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Homicídios femininos no estado de São Paulo, Brasil: uma análise de série temporal de 1980 a 2022

Short title: Female homicides in the state of São Paulo, Brazil

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APPROVAL BY RESEARCH ETHICS COMMITTEE: This study analyses aggregated data from a public health information system and does not identify individuals. Therefore, approval by a Research Ethics Committee is not required.

AUTHORS' CONTRIBUTIONS: EZM: Conceptualization, Data curation, Project administration, Supervision, Software, Formal analysis, Visualization, Writing – original draft. CBS: Visualization, Writing – review & editing. EAS: Methodology, Software, Formal analysis, Writing – review & editing. MLZ: Methodology, Visualization, Writing – review & editing.

ABSTRACT

Objective: This ecological study analyzes the temporal evolution of female homicide rates in the state of São Paulo, Brazil, from 1980 to 2022, using data from the Mortality Information System (SIM). **Methods:** Possible change points in the trend of these rates was identified using the Bayesian Estimator of Abrupt Change, Seasonality and Trend (BEAST) model. **Results:** A total of 29,234 female homicide cases were recorded during the period, including 3,914 among young women aged 15 to 19. The analysis detected two major change points in 1995 and 2004, dividing the time series into three segments: an increasing trend until 1994, a stable period from 1995 to 2003, and a decreasing trend from 2004 onward. Among young women, the data identified three change points, with a significant and consistent decline in homicide rates from 2004 to 2022. **Conclusion**: The number of female homicides in São Paulo has declined significantly since 2004, particularly among girls aged 15–19. Although this is linked to policy changes, the decline is likely due to multiple factors. The study highlights the importance of ongoing gender-focused policies and robust analytical tools in guiding public safety efforts.

Keywords: Violence against women; Gender-based violence; Brazil; Homicide; Public health surveillance

RESUMO

Objetivo: Este estudo ecológico analisa a evolução temporal das taxas de homicídio feminino no estado de São Paulo, Brasil, de 1980 a 2022, usando dados do Sistema de Informações sobre Mortalidade (SIM). **Métodos**: Possíveis pontos de mudança na tendência dessas taxas foram identificados usando o modelo Bayesian Estimator of Abrupt Change, Seasonality and Trend (BEAST). **Resultados**: Um total de 29.234 casos de homicídio feminino foi registrado durante o período, incluindo 3.914 entre mulheres jovens de 15 a 19 anos. A análise detectou dois pontos de mudança importantes em 1995 e 2004, dividindo a série temporal em três segmentos: uma tendência crescente até 1994, um período estável de 1995 a 2003 e uma tendência decrescente de 2004 em diante. Entre as mulheres jovens, os dados identificaram três pontos de mudança, com um declínio significativo e consistente nas taxas de homicídio de 2004 a 2022. **Conclusões**: O número de homicídios femininos em São Paulo diminuiu significativamente desde 2004, principalmente entre as jovens de 15 a 19 anos. Embora isso esteja ligado a mudanças de políticas, o declínio provavelmente se deve a vários fatores. O estudo destaca a importância de políticas contínuas com foco em gênero e ferramentas analíticas robustas para orientar os esforços de segurança pública.

Palavras-chave: Violência contra a mulher; Violência de gênero; Brasil; Homicídio; Vigilância em saúde pública

Introduction

As a World Health Organization (WHO) report has observed, violence against women is not a new phenomenon, nor are the consequences for their physical, mental, and reproductive health[1]. However, the growing recognition that these acts violate women's and girls' rights, limiting their participation in society and damaging their health and well-being, is a more recent development[1]. This WHO report defines ‘violence against women’ as encompassing various forms of violence, such as intimate partner violence, rape, sexual assault and other forms of sexual violence perpetrated by individuals other than partners. It also covers female genital mutilation, honor killings and the trafficking of women[1].

Brazil has implemented various initiatives to address and reduce violence against women. In 2006, Law 11.340/2006 was introduced, also known as the Maria da Penha Law[2], which acknowledges that violence against women is rooted in gender inequality and constitutes a human rights violation. Prior to this law, situations of violence against women were, in most cases, considered crimes of lesser offensive potential. The penalties for these crimes were often symbolic, such as the distribution of basic food baskets or community labor, which contributed to a feeling of impunity[3]. In 2015, the Brazilian government formally recognized 'feminicide' as a specific and aggravated form of homicide by including this term in Law 13.104/2015 within the penal code, thus categorizing it as a heinous crime[4].

Despite the progress made in legislation to protect women from violence, Brazil is still reported to be one of the most violent countries for women[5]. A study using data from the 2019 National Health Survey showed that 19.38% of Brazilian women reported experiencing violence[6]. Psychological violence was the most common subtype, both in isolation and in conjunction with other subtypes. Furthermore, the Global Burden of Disease Study (GBD) on interpersonal violence against women showed that Brazil's homicide rates among women aged 15 to 49 have remained consistently high between 1990 and 2019, indicating an inability of conservative Brazilian society to protect women[7].

As the analysis of the temporal evolution of health issues is an important tool for evaluating and planning public health and safety policies, this article aims to use time series analysis to identify potential change points in the annual female homicide rate in São Paulo, Brazil, from 1980 to 2022, using data from the Brazilian Mortality Information System (SIM, in Portuguese). For the purposes of this article, 'female homicide' refers to the murder of women in the broadest sense. This includes cases of femicide, which are related to gender issues, as well as cases involving general delinquency. As SIM data is based on death certificates that do not detail the circumstances of the crime, analyzing data on female homicides can provide insight into how femicide cases have evolved within the Brazilian population.

Methods

Study design and data source

This ecological and descriptive study is based on data from the Brazilian Mortality Information System. It considers the annual number of female homicides in São Paulo, Brazil, from 1980 to 2022, categorizing deaths according to place of residence. In view of the potential demographic changes resulting from a reduction in the proportion of young people in the population over the period, the analyses considered homicides in all age groups, as well as among those in the final phase of adolescence (15-19-year-olds).

Up to 1995, female homicides were identified using codes from the 9th Revision of the International Classification of Diseases (ICD-9): E960–E978 (homicides and intentional injuries to other people) and E990–E999 (legal interventions). After 1995, the following

ICD-10 codes are considered: X85–Y09 (aggression) and Y35 (legal intervention). To calculate the mortality rates, population projections for each federative unit by sex for each year, as well as population counts, provided by the Brazilian Institute of Geography and Statistics (IBGE), were used as the denominator.

Brazil is the fifth largest country in the world by area, spanning a territory of 8,514,876 square kilometers. For administrative purposes, it is organized into 26 states and one federal district, which are grouped into five main geographic regions: North, Northeast, Southeast, South and Midwest. The state of São Paulo, located in the southeast region, is the most populous state in Brazil, accounting for around a fifth of the country's population. As this study used secondary data and no individuals were identified, it was not submitted to a research ethics committee. This is in accordance with national and international legislation regulating research involving humans.

Statistical analysis

The Change Point Analysis (CPA) method includes statistical tools used to investigate potential changes occurring within a series of data points. The Bayesian Estimator of Abrupt Change, Seasonal Change and Trend (BEAST) is a flexible CPA method that detects abrupt changes (i.e., change points), cyclic variations, and nonlinear trends in time series observations[8]. Consider a time series denoted by (t_i, y_i), where $i = 1,\ldots,n$, and y_i are observations of a variable at the time t_i. In a general manner, BEAST assumes that this time series comprises three components, trend (T), seasonality (S), change point and noise. The global model is thus given by

$$y(t_i,\Theta) = T(t_i,\Theta_T) + S(t_i,\Theta_S) + e_i,\ i = 1,\ldots,n,$$

where the parameters Θ_T and Θ_S specify the trend and seasonal factors and implicitly encode the abrupt change points. In addition, e_i are the residuals of the model. By "abrupt", the authors of the BEAST algorithm refer to "any turning points or breakpoints at which trend or seasonal signals start to deviate from the previous regular trajectories" [8]. The method thus calculates the probability of a change point occurring at each year of the study period, denoted by cpPr, and the probability distribution of the number of change points in the trend component. The mode of this distribution corresponds to the optimal number of change points. Further details can be obtained from the original article by Zhao et al.[8].

In the present study, we do not consider the presence of seasonal factors. For estimating the unknown parameters, the Bayesian approach is considered, where the Markov Chain Monte Carlo (MCMC) sampling technique is employed to obtain random samples for posterior inference. Three MCMC chains were simulated, each with 100,000 samples. The first 1,000 samples from each chain were discarded to avoid the effect of the initial values. This analysis has been performed on R (version 4.4.1) using the "Rbeast" package.

In the time series intervals in which the BEAST model suggests an approximately linear trend, it is possible to calculate the annual percentage rate change (APC)[9]. This is calculated using the equation APC = $(e^b - 1)100\%$, where e is the base of the natural logarithm and b is the angular coefficient of the Prais-Winsten regression model. This analysis used the "prais" package in R.

Results

From 1980 to 2022, a total of 29.234 cases of female homicide were reported in the state of São Paulo, of which 3,914 were among women aged 15 to 19.

Figure 1 (panel A) shows the results of using the BEAST algorithm to perform sequence decomposition and change-point analysis on the time series of female homicide rates in the state of São Paulo, where is founded a 69.1% probability that the trend component has two change points. The results indicate two abrupt change points occurring in 2004 and 1995, with respective probabilities (cpPr) of 0.9405 and 0.7742. These two change points divide the trend factors within the time series into three segments. The first segment shows an approximately linear increase from 1980 to 1994, with rates ranging from 2.78 to 4.69 homicides per 100,000 inhabitants and an annual percentage change (APC) of 12.1% (95% confidence interval (CI): 6.93% to 17.5%). The second segment shows an increase from 1995 to 1999, when the homicide rate peaked at 6.18 per 100,000 inhabitants, followed by a decrease until 2003. In a visual interpretation of the graph in Figure 1, if a horizontal line segment is fully included within the 95% credibility interval represented by the shaded area, as occurred between 1995 and 2003, then there is no statistically significant upward or downward trend during that period (similar to $p<0.05$). Finally, the third segment shows a linear decrease from 2004 until the end of the series. In 2004, the rate of female homicides was 4.25 per 100,000 inhabitants, and by 2022, this rate had fallen to 1.53, the lowest rate recorded during the entire study period (APC -12.8%, 95%CI: -14.5% to -11.0%).

Figure 1 (panel B) shows the results of applying the BEAST algorithm to the time series of homicide rates among young females (aged 15 to 19) in the state of São Paulo. It was found that there is a 53.3% probability of three change points in the trend component: in 1984 (cpPr 0.2509), 1995 (cpPr 0.8843) and 2004 (cpPr 0.9981). Between 1984 and 1994, the rate of homicides per 100,000 people increased from 6.76 to 7.89, with a not significant APC (9.6%, 95%CI: -4.0% to 25.2%, $p=0.16$). Between 1995 and 2023, the rate varied relatively little. In 1995, the rate was 9.61 homicides per 100,000 people. A peak of 10.84 homicides per 100,000 inhabitants was reached in 1997, followed by a decrease until 2003, when the rate equaled 9.70 homicides per 100,000 inhabitants. From

2004 to 2022, there was a reduction from 7.42 to 1.93 homicides per 100,000 inhabitants, with an APC of -23.4% (95%CI: -26.72 to -19.82).

Details of the results of the BEAST analysis and R codes are provided in the Supplementary Material.

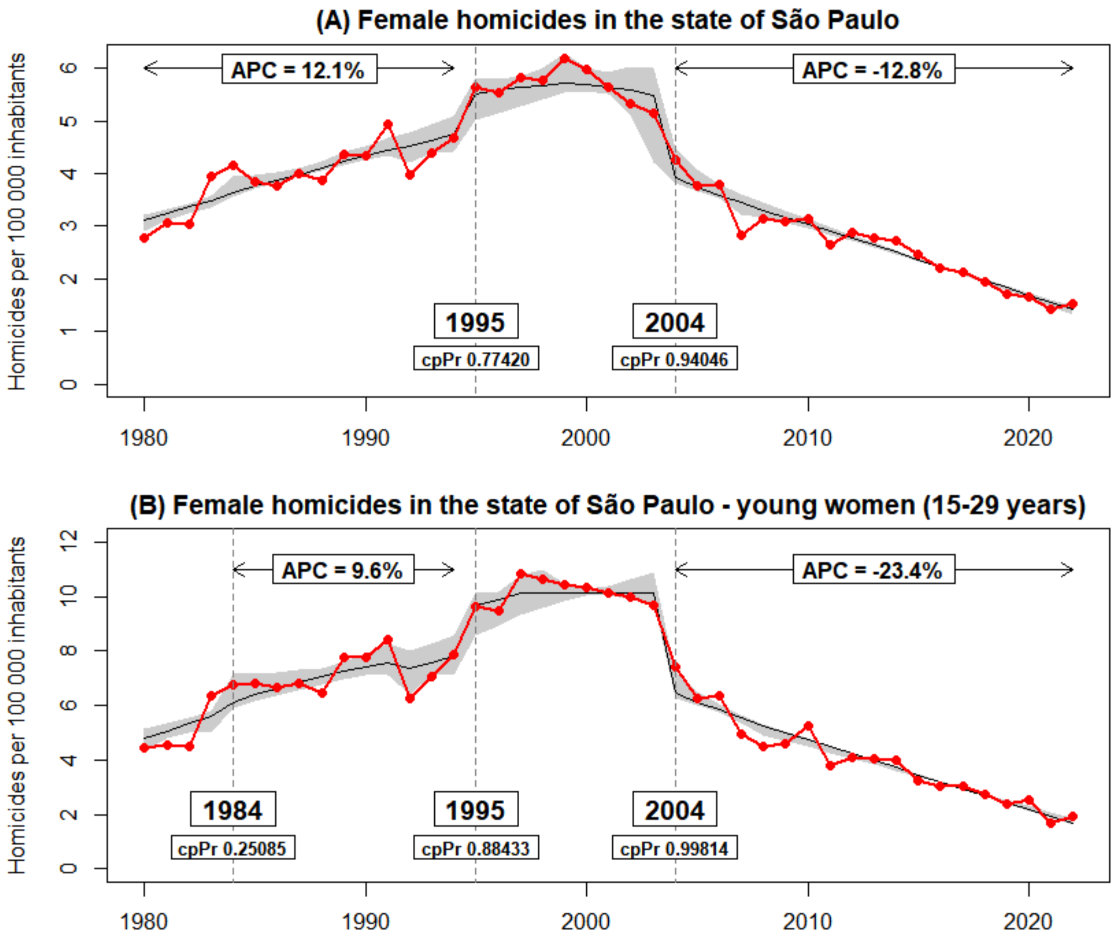

Figure 1. The red line shows the observed annual homicide rate for (A) all female age groups and (B) young women (aged 15–19) per 100,000 inhabitants in the Brazilian state of São Paulo from 1980 to 2022. The black line shows the trend estimated using the BEAST algorithm, and the shaded area represents a 95% credibility interval. The dashed vertical lines indicate the change points and cpPr denotes the corresponding probability of occurrence.

Discussion

The BEAST approach is a common method to decompose time series into trend and seasonality and for detecting abrupt changes in these two components. It has been used in a wide range of applications, including studies of land surface temperature[10], climate change detection[11] and the dynamics of infectious diseases[12]. Compared to joinpoint regression, which is currently widely used in time series studies in epidemiology, the BEAST approach may be more suitable for evaluating the dynamics of some health events, given that in the joinpoint approach, each segment between the change points is linear[13]. In contrast, the BEAST approach can detect nonlinear trends between successive change points using functions such as spline smoothing. In this study, BEAST was shown to be suitable for describing the behavior of female homicide data series, enabling significant periods to be identified.

Our analyses have highlighted a significant decrease in the rate of female homicides in the state of São Paulo, particularly since 2004 and among young women. While this reduction has also been observed by other researchers [14-20], the present article provides new insights. Firstly, it demonstrates the usefulness of the BEAST method for exploring trends and time series behavior, and this approach is straightforward to implement using free software such as R. Secondly, it updates previous study results by presenting a broader time series from 1980 to 2022, in line with the current availability of data in official information systems. A third contribution is its focus on female homicides. Although the findings do not specifically address femicide this focus enables a more targeted discussion grounded in gender-specific dynamics and legislation, as well as the consideration of particular vulnerabilities that might remain hidden in analyses of the general population.

Analyzing public safety indicators in the municipality of São Paulo between 1996 and 2008, Peres et al.[14] list three main explanatory hypotheses for the reduction in homicides: investment in public safety actions, socio-economic changes with improved quality of life and demographic changes with a reduction in the proportion of young people in the population. Consistent with the idea that investment in public safety measures could account for the decline in homicide rates, Goertzel and Kahn[15] suggest that the figures in São Paulo city and state between 2001 and 2007 may be attributable to more effective policing methods, such as the stricter enforcement of gun control legislation. The authors also noted that, in October 2003, the Brazilian federal government introduced new legislation to restrict the import of firearms, prohibit the ownership of unregistered guns, and ban carrying guns in public, while also increasing penalties for violations of gun control laws. This legislation also provided for a weapons buy-back program involving the federal and municipal governments, as well as civil society[21]. Between July 2004 and October 2005, 470,000 guns were handed in voluntarily in Brazil in exchange for up to $100 in compensation. At the time, this was considered the second-largest buy-back campaign ever carried out worldwide[21]. In addition, Peres et al.[16] cite a 169.5 per cent increase in investment in public security in the state of São Paulo between 1997 and 2008, particularly between 1997 and 2001 when investment rose from 2.8 to 8.8 per cent, representing an increase of 219.3 per cent. For his part, Nadanovsky[17] attributed the decrease in homicide rates in the state of São Paulo to an increase in incarceration. He noted that the number of prisoners per 100,000 inhabitants had risen from 182 in 1996 to 341 in 2005.

In addition to the possible impact of changes in the demographic composition of the population on the reduction in homicide mortality rates in the state of São Paulo, the following factors, which are not related to public safety, have been identified: changes in the demographic composition of the population, particularly a decrease in the proportion of young people; investment in social policies and subsequent changes in socioeconomic indicators and quality of life; greater social participation, based on the emergence and consolidation of organized civil society initiatives; a decrease in the unemployment rate; and state investment in education and culture[16,18-20]. Another hypothesis for the decline in homicide rates is linked to the activities of groups that control all local criminal organizations[22-24]. The consolidation of a faction's hegemony over the criminal underworld in the state of São Paulo would have helped to establish peace in the markets for drugs, arms, vehicles and contraband, as well as the legal markets associated with them[23]. This would have reduced conflicts and, consequently, the number of homicides.

All the cited articles above are relevant to help to explain the reduction in the number of homicides observed in our data from 2004 onwards. However, except for Martins et al.[20], the ecological studies[14-19] focused on the general population in São Paulo, rather than specifically on female homicides. In this specific context, some key events that align with the beginning of the decline in homicide rates in 2004 include the launch of the National Plan for Policies for Women, which brought together the outcomes of the First National Conference on Policies for Women, that prioritized the coordination of support networks, and its expanding and improving[25]. Also in 2004, a consortium of feminist nongovernmental organizations and experts proposed a law on domestic and family violence against women, along with a justification highlighting the need to address this issue through comprehensive legislation and public policies. These efforts resulted in the Law to Combat Domestic and Family Violence against Women (Maria da Penha Law), sanctioned on 2006. This law marks a turning point in Brazil's efforts to protect women from violence. It introduces new tools to prevent abuse, ensures stronger punishment for offenders, and offers support and protection to women in vulnerable situations[26].

Nearly two decades after its enactment, the Maria da Penha Law remains a key tool for protecting women in Brazil. Our data suggests that the introduction of this law in 2006 did not result in a sudden change in the trend of female homicide rates in the state of São Paulo. However, as previously mentioned, in 2004 there was already a great national movement and mobilization for its elaboration and promulgation. Over the years, the law has been improved and updated to increase its effectiveness and better fulfill its purpose. Updates include immediate arrest of aggressors, preventive detention, increased sentences for minor injuries, and protective measures like removing the abuser from the home and banning contact with the victim and her children. All the amendments and revisions to the Maria da Penha Law since its enactment have certainly contributed to maintaining the steady decline in rates observed since 2004 in our analysis.

In addition to these legal protections, in March 2015, Law No. 13,104/2015, also known as the Feminicide Law, was enacted. It classifies feminicide as an aggravated form of homicide, defining it as the killing of a woman due to her gender. The law specifically recognizes cases involving domestic and family violence, or acts of contempt or discrimination based on the victim's gender.[26]. However, similar to the Maria da Penha Law, the Feminicide Law did not result in an immediate shift in the trend of female homicide rates in the state of São Paulo in our analysis. Nevertheless, its enactment is undeniably important for sustaining the gradual decline in the homicide rates within the state.

Some authors have discussed the possibility that the Covid-19 pandemic may have contributed to an increase in violent crimes against women in various contexts and geographical regions[27,28]. According to Marques et al.[29], factors linked to social isolation that contributed to the increase in these crimes include the victim's isolation, making her more vulnerable, the aggressor's use of alcohol or illicit drugs, which intensifies violence, greater ease for the aggressor to control the victim, and unemployment. A study by Nunes et al.[30] showed that the mortality rate due to intentional violent crimes against women in Alagoas, Brazil, was higher in 2020 (5.33 per 100,000 people) than in the years prior to the pandemic. Other Brazilian studies include that by Leite et al.[31], which showed that psychological, physical, and sexual violence perpetrated by the intimate partners during the pandemic was widespread among women living in Vitória, in the Brazilian state of Espírito Santo. However, this trend does not appear in our data.

This study has several potential limitations. Firstly, and perhaps most importantly, the mortality rates found in this study may be biased due to underreporting issues, as well as the fact that they are based on population projections provided by the IBGE for each year, which may differ from actual census data. Another limitation lies in the fact that we were unable to ascertain the type of homicide, the circumstances surrounding it, or the weapon used. For example, analyzing homicides by type of weapon can reveal the potential effect of firearm possession legislation on violent deaths. Cerqueira and Lins[32] highlight the possibility of there being a number of 'hidden homicides' within the mortality information system, i.e. homicides that are not officially recorded as such. To address this issue, the authors propose using machine learning techniques to estimate the probability that a violent death from an undetermined cause was actually a homicide. However, this strategy was not employed in the present study. Furthermore, when considering the number of unrecorded homicides in the country, it is necessary to consider cases where there is no death certificate, for example when perpetrators conceal their victims' bodies. This could also introduce bias into the results of this study, particularly given that the occurrence of this type of homicide may have increased over the period considered.

Despite these limitations, our study also presents some strengths. The temporal coverage of over four decades (1980–2022) enables the identification of long-term trends and structural shifts in female homicide rates, and it includes recent data not typically available in earlier studies, extending the analysis beyond previous research, which often ends in the early 2000s or 2010s[14-20]. Using the BEAST model is a methodological strength because, compared to more conventional linear models (e.g. joinpoint regression), BEAST can detect nonlinear trends and multiple change points. It also allows for a probabilistic interpretation of changes and accommodates model uncertainty in trend estimation. The results obtained can inform evidence-based public policy regarding violence against women.

In conclusion, this study describes a substantial and enduring decrease in the rate of female homicides in the Brazilian state of São Paulo, particularly since 2004, with a more pronounced reduction observed among adolescent females aged 15 to 19. Although the observed trends coincide with major legislative and policy developments, female homicide is a complex phenomenon influenced by multiple interrelated factors. These factors may include demographic changes, socio-economic improvements, shifts in criminal dynamics, civil society engagement and evolving gender norms. While the statistical analysis provides evidence of significant temporal shifts, it does not allow for causal inferences. Nevertheless, the study highlights the importance of continued investment in gender-sensitive policies and emphasizes the value of advanced analytical tools for monitoring public health and safety indicators in complex social contexts.

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Supplementary Material to: Female homicides in the state of São Paulo, Brazil: a time series analysis from 1980 to 2022

This document provides supplementary material to our paper "Female homicides in the state of São Paulo, Brazil: a time series analysis from 1980 to 2022". It contains further details on the methods of analysis and results that are summarized in the main report.

Statistical details of BEAST method

The Bayesian model averaging time-series decomposition algorithm (BEAST) is a parametric regression method developed by Zhao et al.[1]. It can capture various types of uncertainty, identify abrupt shifts of any size and reveal intricate nonlinear patterns in time series data. Let $\mathcal{D} = \{t_i, y_i\}_{i=1,\ldots,n}$ the observed data, where y_i denotes observations of a variable at n time points t_i. The statistical model for the time series $y(t_i)$ is given by

$$y(t_i) = S(t_i;\mathbf{\Theta}_\mathrm{S}) + T(t_i;\mathbf{\Theta}_\mathrm{T}) + e_i,\ i = 1,\ldots,n,$$

where the parameters $\mathbf{\Theta}_\mathrm{S}$ and $\mathbf{\Theta}_\mathrm{T}$ are estimated from the data $\mathcal{D}$, and they also implicitly encode the abrupt change points. We assume that the noise e_i is Gaussian with a magnitude of σ, capturing the remainder of the data that is not explained by the seasonal (S) and trend (T) components[1,2]. To evaluate the unknown parameters, the algorithm employs Bayesian inference.

The R package `Rbeast` can be used to perform this analysis. Consider `wt` a data frame containing the variables `wt$ANO` (years from 1980 to 2022) and `wt$SP` (the female homicide rates in São Paulo from 1980 to 2022).

```
# Data
wt <- data.frame(
  ANO = 1980:2022,
  SP  = c(2.78, 3.07, 3.03, 3.94, 4.15, 3.85, 3.76, 4.00, 3.88,
          4.37, 4.34, 4.94, 3.97, 4.39, 4.69, 5.63, 5.54, 5.83,
          5.78, 6.18, 5.98, 5.64, 5.32, 5.14, 4.25, 3.78, 3.80,
          2.84, 3.14, 3.08, 3.13, 2.65, 2.89, 2.78, 2.72, 2.46,
          2.21, 2.14, 1.95, 1.72, 1.67, 1.43, 1.53))
```

The BEAST model can be fitted to data in the following way:

```
# Bayesian changepoint detection algorithm
library(Rbeast)
myts <- ts(wt$SP, start=c(1980), end=c(2022))
out <- beast(myts, season='none',
```

```
        dump.ci = TRUE, mcmc.burnin = 1000, mcmc.samples = 100000)
plot(out)
print(out)
```

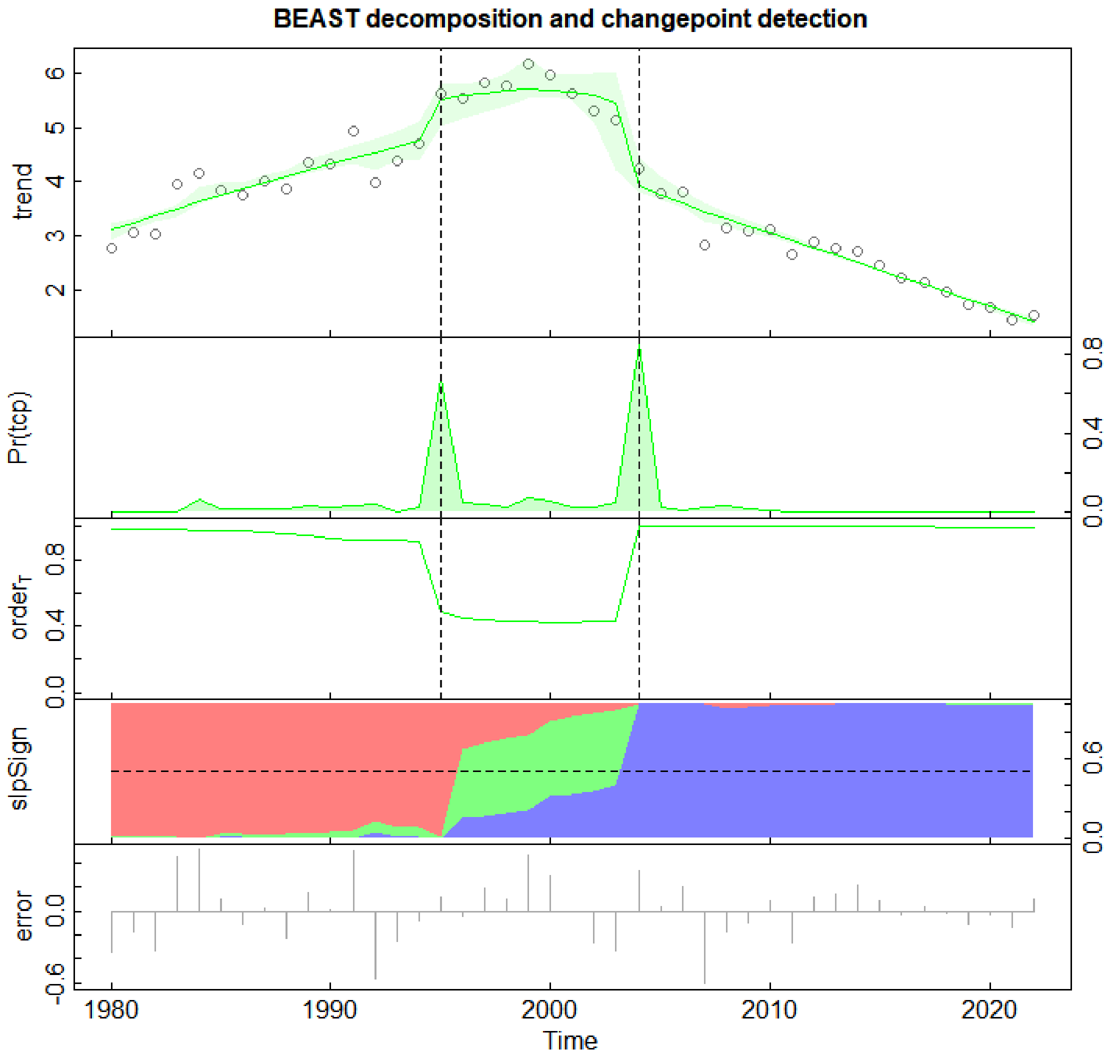

Figure S1. Results of BEAST of female homicides time series in São Paulo from 2000 to 2022.

In this R code, **`library`**`(Rbeast)` is used to load the `Rbeast` package, and the **`ts`** function is used to create the time-series object `myts` containing `wt$SP`. The **`beast`** function in the `Rbeast` package is then used to fit the BEAST model to the data, where the argument `season='none'` is used to specify that the seasonal component $S(t_i;\boldsymbol{\Theta}_S)$ will not be used in our analysis, and `dump.ci = TRUE` is used to create credible intervals for the estimated trend component. The argument `mcmc.burnin = 1000` specifies the number of burn-in samples discarded at the start of each chain (the default number of MCMC chains is three), while `mcmc.samples` specifies the number of samples to be collected per MCMC chain.

Figure S1 shows the results obtained from the **`beast`** function. The dashed vertical lines mark the most likely locations of changepoints and the green curve of Pr(tcp) shows the point-wise probability of changepoint occurrence over time. The "order$_T$" curve provides an estimate of the mean order of the piecewise polynomials required to adequately fit the trend (the 0-th order is constant and the 1st order is linear). An average order toward 0 means that the trend is more likely to be flat and an order close to 1 means that the trend is linear. "slpSign" are the probabilities of the trend slope being positive (red part), zero (green), or negative (blue). Finally, "error" are the residual errors between the observed and BEAST-modelled values.

The **`print`**`(out)` function summarizes and prints the results obtained from the BEAST time series decomposition and segmentation, as shown below.

```
> print(out)
#####################################################################
#                     Seasonal  Changepoints                        #
#####################################################################
No seasonal/periodic component present (i.e., season='none')

#####################################################################
#                     Trend  Changepoints                           #
#####################################################################
.-------------------------------------------------------------------.
| Ascii plot of probability distribution for number of chgpts (ncp) |
.-------------------------------------------------------------------.
|Pr(ncp = 0 )=0.000|*                                               |
|Pr(ncp = 1 )=0.080|******                                          |
|Pr(ncp = 2 )=0.691|*********************************************** |
|Pr(ncp = 3 )=0.196|**************                                  |
|Pr(ncp = 4 )=0.031|***                                             |
|Pr(ncp = 5 )=0.003|*                                               |
|Pr(ncp = 6 )=0.000|*                                               |
|Pr(ncp = 7 )=0.000|*                                               |
|Pr(ncp = 8 )=0.000|*                                               |
|Pr(ncp = 9 )=0.000|*                                               |
.-------------------------------------------------------------------.
|    Summary for number of Trend ChangePoints (tcp)                 |
.-------------------------------------------------------------------.
|ncp_max    = 9    | MaxTrendKnotNum: A parameter you set           |
|ncp_mode   = 2    | Pr(ncp= 2)=0.69: There is a 69.1% probability  |
|                  | that the trend component has  2 changepoint(s).|
|ncp_mean   = 2.19 | Sum{ncp*Pr(ncp)} for ncp = 0,...,9             |
|ncp_pct10  = 2.00 | 10% percentile for number of changepoints      |
|ncp_median = 2.00 | 50% percentile: Median number of changepoints  |
|ncp_pct90  = 3.00 | 90% percentile for number of changepoints      |
.-------------------------------------------------------------------.
| List of probable trend changepoints ranked by probability of      |
```

```
| occurrence: Please combine the ncp reported above to determine    |
| which changepoints below are practically meaningful               |
'-------------------------------------------------------------------'
|tcp#              |time (cp)                  |prob(cpPr)          |
|------------------|---------------------------|--------------------|
|1                 |2004.000000                |0.94046             |
|2                 |1995.000000                |0.77420             |
|3                 |1992.000000                |0.11254             |
|4                 |1984.000000                |0.09895             |
.-------------------------------------------------------------------.
```

This output shows that there is a 69.1% probability that the trend component has two change points (the mode for the probability distribution for number of change points, denoted by `ncp_mode`). The locations where these two change points occur and the probabilities associated with each change point are 2004 (94.06%) and 1995 (77.42%).

Statistical details of the APC estimation

When the BEAST model suggests an approximately linear trend in an interval on the time series, it is possible to calculate the correspondent annual percentage rate change (APC)[3]. This is calculated using the equation

$$\text{APC} = (e^{b} - 1)100\%,$$

where e is the base of the natural logarithm and b is the angular coefficient of the Prais-Winsten regression model. We let y_t denote observations of a variable at n time points $t = 1,\ldots,n$. The regression model is given by

$$y_t = a + bt + e_t,$$

where a and b are unknown coefficients and e_t is a mean zero error representing other determinants of the outcome. We assume that t is independent of e_t. The Prais-Winsten method involves estimating the correlation between the error at t and $t-1$, assuming that

$$e_t = \phi_1 e_{t-1} + \eta_t,$$

where ϕ_1 is an autoregressive (AR) parameter with $|\phi_1| < 1$ and η_t are independent disturbances with zero mean and variance σ_η^2. The constraint ϕ_1 ensures that the process is stationary, that is, the covariance between e_t and e_{t+h} is independent of t, and therefore that the variance remains constant over time. In our article, this analysis used the function `prais_winsten` of the `prais` package in R.

For example, to estimate the APC of the of female homicide rates time series between 1980 and 1994, we can use the following R code:

```
# APC estimation based on the Prais-Winsten regression model
# 1980 to 1994
library(prais)
pw <- c()
ay <- 1980
by <- 1994
NY    <- length(ay:by)
seqt  <- (ay-1979):(by-1979)
pw_sample <- data.frame("x" = wt$ANO[seqt], "y" = wt$SP[seqt],
               "time" = seqt)
pw    <- prais_winsten(y ~ x, data = pw_sample, index = "time")
a     <- summary(pw)
b1    <- a$coefficients[2,1]   # angular coefficient
se    <- a$coefficients[2,2]   # standard errors
APC   <- exp(b1)-1             # APC
L_APC <- exp(b1-se*qt(1-0.05/2,NY-1))-1
U_APC <- exp(b1+se*qt(1-0.05/2,NY-1))-1
message("APC ",round(100*APC,2)," 95%CI (",round(100*L_APC,2),
        " , ",round(100*U_APC,2),")")
```

The following output is then obtained for the Prais-Winsten regression model analysis:

```
Call:
prais_winsten(formula = y ~ x, data = pw_sample, index = "time")

Residuals:
     Min       1Q   Median       3Q      Max 
-0.54207 -0.21143 -0.05033  0.16857  0.55096 

AR(1) coefficient rho after 5 iterations: 0.08555

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -222.83477   43.69461   -5.10 0.000204 ***
x              0.11413    0.02199    5.19 0.000174 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3428 on 13 degrees of freedom
Multiple R-squared:  0.6217,    Adjusted R-squared:  0.5926 
F-statistic: 21.36 on 1 and 13 DF,  p-value: 0.0004782

Durbin-Watson statistic (original): 1.743 
Durbin-Watson statistic (transformed): 1.899
```

We can note that the estimated values for the parameters ϕ_1 and b are 0.08555 and 0.11413, respectively. Thus, the APC is estimated to be

$$\mathrm{APC} = (e^{0.11413} - 1)100\% \cong 12.1\%.$$

The lower and upper limits of the 95% confidence interval for the APC can be obtained using the following expressions, respectively:

$$[\exp(b - \mathrm{se}(b) \times t_{(1-0.05/2,\mathrm{df})}) - 1]100\%$$

and

$$[\exp(b + \mathrm{se}(b) \times t_{(1-0.05/2,\mathrm{df})}) - 1]100\%.$$

In these expressions, se(b) is an estimate of the standard error of b. In the R output, we have se(b) equal to 0.02199. In addition, $t_{(1-0.05/2,\mathrm{df})}$ is the (1–0.05/2) percentile of a Student's t distribution with degrees of freedom (df) given by $n^* - 1$, where n^* is the length of the interval. This percentile is obtained using the R function `qt`.

The R code above gives us:

```
APC 12.09 95%CI (6.93 , 17.5)
```

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