assistance beneficiaries, and areas with an elevated number of high consumers strongly determine drug crimes.

Table 4. *Random forest significance coefficients for Drug crimes per 1,000 persons.*

Variables	Significance coefficient
Population assisted by the Municipal Family Assistance Center per 1,000 persons	**0.799657**
Consumption expenses (PLN) per one person	**0.782566**
Unemployment per 1,000 persons	**0.766177**
Share of green areas in percentage	0.671787
Disposable income (PLN) per one person	0.661747
Population density per sq km	0.595129

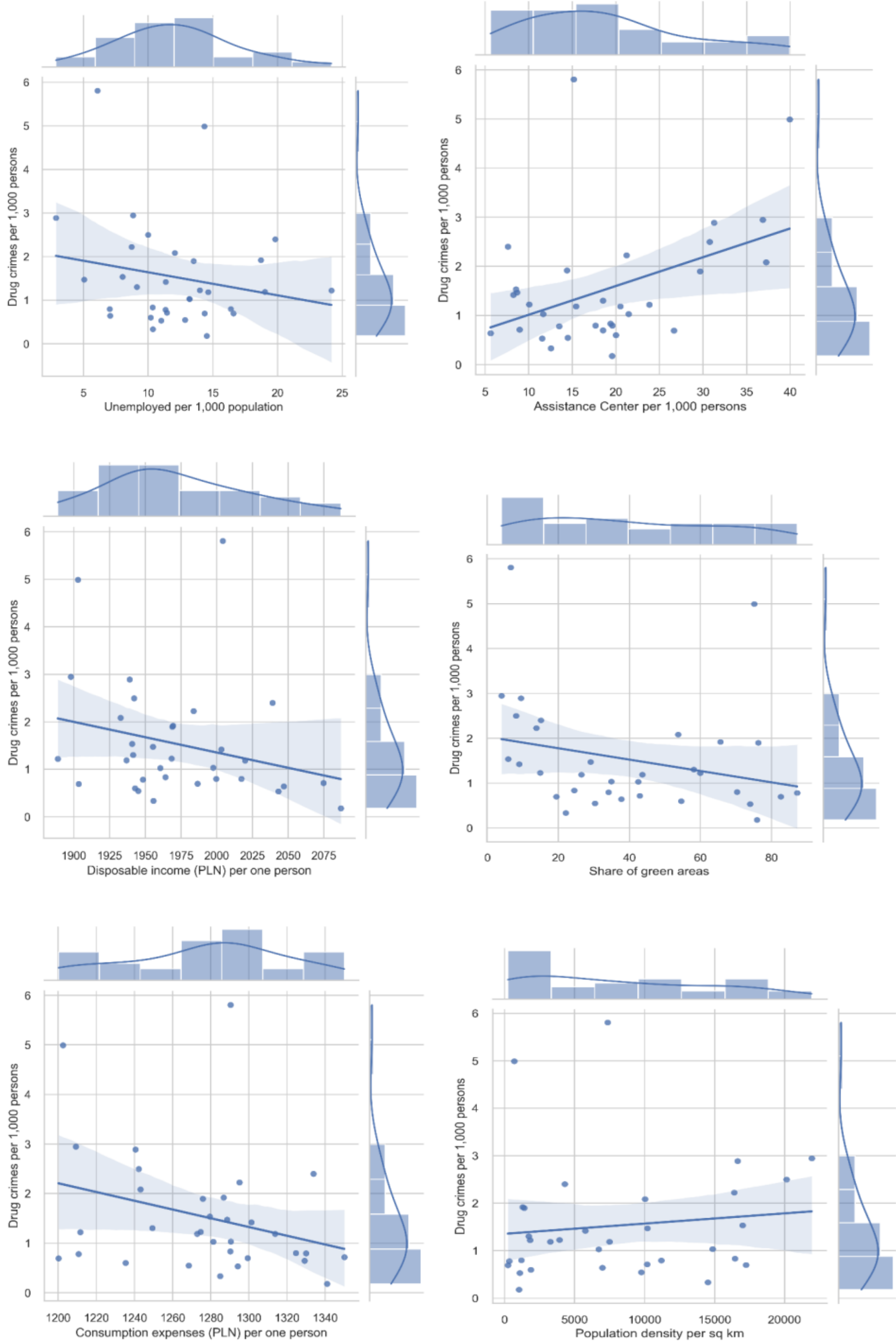
Note: *Significance coefficients above 0.7 (below 0.4) indicate a variable's strong influence (no influence).*
Source: *Own study.*

Property damage is a common crime. The mean for analyzed police beats is 2.12 per 1,000 persons, which is similar to most other types of crimes; however, some areas are free of property damage.

Property damage was characterized by the lowest differentiation among those analyzed and some deviation from the normal distribution, indicating that it is evenly distributed throughout the city. The coefficient of variation was 86% and the skewness coefficient was 0.53. Both indicators belonged the lowest among those analyzed.

The type of kurtosis is leptokurtic, revealing that compact deviations from the mean were equally numerous and positive and negative, with few extreme outliers. This means that no police beats had both a higher and lower number of property damage. The model predicted property damage crimes with 55% accuracy, which is moderate. Two variables exhibited a strong influence on the level and distribution of property damage, including the poverty variable of population assisted by the Municipal Family Assistance Center per (0.74) and the prosperity variable of share of green areas (0.72).

Figure 4. *Regression analysis between the independent variable drug crimes and six dependent prosperity and poverty variables.*



Source: *Own study.*

Table 5 demonstrates that property damage increased with the number of beneficiaries of social assistance. In contrast, an increase in the share of green areas led to a comparable decrease in property damage. Two other variables exhibited relatively similar (ca 0.5), but statistically insignificant, effects. In addition, two prosperity variables of disposable income (PLN) (0.3) and consumption expenses (PLN) (0.19) had no influence (below 0.4).

Regression analysis using ML methods confirmed the results (Fig. 5), also indicating that unemployment is an important variable for explaining the occurrence of property damage crimes.

In conclusion, it is notably difficult to explain the variables determining property damage, which could not be unambiguously assigned to prosperity or poverty; however, these variables are explainable.

Property damage was focused in areas of poverty where potential perpetrators reside and relatively sparsely populated green areas where the level of social control of the public space was low. Prosperous areas were clearly not conducive to committing this type of crime, as demonstrated by the insignificance of the variables.

Table 5. *Random forest significance coefficients for Property damage per 1,000 persons.*

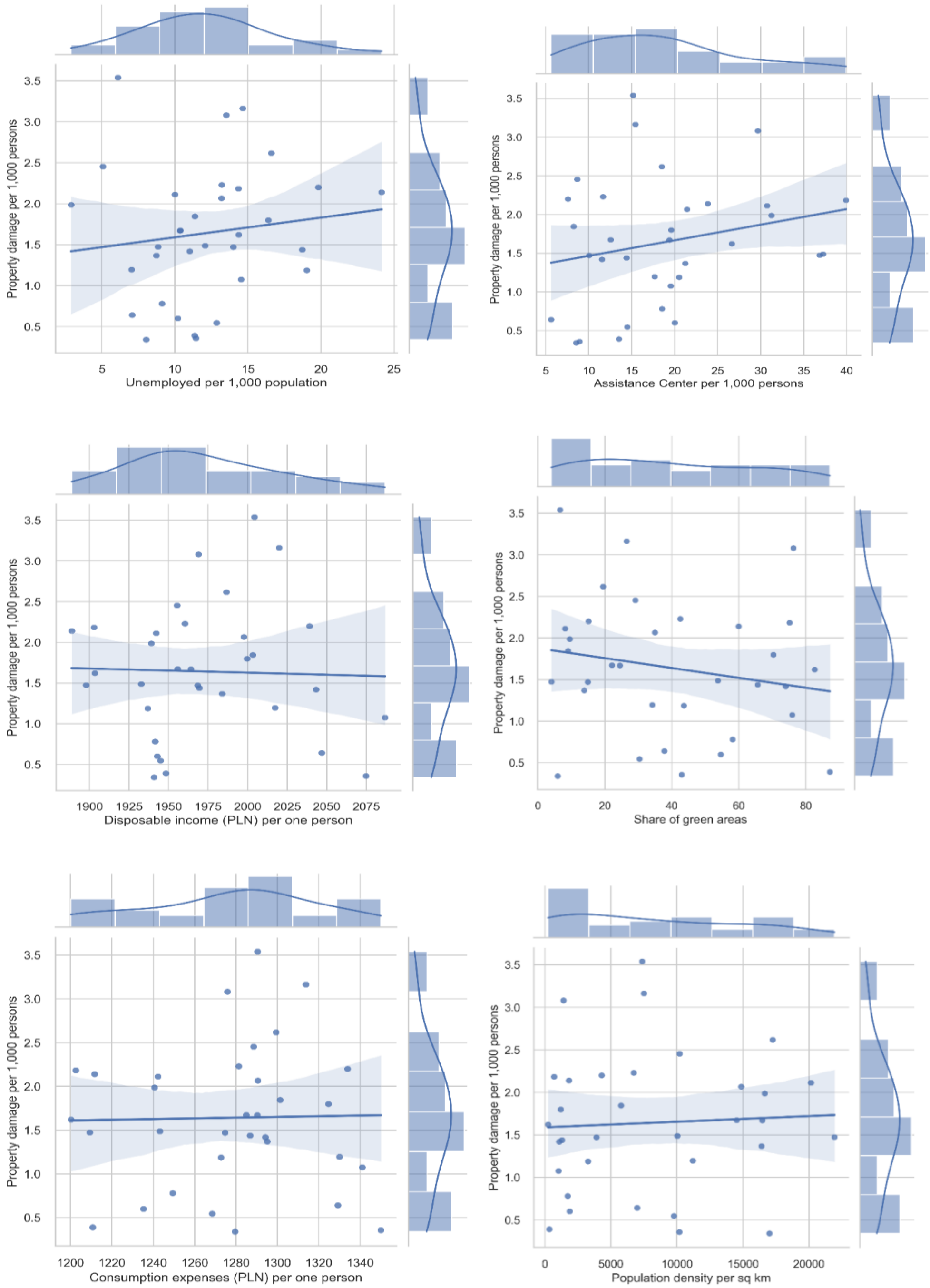
Variables	Significance coefficient
Population assisted by the Municipal Family Assistance Center per 1,000 persons	**0.742851**
Share of green areas in percentage	**0.719940**
Unemployment per 1,000 persons	0.651193
Population density per sq km	0.427162
Disposable income (PLN) per one person	**0.297915**
Consumption expenses (PLN) per one person	**0.185923**

Note: *Significance coefficients above 0.7 (below 0.4) indicate a variable's strong influence (no influence).*
Source: *Own study.*

Car-related crimes occurred rather rarely. The mean for the police beats analyzed was up to 1.15 per 1,000 person, and only apartment burglaries were committed less often.

This type of crime was characterized by moderate differentiation among the variables analyzed and a relatively low deviation from the normal distribution, indicating that it was evenly distributed throughout the city; however, there are small differences in intensity between individual police beats. The coefficient of variation is 87% and the skewness coefficient is 1.00.

Figure 5. *Regression analysis between the independent variable property damage and six dependent prosperity and poverty variables.*



Source: *Own study.*

The type of kurtosis is almost mesokurtic, which is strongly similar to a normal distribution, without outliers. RF could predict car crimes in only 48% of cases, which is the lowest in this study.

For a better fit and a higher correlation coefficient for the model, the influence variables should have a similar distribution, which is unlikely.

None of the prosperity or poverty variables showed a strong influence on the level and distribution of car-related crimes. The influence of all three poverty variables was moderate but statistically insignificant (ca 5.5). In contrast, three prosperity variables of disposable income (PLN) (0.40), consumption expenses (PLN) (0.28), and population density per sq km (0.11) showed no influence on car crimes (below 0.4).

The analysis of the significance coefficient (Table 6) and the linear regression results (Fig. 6) revealed some tendencies, indicating that growth in car crimes was correlated with a slight growth in unemployment and a slight decrease in consumption expenses (PLN).

This means that prosperous areas did not generate car crimes, and although the influence of prosperity variables is noticeable, it is not statistically relevant. This conclusion is not obvious and requires further research. In summary, no grounds emerged to determine whether car crimes are related to prosperity or poverty.

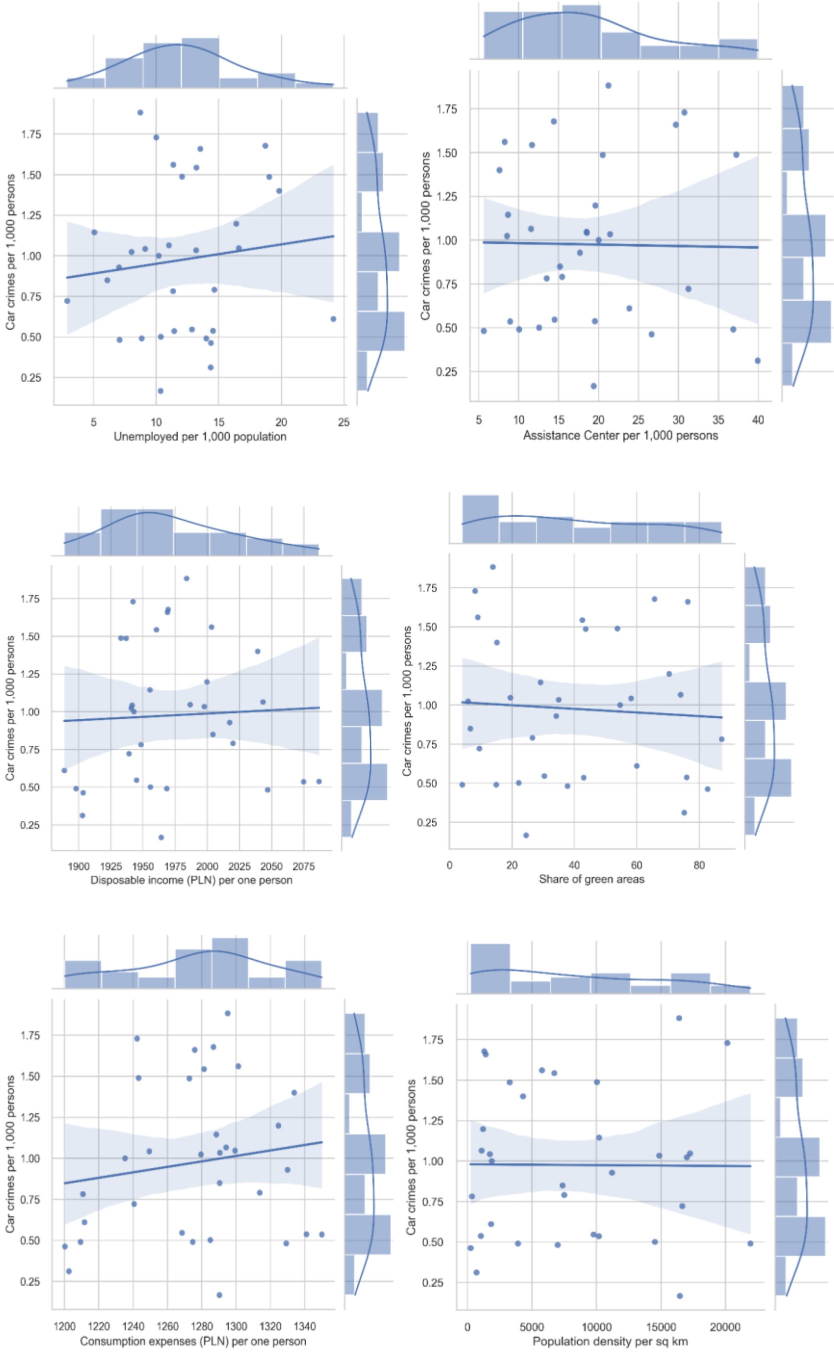
Table 6. *Random forest significance coefficients for car crimes per 1,000 persons.*

Variables	Significance coefficient
Consumption expenses (PLN) per one person	0.608057
Unemployment per 1,000 persons	0.559754
Share of green areas in percentage	0.487081
Disposable income (PLN) per one person	**0.398368**
Population assisted by the Municipal Family Assistance Center per 1,000 persons	**0.278452**
Population density per sq km	**0.113448**

Note: *Significance coefficients above 0.7 (below 0.4) indicate a variable's strong influence (no influence).*
Source: *Own study.*

Apartment break-ins were committed the least frequently. The mean for analyzed police beats is only 0.35 per 1,000 persons, which is a value several times smaller than that for most other types of crimes analyzed, and some areas were free of apartment break-ins.

Figure 6. *Regression analysis between the independent variable Car crimes and six dependent prosperity and poverty variables.*



Source: *Own study.*

This type of crime was characterized by moderate differentiation among the variables analyzed and a slight deviation from the normal distribution, suggesting that it was moderately evenly distributed throughout the city. The coefficient of variation is equal to 101% and the skewness coefficient is 0.42.

Both indicators were the lowest among those analyzed. Apartment burglary is the only platykurtic among the crimes analyzed, exhibiting elongated deviations from the mean that were equally numerous and positive and negative with more extreme outliers. This means that there were numerous police beats with moderate positive and negative deviations from the mean of the number of apartment break-ins. Break-in crimes are quite predictable, and the RF model reached 67% for this variable, which was the highest in this study.

Only the unemployment poverty variable exhibited a strong influence on the level and distribution of apartment break-ins. Table 7 shows that as unemployment grows, apartment burglaries rapidly rise. Only the prosperity variable of consumption expenses (PLN) had no influence (below 0.4). The influence of the remaining four variables was moderate (ca 0.5) and statistically insignificant.

The decline of apartment burglaries was statistically insignificant, but is visible in the chart, showing a slight decline in the two prosperity variables of population density per sq km and disposable income (PLN). The two remaining variables of prosperity and poverty exhibited relatively similar (ca 0.45) but statistically insignificant effects. We confirmed the results obtained with ML tools using linear regression analysis (Fig. 7), revealing a positive correlation with unemployment and a negative correlation with population density.

In conclusion, explaining the variables determining apartment break-ins is difficult and cannot be unambiguously assigned to prosperity or poverty; however, these variables are explicable. Apartment break-ins occur in areas of poverty where potential perpetrators live, and prosperous areas are definitely not conducive to committing this type of crime. The explanation is the absence of the unemployment variable.

Table 7. *Random forest significance coefficients for apartment break-ins per 1,000 persons.*

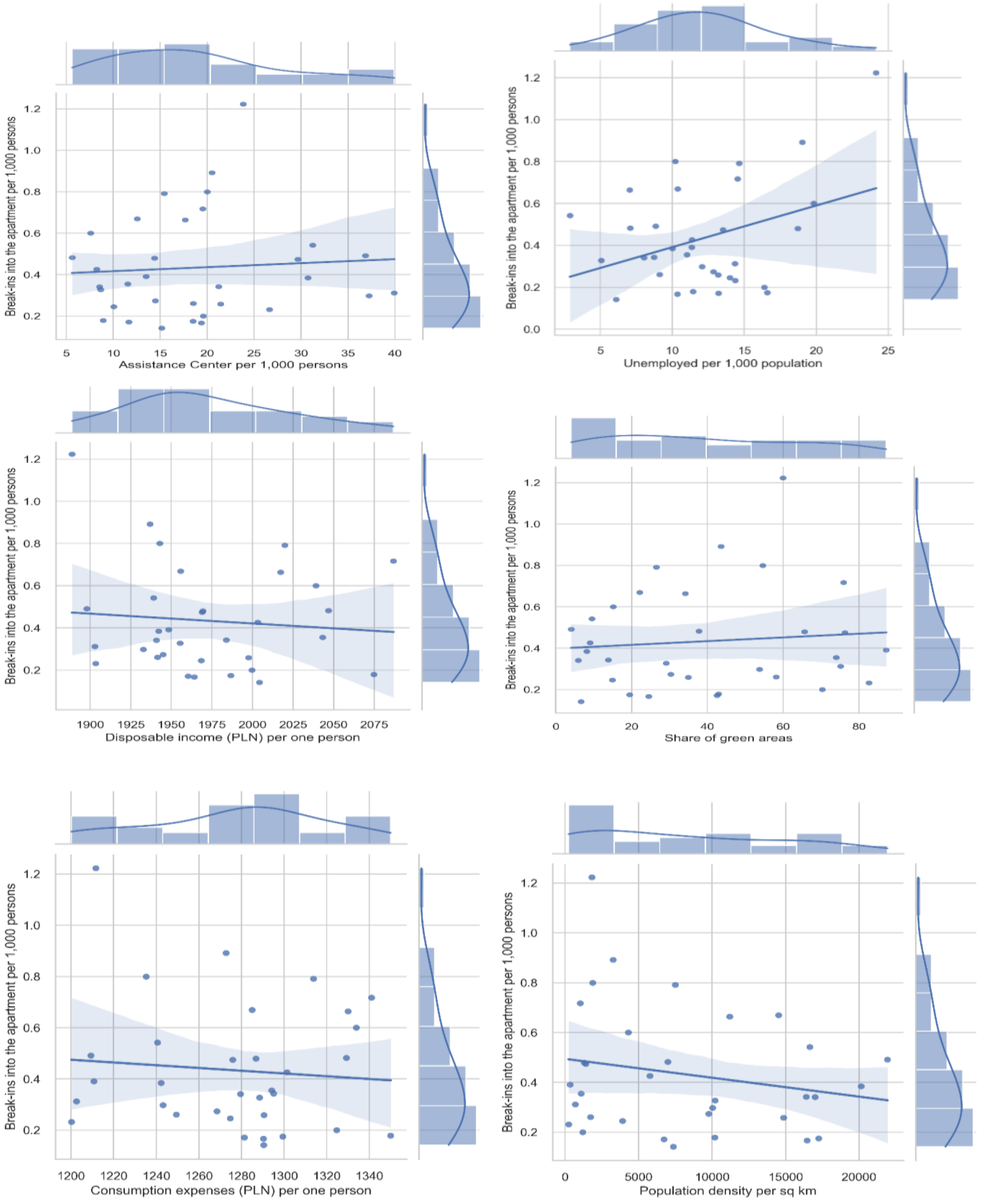
Variables	Significance coefficient
Unemployment per 1,000 persons	**0.826685**
Population density per sq km	0.619486
Disposable income (PLN) per one person	0.586691
Population assisted by the Municipal Family Assistance Center per 1,000 persons	0.474329
Share of green areas in percentage	0.433476
Consumption expenses (PLN) per one	**0.252369**

person	

Note: *Significance coefficients above 0.7 (below 0.4) indicate a variable's strong influence (no influence).*

Source: *Own study.*

Figure 7. *Regression analysis between the independent variable Apartment break-ins and six dependent prosperity and poverty variables.*



Source: *Own study.*

6. Conclusions

The findings of this study underscore the complex interplay between socioeconomic factors and crime, highlighting the nuanced influence of poverty and prosperity variables on different types of criminal activities. A critical examination of these results provides a deeper understanding of the mechanisms through which economic conditions impact societal behaviors and crime rates.

This summary defines the level of influence of the prosperity and poverty variables and types of crime (Table 8). Among the 36 correlation indicators analyzed to measure the influence on crime, only eight variables exhibited a strong influence, of which six concerned poverty. Eight variables also had no influence, of which five were related to prosperity.

None of the variables had a strong overall effect; however, the average influence of poverty variables was slightly higher (0.562) than that of the prosperity variables (0.491). A preliminary conclusion can be drawn that poverty variables have a stronger influence on total crime than those of prosperity. This conclusion is confirmed and detailed by the analysis of the impact of individual variables on the types of crime.

Table 8. *The influence of variables by prosperity and poverty and types of crime.*

	Fights and battery per 1,000 persons	Drug crimes per 1,000 persons	Theft of property per 1,000 persons	Property damage per 1,000 persons	Apar-tment break-ins per 1,000 persons	Car crimes per 1,000 persons	Total	Mean
Disposable income (PLN) per one person	0.465	0.662	0.467	0.298	0.252	0.398	2.542	0.424
Consumption expenses (PLN) per one person	0.465	0.783	0.351	0.186	0.608	0.608	3.001	0.500
Share of green areas in percentage	0.413	0.672	0.571	0.720	0.433	0.487	3.297	0.549
Prosperity total							8.839	0.491
Population assisted by the Municipal Family Assistance Center per 1,000 persons	0.716	0.800	0.425	0.743	0.474	0.278	3.436	0.573
Unemployed	0.782	0.766	0.288	0.651	0.827	0.560	3.874	0.646

per 1,000 persons								
Population density per sq km	0.454	0.595	0.599	0.427	0.619	0.113	2.809	0.468
Poverty total							10.119	0.562
Total	3.296	4.277	1.814	3.025	3.214	2.445		
Mean	0.549	0.713	0.302	0.504	0.536	0.408		

Source: *Own study.*

The prosperity variables also showed no impact, including disposable income (PLN) in relation to car crimes, property damage, and apartment break-ins, and consumption expenses (PLN) in relation to theft of property and property damage. The analysis of the combined impact of variables' influence revealed that only drug crimes were strongly conditioned. No impact occurred in relation to theft of property.

This study demonstrated that the variables of poverty related to low income have the strongest influence on crime, including population assisted by the Municipal Family Assistance Center and unemployment. Variables of prosperity associated with high incomes, disposable income (PLN), and consumption expenses (PLN) exhibited a complete lack of explanatory power.

Drug crimes were the most strongly conditioned, while theft of property had no impact. The prosperity variable of share of green areas and the poverty variable of population density per sq km did not contribute anything in the analysis. The level and diversity of theft of property is expected to be explained by variables other than those included in this study.

Armin and Idris (2020) found poverty and income inequality to have a positive and significant effect on crime. The authors recommended that the government must control how society's needs are met to reduce crime. Research conducted by Answer et al. (2020) in 16 countries also advocated increased social assistance to the poor to reduce the crime rate.

Our research demonstrated that controlling the needs of society and increasing support by the Municipal Family Assistance Center in Poland strongly determined drug crimes, property damage, and fights and battery.

Studies that have examined the relationship between unemployment and crime rates have indicated that unemployment rate has a unidirectional causal relationship with crime, and reductions in unemployment lower crime rates (Armin and Idris, 2020; Khan et al., 2015, 2015; Mittal et al., 2019; Raphael and Winter-Ebmer, 2001). The test results obtained in this study confirm the results obtained in previous studies. Dickinson (1994) conducted research in the UK, obtaining analogous results regarding the impact of unemployment on burglaries and drug crime among minors. Particularly in poor regions, it was clear that opportunistic crime related to burglaries and drug crime increased rapidly as unemployment rose.

Research conducted in the Netherlands by Beki *et al.* (1992) concluded that consumption fluctuations derived from income per person had a motivating effect on property theft, demonstrating that as consumption increases, material benefits may be legal; thus, the incentive to steal is significantly reduced.

Khan et al. (2015) determined that higher GDP per capita reduces crime in the short term and increases it in the long term by attracting criminals to affluent areas with multiple lucrative targets. No clear result was obtained by this study to confirm the impact of consumption expenses (PLN) on theft of property.

The study highlights the strong influence of poverty, particularly unemployment, on crime rates and suggests limited impact of prosperity on crime prevention. To address this, key policy recommendations include:

- Enhanced Social Support Programs: increase funding for social assistance to vulnerable groups, focusing on financial aid, healthcare, and education to tackle poverty's root causes.
- Unemployment Reduction Strategies: implement job creation initiatives, like support for small businesses, education organizations, and startups, to reduce unemployment and its link to crime.
- Education and Vocational Training: expand programs that provide market-relevant skills, targeting disadvantaged individuals to improve employability and offer alternatives to crime.
- Community Development Initiatives: invest in projects that enhance living conditions and community infrastructure, indirectly reducing crime by fostering well-being and social cohesion.
- Crime Prevention and Rehabilitation Programs: develop targeted interventions for common and severe crimes, emphasizing prevention, education, and support for offender rehabilitation.
- Economic Policy Adjustments: adjust economic policies to reduce income inequality and create equitable wealth opportunities, aiming to decrease economic-related crimes.
- Research and Data Analysis: continue analyzing the socio-economic factors affecting crime rates and explore additional variables for a deeper understanding to inform policy and interventions.
- Intersectoral Collaboration: promote cooperation across government, private sector, NGOs, and community groups to comprehensively address the complex issues surrounding crime through social, economic, and environmental strategies.

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