UNIVERSIDAD DE COSTA RICA | CCP Centro Centroamericano de Población
Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Art. Sci. july-december 2025

Población y Salud en Mesoamérica

Using Google Trends Data to forecast homicide mortality: the case of Mexico

Eduardo Vazquez y Eliud Silva

How to cite this article:

Vazquez, E. y Silva, E. (2025). Using Google Trends Data to forecast homicide mortality: the case of Mexico. *Revista Población y Salud en Mesoamérica, 22*(2). https://doi.org/10.15517/c57dzg81

ISSN-1659-0201 http://ccp.ucr.ac.cr/revista/

Revista electrónica semestral
Centro Centroamericano de Población
Universidad de Costa Rica

Población y Salud en Mesoamérica

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

Using Google Trends Data to forecast homicide mortality: the case of Mexico

Uso de Google Trends para pronosticar la mortalidad por homicidio: el caso de México

Eduardo Vazquez [1] and Eliud Silva[2]

Abstract: Introduction: In Mexico a major public safety concern is how to predict and reduce homicides to implement effective mitigation policies. **Methodology**: This study aims to compare traditional forecasting models —ARIMA and Vector Autoregressive (VAR)—with and without Google Trends data, the research explores ways to enhance prediction accuracy. Using homicide records from the National Institute of Statistics and Geography (INEGI, for its Spanish acronym) and Google Trends data from 2006–2020, the study highlights the integration of real-time online data to complement official statistics. **Results**: Considering a forecast horizon of 15 months up to March 2020, results show that VAR models with Google Trends provide the best performance for both female and male homicides. **Conclusions**: The findings underscore the potential of integrating digital data sources into traditional models to provide more accurate and timely tools for public safety planning and intervention.

Keywords: Homicides, forecasting, Google Trends, VAR model.

Resumen: Introducción: En México una de las principales preocupaciones en materia de seguridad pública es cómo predecir y reducir los homicidios para implementar políticas de mitigación efectivas. **Metodología**: Este estudio compara modelos tradicionales de pronóstico —ARIMA y Vector Autorregresivo (VAR)— con y sin datos de Google Trends, explorando formas de mejorar la precisión en las predicciones. Utilizando registros de homicidios del Instituto Nacional de Estadística y Geografía (INEGI) y datos de Google Trends correspondientes al periodo 2006–2020, se destaca la utilidad de integrar datos en línea en tiempo real como complemento a las estadísticas oficiales. **Resultados**: Considerando un horizonte de pronóstico de 15 meses hasta marzo de 2020, los resultados muestran que los modelos VAR con Google Trends ofrecen el mejor desempeño tanto para los homicidios de mujeres como de hombres. **Conclusiones**: Estos hallazgos subrayan el potencial de integrar fuentes de datos digitales en los modelos tradicionales para proporcionar herramientas más precisas y oportunas para la planificación e intervención en materia de seguridad pública.

Palabras clave: Homicidios, pronóstico, Google Trends, modelo VAR.

Recieved: 30 apr, 2025 | **Corrected:** 23 sep, 2025 | **Accepted:** 29 sep, 2025

[1] Universidad Anáhuac, MEXICO. eduardo.vazquezhe@anahuac.mx

[2] Universidad Anáhuac - Universidad Nacional Autónoma de México, MEXICO. jose.silva@anahuac.mx

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

1. Introduction

A crime is defined as any act or omission punishable by law, with its interpretation varying across societies depending on time and place (Sahni & Phakey, 2021). Among crimes, homicides have a profound societal impact. According to the United Nations Office on Drugs and Crime (2019), intentional homicide is the gravest crime, with effects that extend far beyond the initial loss of life. It devastates families and communities, often described as "secondary victims", while fostering a violent environment that undermines societal stability, economic progress, and institutional trust. Homicide affects people across all demographics, irrespective of age, gender, ethnicity, socioeconomic background, or other factors, making its prediction a crucial endeavor.

The homicide rate serves as a key indicator of public security in cities, regions, and nations, necessitating accurate forecasts to guide interventions and promote social peace. Forecasting enables proactive measures, allowing law enforcement to allocate resources effectively and potentially prevent crimes (Pearsall, 2010). While research on crime forecasting was limited before 2018, interest has surged since with studies increasing annually. Homicides remain a pressing concern in Mexico, ranking among the top 10 causes of death, trailing only health-related illnesses and accidents. The national homicide rate rose from 8.1 per 100,000 inhabitants in 1990 to 25 in 2020, before declining to 12 in 2023 (INEGI, 2023). However, state-level rates reveal stark contrasts, with some cities ranked among the world’s most dangerous (Observatorio Nacional Ciudadano, 2017).

This study aims to compare forecasting strategies to predict national homicide rates by sex, using INEGI death records and Google Trends data. Three approaches are employed: (1) univariate forecasting with ARIMA, (2) multivariate forecasting with VAR(p), and (3) incorporating Google Trends data as an explanatory variable in both models. Google Trends, which accounts for a significant share of global web searches, provides complementary insights beyond official statistics.

The motivation for using supplementary data stems from Mexico's high crime underreporting rate for all kinds of crimes, with 94% unreported and less than 1% of reported cases resolved (for details, see https://www.impunidadcero.org/impunidad-en-mexico/#/). This underreporting skews official statistics, often misclassifying incidents as disappearances, of which nearly 100,000 remain unresolved. Missing persons, while part of the broader homicide crisis, fall outside this study’s scope due to limited data availability, despite efforts by civil associations to address this gap. The paper is organized as follows: a literature review that highlights the growing role of homicide forecasting as a decision-making tool; the methods section details the forecasting strategy and accuracy comparisons; the results section presents key findings; and the conclusion summarizes the most significant insights.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

2. Literature review

Recent studies have increasingly employed machine learning techniques to forecast and address criminal activities, offering innovative approaches to crime detection and prediction. This review explores various methodologies, including supervised classification, clustering algorithms, and optimization methods, aimed at improving crime forecasting and resource allocation for public safety. Notable useful cases include predicting homicides in violent municipalities and analyzing large-scale data using machine learning and time-series methods to identify the most effective algorithms.

Calvo et al. (2017) proposed a model integrating crime forecasting, clustering, and patrol route optimization. Their methodology utilized supervised classification, clustering for detecting criminal hotspots, and the ant colony algorithm for optimizing patrol routes. Applied to Cuautitlán Izcalli, Mexico, and Sacramento, California, their "CR-Ω+" model demonstrated spatio-temporal accuracy in predicting crime and improving police patrol effectiveness. Similarly, García-Gómez et al. (2022) forecasted homicide counts in Mexico's 15 most violent municipalities using regression techniques like Bayesian Ridge and Support Vector Regression models. They found these methods were effective in predicting homicides using sliding and rolling time windows.

Feminicide trends were explored by Hernández-Gress et al. (2023), who analyzed data from January 2016 to March 2022 across Mexican states. Their findings highlighted an increasing trend in feminicides, unlike other crimes against life, with states such as Mexico City, Veracruz, and the State of Mexico showing the highest numbers. Their analysis included descriptive statistics, hypothesis testing, and short-term projections using single exponential smoothing.

On an international scale, Santos-Marquez (2021) evaluated homicide forecasting models in Colombia, including ETS, ARIMA, and spatial beta-convergence models, finding STAR and beta-convergence models to be the most accurate. In the US, Ramallo et al. (2023) developed a Dynamic Factor Model (DFM) combining multiple data sources (official homicide counts, media files, and crowdsourced information) to predict firearm homicides with high accuracy, outperforming traditional methods.

Google Trends has emerged as a complementary data source for forecasting in various fields, including crime. Piña-García and Ramírez-Ramírez (2019) examined crime dynamics in Mexico City using police reports, Twitter posts, and Google searches. Their study found that integrating Google Trends data enhanced ARIMA-based crime forecasts, identifying terms like “denuncia” (crime report) and “asesinato” (murder) as predictive variables.

Swedo et al. (2023) extended this approach by using Google Trends and other real-time data sources to forecast firearm homicides in the US. Their ensemble model demonstrated superior accuracy,

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

reducing reporting lag from months to weeks. These studies collectively illustrate the growing importance of combining traditional crime data with advanced machine learning models and real-time digital data sources. Such approaches enhance predictive accuracy and enable timely interventions, underscoring their potential as tools for public safety and policy-making.

3. Methodology

3.1 Approach

Our study adopts a quantitative focus, comparing the performance of classic forecasting models: ARIMA and VAR, in predicting homicide trends, both independently and when combined with Google Trends data. Using official records from INEGI and online search activity from 2006 to 2020, we describe the dynamics of violence and explore how digital behavior might improve predictive accuracy. By generating forecasts up to 15 months in advance, disaggregated by sex, the study provides valuable insights into how integrating real-time digital data with official statistics can support smarter and more responsive public safety policies.

3.2 Study population

We use official, aggregated mortality data from INEGI, and the study does not involve individual participants. More specifically, it analyzes monthly homicide records in Mexico from 2006 to 2020, disaggregated by sex. In parallel, we incorporate anonymized Google Trends data to capture public interest in violence-related topics over the same period. Since both sources are aggregated and contain no personally identifiable information, informed consent is not required. The selected time frame reflects the period for which both datasets are consistently available and aligned for analysis.

3.3 Collection techniques

We rely on official records from INEGI, as it provides comprehensive mortality statistics based on death certificates and general health administration records. These data offer a detailed view of the circumstances surrounding deaths, including victim characteristics. INEGI’s rigorous cross-verification with Registry Offices and law enforcement agencies ensures high reliability for analyzing homicide trends and understanding sociodemographic factors. Additionally, the classification system used adheres to the World Health Organization’s International Statistical Classification of Diseases and Related Health Problems (ICD), ensuring reliable and internationally comparable homicide statistics across time (World Health Organization, 2015).

Specifically, this study utilizes administrative and vital records, focusing on statistics from registered deaths (EDR, for its Spanish acronym) from 2006 to 2018 to estimate the models, and from 2019 to 2020 to evaluate the forecasts. It is important to note that the registration date reflects when the crime was discovered and reported, while the occurrence date corresponds to the actual event. This

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

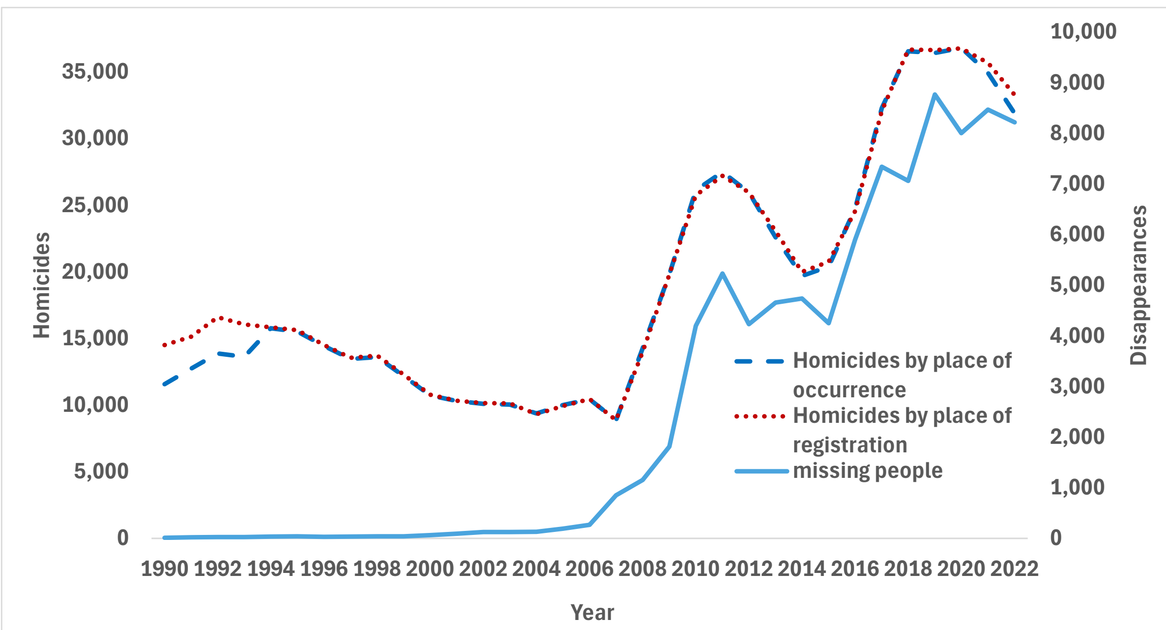
Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

distinction is critical for accurately interpreting the timing of homicides within broader temporal analyses.

We do not consider missing persons, as their vital status as deceased cannot be confirmed. We recognize that missing persons, whose disappearance must be investigated by authorities until their whereabouts are determined, have profound psychological and social impacts (Gutiérrez & Hernández, 2024). Before 2017, the only official record, the National Registry of Missing or Disappeared Persons (RNPED), maintained by the Executive Secretariat of the National Public Security System (SESNSP), exhibited deficiencies such as incomplete and anonymized data (Delgadillo & Torres, 2023). Following persistent criticisms, the General Law on Forced Disappearance of Persons established the National Registry of Disappeared and Unlocated Persons (RNPDNO) in November 2017. The pattern of both homicides and missing persons is illustrated in Figure 1.

Figure 1

Temporal patterns of homicides and missing persons in Mexico, 1990–2022



In addition to official records, we incorporate data from Google Trends, which provides anonymized, relative search volume information indicating public interest in specific topics over time and location. For this study, we retrieved search data covering the entire country of Mexico during the reference period. Although Google Trends is a powerful tool, it presents limitations related to sampling variability and the lack of transparency in its data generation process (Medeiros & Pires, 2021; Cebrián & Domenech, 2024), which may introduce inconsistencies, particularly for low-frequency searches or long time spans.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

To address these challenges in the present work, we conducted repeated queries under identical parameters and used averaged results to mitigate sampling variability. We carefully selected search terms to ensure sufficient search volume across the study period and verified consistency across query replications. These strategies enhanced the robustness of our findings and reduced potential biases, allowing us to integrate Google Trends data as a complementary indicator within our overall analytical framework.

3.4 Analysis processing

The analysis processing was divided into two main stages: Extraction and Transformation. In the Extraction stage, data were retrieved from two primary sources: mortality databases provided by INEGI, focusing specifically on homicide cases for both sexes, and Google Trends search data. In the Transformation stage, the extracted information was organized, cleaned, and compiled into structured data tables to facilitate analytical modeling. Both processed datasets served as inputs for forecasting homicide trends.

Regarding the INEGI mortality data, digital datasets spanning from 1990 to 2023 (INEGI, 2023) were consolidated and standardized to improve information management. To align with the availability of Google Trends data, which begins in 2004, the homicide records were initially aggregated to a monthly frequency for the period from 2004 to March 2020, ensuring consistency across datasets. However, to obtain valid models, we restrict the sample to the period 2006-2018. Records with missing occurrence year were excluded from the analysis, as the study relies on the precise year in which the homicide took place.

In the case of Google Trends, data were collected through its Application Programming Interface (API), which provides access to keyword popularity over time based on user search behavior. The platform assigns a relative score from 0 to 100, where 0 represents minimal interest and 100 indicates peak interest within a selected period and region. This feature allows researchers to monitor search trends across customizable parameters such as time range, geographic region, and search type (e.g., web search, news, YouTube). Although Google Trends data are influenced by major news events, the platform does not incorporate news headlines directly but purely reflects user search activity.

Specifically, we used the R package gtrendsR (Massicotte & Eddelbuettel, 2025), which provides standardized monthly averages of search intensity. This helped to reduce part of the variability that is often present in Google Trends data. We applied this procedure to all selected keywords, and because the package already returns consistent monthly averages, it was not necessary to perform manual replications. The script was developed to collect information from Google Trends and analyze the interest in Mexico regarding terms related to homicides and violence against adult men and women. For this purpose, we used the function gtrends(), which allows us to retrieve historical search series based on specific keywords. The results were organized with the interest_over_time()

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

component, which shows the temporal evolution of relative search volume and provides the corresponding averages, making it possible to identify and compare trends over time.

The keywords were selected based on the authors' perception of the terms most frequently used in Mexican media, including television, radio, newspapers, and social networks, when reporting public insecurity and homicide events, complemented by the reference of Piña and Ramírez (2019). The initial list included: report, to report, homicide, injuries, theft, assault, murder, missing (female), missing (male), rape, firearm, corpse, femicide, accused, pistol, aggressor, extortion, soldier, police, and trafficking.

A first PCA showed that the first component explained about 50% of the variability. To increase explanatory power, we retained only the most correlated variables, resulting in a refined list: report, to report, missing person, femicide, accused, pistol, extortion, soldier, police, and trafficking. A second PCA raised the explained variability of the first component to 71.2%. This refinement was the result of an analytical process in which keywords that contributed little to the PCA, such as aggressor, were discarded even though they might have seemed conceptually appropriate. The analysis in Google Trends confirmed that these terms had lower search volumes compared to others like pistol or soldier, which reached scores of 50 to 70 points in the relevance of user searches. In short, keywords with low search volumes were excluded to ensure that the constructed indicator captured the most informative and representative signals of public attention.

It is interesting to note that in other studies, such as Ramallo et al. (2023) for the United States, only one term (homicide) was employed. Although the two contexts, that is the Mexican and the United States, are not directly comparable, this contrast suggests that the dynamics of violence in Mexico may be reflected through a broader and more complex vocabulary. We also recognize that the diversity of words in Mexico may be related to other violence perception in the population. For this reason, the inclusion of several terms was considered necessary to capture public attention with greater accuracy.

Following data extraction, a variable summarizing Google Trends information was estimated using Principal Component Analysis (PCA), retaining the first component that captures the highest variance among the search queries. Subsequently, both ARIMA and VAR models were estimated, with and without including the PCA-derived explanatory variable. Finally, forecasts were generated for each of the four models, and their predictive accuracies were compared to identify the most effective approach for homicide trend forecasting.

According to the literature, there are several alternatives for dimensionality reduction besides PCA, such as Factor Analysis, Independent Component Analysis (ICA), and Dynamic Factor Analysis (DFA), among others. Each of these methods provides different advantages. For instance, Factor Analysis assumes latent constructs, underlying observed correlations (Fabrigar et al., 1999); ICA seeks statistically independent signals (Hyvärinen & Oja, 2000); DFA captures both latent factors and

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

dynamic time-series relationships (Clements & Hendry, 2011). However, these approaches generally involve higher technical complexity and interpretation challenges. For this reason, PCA was adopted in this study as a first approximation: it combines statistical robustness with conceptual simplicity, is widely accepted in the social sciences, and effectively extracts the maximum variance from correlated Google Trends series. Future research may extend this approach by exploring more sophisticated methods, as mentioned above.

3.5 Statistical models

The employed statistical models were: ARIMA (AutoRegressive Integrated Moving Average) and Vector Autoregressive Models. Undoubtedly, the ARIMA model is a cornerstone of time series analysis (Box et al., 2015). This model can be represented as ARIMA(p,d,q) where p is the number of lag observations (AR); d is the number of times that the raw observations are differenced (I); and q is the size of the moving average window (MA). The general equation for an ARIMA model is given by

$$y_t = \mathrm{c} + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots \phi_1 y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots \theta_q \varepsilon_{t-q} + \varepsilon_t$$

where y_t is the actual at time t, c is constant, $\phi_1, \phi_2, \ldots, \phi_p$ are the coefficients of the AR terms, $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients of the MA terms, ε is the error at the time t.

The Vector Autoregressive (VAR) model was developed by Sims (1980) in response to the limitations of traditional simultaneous equation models. In these traditional models, variables are divided into two categories: endogenous (dependent) and exogenous (independent or predetermined). Sims critiqued this distinction, arguing that if there is genuine simultaneity among a set of variables, all variables should be treated equally without making a priori assumptions about which are endogenous or exogenous.

The conceptual idea of the VAR model is rooted in Granger causality tests, which treat variables as endogenous pairs without the inclusion of exogenous variables (Gujarati & Porter, 2009). Building on this approach, the VAR model incorporates the lagged values of multiple variables, allowing it to capture their dynamic interdependencies (for details see Wei, 2019).

In essence, the VAR model treats all variables as endogenous, modeling each variable as a function of its own lagged values and the lagged values of all other variables in the system. This framework enables the VAR model to provide a comprehensive view of the interactions and feedback loops within a multivariate time series framework. For a set of k variables, the model can be written as

$$Y_{1,t} = c_1 + A_{11,1} Y_{1,t-1} + A_{12,1} Y_{2,t-1} + \ldots + A_{1k,p} Y_{k,t-p} + u_{1,t}$$

$$Y_{2,t} = c_2 + A_{21,1} Y_{1,t-1} + A_{22,1} Y_{2,t-1} + \ldots + A_{2k,p} Y_{k,t-p} + u_{2,,t}$$

$$\ldots$$

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

$$Y_{k,t} = c_k + A_{k1,1} Y_{1,t-1} + A_{k2,1} Y_{2,t-1} + \ldots + A_{3k,p} Y_{k,t-p} + u_{3,,t}$$

where $Y_{j,t}$ is the j-th variable at time t, c is the intercept for the j-th variable, $A_{ji,i}$ are the coefficients of the lagged i-th variables for the j-th equation, u_{j-t} is the error term for the j-th variable at time t.

For the ARIMA models, applied to the univariate time series, we followed the standard Box–Jenkins procedure. First, we examined whether variance stabilization was needed and applied transformations when appropriate. Second, we determined the order of differencing required to achieve stationarity in the mean, confirmed by Augmented Dickey–Fuller (ADF) tests. Third, we inspected the autocorrelation and partial autocorrelation functions to identify candidate AR and MA orders. Competing specifications, both with and without Google Trends variables, were then estimated and compared using AIC, and the model with the lowest values was retained. The statistical significance of the estimated coefficients was verified using t-tests, and residual diagnostics were performed to confirm the assumptions of normality, homoscedasticity, and independence.

Regarding the VAR models, we also followed a systematic procedure. Candidate models with different lag lengths were estimated, and the final specification was selected based on the lowest AIC values, while favoring the most parsimonious choice. In each case, we compared versions of the model with and without Google Trends variables. Stability was verified by examining the inverse roots of the characteristic polynomial to ensure they lay inside the unit circle. The statistical significance of the estimated coefficients was verified using t-tests, and residual diagnostics were applied to evaluate normality, homoscedasticity, and independence, using appropriate statistical tests.

3.6 Measuring forecast accuracy

In terms of forecasting accuracy, we employ the following statistics to make a comparison between the estimated models. In all expressions, we have that y_t is the actual value, $\widehat{y_\iota}$ is the predicted value both at point t, and n is the number of observations.

a) Mean Error (ME): average of the differences between predicted and actual values. It retains the direction of the error, meaning it can be positive or negative. A positive ME suggests that the model tends to overestimate the actual values, while a negative ME indicates a tendency to underestimate. This is given by $ME = \frac{1}{n} \sum_{t=1}^{n} (y_t - \widehat{y_\iota})$.

b) Root Mean Squared Error (RMSE): the square root of the average squared differences between the predicted and actual values. RMSE penalizes larger errors more heavily, making it a sensitive measure for outliers. It is useful in cases where larger errors are especially costly or undesirable. Its expression is RMSE $RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \widehat{y_\iota})^2}$.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

c) Mean Absolute Error (MAE): the average absolute difference between predicted and actual values. Lower MAE values indicate better model performance. The formula is $MAE = \frac{1}{n}\sum_{t=1}^{n} | y_t - \widehat{y_\imath} |$.

d) Mean Percentage Error (MPE): measures the average percentage difference between the predicted and actual values. It retains the direction of errors, meaning it can show whether a model consistently overestimates (positive MPE) or underestimates (negative MPE) the actual values. Its formula is $MPE = \frac{1}{n}\sum_{t=1}^{n}\frac{(y_t - \widehat{y_\imath})}{y_i} \times 100$.

e) Mean Absolute Percentage Error (MAPE): the average of the absolute percentage errors between predicted and actual values. It expresses accuracy as a percentage, making it easy to interpret and compare across different datasets. MAPE is widely used, but it can be problematic when actual values are close to zero, leading to disproportionately high percentage errors. Mathematically is given by $MAPE = \frac{1}{n}\sum_{t=1}^{n}|\frac{(y_t - \widehat{y_\imath})}{y_i}| \times 100$.

The forecast horizon considered in this study to assess the accuracy of the proposed models was set at 15 months, covering the period from 2019 to March 2020. This marks the point when the Mexican economy was shut down due to the COVID-19 pandemic. It is important to note that after March 2020, the nationwide lockdown led to a shift in homicide dynamics, exceeding the scope of this research.

4. Results

To estimate the models, we will utilize the year of occurrence of homicides, as it offers more precise information for generating forecasts. Our objective is to identify the key terms that account for the majority of the data's variability through a Principal Component Analysis (PCA) (Jolliffe, 2013). The final selected set of words effectively captured 71.2% of the variability in the data. The final standardized loading matrix showed that all keywords contributed positively to this component (PC1), with loadings ranging from 0.206 (missing) to 0.360 (pistol) (see Table 1). The highest contributions corresponded to pistol (0.360), police (0.355), and report (0.352), closely followed by to report, extortion, and trafficking. This relatively balanced pattern indicates that the first component does not depend on a single term but rather reflects a broad common factor of public attention to violence and insecurity, integrating aspects such as weapons, institutional responses, reporting practices, and organized crime. So, the PCA results will be incorporated into the homicide database.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

Table 1

Final standardized loading matrix

Keyword	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
report	0.352	-0.032	-0.029	-0.262	-0.151	-0.302	-0.210	-0.559	-0.521	-0.251
to report	0.347	-0.129	-0.095	-0.285	-0.084	-0.301	-0.325	0.612	0.242	-0.371
missing	0.206	-0.855	0.335	0.275	-0.022	0.003	0.194	-0.028	0.000	-0.020
feminicide	0.244	0.344	0.865	-0.141	0.224	0.024	-0.003	0.041	0.035	0.020
accused	0.313	0.148	0.050	0.060	-0.789	0.495	0.054	0.034	0.052	0.003
pistol	0.360	0.020	-0.116	-0.075	-0.069	-0.339	0.120	0.183	-0.136	0.816
extortion	0.339	0.081	-0.230	-0.086	0.348	0.313	0.564	0.261	-0.394	-0.240
soldier	0.276	0.280	-0.060	0.857	0.074	-0.214	-0.166	0.054	-0.079	-0.142
police	0.355	0.095	-0.172	-0.058	0.097	-0.154	0.364	-0.429	0.689	-0.086
trafficking	0.332	-0.132	-0.168	-0.029	0.395	0.539	-0.564	-0.143	0.104	0.220

The model was estimated using R software (version 4.4.2) to analyze the dynamic relationships among the time series: “homicides”, “adult male homicides”, “adult female homicides” and “pca_google_trends” (the latter, differenced as explained in the previous section). The model focuses on a subset of data within a specified time period, selects the optimal lags, assesses the autocorrelation and normality of the residuals, and generates future forecasts. We focus on the mentioned period due to significant changes in the government's security strategy that profoundly impacted the growth rate of homicides. Furthermore, civil society organizations skepticism was expressed about the homicide data released by the government in 2020, as it showed an unexpected and substantial decline in reported figures.

To identify the best model for forecasting male and female homicides, we evaluated six approaches: an ARIMA model for adult males and females, an ARIMA model incorporating Google Trends for both groups, a VAR model for adult males and females, and a VAR model enhanced with Google Trends for both groups. Incorporating exogenous variables in these models allows us to account for external factors that influence the time series, thereby improving predictive accuracy. This strategy is based on the hypothesis that leveraging external insights enhances the analysis, resulting in more accurate and robust forecasts.

The analysis examines key statistical metrics to validate the improvements achieved using the selected predictors. These metrics include adjusted R^2, the significance of variables, the Ljung-Box and Portmanteau tests, and the normality in the residuals of the estimated models, respectively. The objective is to identify the model with the best fit, the highest number of significant variables, and one that meets both autocorrelation and normality criteria. Additionally, forecast accuracy will be assessed using the following error metrics: Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE).

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

4.1 ARIMA models per sex

For female homicides the best estimated model was an ARIMA (0,1,1)(1,0,1) given by (in parenthesis the standard error)

$$\Delta\widehat{\mathrm{Y}}_{\mathrm{t}} = -0.5687(0.0623)\mathrm{e}_{\mathrm{t}-1} + 0.9942(0.0407)\mathrm{Y}_{\mathrm{t}-12} - 0.9629(0.1349)\mathrm{e}_{\mathrm{t}-12}$$

where $\Delta\widehat{\mathrm{Y}}_{\mathrm{t}}$ is the first difference of the series. The residual variance $\widehat{\sigma}^2$ is estimated at 402, and the model achieved a log-likelihood value of -682.24, the AIC statistics was 1,372.48. The Ljung-Box test yields a Q value of 11.81 with 21 degrees of freedom and a p-value of 0.9446. This result also supports the absence of significant autocorrelation in the residuals. Regarding normality, the Anderson-Darling test provided a p-value = 0.1872.

The estimated ARIMA(2,1,0)(1,0,0) model for male homicides effectively captures short-term and seasonal dynamics, and it was

$$\Delta\widehat{Y}_t = 0.6252(0.0747)Y_{t-1} + 0.3464(0.0756)Y_{t-2} + 0.2493(0.0811)Y_{t-12} + 1530.7580(382.2095)$$

The residual variance $\widehat{\sigma}^2$ was 17,048, and log-likelihood -983.33. The AIC statistics was 1976.66. Likewise, Ljung-Box test results (Q = 16.952, p = 0.714) confirm no significant autocorrelation in residuals. Additionally, the Anderson-Darling test for normality of the residuals returned a p-value of 0.46694, which indicates normality.

4.2 ARIMA models per sex + Google Trends

The following set of models considers incorporating the Google Trends variable into an ARIMA model. For the case of female homicides, the model is specified as an ARIMA(1,0,1)

$$\Delta\widehat{Y}_t = 0.9931(00.0081)Y_{t-1} - 0.5472(0.0653)\varepsilon_{t-1} + 197.2943(61.9742) - 3.2699(1.5716)X_t$$

The autoregressive coefficient (0.9931) captures the relationship between the current value and its immediate lag, indicating strong persistence in the series. The moving average coefficient (-0.5472) reflects the influence of past forecast errors on the current value. The intercept term (197.2943) represents the baseline level of the series, while the X_t coefficient (-3.2699) quantifies the effect of the external variable. The residual variance ($\widehat{\sigma}^2$ = 403.2) and the log-likelihood value (-688.83) confirm the model's reliability. The AIC statistics had a value of 1,387. Diagnostics in the data reveal no significant autocorrelation in the residuals, as evidenced by the Ljung-Box test with a p-value of 0.9182. Furthermore, residuals satisfy normality assumptions, supported by the Anderson-Darling test p-value = 0.5891.

The equation for the male homicide model, incorporating Google Trends data, ARIMA (0,1,2) is as follows

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

$$\Delta\hat{Y}_t = -1.3695(0.0706)\varepsilon_{t-1} + 0.4040(0.0762)\varepsilon_{t-2} - 20.5975(9.5206)X_t.$$

The external regressor, Google Trends data (X_t), is incorporated to capture the influence of external factors on the series. The coefficients for the moving average terms (-1.3695 and 0.4040) indicate the impact of past error terms on the current value, while the xreg coefficient (-20.5975) suggests a significant negative relationship between the Google Trends variable and the dependent series. The error term with variance $\hat{\sigma}^2$ has a value 18,006. The residual variance and log-likelihood (-973.17) indicate a good fit. Diagnostic checks reveal no significant residual autocorrelation, validating the model for forecasting. The Ljung-Box test further supports the model's adequacy, with a p-value of 0.3969, indicating no autocorrelation in the residuals. Furthermore, we have a p-value of 0.06421 to assess normality.

4.3 VAR model for adult males and females

It is worth noting that all inverse roots of the characteristic polynomials associated with the VAR models were less than 1. Similarly, the AIC criterion was used to determine the order p of the two VAR models. In particular, in the VAR model for male and female homicides, the results suggest a complex relationship between the two variables (see Table 2). The first lag of male homicides (hombre_hom_var.l1) has a significant positive impact on both male ($p < 0.01$) and female homicides ($p < 0.05$), indicating that an increase in male homicides in the previous period tends to lead to an increase in both types of homicides in the subsequent period. This highlights a possible shared set of factors influencing both male and female homicide rates. Additionally, the first lag of female homicides (Female var.l1) affects female homicides, with no notable impact on male homicides. This suggests that past female homicide trends slightly affect future female homicides but do not directly influence male homicides.

The model also reveals a mix of positive and negative influences from higher-order lags, particularly for male homicides, suggesting that the relationship between homicide trends is not immediate. For instance, the second lag of male homicides (hombre_hom_var.l2) has a positive effect on both male and female homicides, while the ninth lag shows a negative impact on female homicides. The presence of a significant constant term and trend indicates an overall upward trend in homicides over time, suggesting that interventions should target the growing rates of both male and female homicides. With R^2 values of 0.9382 and 0.9148, the model demonstrates a high explanatory effect, making it effective for forecasting future trends in homicide rates. Likewise, F Statistic were 191.7 and 135.7, respectively. JB-Test (multivariate) and Portmanteau Test had the p-values 0.1845 and 0.1794.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

Table 2

VAR Model for adult male and females without Google Trends

Variables	Male	Sig.	Female	Sig.
Female_var.l1	-0.54740		0.055135	
Male_var.l1	0.55113	***	0.041718	**
Female_var.l2	-1.32964		0.099205	
Male_var.l2	0.35950	***	0.012362	
Female_var.l3	-0.61583		0.098725	
Male_var.l3	0.20984		0.002758	
Female_var.l4	0.68940		0.054528	
Male_var.l4	0.02679		-0.16206	
Female_var.l5	-1.05120		-0.082979	
Male_var.l5	0.03760		0.023436	
Const	130.24310	**	20.726138	**
Trend	1.64182	**	0.34625	***

Sig. codes: 0 "***", 0.001 "**", 0.01 "*", and 0.05 ".".

4.4 VAR model for adult males and females + Google Trends

The estimated VAR model examines the relationship between female and male homicides over time while incorporating Google Trends data as an exogenous variable. The model includes six lags of the homicide variables for both genders, allowing for the assessment of past influences on current homicide trends. Significant coefficients are observed for some lags, particularly for Male_var.l1 and Male_var.l2, indicating that past male homicide rates strongly predict current male homicide rates. The constant and trend variables are also significant, suggesting underlying temporal patterns.

Model diagnostics indicate strong explanatory context, with R^2 values of 0.9298 for female homicides and 0.9565 for male homicides. The adjusted R^2 values confirm the model's robustness, and the high F-statistics suggest the model is statistically significant. The JB-Test for normality yields a p-value of 0.6302. Additionally, the Portmanteau test for autocorrelation results in a p-value of 0.2577. These findings confirm that the VAR model is well-specified and capable of capturing the dynamics of homicide rates over time.

4.5 Forecast comparisons

4.5.1 Females

The prediction of female homicides in Mexico presents significant challenges due to the complex interplay of socioeconomic, cultural, and institutional factors. A comparative evaluation of forecast accuracy from the estimated models ARIMA, ARIMA + GT, VAR, and VAR + GT, shows important insights into their applicability. The VAR + GT model emerges as the most robust framework, achieving the lowest RMSE = 18.02 and MAE = 14.89, outperforming both the VAR (RMSE = 20.33, MAE = 17.01), and ARIMA-based specifications. This improvement underscores the value of

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

integrating exogenous data, such as search trends, into multivariate systems that capture interdependencies between variables (e.g., male and female homicide dynamics). While the VAR + GT exhibits a slightly higher mean error (ME = -2.99) compared to the standard VAR (ME = -0.39), its lower MAPE = 5.28% suggests greater consistency in minimizing proportional forecast deviations, a critical feature for policy-oriented applications.

ARIMA models demonstrate weaker performance, particularly when augmented with GT (RMSE = 23.14, MAPE = 7.13%), likely due to their univariate structure, which fails to account for cross-variable feedback effects inherent in homicide dynamics. The ARIMA model (RMSE = 19.20, MAPE = 5.49%) also underperforms relative to VAR + GT, highlighting limitations in addressing systemic complexity through autoregressive mechanisms. The negative mean errors (ME) across all models, most pronounced in ARIMA (ME = -10.83) indicate a systematic underestimation of homicide counts, possibly reflecting unobserved shocks or structural breaks in the data. These results advocate for the adoption of multivariate frameworks like VAR + GT in contexts where exogenous indicators (e.g., GT) may proxy latent societal attention or risk perception, even if their statistical significance is marginal (see Table 3).

Table 3

Forecasting Model Results

Model	ME	RMSE	MAE	MPE	MAPE
Female					
ARIMA	-10.8303	19.2040	15.1015	-4.1284	5.4938
ARIMA +GT	0.0373	23.1410	20.1676	-0.5460	7.1293
VAR	-0.3923	20.3284	17.0104	-0.6308	6.0221
VAR + GT	-2.9899	18.0250	14.8871	-1.4215	5.2841
Male					
ARIMA	142.7224	167.5095	142.7828	5.91057	5.9131
ARIMA+GT	-67.9903	112.9804	81.37032	-2.9404	3.4834
VAR	78.15034	113.0374	96.10626	3.1845	3.9697
VAR+GT	43.4894	91.3555	73.13203	1.7737	3.0512

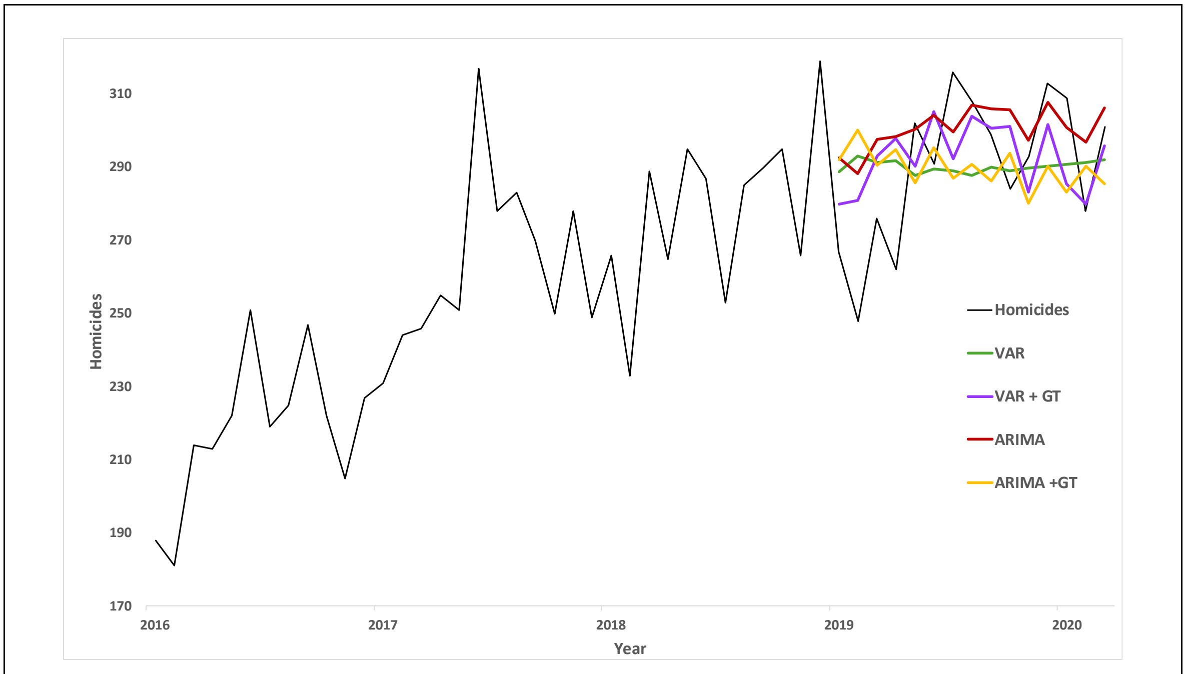
As shown in Table 2, VAR with Google Trends provides the best forecasts for both sexes, but the relative improvements differ. For females, the gains are substantial in RMSE and MAE, reflecting that terms linked to gender-based violence and disappearances generate strong and consistent search patterns. For males, the relative gain is even more evident: errors decrease sharply when adding Google Trends to ARIMA and reach their lowest levels with VAR+GT. The final forecasts are presented in Figure 2.

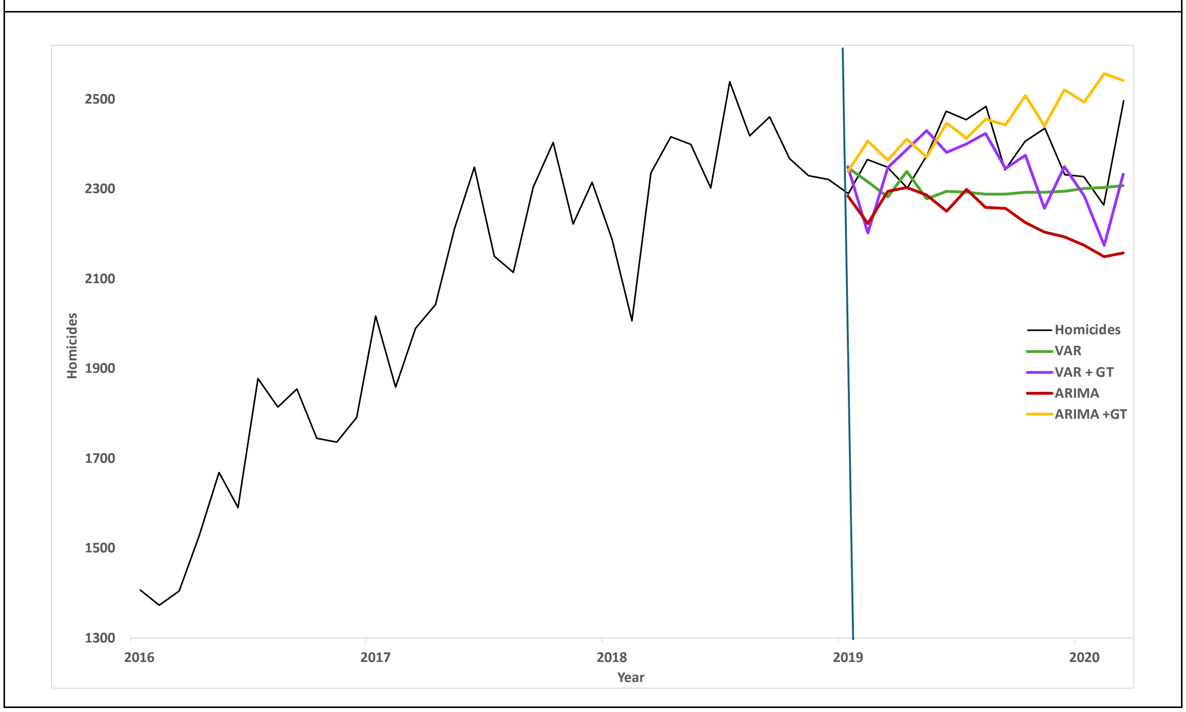
ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

Figure 2

Female and male homicide forecasting: VAR and ARIMA with and without Google Trends





4.5.1 Males

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

The prediction of male homicides in Mexico, a context marked by systemic violence and sociopolitical complexity, demands rigorous analytical frameworks to account for dynamic interdependencies and external influences. A comparative assessment of four forecasting models reveals stark contrasts in the accuracy of prediction. The VAR + GT model demonstrates superior performance, achieving the lowest root mean squared error (RMSE = 91.36), and mean absolute error (MAE = 73.13), alongside the smallest mean absolute percentage error (MAPE = 3.05%). These metrics highlight its capacity to reduce both dispersion and proportional forecast errors compared to the VAR (RMSE = 113.04, MAPE = 3.97%). The integration of Google Trends mitigates the overestimation bias observed in the standard VAR, lowering the mean error (ME) from 78.15 to 43.49, which suggests that exogenous search data captures latent factors—such as public attention to violence or real-time risk perceptions—that refine predictive precision.

In contrast, ARIMA-based models exhibit significant limitations. The ARIMA shows pronounced overestimation (ME = 142.72, RMSE = 167.51), while the ARIMA + GT model introduces a substantial negative bias (ME = -67.99), reflecting sensitivity to exogenous inputs within univariate structures. Although ARIMA + GT marginally improves RMSE (112.98) over the ARIMA, its higher MAPE (3.48% vs. 3.05% for VAR + GT) and residual volatility underscore the inadequacy of univariate approaches in modeling homicide dynamics, which are inherently multivariate and dependent. The performance of VAR + GT aligns with theoretical expectations context, as multivariate systems better accommodate feedback effects between variables (e.g., male and female homicide rates, socioeconomic triggers) and external shocks proxied by GT. Nevertheless, the persistent biases across models signal unobserved structural factors -such as cartel activity or policy shifts- that warrant integration into future frameworks. These findings advocate for prioritizing VAR based models augmented with real-time data to inform targeted violence prevention strategies in Mexico.

5. Conclusions

This study estimates predictive models for homicides in Mexico by integrating statistical methodologies with Google Trends data. The modeling approach consists of three primary stages: data extraction, transformation, and modeling. Initially, homicide records from INEGI and Google search trends were collected and structured for analysis. PCA was applied to derive a key variable representing search trends, which was then incorporated into forecasting models. The research employs both ARIMA and VAR models to assess their predictive accuracy, comparing models with and without the inclusion of Google Trends as an exogenous variable.

Currently, the official dataset goes from 2004 to 2023, consolidating digital records on mortality, demographic characteristics, and regional crime trends. Given the constraints of data availability, the analysis focuses on the period from 2006 to March 2020, aligning with significant shifts in governmental security policies. Data preprocessing involved handling missing values, standardizing temporal aggregations, and ensuring consistency across sources. Google Trends data was used to track search queries related to violent crimes, including terms such as homicide, assault, and

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

trafficking. The PCA-derived component accounted for 71.2% of the variance, offering a compact yet informative representation of search behavior related to crime.

ARIMA models were estimated separately for male and female homicides, with and without Google Trends as an explanatory variable. Model diagnostics confirmed statistical adequacy through metrics such as the statistics of log-likelihood, AIC, and residual non-autocorrelation and normality tests. The results showed that ARIMA models captured short-term and seasonal variations effectively, but their univariate nature limited their explanatory power. The addition of Google Trends data slightly improved predictive performance, particularly for female homicides, where search trends were found to be moderately correlated with fluctuations in homicide rates.

VAR models were then employed to capture interdependencies between male and female homicide dynamics over time. The inclusion of lagged variables revealed a strong relationship between past male homicide rates and subsequent trends in both male and female homicides. Statistical tests for autocorrelation and normality confirmed the robustness of these models. When Google Trends was incorporated as an exogenous variable, the models demonstrated improved predictive accuracy. The VAR + Google Trends model exhibited higher explanatory power, as evidenced by superior fit measures and lower forecast errors, suggesting that digital search behavior provides valuable insights into homicide trends.

A comparative evaluation of model performance was conducted using forecast error metrics. For female homicides, the VAR + Google Trends model achieved the highest accuracy, outperforming standard ARIMA and VAR models. A similar trend was observed for male homicides, using the VAR + Google Trends model. The findings underscore the benefits of integrating external data sources into multivariate time series models for improved crime prediction.

The study highlights the potential of Google Trends data as a proxy for public concern and latent risk perception. While ARIMA models provided a baseline for univariate forecasting, the VAR + Google Trends approach proved to be the most effective in capturing the complex interactions between gender-specific homicide trends and external search behavior. These results support the use of multivariate models with exogenous variables in policy-oriented research, particularly for crime prevention strategies.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

6. References

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control*. John Wiley & Sons.

Calvo, H., Godoy-Calderón, S., Moreno-Armendáriz, M. A., & Martínez-Hernández, V. M. (2017). Forecasting, clustering and patrolling criminal activities, *Intelligent Data Analysis*, 21(4), 697–720. https://doi.org/10.3233/IDA-170883

Cebrián, E., & Domenech, J. (2024). Addressing Google Trends inconsistencies, *Technological Forecasting and Social Change*, 202, 123318. https://doi.org/10.1016/j.techfore.2024.123318

Clements, M. P., & Hendry, D. F. (Eds.). (2011). The Oxford handbook of economic forecasting. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195398649.001.0001

Delgadillo, G., & Torres, D. (2023). ¿Qué es y cómo funciona el Registro Nacional de Personas Desaparecidas y No Localizadas (RNPDNO)? [What is and how does the National Registry of Disappeared and Unlocated Persons (RNPDNO) work?]. Animal Político. https://animalpolitico.com/analisis/organizaciones/el-blog-del-seminario-sobre-violencia-y-paz/registro-nacional-personas-desaparecidas-que-es-como-funciona?rtbref=rtb_krqfxr3j12dhx0dkl7c2_1714875535898

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4(3), 272–299. https://doi.org/10.1037/1082-989X.4.3.272

García-Gómez, J., Valdez, S., & Carlos, H. (2022). Homicide forecasting for the state of Guanajuato using LSTM and geospatial information in 2022 *IEEE Mexican International Conference on Computer Science (ENC)*, 1-6. https://doi.org/10.1109/ENC56672.2022.9882957

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics*. McGraw-Hill Companies.

Gutiérrez, F., & Hernández, D. M. (2024). Desaparición forzada [Forced disappearance]. *Constructos Criminológicos*, 4(6), 43–56. https://doi.org/10.29105/cc4.6-59

Hernández-Gress, E., Flegl, M., Krstikj, A., & Boyes, C. (2023). Femicide in Mexico: statistical evidence of an increasing trend, *PLOS ONE*, 18(12), e0290165. https://doi.org/10.1371/journal.pone.0290165

Instituto Nacional de Estadística y Geografía. (2023). *Estadísticas vitales de Mortalidad, 1990 – 2023*. Dirección General de Estadística, México.

Hyvärinen, A., & Oja, E. (2000). Independent component analysis: Algorithms and applications. *Neural Networks*, 13(4–5), 411–430. https://doi.org/10.1016/S0893-6080(00)00026-5

Jolliffe, I. (2013). *Principal component analysis*, Springer Science & Business Media.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

Massicotte, P., & Eddelbuettel, D. (2025). gtrendsR: Perform and display Google Trends queries (Version 1.5.2) [R package]. Comprehensive R Archive Network (CRAN). https://cran.r-project.org/package=gtrendsR

Medeiros, M. C., & Pires, H. F. (2021). The proper use of Google Trends in forecasting models, arXiv:2104.03065. https://doi.org/10.48550/arXiv.2104.03065

Observatorio Nacional Ciudadano. (2017). Desapariciones forzadas e involuntarias. El Registro Estadístico de la Desaparición: ¿Delito o Circunstancia? [Forced and involuntary disappearances. The Statistical Registry of Disappearance: Crime or Circumstance?]. Ciudad de México.

Pearsall, B. (2010). Predictive policing: The future of law enforcement, *National Institute of Justice Journal*, 266(1), 16-19.

Piña-García, C. A., & Ramírez-Ramírez, L. (2019). Exploring crime patterns in Mexico City, *Journal of Big Data*, 6, 1-21. https://doi.org/10.1186/s40537-019-0228-x

Ramallo, S., Camacho, M., Ruiz Marín, M., & Porfiri, M. (2023). A dynamic factor model to predict homicides with firearms in the United States, *Journal of Criminal Justice*, 86, 102051. https://doi.org/10.1016/j.jcrimjus.2023.102051

Sahni, S. P., & Phakey, N. (2021). Criminal psychology: Understanding criminal behaviour, *Criminal Psychology and the Criminal Justice System in India and Beyond*, 21-30. https://doi.org/10.1007/978-981-16-4570-9_2

Santos-Marquez, F. (2021). Spatial beta-convergence forecasting models: Evidence from municipal homicide rates in Colombia, *Journal of Forecasting*, 41(2), 294–302. https://doi.org/10.1002/for.2816

Sims, C. A. (1980). Macroeconomics and Reality, *Econometrica*, 48(1), 1–48. https://www.jstor.org/stable/1912017

Swedo, E. A., Alic, A., Law, R. K., Sumner, S. A., Chen, M. S., Zwald, M. L., Van Dyke, M. E., Bowen, D. A., & Mercy, J. A. (2023). Development of a machine learning model to estimate US firearm homicides in near real time, *JAMA Network Open*, 6(3), e233413. https://doi.org/10.1001/jamanetworkopen.2023.3413

United Nations Office on Drugs and Crime. (2019). Global study on homicide. https://www.unodc.org/documents/data-and-analysis/gsh/Booklet1.pdf

Wei, W. W. (2019). *Multivariate time series analysis and applications*, John Wiley & Sons.

World Health Organization. (2015*). International Statistical Classification of Diseases and Related Health Problems: 10th Revision (ICD-10)* (5th 2016 Revision ed.). World Health Organization.

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/

Doi: https://doi.org/10.15517/c57dzg81
Volume 22, issue 2, Sci.Art july-december 2025

Población y Salud
en Mesoamérica

¿Quiere publicar en la revista?
Ingrese **aquí**

O escríbanos:
revista.ccp@ucr.ac.cr

1° Revista
Electrónica

13 años de liderazgo
Cuartil A del
UCR Index

SALALM
Enlace Award, 2007

POPULATION INSTITUTE
Global Media Awards
Excellence in Population Reporting

Población y Salud en Mesoamérica (PSM) es la revista electrónica que cambió el paradigma en el área de las publicaciones científicas electrónicas de la UCR. Logros tales como haber sido la primera en obtener sello editorial como revista electrónica la posicionan como una de las más visionarias.

Revista PSM es la letra delta mayúscula, el cambio y el futuro.

Indexada en los catálogos más prestigiosos. Para conocer la lista completa de índices, ingrese **aquí.**

Elsevier Scopus SciELO DOAJ latindex redalyc.org Dialnet

Revista Población y Salud en Mesoamérica -

Centro Centroamericano de Población
Universidad de Costa Rica

ISSN-1659-0201
http://ccp.ucr.ac.cr/revista/