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ORIGINAL RESEARCH

The Effect of Counting Rules on Cross-National Comparisons of Homicide

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Abstract
Cross-national crime comparisons often rely on police-recorded data. Most frequently, such comparisons focus on homicide, as it is expected to be the crime type least likely to go undetected. This study examines how different statistical counting rules and legal definitions employed across European countries affect the reliability of cross-national homicide comparisons. We analyze homicide data from 41 European countries (1998-2022) obtained from Eurostat and compare them with three sources of vital statistics from the World Health Organization and the Institute for Health Metrics and Evaluation. We assess correspondence rates between police-recorded homicides and vital records descriptively and graphically to identify cross-national and temporal variations. Additionally, we estimate within-between models to quantify the impact of statistical counting rules and legal definitions on cross-national homicide comparisons. Statistical counting rules and legal definitions for homicide vary widely across countries, shaping the likelihood of homicides being recorded in police statistics and compromising cross-national comparability. Countries that record data when crimes are first reported to the police have approximately 13-15% higher homicide counts than those using process-based or output-based systems. Additionally, broader definitions of homicide (e.g., those including terrorism-related deaths) are associated with higher recorded homicide. National counting rules and legal definitions substantially impact the reliability of cross-national homicide comparisons based on police data. This challenge is likely even greater in regions with less standardized counting rules and legal frameworks or for crime types more susceptible to under-recording, posing a significant challenge for comparative criminological research, international policy benchmarking, and resource allocation decisions.

Keywords Homicide measurement · Crime statistics · Eurostat · WHO · Vital statistics

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1 Introduction

The study of cross-national crime comparisons is as old as the first criminal justice statistics (de Candolle, 1832; Quételet, 1832) and remains one of the fastest-growing areas in criminology and criminal justice research (Eisner, 2023; Tonry, 2015; van Dijk et al., 2022). Researchers increasingly utilize open-source data to assess cross-national crime trends, explore associations between crime and a growing range of predictors such as population composition and economic conditions, and develop theories of crime to explain observed international differences (Bennett, 2004; LaFree, 2021). However, these types of cross-national comparative studies have faced considerable criticism for overlooking crime reporting propensities, crime recording practices, and other policy factors influencing the likelihood of crimes being reported and recorded (Aebi, 2010; Bennett & Lynch, 1990). For instance, von Hofer (2000) argued that Sweden's rate of recorded rapes, which was three times higher than that of other European countries, was likely due to the statistical rules and legal definitions used to record rape in Sweden rather than to substantive differences in crime.

Comparative criminologists have sought to minimize the limitations of official crime records by focusing on the most severe crime type, homicide. The focus of comparative criminology on homicide relies on the assumption that homicides are more likely to be recorded in crime statistics than other types of crime, therefore allowing for reliable cross-national crime comparisons. As LaFree (2021: 59) argues, the emphasis on homicide in international criminology "reflects the defensible assumption that […] homicides are more likely to be reported to police, police are more likely to record homicides […], and legal systems can be expected to spend more time and resources collecting information on homicides."

While it is difficult to dispute that homicides are more likely to be recorded by the police than other offenses, cross-national crime comparisons based on police records of homicides still rely on three additional assumptions that are commonly overlooked. These assume that the following factors remain constant across countries and over time: (i) the probability of homicide *detection*, (ii) the *statistical* rules and legal *definitions* used to count homicides, and (iii) the *recording* procedures (Killias & Rau, 2000). Evidence suggests that these assumptions are not met in practice (Aebi et al., 2024; Eurostat, 2024). Aebi (2008), for example, noted that Russia's remarkably high rate of completed intentional homicides was partly influenced by the fact that attempted homicides were potentially not excluded from these records.

A complex interplay of factors determines how crimes are recorded across countries. These factors can be categorized into four main types (Aebi, 2010; von Hofer, 2000). First, *statistical factors* pertain to the counting rules that determine whether and how known incidents are included in official records. For instance, while some countries register a crime the moment it is reported to the police—known as *input-based systems*—others document it only at later stages, such as during the investigation (*process-based systems* or *intermediate systems*) or upon its conclusion (*output-based systems*). As a result, two countries with identical crime rates may report different figures simply due to variations in when incidents are logged, with input-based systems recording higher numbers (Aebi, 2008). Second, *legal* *factors* pertain to differences in the laws governing criminal justice, including variations in legal procedures and offense definitions. For instance, some countries adopt narrow definitions of homicide, not counting terrorism-related deaths as homicides, while others include them; similarly, assisted euthanasia may or may not be legally defined as homicide, further complicating cross-national comparisons (Chon & Clifford, 2021; Harrendorf, 2012, 2018). Third, some *substantive factors* shape recorded crime rates independently of actual crime levels. For instance, differences in the public's willingness to report crimes to law enforcement significantly shape crime statistics (Estienne & Morabito, 2016), as does the likelihood of those reported crimes being formally recorded by the police (Boivin & Cordeau, 2011). Finally, *criminal policy factors* also play a critical role in shaping crime statistics. Shifts in law enforcement priorities, such as intensified crackdowns on drug-related offenses or increased attention to gender-based violence, can lead to fluctuations in recorded crime rates even if actual crime levels remain unchanged (Aebi, 2010).

International efforts to document cross-national differences in crime statistics began in the 1990 s with the work of the expert group responsible for the *European Sourcebook of Crime and Criminal Justice Statistics* (CoE, 1999). The methodology developed by this group for collecting *metadata*—data about data, specifically on how criminal statistics are compiled and reported across countries—relies on a structured set of questions addressing these factors, which are distributed to national correspondents in each country. This approach was later adopted in the 2000 s by the United Nations Office on Drugs and Crime (UNODC) and Eurostat (Eurostat, 2024). Since then, these metadata collection efforts have systematically documented variations in counting rules and recording practices across countries. However, they are not always taken into account when conducting cross-national comparisons.

In this study, we examine the association between *statistical* counting rules and *legal* definitions and the recording of homicides in Eurostat criminal justice records across 41 European countries over a period of 25 years (1998–2022). The core research question we address is: "How do statistical counting rules and legal definitions distort cross-national crime comparisons based on police statistics?" We use homicide as a case study due to its aforementioned high recording rates compared to other crime types. Throughout this paper, we use the terms "police statistics" and "police-recorded data" interchangeably to refer to homicide counts recorded by law enforcement agencies.

Specifically, we explore the reliability of homicide data reported by Eurostat, which compiles police statistics from European Union (EU) member states. To do so, we compare Eurostat records with vital statistics from the World Health Organization (WHO) Mortality Database, as well as with estimates from the WHO Global Health Estimates (GHE) and the Institute for Health Metrics and Evaluation (IHME). We use these sources of vital statistics to assess cross-national variation in the *recording* of homicides in police data. As part of our analysis, we assess the geographic and temporal variability in the differences observed across measures of homicide, and analyze the influence that documented counting rules have on those disparities. We conclude by providing recommendations for researchers and policymakers on how to enhance interpretations of cross-national crime comparisons.

2 Measuring Homicide Across Countries

2.1 Early Recognition of the Comparability Problem

Once the first official crime statistics became available in a few European countries in the nineteenth century, scholars began to compare them across nations. Early comparative criminologists included French-speaking authors such as Quételet (1832), followed by members of the Italian Positive School, notably Cesare Lombroso and Enrico Ferri, who also incorporated international comparisons into their work. Remarkably, some of these early thinkers already recognized the challenges inherent in comparing crime data across countries: de Candolle (1832) was among the first to acknowledge the "dark figure" of crime and to argue that international comparisons were nearly impossible due to variations in data recording practices, criticizing Quételet's methodology in the process. Despite these early warnings, the fundamental challenges de Candolle identified persist nearly two centuries later, as reflected in the ongoing debates on data comparability outlined in this paper.

Today, the use of police-recorded homicide statistics is widespread in policymaking and research. Politicians, policymakers and the media worldwide rely on trends in homicides recorded by criminal justice agencies as a primary indicator of crime trends over time and as a measure of the effectiveness of crime prevention and justice initiatives.

Internationally, the 'Global Study on Homicide', published by the United Nations Office on Drugs and Crime (UNODC, 2023) primarily relies on official data reported by national criminal justice agencies. From 1954 to 2006, Interpol released annual reports containing homicide figures reported by police agencies across approximately 100 countries. Additionally, the *European Institute for Crime Prevention and Control* (HEUNI), affiliated with the United Nations, and the *European Sourcebook of Crime and Criminal Justice Statistics* (henceforth, European Sourcebook), which is partially linked to the Council of Europe, compile and disseminate police-recorded homicide data across European countries. Within the EU, Eurostat is responsible for compiling, documenting, and disseminating official crime records across member countries, including metadata on statistical and legal counting rules. UNODC and Eurostat jointly collect homicide data in Europe through two harmonized Crime Trends Survey questionnaires, one for each database, sent to Eurostat contact points in each country, thereby avoiding duplication of data collection efforts (Eurostat, 2024).

2.2 Efforts To Standardize Crime Recording

Recognizing the limitations of police-recorded crime data for cross-national comparisons, several initiatives have sought to harmonize definitions and counting rules across countries. The most notable international effort is the *International Classification of Crime for Statistical Purposes* (ICCS) developed by UNODC (Bisogno et al., 2015). The ICCS establishes a conceptual framework for classifying offences consistently across jurisdictions, specifying both statistical counting rules and legal inclusion and exclusion criteria for different types of crime. Within Europe, Eurostat (2024) and the European Sourcebook (Aebi et al., 2021, 2024) have similarly worked to improve data comparability by documenting countries' recording practices and promoting standardization.

However, substantial inconsistencies persist. Among the 41 countries included in Eurostat, twenty-two of them (54%) record an incident when it is first reported to the police (*input*), twelve countries (29%) document it during the investigation process, and seven (17%) only after the police investigation is completed (*output*). Similarly, only nine countries (22%) apply the *principal offense rule*, which records only the most serious crime in cases involving multiple offenses (e.g., robbery followed by homicide). For *serial offenses* occurring in a single incident, thirty-one countries (76%) record all incidents, while five record only one, and five follow mixed systems. For crimes with *multiple offenders*, all countries except Kosovo record a single offense, with Kosovo counting a separate incident for each perpetrator. These statistical counting rules can significantly affect the reliability of recorded crime (Aebi, 2008, 2010; von Hofer, 2000). However, the principal offense rule is less likely to impact homicide records given homicide's position as the most serious offense. Similarly, variations in counting rules for serial offenses are likely to have limited impact on cross-national homicide comparisons due to the low incidence of serial homicides in Europe (Sturup, 2018). Variations in rules for crimes with multiple offenders are largely inconsequential in Europe, as only one country follows a different standard.

In addition to statistical counting rules, legal definitions used to classify behaviors within crime types vary significantly across countries (Albrecht, 1989; Chon & Clifford, 2021). The ICCS mandates including several categories as homicide: honor killing, serious assault leading to death, terrorism-related deaths, dowry-related killings, femicide, infanticide, voluntary manslaughter, extrajudicial killings, and deaths caused by excessive use of force by state officials. However, compliance with these requirements is inconsistent. Among the 38 countries with documented legal definitions, only seven (18%) include all required categories. Countries such as Poland and Slovakia exclude up to five of these categories, while only seventeen of 36 countries (47%) with relevant documentation classify extrajudicial killings as homicide.

The ICCS also specifies eight categories that should be excluded from homicide statistics: attempted intentional homicide, non-intentional homicide, non-negligent or involuntary manslaughter, assisted or instigated suicide, illegal feticide, euthanasia, deaths due to legal interventions, and justifiable homicide in self-defense. Only eleven of 37 countries with relevant documentation (30%) exclude all these categories from their homicide records. Belgium excludes only two, while Lithuania, Netherlands, and Sweden fail to separate four categories from their homicide records. Notably, euthanasia is classified as homicide in seventeen of the 41 countries (42%) for which data are available. Switzerland is the only European country that fully complies with all ICCS homicide inclusions and exclusions.

All these initiatives have successfully documented variation in counting rules and legal definitions; nevertheless, no research has yet quantified the specific magnitude of bias these variations introduce into cross-national comparisons. This study addresses that gap. Extending this line of reasoning, it is important to consider that such variations may also evolve over time. This means that variations in counting rules and legal definitions may affect not only cross-national crime comparisons but also temporal and spatio-temporal analyses if these rules change over time (von Hofer, 2000). Variations in counting rules and legal definitions therefore remain a key obstacle to comparability, with implications for both cross-national and temporal analyses.

2.3 Persistent Inconsistencies and Alternative Data Sources

Despite decades of standardization efforts, cross-national homicide data continue to display inconsistencies arising from statistical, legal, policy, and substantive factors external to crime. Given these limitations in police-recorded statistics, alternative data sources have gained popularity for cross-national homicide comparisons. While victimization surveys provide valid measurements for common crimes like property offenses (van Kesteren et al., 2014) and non-lethal violence (Heise & Kotsadam, 2015), they cannot, by design, capture homicide data. Moreover, survey-based crime estimates are known to be affected by sampling error and memory bias (Brunton-Smith et al., 2024).

Initiatives like the European Homicide Monitor seek to overcome some of the main limitations of police by triangulating sources such as investigation reports, administrative data, and media coverage (Kivivuori et al., 2024). However, it is currently available in only a small number of countries, lacks a centralized database, and also faces challenges related to data harmonization.

In the absence of a *gold standard*, vital records based on death certificates completed by medical professionals serve as an important alternative to police statistics (Koeppel et al., 2013; Nivette, 2011).[1] The WHO Mortality Database, which provides raw counts of homicides recorded by health authorities, is often regarded as the most reliable source of vital homicide records for cross-national research (Rogers & Pridemore, 2023).

Vital records, however, also have limitations. Coverage issues exist as many countries report vital statistics sporadically if at all. Moreover, the WHO lacks mechanisms to ensure global compliance with standardized homicide definitions (Smit et al., 2012). Perhaps most significantly, the WHO Mortality Database consistently shows the lowest homicide counts among all international databases (see Fig. 1), suggesting potential under-recording in most

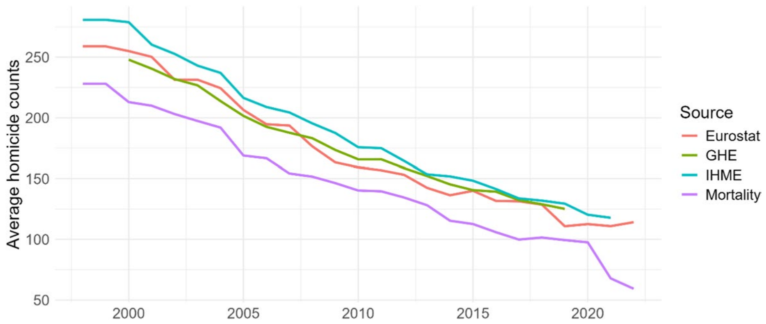

Fig. 1 Trends on average homicide records according to Eurostat, WHO Mortality, WHO Global Health Estimates (GHE), and Institute for Health Metrics and Evaluation (IHME) across 40 European countries (excluding Turkey and Serbia 1998–1999)

[1] Of the 34 homicide studies reviewed by LaFree (1999), eleven used vital records made available by the WHO, whereas the majority (26 studies) used police-recorded crime data from sources such as Interpol, the United Nations, or the Comparative Crime Data File. About a decade later the trend changed, with studies relying on vital records becoming the norm. In Koeppel et al.'s (2015) review of 50 homicide studies published between 1997 and 2011, 26 of them relied on vital records published by WHO, twelve used police-recorded Interpol data, one used United Nations survey data, with the remaining eleven based on a combination of datasets.

countries (Andersson & Kazemian, 2018; Herre & Spooner, 2023; Rogers & Pridemore, 2023; Santos & Testa, 2024).

To address methodological issues in both criminal justice data and raw vital records, international organizations have developed various adjustments (Marshall & Block, 2004). The WHO publishes adjusted homicide estimates through its *Global Health Estimates* (GHE), which combine corrected vital records adjusted for underreporting and misclassification, adjusted criminal justice data, and predicted estimates. The GHE prioritizes vital records when differences between health and criminal justice records are not substantial, resorting to predicted estimates only when reliable data are unavailable from vital and police sources (Kanis et al., 2017; WHO, 2014: 62–66).[2]

Kanis et al. (2017) note that GHE are problematic for analyzing predictors of homicide across countries because some predictors of homicide typically analyzed in research are included in the models producing these estimates. The WHO (2014: 62) recommends using these estimates primarily for "understanding the likely homicide burden within a country." Hence, comparing them to Eurostat records may serve as a proxy for homicide under-recording in police data. Notably, recording rules are not considered in the regression models used to adjust homicide estimates by WHO or other agencies.

The Institute for Health Metrics and Evaluation (IHME) also produces adjusted national homicide estimates in its annual Global Burden of Disease (GBD) reports. These estimates are used by the WHO, other international organizations, and researchers worldwide (Kanis et al., 2017).[3] Like GHE, IHME estimates combine corrected vital records, adjusted criminal justice data, and modeled estimates (using some predictors similar to those employed in GHE procedures), prioritizing vital health records. However, IHME's modeling procedures differ from GHE's, incorporating epidemiological data and surveillance systems for certain countries. The WHO draws on IHME inputs for non-fatal outcomes but not for mortality causes such as homicide. IHME does not share its raw input data, only the final estimates. As Mathers (2020: 9) explains, while transparency regarding analytical decisions has improved, *"full replication even of specific results is in practice not possible,"* and available documentation does not fully explain discrepancies between IHME and WHO estimates (e.g., Alkema & You, 2012). Table 1 presents details of each vital statistics source.

2.4 Why It Matters for Theory and Policy

Different sources of international homicide data lead to varying estimates across countries and time (Andersson & Kazemian, 2018; Rogers & Pridemore, 2023; Santos & Testa, 2024) and different conclusions regarding key predictors of cross-national homicide variation. Nivette's (2011) review of 54 studies examining cross-national homicide found that only studies using police-recorded data (from Interpol, HEUNI, and the Euro-

[2] Among Eurostat countries, the GHE primarily relies on vital registration data in 25 out of 39 nations (64%), criminal justice data in ten of them (26%), adjusted criminal justice data in one (Turkey), estimates with country data in two (Albania and Montenegro), and estimates without country data in one (Bosnia and Herzegovina).

[3] The GBD project was initially commissioned by the WHO in 1992, but it has operated as an independent program since 2007. Originally, IHME followed the same standards and procedures as the WHO's GHE; however, a series of data access and methodological disagreements between WHO and IHME led to different approaches for estimating causes of death across countries (Mathers, 2020; Murray et al., 2004).

Table 1 Summary of vital register datasets (adapted from Rogers & Pridemore, 2023: 450)

	Mortality	Global Health Estimates (GHE)	Institute for Health Metrics and Evaluation (IHME)
Definition of homicide	Killing of a person by another with intent to cause death or serious injury.	Killing of a person by another with intent to cause death or serious injury.	Deaths due to intentional use of physical force, conflict and terrorism, or police conflict and executions.
Inclusions and exclusions	Inclusions: infanticide. Exclusions: reckless or negligent behavior.	Inclusions: infanticide. Exclusions: reckless or negligent behavior.	Inclusions: interpersonal violence, conflict and terrorism, police conflict and executions.
Data collection	Vital registration.	Vital registration, complemented with police and UNODC records.	Vital registration, complemented with police, UNODC and WHO records, NGO reports, and academic sources.
Adjusted or imputed	No	Yes	Yes
URL	https://platform.who.int/mortality/themes/theme-details/topics/indicator-groups/indicator-group-details/MDB/violence	https://www.who.int/data/gho/data/indicators/indicator-details/GHO/ghe-estimates-of-number-of-homicides	https://ghdx.healthdata.org/

While we acknowledge that the GHE and IHME datasets are not strictly based on vital records, as they also incorporate other sources such as police statistics, we refer to them as "vital statistics" throughout our study given they rely primarily on mortality registers

pean Sourcebook) estimated a significant positive association between female labor and homicide, while population sex ratio showed significant association only when using WHO data.

Past research has also shown how inconsistencies in statistical rules and legal definitions across nations affect the validity of cross-national crime comparisons (Aebi, 2008; Harrendorf, 2018; von Hofer, 2000), though no study has yet quantified the specific influence attributable to different counting rules or sought to use these known inconsistencies to estimate adjusted homicide rates. The persistence of these inconsistencies underscores the need for greater transparency and methodological innovation in cross-national crime research. Understanding how counting rules and legal definitions influence homicide recording is not merely a technical issue—it has profound implications for theory testing, evidence-based policymaking, and public trust in official statistics.

This study contributes to this agenda by systematically analyzing how variations in statistical and legal counting rules affect recorded homicide rates across 41 European countries over 25 years. Metadata from Eurostat (2024) and the European Sourcebook (Aebi et al., 2021) detail national differences in counting rules. By comparing Eurostat police data with multiple sources of vital statistics, our analysis seeks to quantify the impact of recording practices on observed homicide patterns. We compare police records with WHO Mortality data as the primary source of comparison, and use WHO GHE and IHME data as additional benchmarks to enhance the robustness of our findings (Dawson, 2018; Frantz, 2019).

3 Data and Methods

3.1 Data

3.1.1 Eurostat Homicide Data

Each year, Eurostat requests national statistical institutes and criminal justice agencies of EU member states to share crime data through a standardized questionnaire. This includes police-recorded offenses at national and regional levels as well as in some large cities, aggregated data on suspects' characteristics (age, sex, legal status, citizenship), victim-offender relationship, and relevant judiciary and prison records. These data are stored across various portals on the EU's official website.[4]

Eurostat defines homicide as "unlawful death purposefully inflicted on a person by another person," with specific inclusions and exclusions as detailed in the previous section. The database encompasses information from 41 countries, though availability varies by country and time period. For example, data from the UK (England and Wales, Northern Ireland, and Scotland) are only available until 2018 due to Brexit; Albania, Bosnia and Herzegovina, and Kosovo have only contributed data since 2008; and Turkey has no data available between 2008 and 2017. Participating countries are requested to comply with ICCS standards, and Eurostat maintains detailed metadata documenting each country's compliance with these standards (Eurostat, 2024).

This metadata provides comprehensive information on various measurement aspects across countries. Eurostat documents whether countries record crime data at input, process, or output stages, whether they apply the principal offense rule, how they count serial offenses of the same type, and their approach to counting offenses committed by multiple suspects. Additionally, the metadata captures information about inclusions and exclusions of specific behaviors in national homicide records as mandated by the ICCS (see Fig. 2). While this information is available for most countries, it is not complete for all. Countries lacking full information were excluded from our analytical sample. For England and Wales, Scotland, and Northern Ireland, we supplemented Eurostat's (2024) metadata with comparable measurement information from the European Sourcebook (Aebi et al., 2021).

We note that while Eurostat's metadata records allow for the analysis of cross-national variation in national counting rules for homicide, they do not capture temporal variation in these rules within EU member states.[5] We adopt the working assumption that counting rules are time-invariant within each country across the window of observation under analysis. This is supported by the relative invariability in these counting rules observed in the successive editions of the European Sourcebook (Aebi & Molnar, 2025).

[4] Eurostat data recorded between 1998 and 2007, and between 2013 and 2022, is openly available from the website of the EU: https://ec.europa.eu/eurostat/web/crime/database. Data recorded between 2008 and 2013 is available from a different URL within the website of the EU: https://ec.europa.eu/eurostat/statistics-explained/index.php? title=Archive: Crime_and_criminal_justice_statistics, _data_2008-2013#Detailed_tables.

[5] As stated on the Eurostat (2024) website, "The comparability of the data over time is checked before dissemination as part of the data validation process. Countries are asked to indicate any change in the methodology used, definition applied or counting rules used […] These are indicated by the flag 'b' for values in the datasets.". No flag 'b' is included in Eurostat's homicide records.

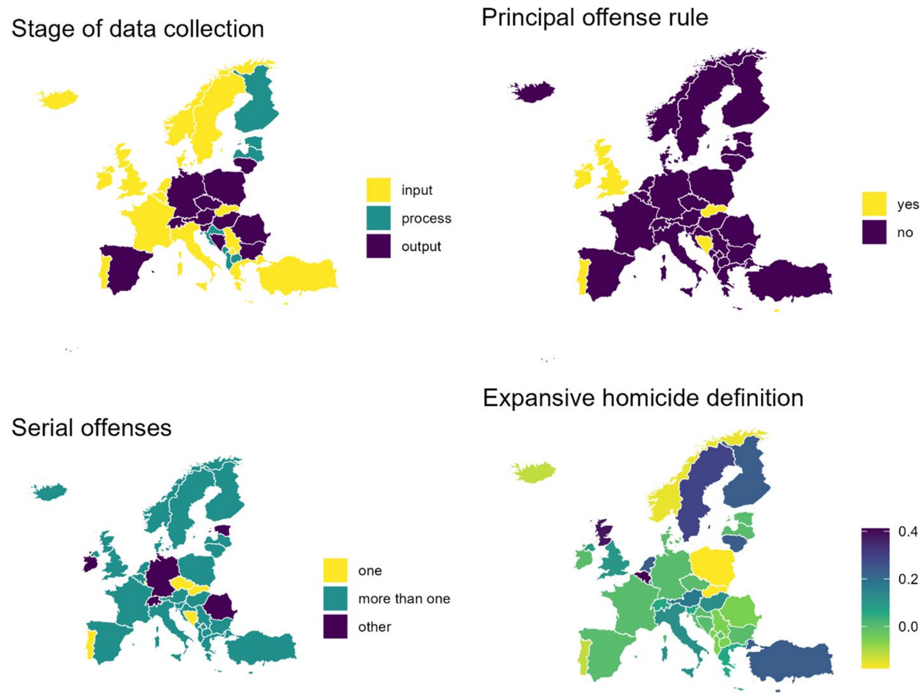

Fig. 2 National counting rules used to record homicides across Eurostat countries. The measure of expansive homicide definition reflects the proportion of possible behaviors included in the homicide measure, centered around its median

3.1.2 Vital Statistics Data

To assess the reliability of police-recorded homicide data, we compare Eurostat statistics with the WHO Mortality Database, which serves as the main source of vital statistics. In addition, to enhance the robustness of our analysis, we compare Eurostat records with two further sources that are partly based on vital records: the WHO Global Health Estimates (GHE) and the Institute for Health Metrics and Evaluation (IHME).

We utilize these vital statistics in two distinct ways. First, we calculate correspondence rates between police and vital records for each country and year, documenting the relationship between police and vital homicide records across time and space. The correspondence rate, CR_{it}, for Eurostat statistics in a given country *i* and year *t*, is calculated as the ratio between the number of Eurostat-recorded homicides, denoted as $Eurostat_{it}$, and the number of homicides recorded in each vital statistics source, denoted respectively as $Mortality_{it}$, GHE_{it} and $IHME_{it}$.

$$\text{Hence, } CR_{it}^{Mortality} = \frac{Eurostat_{it}}{Mortality_{it}},\ CR_{it}^{GHE} = \frac{Eurostat_{it}}{GHE_{it}},\ \text{and } CR_{it}^{IHME} = \frac{Eurostat_{it}}{IHME_{it}}.$$

A measure of 1 indicates perfect correspondence (i.e., equal number of records in Eurostat and vital statistics), while a score between 0 and 1 reflects under-recording in Eurostat data, and values above 1 indicate over-recording in Eurostat data.

Second, we also use vital records as control variables in our models exploring the association of counting rules and police-recorded homicide, ensuring that variations in police counting rules are not confounded with differences in overall homicide levels as reported by vital statistics sources.

3.2 Analytical Strategy

For the first part of our analysis, we describe and visualize the distribution and cross-country variation of correspondence rates (i.e., ratio between police-recorded homicide and vital statistics) using descriptive statistics, histograms, and scatter plots. This exploratory analysis allows us to assess the under- or over-recording of homicide in police statistics, as compared to the three available sources of vital records. We also visualize the correspondence rates across countries and over time, examining whether the identified under- or over-recording of homicide, as compared to vital records, varies across countries and years.

For the second part of our analysis, we employ two sets of 'within-between' hybrid models implemented in a random-effects framework (Fairbrother, 2014; Mundlak, 1978) to estimate the association between statistical counting rules and police-recorded homicide. This approach enables incorporating time-invariant predictors (i.e., counting rules) while explicitly accounting for within-country and between-country effects of time-varying controls (i.e., vital statistics). The within-between model achieves this by decomposing the time-varying controls into within-country components (time-varying deviations) and between-country components (group means). All measures of homicide used in our models are log-transformed to reduce the right-skewness in homicide counts.

Specifically, we augment the random effects model by incorporating both the time-varying measures of vital records (i.e., log-transformed $Mortality_{it}$, GHE_{it} and $IHME_{it}$, respectively) and their country-level group means as control variables. This decomposition enables separate estimation of within-country and between-country effects while isolating the impact of time-invariant predictors, such as counting rules. The observed estimates of counting rules are robust to variations in vital statistics and potential correlations between country-specific effects and the predictors. By pooling information across countries and adjusting for country-specific differences, the within-between model accounts for unobserved heterogeneity and reduces potential omitted variable bias.

The within-between model assumes that the error term has two components, an entity-specific component, u_i, unique to each country, randomly distributed, and constant over time, and an idiosyncratic error term, ϵ_{it}, which varies for each observation. In practice, the within-between model is defined as follows:

$$\log(Eurostat_{it}) = \beta_0 + \gamma_1 \log(Vital_{it}) + \beta_1 \log(\overline{Vital_i}) + \beta_2 CountingRule1_i + \beta_3 CountingRule2_i + \ldots + u_i + \epsilon_{it} \tag{1}$$

Here, β_0 is the overall intercept, γ_1 is the coefficient for the within-country effect of the time-varying control variable of vital records, β_1 is the coefficient for the between-country effect of the group mean of vital statistics, and β_2 and β_3 are the coefficients for our time-invariant predictors (counting rules). u_i and ε_{it} are the two error terms. We use Generalized Least Squares (GLS) for estimation.

We estimate two sets of within-between models. First, we examine the association between general counting rules (i.e., stage of data collection [input], principal offense rule [yes], rule for serial offenses [multiple]) and an overall measure of expansiveness in homicide definitions (i.e., proportion of possible behaviors included in the homicide measure, centered around its median) and police-recorded homicides. Second, we explore how each of the inclusion or exclusion rules used in the legal definition of homicides are associated with recorded homicides. Both sets of analyses include vital statistics as control variables.

As our analysis draws on the complete set of available countries rather than a random sample, statistical inference based on p-values is not appropriate (Bartram et al., 2024; Hirschauer et al., 2020). Our estimates represent conditional associations for the observed countries rather than probabilistic inferences about an unobserved population. We therefore present point estimates with 95% confidence intervals but omit significance tests.

As a robustness check, to ensure that the observed effects are not confounded by countries' overall government and regulatory effectiveness, which can influence both the adoption of international standards and crime control, we include two additional control variables in our models and report the results in the Appendix. Specifically, we use World Bank estimates of (a) 'government effectiveness', which captures perceptions of the quality of public services, the competence and independence of the civil service, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies; and (b) 'regulatory quality', which reflects perceptions of the government's ability to formulate and implement policies and regulations to promote economic development (Kaufmann et al., 2011).

Lastly, we use the conditional association of each counting rule on police-recorded homicides to adjust homicide estimates for the inconsistencies in the use of counting rules across countries. First, we select the set of predictors (counting rules) that show a consistent association across our three models (i.e., regression estimates that point in the same direction) and that demonstrate sufficient precision (i.e., their 95% confidence intervals lie entirely on one side of zero in at least one of the three models). That is, we select counting rules that appear to have a consistent association with police recording of homicides across countries. Second, we use regression coefficients calculated from our within-between models and determine the average effect size across the three models. In the final stage, we apply these averaged regression coefficients to derive counting rules-adjusted estimates of police-recorded homicide rates, showing how rankings shift when known sources of measurement error are addressed.

All analyses were conducted in R (R Core Team, 2024) with the assistance of the 'plm' package (Croissant & Millo, 2008) to estimate our within-between effect models. The analytic code and input data are available on GitHub (https://github.com/davidbuilgil/counting-homicide).

4 Results

When compared to GHE and IHME estimates, Eurostat homicide records appear to underestimate homicide in most countries (see Fig. 3). The mean correspondence rate is 0.90 for GHE and 0.98 for IHME, with 73% and 63% of countries, respectively, showing underestimation in Eurostat records over time. In contrast, correspondence rates show the opposite pattern when comparing Eurostat records with WHO Mortality data.[6] Here, the mean correspondence rate is 1.31, with 66% of countries showing overestimation in Eurostat records. While GHE and IHME suggest that Eurostat data underestimates homicide, WHO Mortality registers report even fewer offenses than Eurostat in most countries. [7] This discrepancy is evident in both the histograms and scatter plots in Fig. 3.

This is further illustrated in Fig. 4, which analyzes temporal and geographic variations in correspondence rates. While correspondence rates derived from GHE and IHME exhibit overall temporal stability, correspondence rates with WHO Mortality show a growing divergence, suggesting an increasing under-recording in Mortality data.

When examining geographic variations in correspondence rates, also in Fig. 4, clear differences emerge depending on the vital statistics data used for comparison. For example, if we were to rely on GHE data, Turkey and Iceland emerge as the countries where police data underestimates homicides the most. In contrast, Poland, North Macedonia, Albania, and Serbia are highlighted as having the lowest recording rates based on the comparison

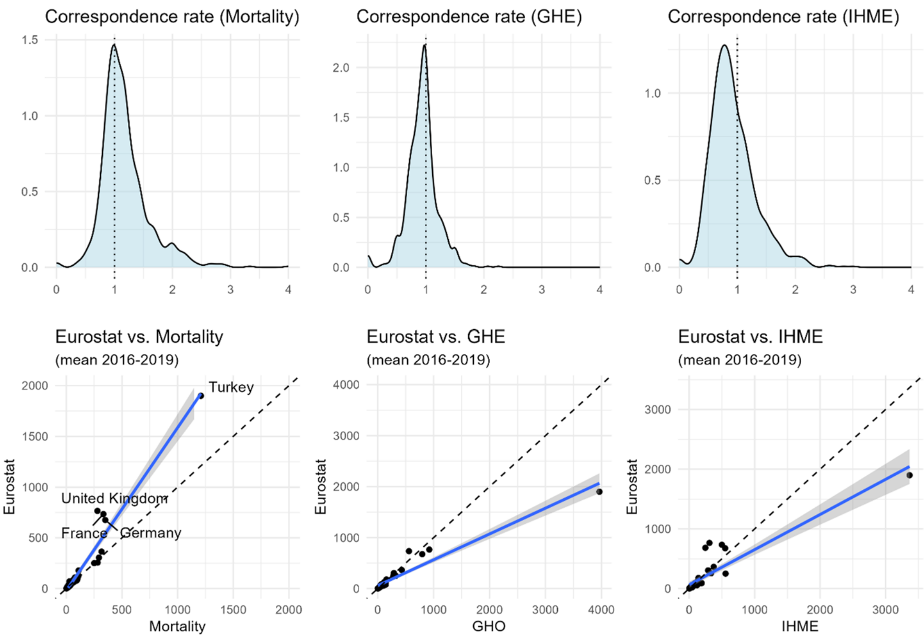

Fig. 3 Comparison of Eurostat and vital records according to WHO Mortality, GHE, and IHME. Notice how Eurostat records tend to overestimate homicide counts compared to WHO Mortality, but underestimate it compared to IHME and GHE, although there is a great degree of between-country variability

[6] Four countries (Turkey, United Kingdom, France, and Germany) appear as outliers in Fig. 3. Their influence is controlled for in the models presented below through the inclusion of vital records. When we repeat this analysis without the four outliers (not shown here), we find associations pointing in the same direction.

[7] While the magnitude of the correspondence rates varies significantly depending on the vital statistics measure used, all three correspondence rates are moderately correlated with one another. Bivariate correlations range from 0.53 (between correspondence rates calculated from the two WHO sources, GHE and Mortality) to 0.58 (between Mortality and IHME) and 0.71 (between IHME and GHE). Overall, correspondence rates derived from GHE and IHME are more consistent than those based on Mortality records.

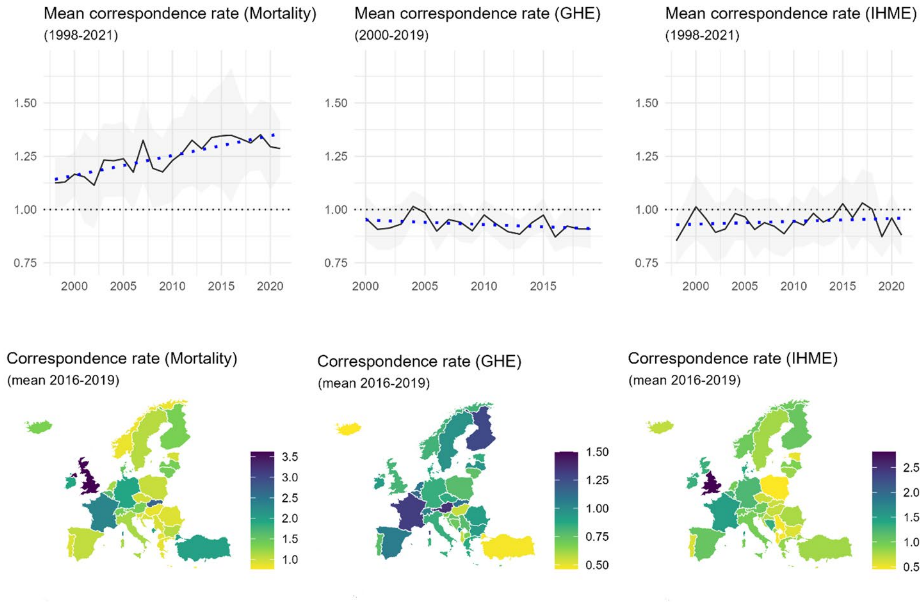

Fig. 4 Temporal and geographic variation in correspondence rates. Top: whereas GHE and IHME correspondence rates appear stable over time, Mortality correspondence rates indicate a growing divergence in the last couple of decades. Bottom: country-specific correspondence rates vary considerably depending on the source of vital statistics used for analysis (note the change in scales across the three maps)

with IHME, while Cyprus, Norway, and Hungary show the lowest rates according to the comparison with WHO Mortality. At the opposite end of the spectrum, some consistency is observed, with France consistently identified as having a relatively high correspondence rate (ranking in the top five across all three comparisons). Similarly, the United Kingdom is noted for its high rate according to Mortality and IHME, and Malta for its high rate according to GHE and IHME. Overall, however, the ranking of correspondence rates appears to be heavily influenced by the choice of vital statistics measure used in the analysis.

Next, we analyze the association of national counting rules with Eurostat homicide counts, conditional on homicide counts from the three vital statistics sources. The results displayed in Table 2 examine the relationship between general counting rules and homicide counts from Eurostat, while those in Table 3 focus on its association with different inclusion and exclusion criteria in the legal definition of homicide used by police statistics in each country. Although we have argued that principal offence and serial offenses rules should not substantially bias cross-national analyses of homicide, we include them as explanatory variables in our models to assess their potential influence empirically.

In the first set of analyses, the estimates from all three models show that an expansive definition of homicide, where a broader range of incidents are classified as homicides, is associated with higher homicide recording. This estimated relationship appears less precise (i.e., exhibits wider confidence intervals) in the model controlling for Mortality estimates. The stage of data collection shows a consistent positive association with police-recorded crime across all datasets: countries where homicides are recorded at the point when the offence is first known to the police (*input* stage) report approximately 13–15% higher homi-

Table 2 Within-between models exploring the association of general counting rules with log-transformed police-recorded homicide counts per country

	Mortality		Global Health Estimates (GHE)		Institute for Health Metrics and Evaluation (IHME)	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
(Intercept)	−0.23	(−0.56, 0.10)	−0.30	(−0.50, −0.10)	−0.45	(−0.86, −0.05)
Stage collection (input)	0.14	(−0.02, 0.30)	0.13	(0.03, 0.23)	0.12	(−0.09, 0.33)
Principal offense rule	0.06	(−0.18, 0.30)	−0.07	(−0.22, 0.08)	0.15	(−0.11, 0.40)
Serial offenses (more than one)	−0.05	(−0.24, 0.13)	−0.08	(−0.19, 0.04)	−0.10	(−0.33, 0.13)
Expansive definition	0.26	(−0.29, 0.82)	0.33	(−0.01, 0.68)	0.87	(0.18, 1.56)
log(vital records)	0.77	(0.74, 0.81)	0.66	(0.60, 0.72)	0.91	(0.85, 0.97)
log(mean vital records)	0.29	(0.22, 0.36)	0.39	(0.32, 0.45)	0.14	(0.05, 0.23)
Parameters	σ^2_{within} = 0.04 σ^2_u = 0.04 θ = 0.79		σ^2_{within} = 0.07 σ^2_u = 0.01 θ = 0.55		σ^2_{within} = 0.06 σ^2_u = 0.08 θ = 0.82	
Observations	n=748 T=1–25 N=36		n=690 T=10–20 N=36		n=885 T=14–24 N=39	
R^2/R^2 Adjusted	0.832/0.831		0.880/0.879		0.702/0.700	

σ^2_{within} represents the residual variance within countries, σ^2_u represents the "random intercept" variance at the country level (i.e., between-group variance), and θ represents the proportion of the total variance attributable to differences between countries. R^2 indicates the proportion of variance explained by the predictors, and R^2 Adjusted is the R^2 adjusted for the number of predictors. N refers to the number of unique countries, T to time periods (years) and n to total observations (countries/years)

cide counts than those using *process*- or *output*-based systems. By contrast, the application of the principal offence rule and the treatment of serial offences as multiple events produce estimates with wide confidence intervals, suggesting low precision in their estimated relationship with police-recorded homicide. Lastly, it is worth noting how controlling for vital records, both in their original time-varying form and their country-level mean, improves model fit, and these show strong and stable effect sizes.

We proceed to analyze the association of each legal inclusion and exclusion criteria on Eurostat homicide records. The inclusion of terrorism in criminal justice records of homicide is associated with approximately 23–36% higher recorded counts, with relatively strong effect sizes and high precision across all three models. Similarly, the inclusions of femicide and assisting or instigating suicide are strongly associated with higher homicide levels in the models controlling for GHE statistics, while in the model controlling for IHME estimates, this also applies to the inclusion of euthanasia. Although the precision of these estimates varies across models, we observe that for the above highlighted factors, the direction of their associations, and in many cases their effects sizes, remain remarkably consistent across models.

Robustness checks incorporating two additional controls, measuring government effectiveness and regulatory quality, show no substantial differences from the results presented in Tables 2 and 3. Details of this robustness check are provided in the Appendix.

Table 3 Within-between models exploring the association of categories included in legal definitions of homicide with log-transformed police-recorded homicide counts per country

	Mortality		Global Health Estimates (GHE)		Institute for Health Metrics and Evaluation (IHME)	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
(Intercept)	−0.08	(−0.90, 0.73)	−0.81	(−1.21, −0.41)	−1.13	(−2.03, −0.23)
Serious assault leading to death	0.09	(−0.16, 0.33)	0.03	(−0.10, 0.15)	0.11	(−0.18, 0.39)
Terrorism	0.27	(0.00, 0.54)	0.21	(0.08, 0.35)	0.31	(−0.00, 0.62)
Femicide	−0.13	(−0.74, 0.47)	0.34	(0.05, 0.63)	0.38	(−0.25, 1.00)
Infanticide	−0.24	(−0.65, 0.17)	−0.10	(−0.31, 0.11)	−0.16	(−0.64, 0.32)
Voluntary manslaughter	−0.04	(−0.28, 0.19)	−0.08	(−0.20, 0.04)	0.01	(−0.26, 0.29)
Extrajudicial killing	0.03	(−0.20, 0.26)	0.07	(−0.04, 0.19)	0.12	(−0.14, 0.38)
Excessive force law enforcement	−0.15	(−0.37, 0.07)	−0.04	(−0.15, 0.07)	−0.04	(−0.30, 0.21)
Attempted intentional homicide	0.04	(−0.24, 0.33)	0.06	(−0.09, 0.20)	0.06	(−0.28, 0.39)
Non-intentional or justifiable homicide	−0.03	(−0.15, 0.09)	−0.04	(−0.10, 0.03)	−0.07	(−0.21, 0.07)
Assisting/instigating suicide	0.08	(−0.17, 0.33)	0.16	(0.03, 0.29)	0.12	(−0.17, 0.41)
Illegal feticide	0.08	(−0.19, 0.35)	0.07	(−0.07, 0.21)	0.12	(−0.20, 0.43)
Euthanasia	0.14	(−0.05, 0.33)	−0.02	(−0.11, 0.08)	0.22	(0.00, 0.43)
Death during legal interventions	0.07	(−0.18, 0.31)	0.03	(−0.10, 0.15)	0.15	(−0.13, 0.44)
log(vital records)	0.77	(0.73, 0.81)	0.65	(0.59, 0.71)	0.94	(0.88, 1.00)
log(mean vital records)	0.29	(0.21, 0.38)	0.42	(0.35, 0.49)	0.11	(0.00, 0.21)
Parameters	σ^2_{within} = 0.04 σ^2_u = 0.05 θ = 0.81		σ^2_{within} = 0.07 σ^2_u = 0.01 θ = 0.47		σ^2_{within} = 0.06 σ^2_u = 0.07 θ = 0.80	
Observations	n=729 T=1–25 N=35		n=670 T=10–20 N=35		n=798 T=14–24 N=35	
R^2/R^2 Adjusted	0.828/0.824		0.907/0.905		0.725/0.720	

Finally, we use the regression coefficients from the within-between models to adjust police-recorded homicide rates (per 100,000 population), enabling the estimation of counting rules-adjusted homicide rates across countries. For this purpose, we select a set of relevant counting rules that our regression models have shown to be most likely affecting police-recorded homicide across countries. Specifically, we use the data collection stage and the legal inclusion or exclusion criteria influencing homicide recording (terrorism and assisting or instigating suicide). We conduct three nested adjustments: first, we adjust national homicide rates based solely on the calculated mean correspondence rate for each country and across the three measures of vital statistics considered; second, we adjust homicide rates to account for under-recording and the data collection stage (input versus other); and third, we adjust rates to include under-recording, the data collection stage, and legal inclusions and exclusions.

These adjusted country homicide rates and the original rates derived from Eurostat are presented in Fig. 5. Our adjustments illustrate the large impact that counting rules have on the reliability of cross-country comparisons of police-recorded homicide and international rankings. The Mean Absolute Change suggests that, on average, the adjusted rates differ from the original rates by 0.31 points; about 31 cases per year in a population of 10 million, or about 53 cases in a population of 17 million (the mean across the countries analyzed).

The adjusted rankings shift by 4.2 places on average. For example, Portugal, initially ranked in position twenty-seventh (at the low-tier homicide rate within Europe), moves to position eighteenth after adjusting for under-recording, and seventeenth when the data collection stage and legal-definitional variations are also accounted for. Portugal's homicide rate increased by 51.5% after applying our adjustments. Similar shifts are observed for countries such as Iceland (rising from thirty-sixth to twenty-sixth), North Macedonia (from eighteenth to nineth), and Slovenia (from thirtieth to twenty-fourth). Albania, originally ranked sixth, climbs to second after adjustments for under-recording and counting rules, with a 94.5% increase in its homicide rate following our adjustments. Conversely, Slovakia, Germany, and France experience the largest declines in rank, falling from twelfth, twenty-second and seventeenth to twenty-third, thirty-third and twenty-fifth, respectively.

Overall, with the sole exceptions of Hungary and Czechia, all Central European countries show decreases in their homicide rate rankings after adjusting for under-recording and counting rules. In contrast, all Balkan countries except Montenegro and Bosnia and Herzegovina rise in the rankings following these adjustments. Most Southern European countries except Spain and Turkey also rise in rank. In Western Europe, all countries except the Netherlands and Luxembourg show declines. Similarly, our adjustments affect Northern European countries in varied ways: Iceland and Sweden rise in rank, while the remaining countries either decline or remain stable. Finally, Eastern Europe displays mixed trends: Estonia and Lithuania drop in rank, while Latvia and Romania rise. Table 4 summarizes these regional patterns following adjustment.

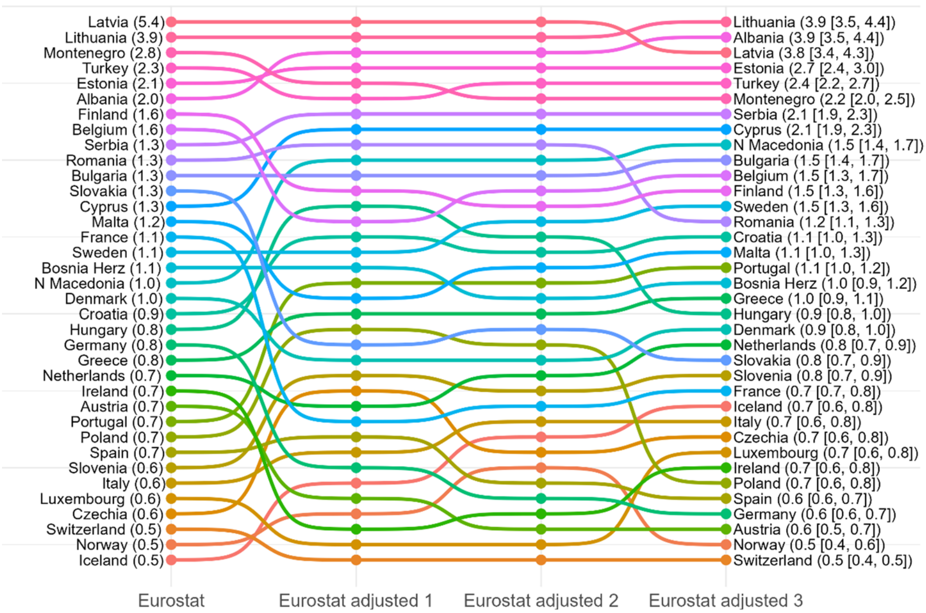

Fig. 5 Eurostat homicide rate per 100,000 population adjusted for correspondence rates (adjustment 1), data collection stage (adjustment 2) and legal-definitional variations (adjustment 3). 95% confidence intervals of adjusted rates are shown in brackets for adjustment 3. This figure excludes Kosovo, Liechtenstein and United Kingdom, for which full information was not available

Table 4 Summary of regional patterns in Eurostat homicide rates per 100,000 population, adjusted for correspondence rates, data collection stage, and legal-definitional variations

Region	Countries with data	Mean homicide rate before adjustment	Mean homicide rate after adjustment	% countries rise in rank	Top 10 movers
Balkan	8	1.38	1.78	75%	Albania (+94.5%) Serbia (+57.5%) North Macedonia (+48.8%)
Central	7	0.78	0.68	29%	Slovakia (−40.9%)
Eastern	4	3.16	2.91	50%	
Northern	5	0.92	1.00	40%	Iceland (+46.7%) Sweden (+36.2%)
Southern	7	1.08	1.29	57%	Cyprus (+61.8%) Portugal (+51.5%) Greece (+33.5%)
Western	5	0.94	0.88	40%	France (−32.9%)

5 Discussion and Conclusions

Cross-national criminological research has predominantly focused on homicide as the crime type least affected by recording inconsistencies, operating under the assumption that its severity ensures more reliable measurements compared to other offenses (LaFree, 2021). Our study challenges this assumption, showing that even homicide exhibits substantial measurement distortions that vary across countries and can substantially alter international rankings. Statistical counting rules and legal definitions for homicide vary extensively across European countries, and these methodological differences affect the reliability of cross-national homicide comparisons.

Our findings reveal two patterns. First, countries recording crimes at the input stage—when incidents are first reported to authorities, usually the police—report approximately 13–15% higher homicides than those using process-based or output-based recording systems. Second, broader legal definitions of homicide, which include categories such as terrorism-related deaths and cases of assisting or instigating suicide, are associated with higher homicide records. While Europe experiences relatively few deaths due to terrorism each year—between 1998 and 2020, an average of 181.3 deaths were recorded annually (with a standard deviation equal to 251.9, and range going from a minimum of 21 in 2010 to a maximum of 1,178 in 2016) (START, 2022)—our analysis shows that the decision to include or exclude terrorism-related deaths from homicide records can substantially affect cross-national comparisons. There are no centralized international records of illegal cases of assisted or instigated suicide, but records from the United Kingdom show that 199 such cases were referred to the prosecution service between April 2009 and March 2025 in this country alone (Crown Prosecution Service, 2025). Although these categories represent a small share of total homicides, their inclusion or exclusion from crime statistics introduces systematic differences that can distort cross-national comparisons.

These findings align with previous research on how measurement disparities distort cross-national crime comparisons (Aebi, 2008; Harrendorf, 2018; von Hofer, 2000) and extend that work by using more advanced statistical techniques to quantify the specific impact of different counting rules on homicide records. Whereas prior work has established that differences in national counting rules can hinder cross-national comparability, our study provides the first quantitative estimate of how these differences impact the reliability of homicide records across Europe.

We emphasize that this study captures only two sources of cross-national variation in homicide recording: statistical counting rules and legal definitions. We have not addressed substantive factors beyond actual crime levels, such as cross-country differences in crime reporting propensities and the likelihood of crime being recorded by authorities (Boivin & Cordeau, 2011; Estienne & Morabito, 2016). Nor have we examined policy priorities that influence the recording of certain criminal behaviors (Aebi, 2010). These factors vary significantly across nations and evolve over time. As a result, our study likely underestimates the full extent of cross-national disparities in homicide recording.

While vital records are often proposed as an alternative to police statistics for measuring homicide cross-nationally (Kanis et al., 2017; Rogers & Pridemore, 2023), our analysis demonstrates the limitations of this approach. Treating WHO Mortality data or other vital statistics as the *gold standard* introduces distinct yet equally problematic challenges for comparative analyses, as well as for policy and theoretical developments. Beyond the well-documented limitations of vital statistics—such as geographic coverage gaps and low recording rates in certain regions (Andersson & Kazemian, 2018; Herre & Spooner, 2023; Santos & Testa, 2024)—there is limited transparency regarding countries' compliance with standardized definitions of homicide in these systems (Smit et al., 2012) and the statistical rules applied in compiling them. WHO vital statistics are based on the classification of causes of death using the *International Classification of Diseases* (ICD). However, while international guidelines exist for compiling this data, to our knowledge, compliance with these standards is not systematically documented in international databases. As a result, researchers cannot empirically assess how variations in counting rules affect vital records across nations, nor can they predict their impact on cross-country comparisons. This asymmetry in transparency is consequential: while researchers can adjust police data for known disparities in counting rules (as we demonstrate), equivalent adjustments cannot be made for vital statistics because the necessary metadata are unavailable. The WHO Mortality Database, as well as the GHE and IHME estimates, should systematically document and adjust for cross-national variation in compliance with ICD guidelines for mortality data. Likewise, GHE and IHME should account for cross-national differences in counting rules for criminal justice data.

For most crime types beyond homicide, vital records simply do not exist. Consequently, until ongoing efforts to relaunch cross-national crime surveys (Bijleveld, 2023; van Dijk et al., 2022) reach success, researchers will have to rely on official crime measures, mainly police and conviction statistics.

Our analysis also suggests that documenting counting rules can enhance the reliability of cross-national crime data comparisons. This is the first study to propose a method for adjusting cross-national crime rates based on documented differences in counting rules, and a transparent and reproducible set of assumptions. By identifying and quantifying the impact of specific counting rules on national homicide rates, we showed that methodological adjustments can substantially improve cross-national comparability. Adjustments were derived directly from Eurostat's metadata and implemented through clearly specified criteria informed by the estimated effect of inconsistent counting rules and definitions of homicide. Unlike the often-obscure model-based imputations undertaken for the GHE and IHME, our approach prioritizes transparency and reproducibility. That is not to say that our approach is without flaws. Most critically, it relies on the assumption that metadata accurately reflect national recording practices during the study period, and in the absence of relevant confounders. Our adjustments do not produce a new "gold standard" for cross-national homicide measurement but rather provide a transparency-oriented correction to existing police data. Unlike GHE and IHME, which rely on complex, and often undisclosed, modeling assumptions to maximize global coverage, our approach directly addresses known sources of measurement error identified in Eurostat metadata. The resulting adjusted series therefore enhances comparability across European countries while maintaining a clear link to official criminal justice records. When we adjusted homicide rates based on data collection stage and legal definitional variations, we observed significant changes in international rankings that likely better reflect genuine cross-national differences in homicide prevalence.

Namely, we observe that most Central European countries—and, to some extent, those in Western and Northern Europe—dropped in rank after applying the adjustments based on counting rules, while the majority of countries in the Balkans and Southern Europe rose in rank. This suggests that homicide rates in the Balkans and Southern Europe may be underestimated in the original Eurostat data. Interestingly, we do not find evidence that these differences stem from weaker compliance with ICCS standards. On the contrary, Balkan countries comply on average with 87% of the ICCS mandates for homicide recording considered in this study, and Southern European countries with 82%, compared with notably lower compliance among Central (77%) and Western European nations (74%). Hence, the opposite argument could be made, partial non-compliance leads to a relative overestimation of their homicide figures. Weaker institutional capacity to record official crime statistics in the Balkans and Southern Europe may also partly explain their lower correspondence rates and, in turn, some of the observed changes in rank after applying adjustments (Kaufmann et al., 2011). Further research is needed to clarify the sources of these divergences.

These findings also have implications for research examining predictors of cross-national homicide variation. Previous studies have reached inconsistent conclusions regarding which factors significantly predict homicide rates across countries, with results varying depending on whether analyses use police-recorded data or vital statistics (Nivette, 2011). Accounting for counting rule variations in statistical models may help reconcile these inconsistencies.

Our findings have implications extending well beyond homicide research in Europe. First, homicide is internationally recognized as the crime type with the highest recording rates and arguably the fewest measurement issues. The methodological inconsistencies we identified for homicide would almost certainly be magnified for other crime types where cross-national variation in counting rules is even more pronounced (Aebi et al., 2021; Eurostat, 2024). For instance, non-lethal violence (Enzmann & Podana, 2010), rape and sexual offenses (Chon & Clifford, 2021; von Hofer, 2000), property crimes (Gruszczyńska & Heiskanen, 2012), and emerging crime modalities such as fraud and cybercrime, whose definitions remain largely unstandardized internationally (Correia-Hopkins, 2024), will face even greater cross-national comparability challenges.

Second, our geographic focus on Europe—a region with relatively standardized crime recording practices—likely represents a best-case scenario for data comparability. The European context benefits from standardization efforts by UNODC through its ICCS (Bisogno et al., 2015), as well as initiatives by Eurostat and the *European Sourcebook* project (Aebi et al., 2024). In contrast, regions with less standardized recording practices would likely exhibit even greater cross-national disparities than those observed in our analysis. This issue is particularly relevant to cross-continental crime comparisons, which are increasingly facilitated by open data initiatives (Buil-Gil et al., 2024).

Drawing from our findings, we propose several recommendations to improve the reliability of cross-national crime data. Institutions such as Eurostat, WHO, and IHME should strengthen efforts to document counting rules across countries. Similarly, efforts to promote standardized definitions (such as the ICCS) and recording practices deserve also to be encouraged. For researchers conducting cross-national crime analyses, we recommend incorporating counting rule variables as controls in statistical models examining crime predictors. For policymakers relying on cross-national crime comparisons, we suggest (1) prioritizing adjusted crime rates that account for documented counting rule differences; (2) requiring metadata transparency as a condition for international data collection; (3) incorporating measurement uncertainty into funding allocation formulas; and (4) avoiding mechanical reliance on rankings from a single data source. Such methodological caution is not merely theoretical; it is essential for evidence-based policy instruments whose allocation mechanisms rely on cross-national crime figures. For example, the EU administers the Internal Security Fund (ISF) to strengthen the capabilities of law enforcement agencies, with a budget of approximately €1.9 billion for the 2021–2027 period. When allocating this funding across member states, crime rates in their raw, non-adjusted form should not serve as the primary reference, as this may lead to inaccurate assessments and misallocation of resources.

Several limitations of this study should be acknowledged. First, as noted earlier, we examined only statistical counting rules and legal definitions affecting crime recording, not substantive or policy-driven factors. While our adjustments improve cross-national comparability, they do not address all sources of measurement variation, such as differences in reporting propensities, medical certification quality, or data processing delays, all of which are likely to influence recorded homicide rates. Second, our adjustment methodology, while representing an improvement over unadjusted comparisons, relies on estimated associations between counting rules and recorded homicide that may not fully capture the complexity of these relationships. Third, our models using GHE and IHME data as controls may suffer from endogeneity issues, as both incorporate police-recorded data in their estimation approaches for certain countries, potentially introducing circularity when these sources are used as control variables to assess the reliability of police statistics. Specifically, we could anticipate that this problem would lead to an attenuation of the estimated effect of counting rules and homicide definitions. We partly address this limitation by relying on three separate sources of vital statistics, each with its own documented constraints. Moreover, we note that results obtained using GHE and IHME controls do not change markedly from those based on WHO Mortality data. Fourth, our analysis focused on European countries with relatively complete data, potentially limiting the generalizability of findings to other regions. Fifth, the study captures recording inconsistencies within the Eurostat database, which may not accurately reflect how police-recorded homicide data are compiled in other international databases, such as those maintained by Interpol or HEUNI. And sixth, relatedly, according to Eurostat, no temporal variation in counting rules for homicide has occurred in any country during the study period; an assumption that we have adopted in our analytical approach and which should be thoroughly examined in future research.

Looking ahead, the growing availability of metadata from Eurostat, the European Sourcebook, and UNODC creates unprecedented opportunities to refine cross-national crime measurement. Our findings demonstrate that transparent, metadata-based adjustments can meaningfully enhance comparability—provided that researchers and policymakers actively incorporate them into practice. The ultimate test of this work lies in its capacity to inform and improve real-world data practices.

Appendix

To check that the observed effects are not confounded by countries' overall government and regulatory effectiveness, which can influence both the adoption of international standards and crime control, we included two additional control variables in our models. Specifically, we used the World Bank's estimates of (a) 'government effectiveness', which capture perceptions of the quality of public services, the competence and independence of the civil service, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies; and (b)'regulatory quality', which reflects perceptions of the government's ability to formulate and implement sound policies and regulations that promote economic development (Kaufmann et al., 2011). Both indicators are expressed as standardized scores ranging approximately from −2.5 (weak governance performance) to +2.5 (strong governance performance) and are available on an annual basis from the World Bank's Worldwide Governance Indicators database (https://databank.worldbank.org/metadataglossary/worldwide-governance-indicators/series/GE.EST).

Robustness checks incorporating these two additional controls, presented in Tables 5 and 6, show no substantial differences from the main results reported in Tables 2 and 3. This suggests that the associations identified in our models are not driven by broader differences in governance capacity or regulatory performance across countries.

Table 5 Within-between models exploring the association of general counting rules with log-transformed police-recorded homicide counts per country, controlling for government effectiveness and regulatory quality

	Mortality		Global Health Estimates (GHE)		Institute for Health Metrics and Evaluation (IHME)	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
(Intercept)	−0.11	(−0.47, −0.25)	−0.38	(−0.62, −0.15)	−0.21	(−0.65, 0.23)
Stage collection (input)	0.18	(0.02, 0.34)	0.11	(0.01, 0.21)	0.16	(−0.04, 0.36)
Principal offense rule	0.02	(−0.22, 0.26)	−0.04	(−0.18, 0.11)	−0.05	(−0.35, 0.25)
Serial offenses (more than one)	−0.08	(−0.26, 0.10)	−0.05	(−0.16, 0.07)	−0.18	(−0.42, 0.05)
Expansive definition	0.40	(−0.16, 0.96)	0.25	(−0.10, 0.60)	0.96	(0.25, 1.66)
Government effectiveness	−0.13	(−0.22, −0.04)	0.02	(−0.09, 0.12)	−0.11	(−0.21, −0.00)
Regulatory quality	0.07	(−0.03, 0.18)	0.04	(−0.09, 0.16)	0.06	(−0.06, 0.18)
log(vital records)	0.78	(0.73, 0.82)	0.64	(0.58, 0.71)	0.95	(0.88, 1.02)
log(mean vital records)	0.27	(0.20, 0.35)	0.40	(0.33, 0.47)	0.07	(−0.03, 0.16)
Parameters	$\sigma^2_{within} = 0.04$ $\sigma^2_u = 0.04$ $\theta = 0.77$		$\sigma^2_{within} = 0.07$ $\sigma^2_u = 0.01$ $\theta = 0.50$		$\sigma^2_{within} = 0.06$ $\sigma^2_u = 0.07$ $\theta = 0.79$	
Observations	n=688 T=1–23 N=36		n=654 T=9–19 N=36		n=756 T=12–22 N=36	
R^2/R^2 Adjusted	0.838/0.836		0.891/0.890		0.720/0.717	

Table 6 Within-between models exploring the association of categories included in legal definitions of homicide with log-transformed police-recorded homicide counts per country, controlling for government effectiveness and regulatory quality

	Mortality		Global Health Estimates (GHE)		Institute for Health Metrics and Evaluation (IHME)	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
(Intercept)	−0.15	(−0.95, 0.65)	−0.77	(−1.15, −0.38)	−1.14	(−2.08, −0.20)
Serious assault leading to death	0.06	(−0.18, 0.30)	0.05	(−0.08, 0.17)	0.09	(−0.21, 0.39)
Terrorism	0.32	(0.06, 0.59)	0.21	(0.07, 0.34)	0.34	(0.02, 0.67)
Femicide	−0.06	(−0.66, 0.54)	0.30	(0.02, 0.58)	0.41	(−0.24, 1.07)
Infanticide	−0.21	(−0.61, 0.19)	−0.13	(−0.33, 0.08)	−0.14	(−0.64, 0.36)
Voluntary manslaughter	−0.02	(−0.25, 0.21)	−0.09	(−0.20, 0.03)	0.03	(−0.26, 0.31)
Extrajudicial killing	0.05	(−0.17, 0.27)	0.07	(−0.04, 0.18)	0.13	(−0.15, 0.40)
Excessive force law enforcement	−0.18	(−0.39, 0.04)	−0.04	(−0.15, 0.06)	−0.07	(−0.34, 0.19)
Attempted intentional homicide	0.06	(−0.23, 0.34)	0.02	(−0.12, 0.17)	0.04	(−0.31, 0.40)
Non-intentional or justifiable homicide	−0.02	(−0.14, 0.10)	−0.03	(−0.09, 0.03)	−0.06	(−0.20, 0.09)
Assisting/instigating suicide	0.13	(−0.12, 0.39)	0.12	(−0.01, 0.25)	0.17	(−0.15, 0.48)
Illegal feticide	0.10	(−0.16, 0.37)	0.05	(−0.09, 0.18)	0.13	(−0.20, 0.46)
Euthanasia	0.15	(−0.03, 0.34)	−0.03	(−0.12, 0.07)	0.22	(−0.01, 0.44)
Death during legal interventions	0.06	(−0.18, 0.30)	0.04	(−0.08, 0.16)	0.16	(−0.14, 0.45)
Government effectiveness	−0.14	(−0.24, −0.05)	0.00	(−0.10, 0.11)	−0.11	(−0.22, −0.00)
Regulatory quality	0.08	(−0.03, 0.19)	0.05	(−0.07, 0.18)	0.07	(−0.06, 0.19)
log(vital records)	0.77	(0.73, 0.81)	0.64	(0.57, 0.70)	0.95	(0.88, 1.02)
log(mean vital records)	0.28	(0.20, 0.37)	0.42	(0.35, 0.50)	0.09	(−0.02, 0.19)
Parameters	$\sigma^2_{within} = 0.05$ $\sigma^2_u = 0.05$ $\theta = 0.79$		$\sigma^2_{within} = 0.08$ $\sigma^2_u = 0.01$ $\theta = 0.42$		$\sigma^2_{within} = 0.07$ $\sigma^2_u = 0.07$ $\theta = 0.80$	
Observations	n=671 T=1–23 N=35		n=635 T=9–19 N=35		n=734 T=12–22 N=35	
R^2/R^2 Adjusted	0.833/0.829		0.915/0.913		0.718/0.711	

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Data Availability The analytic code and input data used in this study are available on GitHub (https://github.com/davidbuilgil/counting-homicide).

Declarations

Competing interests We have no known conflict of interest to disclose.

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