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Gazilas, Emmanouil Taxiarchis

University of Piraeus, Department of Economics

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Economic Factors Influencing Homicide Rates: A European Perspective

Emmanouil Taxiarchis Gazilas

Academic Researcher, Economics Student, Department of Economics, School of Economics, Business & International Studies, University of Piraeus, Piraeus, Greece (Karaoli & Dimitriou 80, Piraeus 185 34, Greece).

ORCID: <https://orcid.org/0009-0003-0554-500X>

e-mail: mgazilas@unipi.gr

Abstract. Intentional homicide rates represent a critical societal issue, impacting public safety and social stability across Europe. Understanding the socio-economic factors underlying these crimes is paramount for effective policy intervention. This research aims to investigate the socio-economic determinants of intentional homicides in 15 European countries over the period 2010-2021, providing insights into the complex relationship between economic indicators and violent crime rates. The study hypothesizes that economic prosperity, government debt, and access to financial services significantly influence intentional homicide rates, with countries exhibiting higher levels of economic development and financial inclusion experiencing lower homicide rates. Utilizing robust statistical and econometric techniques, including regression analysis and correlation matrices, the research examines the relationships between various socio-economic indicators and intentional homicide rates. Data spanning from national tax authorities, statistical agencies, and international organizations are meticulously analyzed to uncover meaningful patterns and associations. The findings reveal compelling associations between economic indicators and intentional homicide rates. Higher GDP per capita and greater financial inclusion are correlated with lower homicide rates, while elevated levels of government debt exhibit a negative association with homicide rates. These results underscore the multifaceted nature of crime dynamics and highlight the importance of considering broader socio-economic factors in understanding violent crime patterns. The study contributes to both theoretical knowledge and practical policymaking by offering insights into the socio-economic determinants of intentional homicides. These findings can inform evidence-based policy interventions aimed at promoting social stability and enhancing public safety across Europe, emphasizing the importance of addressing underlying economic factors in crime prevention strategies.

Keywords: Intentional Homicides, Socio-Economic Factors, Public Safety, Economic Prosperity, Financial Inclusion, Policy Interventions

JEL: D74, K14, O15, I12, H56

1. Introduction

In the shadows of society, where desperation meets opportunity, lies a haunting truth: the nexus of money and murder. This introduction sets the stage for a captivating exploration into the enigmatic world of homicide investigations, where socioeconomic variables serve as silent witnesses to the deadly dance of dollars. From the bustling corridors of commercial banks to the virtual realm of internet transactions, every financial transaction leaves a trace, a breadcrumb in the chilling narrative of murder for money.

Within the annals of criminology, the study of homicide has long been shrouded in mystery and intrigue. While traditional theories have focused on psychological, sociological, and demographic factors as drivers of violent crime, only a few have delved into the covert complexities that intertwine economic indicators with lethal outcomes. This paper seeks to fill this gap by examining the hidden connections between socioeconomic variables and homicide rates, shedding light on the chilling truths that lie beneath the surface.

The allure of financial incentives—a siren calls that beckons individuals down a perilous path—lies at the heart of the investigation. Unemployment rates, GDP per capita, and financial transactions emerge as unwitting accomplices in the tragic narrative of homicide, their fingerprints etched upon the fabric of statistical analysis. Through regression models and multivariate analysis, the intricate web of correlations is dissected, revealing the hidden pathways that lead from economic distress to lethal outcomes. But beyond the statistical analysis lies a deeper truth: the socioeconomic landscape serves as fertile ground for the seeds of crime, where desperation and opportunity converge in a deadly embrace. In the swirling maelstrom of economic turmoil, individuals are driven to desperate measures, their actions fuelled by a primal instinct for survival. Yet, amidst the darkness, there is hope—a glimmer of light that pierces the shadows and illuminates the path forward.

The analysis uncovers compelling evidence of the intertwining of financial factors and homicide rates. Variables such as unemployment, GDP per capita, and internet purchases emerge as significant predictors of homicide, their influence reaching far beyond the confines of economic theory. But it is not merely the presence of these variables that captivates attention—it is the intricate dance they perform, weaving a tapestry of tragedy and despair.

As the suspenseful journey unfolds, one thing becomes clear: the intertwining of money and murder is a chilling reality that demands attention. By shining a spotlight on the hidden connections between socioeconomic variables and homicide rates, the hope is to provoke further inquiry and inspire action. In a world where human lives are traded for monetary gain, it is imperative to confront the dark truths that lurk beneath the surface and strive for a future where every life is valued and protected.

The purpose of this study is multifaceted and driven by the imperative need to comprehensively understand the intricate relationship between socio-economic factors and the incidence of intentional homicides in 15 European countries spanning the period from 2010 to 2021. Homicide rates, representing a fundamental measure of societal well-being and public safety, pose significant challenges to communities and governments alike.

Therefore, the primary objective of this research is to delve deep into the underlying determinants of intentional homicides, with a particular focus on economic indicators such as GDP per capita, unemployment rates, and government debt. By analyzing these key socio-economic variables, the study seeks to unravel the complex interplay between economic conditions and violent crime, thereby providing valuable insights for policymakers, law enforcement agencies, and stakeholders invested in crime prevention and social development initiatives.

The study hypothesizes that economic prosperity, government debt, and access to financial services significantly influence intentional homicide rates, with countries exhibiting higher levels of economic development and financial inclusion experiencing lower homicide rates.

Moreover, the research aims to explore the potential impact of technological advancements and financial inclusion on homicide rates, recognizing the evolving nature of crime dynamics in an increasingly interconnected world. By elucidating the intricate web of socio-economic factors influencing homicide patterns, this study aspires to contribute to the existing body of knowledge on crime prevention strategies, ultimately fostering safer and more resilient communities across Europe.

2. Literature Review

It is well established in the literature that poverty contributes to feelings of alienation and exploitation [1, 2] that a sense of social deprivation has a strong correlation to lethal violence [3] and that the poorest citizens in a society are more likely to live outside the legal framework of that society [4, 5].

In fact, while the previously mentioned study on poverty clustering found little connection to violent crime rates within poverty clusters themselves, there was a strong relationship to homicide in cities with high levels of poverty clustering [6].

And while there remain those scholars that argue there is no evidence to support that poverty alone causes conflict, other studies have found strong correlations between poverty and violent crime rates regardless of other factors such as age [7] or race [8].

Poverty may be understood in multiple ways. One can be income inequality where individuals perceive poverty relative to the wealthiest and least wealthy individuals in their community and the size of the gap between them. This can be measured by the Gini index, named after the sociologist who, in the early twentieth century, developed the relevant calculations. Data suggests that income inequality is a strong predictor of violent crime and, cross-nationally, explains away previous theories that hot weather was a predictor of crime [9].

Poverty can also be understood through the concept of human capital, essentially involving education attainment and employment. Low educational attainment has long been understood to be a predictor of crime, though most data are within-community rather than cross-national [10].

Likewise, unemployment is associated with crime, though relationships are often context-specific and complex [11]. As such, consideration of these variables can be valuable in understanding violent crime rates cross-nationally.

Some researchers focused on the effect of social structure on homicide rates within geographic units [12]. Overall, this body of research has demonstrated that socially disorganized and economically disadvantaged areas have higher rates of homicide rates than social organized, economically well-off places. There are two general explanations for this pattern. First, some criminologists posit that socially disorganized cities and communities have weak informal social control networks. As a result, the community structure loses its ability to control residents and weakened informal social control mechanisms (collective efficacy) may result in violence going unmonitored. Low levels of informal social control emanate from factors such as

economic deprivation, broken families, high residential turnover, and high population density [13, 14].

Economic deprivation inhibits the foundation and work of social organizations that provide formal and informal social control [15]. Extreme economic deprivation also impedes the ability of communities to sustain basic institutional structures that connect individuals to positive roles within society [16].

Family disruption contributes to levels of social disorganization by decreasing community networks, such as participation in voluntary organizations and local affairs of informal social control, and by inhibiting the informal social control of youths [13]. High residential turnover may contribute to social disorganization by decreasing the ability of neighbourhoods to control its citizens due to lack of social bonds among residents [17].

Along this same line, Hunter [18] hypothesized that mechanisms of social control in neighbourhoods emerge slowly through interactions among the residents over time. Therefore, the greater the level of residential instability that exists in a neighbourhood the less likely it is that such networks will emerge among residents.

Furthermore, Bursik & Grasmick [17] indicate that if the residents hope to leave their communities, institutions pertaining to internal control are difficult to establish because the residents are uninterested. Finally, population density and size are related to high homicide rates via social disorganization because they decrease community integration and hinder surveillance mechanisms in neighbourhoods [13]. Other criminologists posit that economic deprivation contributes to homicide rates by increasing strain in communities as well as diminishing the ability of institutions of social control.

Previous research suggests that economic disadvantage may also create an environment in which violence and aggression are accepted [19, 15]. Concentrated disadvantage not only deprives geographic areas of institutions of social control, but also increases social isolation among residents because as job opportunities flee the geographic area so do the “better off” residents, leaving behind the most economically deprived in the communities [15, 20].

This in turn leads residents of these areas to adopt cultural mechanisms to enable their survival, which include aggressive behaviour [11, 20]. As more people adapt to violent/aggressive strategies, violence in these neighbourhoods rises, leading residents to adopt behavior that is even more violent, which can result in the victimization of family members. These theoretical assumptions have found ample support in the literature. Measures of economic status have shown a relatively consistent positive significant relationship with homicide rates within geographic areas [21, 22].

Two of the numerous studies that have demonstrated a positive relationship between homicide and measures of poverty, are Land and colleagues’ [23] seminal study and Titterton and colleagues’ [24] study.

Land et al. [23] analyses of the structural covariates of homicides showed that measures of poverty were consistently positively related with homicides across units of analysis (e.g., Standard Metropolitan Statistical Areas, cities, and states) and across different time-periods (e.g., the 1960s, 1970s, and 1980s).

More recently, Titterington et al.'s [24] study corroborated the findings of Land et al. Similar to Land et al. [23], they found that homicide rates were higher in areas experiencing high poverty and disadvantage. Measures of family disruption, residential instability, population density, and ethnic heterogeneity have also ample support in the literature. Land et al. [23] found that family disruption, measured as the percentage of children living with only one parent, has a strong relationship with homicides regardless of the geographic unit of analysis.

In terms of residential instability, Sampson et al. [1] found that population turnover is positively related to homicides. Land et al. [23] also found a positive significant relationship between population size and density and homicide rates. Specifically, they found that that population structure, measured as the unit population size and density, have a strong positive invariant effect on homicide rates. Research examining ethnic heterogeneity, however, have found less consistent results.

Most studies that examine ethnic heterogeneity tend to measure this variable as the percentage of non-white or African Americans in geographic areas. Pratt & Cullen [25] found in a meta-analysis of macro-level predictors of crime that racial heterogeneity, when measured as the percent of the population that is not Caucasian or the percent of blacks, is one of the strongest and most stable macro-level indicators of crime.

Numerous studies corroborate these findings by showing a strong positive relationship between percentage of black or non-white residents in geographic areas and homicide rates [26, 27]. Although research has confirmed that social structure is related to overall homicide trends it is still necessary to examine whether the effect is present in specific types of disaggregated incidents.

Research evidence suggests that social structural factors may have a different effect on varying types of homicides because the etiology of this crime varies greatly depending on the precipitating factors that lead to the event [28].

For example, Avakame's [29] findings suggest that the principal predictor of stranger homicides is social disorganization, while gender inequality is the dominant predictor of intimate homicides. Research also suggests that social structure is related to intimate partner homicides; however, the effect is not as robust as with other types of homicides.

One possible reason for this is that collective supervision, which is a key variable in social structural theories (primarily social disorganization) may not extend into the "private" area in which domestic violence occurs [19].

Research [30] indicates that communities suffering from concentrated resource deprivation have a more difficult time creating and maintaining strong institutions of public social control, while [31] suggested that high homicide rates in the United States today are related primarily to the persistence of Southern cultural traditions developed before the Civil War and subsequently spreading over much of the country. Additionally, it is concluded that severe poverty is positively associated with lethal-violence rates for both races [32].

The findings of [33] showed that while all homicide types demonstrated an absolute decrease, domestic homicides had demonstrated a relative increase over time. In other research it is concluded that homicide-suicide can be conceptualized as a

current in the stream analogy of lethal violence, and that the prevention of homicide-suicide would be better facilitated via screening of violence prevention than suicide prevention programs [34].

In conclusion it is worth noting that when poverty is controlled, the traditional age-curve persists only for high-poverty populations, in which young people are vastly over-represented, and homicide rates are elevated for all ages [35]. This finding reiterates that “adolescent risk taking” may be an artifact of failing to control for age-divergent SES. Furthermore, Shulman et al. [36] claim that the age–crime curve is illusory and underscore the danger of drawing inferences about individual behaviour from analysis of aggregated data.

Consequently, it is imperative to further examine this issue. As it was previously mentioned, very little research has focused on untangling the relationship between social structure and homicides. This study contributes to the field of criminology and socioeconomics by offering a comprehensive examination of the relationship between socioeconomic factors and homicide rates across 15 European countries from 2010 to 2021. By an analysis of various socioeconomic indicators, the research sheds light on the underlying mechanisms driving intentional homicides within diverse socio-political contexts. Through advanced statistical techniques, such as regression models and multivariate analysis tailored to the European landscape, the study identifies significant predictors of intentional homicide and elucidates the pathways through which socioeconomic variables influence homicide rates.

3. Research Methodology

The empirical analysis in this study draws from a diverse dataset encompassing 15 European countries: Greece, Italy, Denmark, Sweden, France, Spain, Lithuania, Netherlands, Cyprus, Portugal, Ireland, Austria, Poland, Luxembourg, Malta. Data obtained from national tax authorities, statistical agencies, international organizations, and world data indicators website (WDI).

The countries selected to represent a varied spectrum of economic, cultural, and governance landscapes. The data spans the critical period from 2010 to 2021 and is sourced from national tax authorities, statistical agencies, international organizations, and esteemed research institutions. The reliability and accuracy of the dataset are ensured through meticulous extraction from authoritative databases. Table 1 represents the variables used for analysis.

Table 1. Variables Used

| | |
|---|--------|
| Intentional Homicides (per 100,000 people) | inhm |
| Commercial Bank Branches (per 100.000 people) | banks |
| GDP Per Capita (\$USD) | gdppc |
| Unemployment Rate | unem |
| Card payment number at POS terminals | cardpm |

| | |
|---|--------|
| Internet purchases by individuals | intpur |
| Central government debt, total (% of GDP) | cgdb |

Note: The names listed in the second column of the table correspond to the variables used in the econometric model.

At the core of the analysis lies the dependent variable, "Intentional Homicides (per 100,000 people)" (inhm), which serves as a fundamental indicator of violent crime prevalence within each country. This variable provides a standardized measure of homicide rates, capturing the number of intentional homicides reported per 100,000 population, thus enabling cross-country comparisons and in-depth analysis of crime patterns. Examining the independent variables chosen for analysis unveils the multifaceted socioeconomic dimensions that may impact homicide rates across European nations:

Commercial Bank Branches (per 100,000 people) (banks): This variable signifies the accessibility and availability of banking services within each country, reflecting the economic infrastructure and financial inclusion levels. A deeper analysis may reveal how the presence of commercial bank branches correlates with economic stability, poverty alleviation efforts, and overall societal well-being, thereby potentially influencing homicide rates through various channels.

GDP Per Capita (\$USD) (gdppc): GDP per capita serves as a pivotal indicator of a country's economic prosperity and standard of living. Higher GDP per capita levels are often associated with greater economic development, reduced poverty rates, and improved social welfare. As such, exploring the relationship between GDPs per capita and homicide rates can shed light on the underlying socioeconomic factors that drive violent crime, including income inequality, social deprivation, and access to resources.

Unemployment Rate (unem): The unemployment rate measures the proportion of the labor force that is unemployed and actively seeking employment. High unemployment rates can exacerbate economic hardship, social inequality, and feelings of disenfranchisement, potentially leading to increased levels of violent crime, including homicide. Analyzing the interplay between unemployment rates and homicide rates offers insights into the complex dynamics of labor market dynamics, social policies, and crime prevention strategies.

Card Payment Number at POS Terminals (cardpm): This variable reflects consumer spending behavior and economic activity, providing insights into the level of commercial transactions and financial interactions within each country. A deeper examination may uncover how changes in consumer spending patterns, driven by factors such as economic prosperity, technological advancements, and financial infrastructure, correlate with variations in homicide rates, thus highlighting the intricate linkages between economic factors and violent crime.

Internet Purchases by Individuals (intpur): Internet purchases signify the prevalence of e-commerce and online transactions, reflecting evolving consumer behaviors and digitalization trends within each country. Higher levels of internet purchases may indicate greater economic activity, consumer confidence, and technological advancement, which can have implications for crime patterns and public safety. Exploring the association between internet purchases and homicide rates offers

valuable insights into the role of technology, globalization, and socioeconomic development in shaping crime dynamics.

Central Government Debt, Total (% of GDP) (cgdb): These variable measures the proportion of total government debt relative to GDP, providing insights into fiscal policies, budgetary constraints, and macroeconomic stability. High levels of government debt may signal financial vulnerabilities, austerity measures, and socio-political tensions, which can have implications for public safety and crime rates. Analyzing the relationship between central government debt and homicide rates offers a nuanced understanding of the intersections between economic policy, governance structures, and crime prevention efforts.

The model we will use for the analysis is the Ordinary Least Squares (OLS) regression model. This model is commonly employed in econometrics to estimate the relationships between a dependent variable and one or more independent variables. In our study, we will use OLS regression to examine the association between intentional homicide rates (inhm) and various socioeconomic indicators across the 15 European countries from 2010 to 2021.

The general form of the OLS regression model can be expressed as follows:

$$\text{inhm} = b_0 + b_1 \text{intpur} + b_2 \text{banks} + b_3 \text{gdppc} + b_4 \text{unem} + b_5 \text{cgdb} + b_6 \text{cardpm} + \epsilon,$$

Where:

- inhm is the intentional homicide rate (dependent variable);
- b_0 is the intercept term;
- b_1, b_2, b_3, b_4, b_5 and b_6 are the coefficients associated with the independent variables: intpur, banks, gdppc, unem, cgdb, and cardpm, respectively;
- ϵ is the error term, representing the difference between the observed and predicted values of the dependent variable.

The coefficients b_1, b_2, b_3, b_4, b_5 and b_6 represent the estimated effects of the independent variables on the intentional homicide rate, holding other variables constant. These coefficients indicate the magnitude and direction of the relationships between the independent variables and the dependent variable.

The interplay between these independent variables and the dependent variable, intentional homicide rates, forms the cornerstone of the analysis. By employing advanced statistical techniques such as regression analysis, and diagnostic tests, the study aims to unravel the complex dynamics and causal pathways that link socioeconomic factors to violent crime outcomes across European countries. Through robust empirical analysis and theoretical insights, the research seeks to inform evidence-based policymaking, crime prevention strategies, and societal interventions aimed at fostering safer and more resilient communities in Europe.

4. Results

The dataset for Intentional Homicides comprised 177 observations, with a mean intentional homicide rate of approximately 1.239 per 100,000 people. The standard deviation was approximately 1.241, indicating variability in homicide rates across the sampled countries. The range of observed values spanned from 0 to 7.923. For GDP per capita the dataset contained 180 observations, with a mean GDP per capita of

\$41,393.33 USD. The standard deviation was approximately \$25,101.97 USD, reflecting variability in economic prosperity among the sampled countries. GDP per capita ranged from \$11,526 USD to \$123,679 USD. In Unemployment Rate there were 180 observations, with a mean rate of approximately 9.63%. The standard deviation was approximately 5.35%, indicating variability in employment levels across the sampled countries. Unemployment rates ranged from 3.3% to 27.5% (Table 2).

Table 2. Summary Statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---------------|-----|----------|-----------|----------|----------|
| | | | | | |
| inhm | 177 | 1.238846 | 1.241144 | 0 | 7.923335 |
| gdppc | 180 | 41393.33 | 25101.97 | 11526 | 123679 |
| unem | 180 | 0.096256 | 0.053457 | 0.033 | 0.275 |
| cardpm | 170 | 1847.048 | 2416.565 | 8.56 | 11947.24 |
| cgdb | 84 | 91.79174 | 47.51091 | 30.74369 | 253.1199 |
| intpur | 163 | 28.55288 | 18.088 | 1.22 | 70.29 |
| banks | 180 | 36.00668 | 20.40093 | 6.98342 | 99.39651 |

Source: Provided by Author (Calculated in STATA 14.2)

For Card Payment Number at POS Terminals the dataset comprised 170 observations, with a mean number of approximately 1,847.05 million transactions. The standard deviation was approximately 2,416.57 million transactions, indicating variability in electronic payment usage. The range of observed values spanned from 8.56 million to 11,947.24 million transactions, while for the Central Government Debt, Total % of GDP the dataset contained 84 observations, with a mean of approximately 91.79%. The standard deviation was approximately 47.51%, indicating variability in debt levels relative to GDP. Government debt as a percentage of GDP ranged from 30.74% to 253.12%.

Furthermore, in the Internet Purchases by Individuals variable there were 163 observations, with a mean value of approximately 28.55 units. The standard deviation was approximately 18.09, indicating variability in online purchasing behavior among the sampled countries. Internet purchases ranged from 1.22 to 70.29 units. Additionally, the dataset for Commercial Bank Branches per 100,000 Adults comprised 180 observations, with a mean of approximately 36.01 branches per 100,000 adults. The standard deviation was approximately 20.40, indicating variability in the availability of banking services across the sampled countries. The number of commercial bank branches ranged from 6.98 to 99.40 per 100,000 adults.

The percentiles represent the values below which a given percentage of observations fall. For instance, the 50th percentile (median) is approximately 0.893, indicating that half of the observations have a value below this threshold. The mean value of "INHM" is approximately 1.239, which provides an average estimate of

intentional homicide rates across the sampled countries. Additionally, the standard deviation measures the dispersion of data points around the mean. In this case, it is approximately 1.241, indicating variability in intentional homicide rates among the countries. The variance quantifies the spread of data points. It is calculated as the square of the standard deviation and is approximately 1.540 (Table 3).

Table 3. Detailed Summary Statistics for the Dependent Variable

| Percentiles | Smallest | | | |
|-------------|----------------|------------------|--------------------|----------|
| 1% | 0.1841398 | 0 | | |
| 5% | 0.53074 | 0.1841398 | | |
| 10% | 0.6180974 | 0.3354115 | Obs | 177 |
| 25% | 0.725489 | 0.4758887 | Sum of Wgt. | 177 |
| 50% | 0.8925357 | Mean | 1.238846 | |
| | Largest | Std. Dev. | 1.241144 | |
| 75% | 1.171093 | 6.594108 | | |
| 90% | 1.668415 | 6.806896 | Variance | 1.540438 |
| 95% | 3.581222 | 6.976703 | Skewness | 3.621492 |
| 99% | 6.976703 | 7.923335 | Kurtosis | 16.17383 |

Source: Provided by Author (Calculated in STATA 14.2)

Furthermore, Skewness measures the asymmetry of the data distribution. A positive skewness value (3.621) indicates that the distribution is skewed to the right, with a longer tail on the higher end of the scale. This suggests that there may be outliers or extreme values contributing to the distribution's shape. Kurtosis measures the "tailedness" of the data distribution. A kurtosis value of 16.17383 indicates that the distribution has heavier tails and more outliers compared to a normal distribution.

Firstly, the negative correlation between intentional homicides and GDP per capita suggests a noteworthy pattern: countries with higher levels of economic prosperity tend to exhibit lower intentional homicide rates. This finding underscores the potential role of economic development in reducing violent crime and promoting social stability. Conversely, the positive but weak correlation between intentional homicides and the unemployment rate implies a subtle association between these variables. While causality cannot be inferred from correlation alone, this relationship suggests that unemployment may contribute, albeit modestly, to higher levels of violent crime within certain contexts (Table 4).

Table 4. Correlation Matrix

| | inhm | gdppc | unem | cardpm | cgdb | intpur | banks |
|--|------|-------|------|--------|------|--------|-------|
|--|------|-------|------|--------|------|--------|-------|

| | | | | | | | |
|---------------|----------|----------|----------|---------|----------|----------|---|
| inhm | 1 | | | | | | |
| gdppc | -0.3137* | 1 | | | | | |
| unem | 0.1095 | -0.3957* | 1 | | | | |
| cardpm | -0.1676* | -0.0545 | -0.0664 | 1 | | | |
| cgdb | -0.3803* | -0.2802* | 0.5267* | -0.0123 | 1 | | |
| intpur | -0.3602* | 0.6515* | -0.5621* | 0.0906 | -0.3296* | 1 | |
| banks | -0.2090* | 0.2517* | 0.2951* | -0.0306 | 0.0633 | -0.1928* | 1 |

Source: Provided by Author (Calculated in STATA 14.2)

Furthermore, the negative correlation between intentional homicides and the card payment number at POS terminals suggests a potential linkage between electronic payment methods and crime rates. While the correlation is weak, it hints at the possibility that advancements in digital payment technologies may influence criminal behavior, albeit in a nuanced manner. Similarly, the negative correlations between intentional homicides and central government debt, internet purchases by individuals, and the number of commercial bank branches underscore the multifaceted nature of socio-economic influences on violent crime. These correlations highlight the importance of considering broader economic and financial dynamics when addressing crime prevention strategies.

The multiple regression analysis results reveal compelling associations between intentional homicides and various socio-economic indicators across the sampled European countries. The statistical significance of the regression model is underscored by a substantial F-statistic ($F(6, 65) = 63.67, p < 0.0001$), indicating the collective explanatory power of the independent variables in elucidating the variance observed in intentional homicide rates (Table 5).

Table 5. Regression Analysis

| VARIABLES | inhm |
|---------------------|----------------------------|
| gdppc | -4.18e-05*** (8.25e-06) |
| unem | 5.186** (2.557) |
| cardpm | 5.40e-05* (2.97e-05) |
| cgdb | -0.0259*** (0.00236) |
| intpur | -0.0376*** (0.00635) |
| banks | -0.0500*** (0.00624) |
| Constant | 7.381*** (0.377) |
| Observations | 72 |
| R-squared | 0.855 |

Standard errors in parentheses

***** p<0.01, ** p<0.05, * p<0.1**

Source: Provided by Author (Calculated in STATA 14.2)

The regression model exhibits a commendable level of explanatory power, as evidenced by the substantial R-squared value of 0.8546. This implies that approximately 85.46% of the variability observed in intentional homicide rates across the sampled European countries can be accounted for by the combined effects of the independent variables included in the model. Such a high R-squared value suggests that the socio-economic indicators considered in the analysis capture a considerable portion of the variance in intentional homicide rates, underscoring their relevance in understanding and predicting violent crime patterns.

The Root Mean Square Error (RMSE) is a measure of the model's accuracy in predicting the dependent variable (intentional homicide rates) based on the independent variables included in the regression analysis. In this instance, the RMSE value is approximately 0.64796. The RMSE represents the average difference between the observed values of intentional homicide rates and the values predicted by the regression model. A lower RMSE indicates that the model's predictions are closer to the actual observed values, suggesting a higher level of predictive accuracy. In the context of this analysis, the RMSE value of 0.64796 indicates that, on average, the model's predictions of intentional homicide rates deviate by approximately 0.64796 per 100,000 people from the actual observed values. This level of error suggests that the model provides reasonably accurate predictions of intentional homicide rates based on the socio-economic indicators included in the analysis.

Notably, the negative coefficient of GDP per capita (-0.0000418, $p < 0.0001$) underscores a robust inverse relationship with intentional homicides. This suggests that for every unit increase in GDP per capita, intentional homicide rates are expected to decrease by approximately 0.0000418 per 100,000 people. Such findings resonate with existing literature on the socio-economic determinants of crime, highlighting the pivotal role of economic prosperity in fostering social stability and reducing violent behavior. Similarly, the negative coefficient of central government debt relative to GDP (-0.0258692, $p < 0.0001$) signifies a noteworthy inverse association with intentional homicides.

Specifically, a one-unit increase in central government debt as a percentage of GDP corresponds to a decrease of approximately 0.0258692 intentional homicides per 100,000 people. This unexpected relationship warrants further exploration to delineate the underlying mechanisms driving this phenomenon. Conversely, the positive coefficient of the unemployment rate (5.185659, $p = 0.047$) suggests a concerning positive relationship with intentional homicides. This implies that for every one-percentage point increase in the unemployment rate, intentional homicide rates are expected to increase by approximately 5.185659 per 100,000 people. Such findings underscore the socio-economic challenges associated with unemployment and its potential ramifications on societal well-being and public safety.

Furthermore, the significant negative coefficients of internet purchases by individuals (intpur) (-0.0375932, $p < 0.0001$) and the number of commercial bank

branches (-0.0500289, $p < 0.0001$) highlight intriguing associations with intentional homicides. These findings suggest that higher levels of internet purchases and a greater presence of commercial bank branches are associated with lower intentional homicide rates, pointing towards the potential role of financial inclusion and technological advancements in mitigating violent crime. However, the marginal significance of the coefficient for card payments at POS terminals (0.000054, $p = 0.074$) warrants cautious interpretation, indicating a tentative positive association with intentional homicides. Further research is warranted to elucidate the nuanced relationship between card payments and violent crime, considering potential confounding factors and contextual influences.

The analysis of the Variance Inflation Factor (VIF) indicates that multicollinearity among the predictor variables in the regression model is not a significant concern. The VIF values for all predictor variables are well below the commonly accepted threshold of 10, with the mean VIF at 2.90. This suggests that the predictor variables are not highly correlated with each other, indicating that each variable contributes unique information to the regression model without redundancy (Table 6).

Table 6. Variance Inflation Factor Test

| Variable | VIF | 1/VIF |
|-----------------|------|----------|
| unem | 4.87 | 0.205197 |
| intpur | 3.31 | 0.302393 |
| gdppc | 2.93 | 0.341758 |
| banks | 2.92 | 0.342625 |
| cgdb | 1.97 | 0.507406 |
| cardpm | 1.43 | 0.701135 |
| Mean VIF | 2.9 | |

Source: Provided by Author (Calculated in STATA 14.2)

Low VIF values are favorable as they imply that the estimates of the regression coefficients are stable and reliable. In this case, the VIF values indicate that the regression estimates are unlikely to be inflated due to multicollinearity, enhancing the interpretability and robustness of the regression results. Overall, the results suggest that multicollinearity is not a significant issue in the regression analysis, providing confidence in the validity of the estimated coefficients and their interpretations.

The results of the skewness and kurtosis tests for normality indicate significant departures from normal distribution for all variables in the dataset. This suggests that the distributions of these variables are not symmetric and exhibit heavy tails, indicating potential non-normality (Table 7).

Table 7. Normality Test

| Variable | Obs | Pr(Skewness) | Pr(Kurtosis) | adj chi2(2) | Prob>chi2 |
|----------|-----|--------------|--------------|-------------|-----------|
| inhm | 177 | 0 | 0 | . | 0 |
| gdppc | 180 | 0 | 0.0003 | 41.56 | 0 |
| unem | 180 | 0 | 0.0028 | 36.3 | 0 |
| cardpm | 170 | 0 | 0 | 66.1 | 0 |
| cgdb | 84 | 0.0001 | 0.0378 | 16.21 | 0.0003 |
| intpur | 163 | 0.0392 | 0.0003 | 14.24 | 0.0008 |
| banks | 180 | 0 | 0.1347 | 21.16 | 0 |

Source: Provided by Author (Calculated in STATA 14.2)

Specifically, for each variable, the p-values associated with both skewness and kurtosis tests are extremely low, indicating strong evidence against the null hypothesis of normality. For instance, consider the variable "inhm" representing intentional homicides. The p-values for both skewness and kurtosis tests are 0.0000, indicating a high level of statistical significance. Similarly, other variables such as "gdppc" (GDP per capita), "unem" (unemployment rate), "cardpm" (card payment number at POS terminals), "cgdb" (central government debt), "intpur" (internet purchases by individuals), and "banks" (commercial bank branches) exhibit similarly low p-values, implying significant departures from normality (Figure 1).

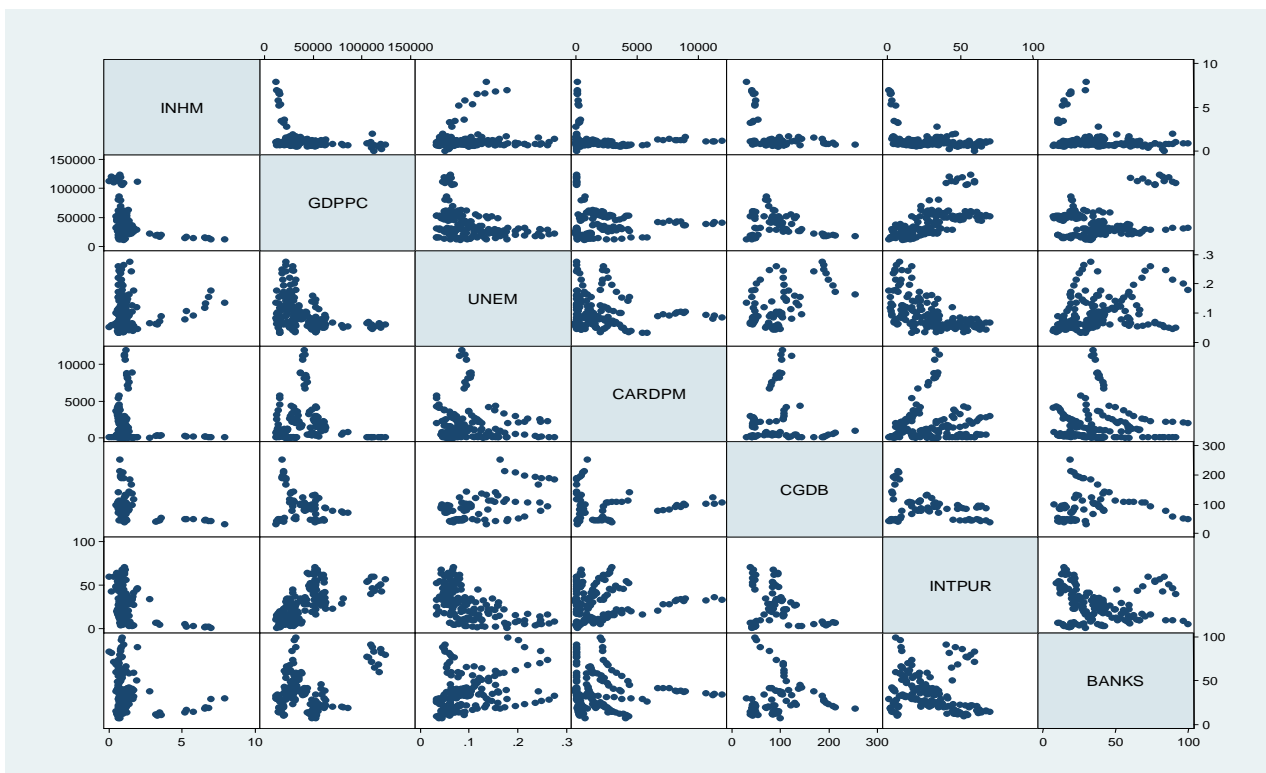


Figure 1. Scatter Plot Matrix

5. Discussion

The findings of this study reveal significant associations between various socio-economic indicators and intentional homicide rates across the sampled European countries. Notably, economic prosperity, as measured by GDP per capita, emerged as a robust predictor of lower homicide rates, corroborating existing literature highlighting the role of economic development in promoting social stability and reducing violent crime. The negative coefficient of GDP per capita in the regression analysis underscores the importance of addressing socio-economic disparities and fostering inclusive economic growth to mitigate the risk of homicides within communities.

Conversely, the positive relationship between unemployment rates and homicide rates suggests that higher levels of unemployment are associated with increased violent crime, albeit to a modest extent. This finding underscores the socio-economic challenges posed by unemployment and the potential ramifications for public safety and societal well-being. Policymakers are urged to prioritize strategies aimed at creating job opportunities and addressing structural inequalities to alleviate the socio-economic pressures driving violent behavior.

The unexpected inverse relationship between central government debt relative to GDP and intentional homicides warrants further examination. While the negative coefficient suggests that higher levels of government debt are associated with lower homicide rates, the underlying mechanisms driving this phenomenon remain unclear.

Future research should explore potential mediators or confounding factors that may elucidate the nuanced relationship between government debt and violent crime. The significant negative coefficients of internet purchases by individuals and the number of commercial bank branches underscore the potential impact of technological advancements and financial inclusion in mitigating violent crime.

These findings suggest that greater access to digital payment methods and banking services may contribute to reducing homicide rates by fostering economic opportunities and social cohesion. Policymakers and stakeholders are encouraged to leverage technology and promote financial inclusion initiatives as part of holistic crime prevention strategies.

The multifaceted nature of homicide dynamics is evident from the diverse array of socio-economic factors influencing violent crime rates. While economic prosperity and employment opportunities play significant roles, other factors such as government policies, social inequalities, and cultural norms also shape the incidence of intentional homicides. Addressing the root causes of violent behavior requires a comprehensive approach that addresses socio-economic disparities, invests in community-based interventions, and promotes social cohesion and resilience.

It is essential to acknowledge the limitations of this study, including the reliance on secondary data sources and the potential for omitted variable bias. Future research should incorporate longitudinal data and employ more sophisticated econometric techniques to account for potential endogeneity and omitted variable bias.

Additionally, qualitative research methods such as interviews and case studies could provide deeper insights into the contextual factors influencing homicide rates across different socio-economic contexts.

In conclusion, this study contributes to the growing body of literature on the socio-economic determinants of intentional homicides by providing empirical evidence of the complex interplay between economic conditions and violent crime.

The findings underscore the importance of addressing socio-economic disparities, promoting inclusive economic growth, and leveraging technological advancements to foster safer and more resilient communities. By understanding the underlying drivers of homicide rates, policymakers and stakeholders can develop evidence-based interventions aimed at reducing violent crime and promoting social cohesion and public safety.

6. Conclusions

The study revealed a robust inverse relationship between GDPs per capita and intentional homicides, indicating that higher levels of economic prosperity are associated with lower homicide rates. This suggests that economic development plays a crucial role in reducing violent behavior within communities.

Conversely, the analysis uncovered a concerning positive relationship between the unemployment rate and intentional homicides, implying that higher unemployment levels may contribute to increased homicide rates. This highlights the socio-economic challenges associated with unemployment and its potential impact on public safety.

Moreover, the study found intriguing associations between technological advancements, financial inclusion, and homicide rates. Higher levels of internet purchases by individuals and a greater presence of commercial bank branches were associated with lower intentional homicide rates, suggesting the potential role of financial access and technological innovations in mitigating homicides.

However, the analysis also identified unexpected findings, such as the inverse association between central government debt relative to GDP and intentional homicides. While further research is needed to understand the underlying mechanisms driving this relationship, the findings underscore the complexity of socio-economic influences on homicides and the need for nuanced policy interventions.

Overall, the study contributes into the relationship between socio-economic factors and homicide rates across European countries. The findings emphasize the importance of addressing socio-economic disparities and promoting economic development to reduce homicides and enhance public safety.

The research findings hold both theoretical and practical significance. The study contributes to theories on the socio-economic determinants of violent crime by identifying robust associations between economic indicators and intentional homicides.

These findings provide empirical support for existing theories and stimulate further theoretical inquiry into crime causation. From a practical standpoint, the research offers valuable insights for policymakers and practitioners. By demonstrating the significant impact of economic prosperity on homicide rates, the study underscores

the importance of prioritizing policies aimed at fostering economic development and reducing socio-economic inequalities.

Additionally, the identification of potential interventions, such as leveraging technological advancements and enhancing financial inclusion, highlights actionable strategies for addressing violent crime at the community level. Overall, the research provides evidence-based guidance for tailoring interventions to specific socio-economic contexts, thereby enhancing public safety and fostering resilient societies.

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