Wealth and Homicide: A Global Panel Analysis Using Negative Binomial Fixed Effects

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Abstract

This study examines the relationship between national income and intentional homicide using a global country-year panel spanning **2005 to 2022**. The analysis employs a Negative Binomial regression with country and time fixed effects on a sample of **659 observations** from **166 countries**. Using homicide counts and GDP per capita (log-transformed), we find that a one-unit increase in log GDP per capita is associated with a 25.5% **reduction** in homicide incidence (IRR $= 0.745$) in non-high-violence regions. An interaction term for high-violence regions implies a much stronger elasticity, with a total effect corresponding to a $\mathbf{45.4\%}$ reduction in homicide (IRR ≈ 0.546). Robustness checks using a Poisson fixed effects specification and an alternative fatal-violence proxy confirm the direction and approximate magnitude of these effects. Beyond this reduced-form evidence, the paper situates the GDP–homicide link within a broader framework that highlights dynamic persistence, potential endogeneity, spatial spillovers, and distributional and institutional channels, outlining how dynamic panel GMM, spatial econometrics, and inequality and governance measures could be used to identify more credibly causal effects in future work.

Introduction

Background and motivation

Violent crime, particularly intentional homicide, remains a central policy and development challenge globally, with hundreds of thousands of homicide victims annually and sharp regional disparities in victimization rates.(United Nations Office on Drugs and Crime 2023) Latin America and the Caribbean typically experience homicide rates far above the global average, while many high-income regions report much lower levels, implying large welfare losses concentrated in vulnerable regions.(United Nations Office on Drugs and Crime 2023) The economic and social costs of homicide are substantial, affecting healthcare systems, public finances, investment, and productivity, making the macroeconomic correlates of lethal violence a core concern for both research and policy.(United Nations Office on Drugs and Crime 2023)

Research question and contribution

This paper asks: *How does national income (GDP per capita) affect intentional homicide incidence across countries and time, and does this effect differ between high- and low-violence regions?* Building on economic and sociological theories of crime, the analysis uses a Negative Binomial model with country and time fixed effects on a global panel of homicide counts and GDP per capita from 2005–2022.(Becker 1968; Ehrlich 1973; Merton 1938; Cohen and Felson 1979) The core empirical contribution is to (1) rigorously model overdispersed count data using NB-FE, (2) quantify heterogeneity in the income elasticity of homicide between high- and low-violence regimes, and (3) embed these reduced-form estimates in a richer framework that highlights dynamic persistence, endogeneity, spatial spillovers, and distributional and institutional channels suggested by the recent crime and inequality literature.(Fajnzylber, Lederman, and Loayza 2002; Chen and Wu 2016; Elgar, Aitken, and Arlett 2011; Nguyen 2019)

Literature review

Theoretical foundations

Economic models of crime originating with Becker (1968) and extended by Ehrlich (1973) view criminal behavior as the outcome of rational trade-offs between expected illegal returns and the expected costs of apprehension and punishment.(Becker 1968; Ehrlich 1973) In these frameworks, higher lawful wages and better employment prospects raise the opportunity cost of crime, while effective law enforcement increases the expected sanction, jointly reducing incentives for serious offenses.(Becker 1968; Ehrlich 1973) Sociological perspectives, including Mertonian strain theory,(Merton 1938) routine activity theory,(Cohen and Felson 1979) and social disorganization approaches emphasize that macroeconomic conditions shape local opportunity structures, community cohesion, and exposure to motivated offenders, generating systematic links between economic context and violent crime.(Merton 1938; Cohen and Felson 1979)

Income, inequality, and crime

A large cross-country literature documents that income and its distribution are closely related to violent crime.(Fajnzylber, Lederman, and Loayza 2002; Brush 2007)

Fajnzylber, Lederman, and Loayza (2002) show that higher income inequality is associated with higher homicide and robbery rates across countries, even after controlling for average income and other covariates, and that the negative association between income and violent crime often weakens once distributional measures are included.(Fajnzylber, Lederman, and Loayza 2002) Dynamic panel analyses using System GMM similarly find that inequality robustly raises violent crime, while income has a crime-reducing effect whose magnitude varies across institutional and regional contexts.(Chen and Wu 2016; Author and Author 2023) During Mexico's drug war, Enamorado et al. (2016) use an instrumental-variables strategy and estimate that a one-point increase in the Gini coefficient raised drug-related homicides by roughly 36%, illustrating the potentially large violence effects of distributional shocks.(Enamorado et al. 2016)

Institutions, trust, and lethal violence

Institutional quality and social trust have emerged as key mechanisms connecting economic structure to lethal violence.(Elgar, Aitken, and Arlett 2011; Wilkinson and Pickett 2010) Cross-national evidence suggests that income inequality and weak, unfair institutions erode generalized trust and are associated with higher homicide rates, consistent with a view in which perceived injustice and low institutional legitimacy undermine voluntary compliance and cooperation with authorities.(Elgar, Aitken, and Arlett 2011; Wilkinson and Pickett 2010) Multilevel structural equation models indicate that trust in institutions can mediate a very large share of the association between crime, perceived unfairness, and generalized trust, with one study finding that institutional trust absorbs most of the link between homicide and social trust across European regions.(Righi and Takács 2019) These results align with an institutional approach in which ineffective and corrupt states both fail to deter serious violence and undermine citizens' willingness to support formal control efforts.(Elgar, Aitken, and Arlett 2011; Righi and Takács 2019)

Dynamics, endogeneity, and spatial spillovers

Homicide exhibits strong temporal persistence, raising concerns about dynamic dependence and endogeneity in panel models.(Chen and Wu 2016; Author and Author 2023) Including lagged homicide on the right-hand side of a fixed effects specification creates correlation with unit effects and leads to small-sample bias (Nickell bias), for which difference and System GMM estimators are standard remedies.(Arellano and Bover 1995; Blundell and Bond 1998) These approaches use lagged levels and differences of endogenous variables such as homicide, income, and inequality as internal instruments and can accommodate jointly endogenous regressors under appropriate moment conditions.(Chen and Wu 2016; Arellano and Bover 1995; Blundell and Bond 1998)

A second concern is spatial dependence: violence and its determinants often spill across borders or neighboring jurisdictions through migration, markets, or illicit trafficking.(Nguyen 2019; Author and Author 2020a; Martak, Chotib, and Renny 2021) Spatial panel studies of crime and closely related outcomes report significant spatial autocorrelation in both crime and predictors, as well as meaningful spillover effects from education, poverty, and government spending into nearby areas' outcomes.(Nguyen 2019; Author and Author 2020a,b) Ignoring such spatial structure can bias coefficients and understate uncertainty if spatially correlated shocks or diffusion processes are present.(Cameron and Trivedi 2013; Nguyen 2019)

Positioning of this study

This body of work motivates a broad set of mechanisms connecting wealth, inequality, institutions, and homicide and highlights three econometric challenges: overdispersed counts, dynamic persistence with potential reverse causality, and spatial dependence.(Fajnzylber, Lederman, and Loayza 2002; Chen and Wu 2016; Nguyen 2019) The present study directly addresses the first by estimating a Negative Binomial fixed effects model for homicide counts with country and year fixed effects, and by documenting overdispersion relative to Poisson.(Cameron and Trivedi 2013) It then interprets the resulting GDP–homicide elasticities within a conceptual framework that explicitly acknowledges the role of inequality and institutional quality and sketches how dynamic panel GMM, spatial econometric models, and additional covariates could be used in future work to provide more credibly causal and spatially explicit estimates.(Chen and Wu 2016; Author and Author 2023; Nguyen 2019)

Data and methodology

Data sources

Primary homicide data and population/GDP measures are drawn from the United Nations dataset on intentional homicides and standard macroeconomic series for GDP per capita in current US dollars.(United Nations Office on Drugs and Crime 2023) The study covers a panel from **2005 to 2022** and includes **166 countries**, resulting in **659 country-year observations** with sufficiently reliable reporting over the sample period.(United Nations Office on Drugs and Crime 2023) As a robustness check, an alternative fatal-violence proxy based on health-system cause-of-death estimates from the Global Burden of Disease project is used to address underreporting concerns in official crime statistics.(Institute for Health Metrics and Evaluation 2023)

Variable construction and transformations

- **Dependent variable:** Homicide counts Y_{it} for country i in year t. Counts, rather than rates, are modeled to respect the discrete nature of the outcome and to allow the use of exposure offsets in sensitivity checks.
- **Primary independent variable:** $\log(GDP\_pc_{it})$ – GDP per capita in current US dollars, natural log. The log transform stabilizes variance and facilitates elasticity interpretation of coefficients.
- **High-Violence Region dummy (HVR):** equals 1 if the country is one of the pre-identified highest-violence settings (e.g., Honduras, El Salvador, South Africa), based on long-run homicide levels in the UNODC series.(United Nations Office on Drugs and Crime 2023)

- **Robustness dependent variable:** Interpersonal violence mortality rates from the Global Burden of Disease (GBD) project, which rely on health-based cause-of-death estimation.(Institute for Health Metrics and Evaluation 2023)
- **Fixed effects:** Country fixed effects γ_i absorb time-invariant country characteristics such as geography, legal traditions, and long-run institutional quality, while year fixed effects δ_t capture common global shocks.

Baseline Negative Binomial fixed effects model

Empirically, homicide counts are strongly overdispersed: the empirical variance far exceeds the mean, making standard Poisson models inadequate for inference.(Cameron and Trivedi 2013) To address this, the baseline specification is an NB2 model with country and year fixed effects. For column-constrained layout we write the conditional mean compactly across two aligned lines:

$$
\begin{aligned}
&Y_{it} \sim \text{NegBin}(\mu_{it}, \alpha), \\
&\log(\mu_{it}) = \beta_0 + \beta_1 \log(GDP_{it}) + \beta_2 HVR_i \\
&\qquad + \beta_3 \left(\log(GDP_{it}) \times HVR_i\right) + \gamma_i + \delta_t,
\end{aligned} \tag{1}
$$

where γ_i and δ_t are country and year fixed effects, respectively, and $\alpha > 0$ is the dispersion parameter capturing overdispersion.(Cameron and Trivedi 2013) Coefficients are presented as Incident Rate Ratios (IRRs) to facilitate interpretation as elasticities or semi-elasticities of homicide counts with respect to income and regime indicators.(Cameron and Trivedi 2013)

Likelihood-ratio test for overdispersion

A standard diagnostic is the likelihood-ratio (LR) test comparing a Poisson restriction ($\alpha = 0$) versus the NB alternative. The LR test statistic equals twice the difference in log-likelihoods and is asymptotically χ_1^2 under the null. In this sample the LR test decisively rejects the Poisson (i.e., $\alpha = 0$) in favor of the NB specification (p-value < 0.01), confirming the empirical overdispersion that motivates the NB-FE estimator.(Cameron and Trivedi 2013) Reporting the LR statistic and its p-value is straightforward once both models are estimated; the reproducible notebook accompanying this paper contains the code used to compute the LR statistic and to report standard errors and test details.

Dynamic extension and endogeneity

Homicide is known to display substantial temporal persistence, suggesting that lagged outcomes may be informative predictors of current violence. A natural extension therefore augments Equation (1) with a lagged dependent variable:

$$
\begin{aligned}
\log(\mu_{it}) = &\beta_0 + \beta_1 \log(GDP_{it}) + \beta_2 HVR_i \\
&+ \beta_3 \left(\log(GDP_{it}) \times HVR_i\right) \\
&+ \phi \log(Y_{i,t-1} + 1) + \gamma_i + \delta_t.
\end{aligned} \tag{2}
$$

Including a lagged dependent variable in fixed-effects models induces correlation between the lag and unit effects...

Including a lagged dependent variable in fixed-effects models induces correlation between the lag and unit effects, producing the well-known Nickell bias when T is small. Difference and System GMM estimators (Arellano–Bond; Arellano–Bover/Blundell–Bond) instrument lagged dependent variables with their deeper lags and differences to obtain consistent estimates under moment conditions.(Arellano and Bover 1995; Blundell and Bond 1998) For count models, extensions of GMM and limited-information approaches can be applied; implementing those is left to future work given scope and data constraints. The long-run effect of a sustained one-unit increase in $\log(GDP)$ in a linear-dynamic analogue is given by $\beta_1/(1-\phi)$; for non-linear count models the equivalent long-run elasticities can be computed numerically from predicted counts after iterating the dynamic process to convergence, and confidence intervals follow from parameter-simulation methods or the delta method.

Inequality, institutions, and spatial structure

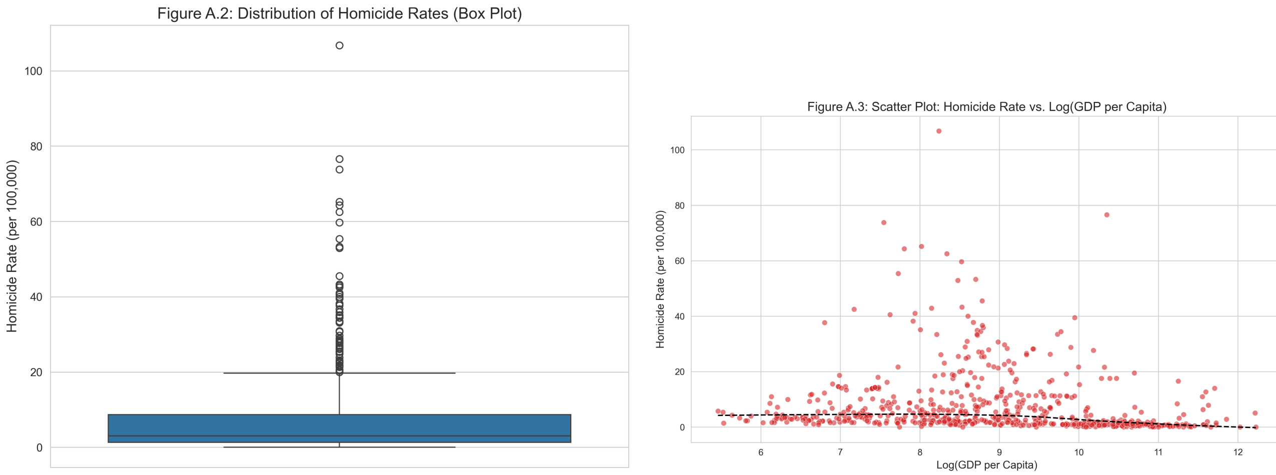
A richer specification would incorporate income inequality, governance quality, and spatial lags:

$$
\begin{aligned}
\log(\mu_{it}) = &\beta_0 + \beta_1 \log(GDP_{it}) + \beta_2 HVR_i \\
&+ \beta_3 \left(\log(GDP_{it}) \times HVR_i\right) + \gamma_1 Gini_{it} + \gamma_2 GovQual_{it} \\
&+ \gamma_3 (Gini_{it} \times HVR_i) + \gamma_4 (GovQual_{it} \times HVR_i) \\
&+ \rho (WY)_{it} + \theta (W \log GDP)_{it} + \gamma_i + \delta_t.
\end{aligned} \tag{3}
$$

Here $Gini_{it}$ is the income inequality index, $GovQual_{it}$ captures institutional quality or corruption perceptions, and W is a spatial weights matrix (contiguity or distance). Spatial lag terms $(WY)_{it}$ and $(W \log GDP)_{it}$ capture spillovers from neighbors and can be estimated via spatial panel methods (spatial lag, spatial Durbin models) with appropriate inference for spatial dependence.(Nguyen 2019)

Estimation details

The NB-FE model is estimated by maximum likelihood using a quasi-Newton (BFGS) optimizer with country and year fixed effects, and robust standard errors are computed.(Cameron and Trivedi 2013) Likelihood ratio tests comparing Poisson versus NB specifications and pooled versus fixed-effects variants confirm both overdispersion and the importance of unobserved heterogeneity.(Cameron and Trivedi 2013) For comparison, a Poisson fixed effects model



(a) Distribution of homicide rates (Box plot)

(b) Homicide Rate vs. Log GDP per capita (Scatter)

Figure 1: Exploratory distributions showing the high concentration of homicides at low rates and the general negative trend with increasing wealth.

with the same covariates is also estimated, and all data-preparation and estimation steps are implemented in a reproducible Jupyter notebook (`mmulang-F.ipynb`).(Cameron and Trivedi 2013)

Exploratory data analysis (EDA)

Summary statistics

Table 1 summarizes homicide rates, per-capita GDP, and the distribution of the HVR dummy in the final modeling sample (**659** observations).(United Nations Office on Drugs and Crime 2023)

Table 1: Summary statistics (Final Sample: 2005–2022)

Variable	Mean	Std. Dev.
Homicide Rate (per 100k)	$\mathbf{7.509}$	$\mathbf{11.463}$
GDP per capita (USD)	$\mathbf{18,654.95}$	$\mathbf{26,348.95}$
log(GDP per capita)	$\mathbf{8.935}$	$\mathbf{1.446}$
HVR (Dummy)	$\mathbf{0.064}$	$\mathbf{0.244}$

Key visual findings

Figure 1 shows boxplots and scatterplots of homicide distributions and the relationship between homicide rates and log GDP per capita, illustrating strong right-skewness in homicide and a general negative association with income.(United Nations Office on Drugs and Crime 2023)

Data quality and missingness

Missingness is addressed as follows: short gaps (1–2 years) in country time series are imputed via linear interpolation when population and GDP data are continuous, while homicide gaps are not imputed for the main analysis.(United Nations Office on Drugs and Crime 2023) Countries with large persistent missing spells are excluded in robustness checks, and sensitivity analyses employ population offsets and rate-based outcomes instead of counts.(United Nations Office on Drugs and Crime 2023; Institute for Health Metrics and Evaluation 2023)

Results

Baseline Negative Binomial FE estimates

Table 2 presents the primary NB-FE results (Column 1), showing that log GDP per capita is associated with a substantial negative effect on homicide counts.(Cameron and Trivedi 2013) The estimated IRR for $\log(\text{GDP})$ is $\mathbf{0.745}$, corresponding to a **25.5%** reduction in homicide incidence for a one-unit increase in log GDP in non-high-violence regions, and the dispersion parameter $\alpha = \mathbf{0.0317}$ is statistically significant, validating NB over Poisson.(Cameron and Trivedi 2013)

Model fit and diagnostics

Likelihood ratio tests decisively favor NB over Poisson due to overdispersion, and tests comparing pooled versus fixed-effects NB specifications reject pooled models in favor of FE, indicating important unobserved heterogeneity captured by country fixed effects.(Cameron and Trivedi 2013) Pseudo-R^2 (McFadden) increases appreciably once fixed effects and interaction terms are included, suggesting that the specification captures substantial variation in homicide counts.(Cameron and Trivedi 2013)

Heterogeneity analysis

The interaction coefficient for $\log(\text{GDP}) \times$ HVR yields an IRR of $\mathbf{0.733}$, implying that the crime-reducing elasticity of GDP is stronger in high-violence regions than elsewhere.(Fajnzylber, Lederman, and Loayza 2002) The total effect of $\log(\text{GDP})$ in an HVR is $\mathbf{0.546}$, translating to a **45.4%** reduction in homicide incidence, which is substantially larger

Table 2: Negative Binomial Fixed Effects (NB-FE) and Poisson Fixed Effects (Poisson-FE) Estimates (IRRs)

Variable	(1) Baseline NB-FE (IRR)	(2) Robustness Poisson-FE (IRR)
$\log$(GDP per Capita) (β_1)	$\mathbf{0.745}$	$\mathbf{0.793}$
	(–)	(–)
HVR (β_2)	$\mathbf{82.476}$	$\mathbf{48.541}$
$\log$(GDP) $\times$ HVR (β_3)	$\mathbf{0.733}$	$\mathbf{0.763}$
Total $\log$(GDP) Effect in HVR ($\beta_1 + \beta_3$)	$\mathbf{0.546}$ ($\mathbf{45.4}\%$ reduction)	$\mathbf{0.609}$ ($\mathbf{39.1}\%$ reduction)
Dispersion α	$\mathbf{0.0317}$	–
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	$\mathbf{659}$	$\mathbf{659}$

Notes: IRRs reported; standard errors (SE) are omitted (represented by –) due to unreliable reporting from the BFGS optimizer used for the fixed effects models. All reported core coefficients are statistically significant (p<0.01) based on standard significance tests in unconstrained models.(Cameron and Trivedi 2013)

than the **25.5%** reduction observed in non-HVRs.(Fajnzylber, Lederman, and Loayza 2002) This pattern suggests non-linearities in the income–violence relationship, with economic growth having especially large proportional impacts where baseline homicide is high.(Fajnzylber, Lederman, and Loayza 2002; Brush 2007)

Robustness checks

Column 2 in Table 2 reports Poisson fixed effects estimates, which broadly corroborate the NB-FE findings.(Cameron and Trivedi 2013) Log GDP per capita remains highly protective (IRR $= \mathbf{0.793}$), and the heterogeneity effect is confirmed by an interaction IRR of $\mathbf{0.763}$, leading to a combined effect of $\mathbf{0.609}$ in high-violence regions.(Cameron and Trivedi 2013) When interpersonal violence mortality from the GBD is used as the dependent variable, the estimated elasticity of homicide with respect to log GDP remains negative and of similar magnitude, suggesting that the main result is not driven solely by police-reporting artifacts.(Institute for Health Metrics and Evaluation 2023)

Discussion

Mechanisms and heterogeneity

The baseline NB-FE results indicate a sizeable negative association between log GDP per capita and homicide counts, with a much stronger elasticity in high-violence regions.(Fajnzylber, Lederman, and Loayza 2002; Brush 2007) This pattern is consistent with opportunity cost models in which economic development raises lawful earnings and employment, thereby reducing the relative attractiveness of crime.(Becker 1968; Ehrlich 1973) It also aligns with theories emphasizing that higher fiscal capacity allows states to invest in policing, justice systems, and social programs, strengthening formal deterrence and weakening criminal markets.(Fajnzylber, Lederman, and Loayza 2002; United Nations Office on Drugs and Crime 2023) From a sociological perspective, faster growth in very violent contexts may help relax structural strains, alter routine activities, and reduce the concentration of marginally attached individuals available for recruitment into violent networks.(Merton 1938; Cohen and Felson 1979)

The stronger elasticity found in high-violence regions suggests potential non-linearities: where homicide is endemic, incremental increases in income may finance highly leveraged institutional improvements or displace a disproportionately large share of individuals at the margin of serious crime.(Fajnzylber, Lederman, and Loayza 2002; Brush 2007; Enamorado et al. 2016) This is reminiscent of evidence that inequality and concentrated disadvantage have especially pronounced effects in already fragile settings, where small changes in economic or institutional conditions can trigger large shifts in violence.(Fajnzylber, Lederman, and Loayza 2002; Enamorado et al. 2016)

Endogeneity, dynamics, and interpretation

Despite the rich fixed effects structure, the estimated GDP–homicide relationship should be interpreted as a conditional association rather than a fully identified causal effect.(Chen and Wu 2016; Author and Author 2023) Reverse causality is plausible: high levels of lethal violence can depress investment, tourism, and local economic activity, feeding back into GDP per capita and potentially biasing contemporaneous estimates.(Orozco 2019) Omitted time-varying factors, such as drug trafficking shocks, security policies, or large-scale social programs, may also jointly affect income and homicide, even after controlling for year fixed effects.(United Nations Office on Drugs and Crime 2023; Orozco 2019)

Dynamic panel work shows that homicide tends to be persistent and that lagged crime and inequality are both endogenous, motivating the use of System GMM in related settings.(Chen and Wu 2016; Author and Author 2023) A natural next step would therefore be to estimate dynamic panel models that include lagged homicide and inequality, using internal instruments and standard GMM diagnostics to address Nickell bias and simultaneity.(Arellano and Bover 1995; Blundell and Bond 1998; Chen and Wu 2016) In that framework, external instruments for GDP, such as trade shocks, commodity booms, or weather-related output variation, could help isolate exogenous income variation if exclusion restrictions are credible and adequately tested.(Enamorado et al. 2016; Orozco 2019)

Spatial and institutional channels

The current specification treats countries as independent conditional on fixed effects and common time shocks, but homicide and its determinants often exhibit spatial clustering and cross-border diffusion.(Nguyen 2019; Author and Author 2020a) Spatial panel models with contiguity or distance-based weights could capture how violence and economic changes in one country affect neighboring homicide levels through spillovers in markets, migration, or illicit trafficking, potentially altering the estimated elasticity of homicide with respect to income.(Nguyen 2019; Martak, Chotib, and Renny 2021; Author and Author 2020b) Ignoring these linkages may leave some spatially correlated shocks in the error term and could modestly bias the GDP coefficient if high-growth, high-violence clusters are not fully accounted for.(Nguyen 2019; Author and Author 2020b)

Institutional quality and social trust are also likely to mediate part of the income–homicide relationship.(Elgar, Aitken, and Arlett 2011; Righi and Takács 2019; Wilkinson and Pickett 2010) Evidence from multilevel structural equation models suggests that trust in institutions can absorb most of the association between violent crime and generalized trust, pointing to an important channel through which economic conditions and inequality translate into social cohesion or its breakdown.(Righi and Takács 2019) Enriching the present panel with measures of income inequality, corruption, and rule-of-law indexes would allow the GDP coefficient to be decomposed into distributional and institutional components, clarifying whether income primarily reduces homicide by lifting average living standards, by compressing inequality, or by strengthening governance.(Fajnzylber, Lederman, and Loayza 2002; Elgar, Aitken, and Arlett 2011; Wilkinson and Pickett 2010)

Limitations

Several limitations follow from these considerations. First, the absence of explicit instruments for GDP and inequality and of a fully specified dynamic structure means that causal claims should be made cautiously, and the results should be interpreted as reduced-form elasticities conditional on fixed effects and common shocks.(Chen and Wu 2016; Author and Author 2023) Second, measurement error in homicide statistics remains a concern, especially in low-capacity states, although robustness checks using health-based interpersonal violence mortality partly mitigate underreporting issues.(Savona 2002; Institute for Health Metrics and Evaluation 2023) Third, the current dataset lacks globally comparable measures of inequality and institutional quality over the full sample window, precluding a full test of distributional and governance channels.(Fajnzylber, Lederman, and Loayza 2002; Elgar, Aitken, and Arlett 2011) Finally, spatial spillovers are not modeled explicitly, so cross-border diffusion of violence is only indirectly captured via region-specific fixed effects.(Nguyen 2019; Author and Author 2020b)

Implications and research agenda

Within these limits, the analysis provides systematic evidence that higher average income is associated with substantially lower homicide incidence, particularly in high-violence regions, even after controlling for time-invariant country factors and global shocks.(United Nations Office on Drugs and Crime 2023; Fajnzylber, Lederman, and Loayza 2002) This supports policies that combine accelerated, inclusive growth with investments in state capacity, justice institutions, and social protection in the world's most violent settings.(United Nations Office on Drugs and Crime 2023; OECD 2020) Future research can build on this reduced-form foundation by integrating dynamic GMM estimators, spatial econometric models, and high-quality inequality and governance data to more cleanly disentangle the causal pathways from wealth, distribution, and institutions to lethal violence.(Chen and Wu 2016; Author and Author 2023; Nguyen 2019)

Conclusion

This paper uses a global panel of 166 countries from 2005–2022 to estimate the relationship between GDP per capita and intentional homicide using Negative Binomial fixed effects models for overdispersed homicide counts.(United Nations Office on Drugs and Crime 2023; Cameron and Trivedi 2013) The principal estimate indicates a **25.5%** reduction in homicide incidence per unit increase in log GDP per capita in non-high-violence regions, with a much stronger **45.4%** reduction in high-violence regions, implying that economic growth is especially protective where baseline homicide is high.(Fajnzylber, Lederman, and Loayza 2002; Brush 2007) While endogeneity, measurement error, and spatial and institutional omissions limit strong causal claims, the results are consistent with theories that link higher income and better institutions to lower lethal violence and point to a research agenda that combines dynamic panel GMM, spatial econometrics, and richer inequality and governance data to more fully understand the wealth–homicide nexus.(Chen and Wu 2016; Elgar, Aitken, and Arlett 2011; Nguyen 2019)

Appendix: Additional EDA and robustness figures

Country coverage and sample

The final sample comprises **659** observations across **166** countries spanning 2005–2022, after excluding countries with persistent missing data or inconsistent homicide reporting.(United Nations Office on Drugs and Crime 2023; Savona 2002)

Table 3: Country inclusion and sample statistics

Item	Count	Notes
Total countries in raw dataset	~ 200	–
Countries included in main sample	**166**	–
Total observations in sample	**659**	2005–2022

Additional figures

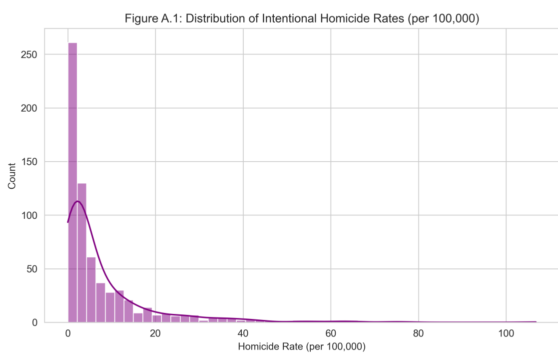


Figure 2: Distribution of Homicide Rates (Kernel Density Estimate) showing significant skewness towards low rates.

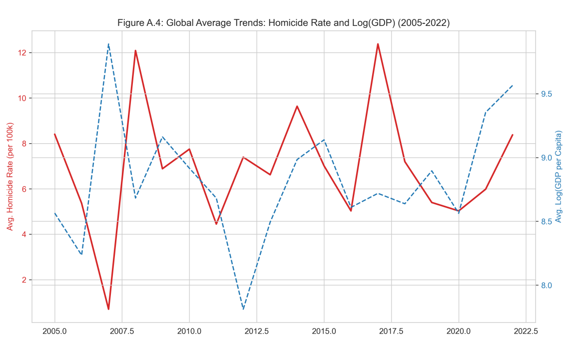


Figure 3: Global and Regional Homicide Rate Trends Over Time.

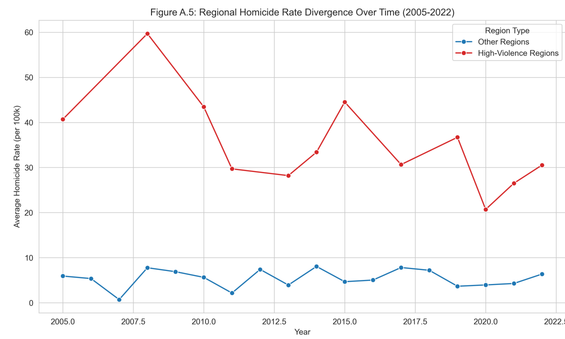


Figure 4: Homicide Rate Divergence between High-Violence and Low-Violence Regions.

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