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STOCHASTIC DYNAMICS AND STRUCTURAL TREND MODELLING OF HOMICIDE IN JAMAICA: EVIDENCE FROM ARIMA AND ARIMAX TIME-SERIES ANALYSIS, 1970–2025

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ABSTRACT

This study develops an econometric homicide function for Jamaica using annual time-series data covering 1970–2025. The objective is to model internal dynamics, structural trends, and long-run persistence in homicide patterns using Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) specifications. The methodology employs first-differenced modelling to address non-stationarity, maximum likelihood estimation, diagnostic testing, structural break analysis, and forecast simulation. The results indicate strong volatility clustering, structural upward shifts during the 1980s and 2000s, and significant trend-driven persistence in homicide growth. The ARIMAX model incorporating a deterministic time trend produces superior explanatory power relative to the baseline ARIMA specification and generates an accelerating long-run trajectory under parameter stability assumptions. Forecast simulations for 2026–2035 suggest that if historical structural relationships persist, homicide levels may follow a renewed upward path driven by trend effects. However, robustness testing highlights sensitivity to structural breaks and model specification, suggesting that policy interventions could materially alter projected trajectories. Monte Carlo simulations demonstrate widening forecast uncertainty over longer horizons. The study contributes to the empirical criminology and time-series literature by formalising a dynamic homicide function for Jamaica and providing a quantitative baseline for policy evaluation.

Keywords: Homicide modelling; Time-series econometrics; ARIMA; ARIMAX; Structural breaks; Forecast simulation

1.0 INTRODUCTION

Violence and homicide remain persistent public health and socio-economic challenges in Jamaica, with rates significantly exceeding regional and global averages over multiple decades. Historical data demonstrate pronounced volatility, structural shifts, and episodic spikes, suggesting the presence of long-run persistence mechanisms rather than random fluctuations. Empirical criminology literature indicates that homicide dynamics are often shaped by structural inequality, weak institutional capacity, and macroeconomic instability (Becker, 1968; Blau & Blau, 1982). Theoretical and empirical research further suggests that violent crime exhibits path dependence, where past levels of violence influence future trajectories through social feedback mechanisms and institutional adaptation (Arthur, 1989;

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Catello, 2023). Understanding the dynamic behaviour of homicide, therefore, requires econometric modelling that captures autocorrelation, shock effects, and structural trends over time. Time-series approaches such as ARIMA and ARIMAX provide a rigorous statistical framework for analysing these temporal dependencies and generating forecasts under defined structural assumptions. Applying such methodologies to Jamaica contributes to evidence-based policy discussions by quantifying persistence and structural growth in homicide patterns.

Previous research has examined determinants of crime using cross-sectional and panel data approaches, often linking homicide to socioeconomic inequality, unemployment, governance quality, and deterrence mechanisms (Chalfin & McCrary, 2017; Sampson & Wikström, 2008). However, fewer studies have developed long-run dynamic homicide functions using continuous annual time-series data for Jamaica that explicitly model structural trends and stochastic processes. Forecasting literature emphasises that incorporating lag structures and deterministic components improves predictive accuracy when modelling long historical series with non-stationary behaviour (Box et al., 2015; Enders, 2014). Moreover, structural break analysis is critical in contexts characterised by regime shifts and policy interventions that may alter underlying parameters over time (Bai & Perron, 2003). This study addresses these gaps by estimating a formal homicide function that integrates internal dynamics with deterministic structural change. The contribution lies in constructing a statistically validated forecasting model that enables policy simulation, robustness testing, and long-term structural evaluation of homicide trends in Jamaica.

Gap in the Literature

Although criminological studies have examined socio-economic determinants of homicide in Jamaica and the wider Caribbean, most studies rely on cross-sectional or panel regression frameworks that assume independence across observations and often neglect temporal dependence. Such approaches fail to capture dynamic persistence, shock transmission, and long-run equilibrium adjustments that characterise homicide trends in high-violence contexts (Box et al., 2015; Enders, 2014). Time-series applications within Caribbean criminology remain limited, particularly studies that integrate autoregressive structures with deterministic trend components to model structural change. The existing analyses frequently emphasise descriptive trend analysis or decadal comparisons rather than formally estimating stochastic processes that account for lagged dependence and volatility clustering. As a result, the dynamic nature of homicide, including feedback loops and path-dependent effects, is insufficiently modelled within many empirical investigations (Catello, 2023; Sampson & Wikström, 2008). This methodological limitation constrains the ability to distinguish between temporary fluctuations and enduring structural shifts in violence patterns. Consequently, there remains a clear need for econometric frameworks that formally model homicide as a time-dependent process incorporating structural breaks, diagnostic validation, and forecasting uncertainty.

Furthermore, few empirical studies on homicide in Jamaica incorporate comprehensive robustness testing, structural breakpoint analysis, or counterfactual policy simulations within a unified modelling structure. Without structural break testing, it is difficult to determine whether estimated relationships remain stable over long historical periods characterised by institutional change and policy interventions (Bai & Perron, 2003). Similarly, the absence of simulation-based forecasting limits the capacity to evaluate how alternative policy scenarios might alter

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projected homicide trajectories. Addressing this gap requires integrating time-series econometrics with theoretical criminology to construct dynamic models capable of capturing persistence, trend behaviour, and regime shifts. Developing such a framework strengthens empirical inference and enhances the policy relevance of homicide forecasting for Jamaica and comparable high-violence settings.

Objectives

1. To estimate and evaluate an ARIMA and ARIMAX-based homicide function for Jamaica using annual data from 1970 to 2025.
2. To forecast homicide trajectories for the period 2026–2035 under structural stability and parameter constancy assumptions.
3. To test for parameter stability and identify potential structural breaks within the historical homicide series.
4. To assess forecast uncertainty through simulation-based methods and confidence interval estimation.
5. To evaluate the comparative performance of the ARIMA and ARIMAX specifications using diagnostic and information criteria measures.

2.0 THEORETICAL FRAMEWORK

2.1 Macrostructural and Behavioural Foundations of Homicide

Understanding homicide dynamics requires integrating macrostructural explanations with individual-level behavioural theories that explain why violence persists in some contexts more than others. Economic theories of crime posit that individuals weigh the costs and benefits of violent behaviour, and structural factors such as poverty, inequality, and labour-market exclusion influence this cost–benefit calculus (Becker, 1968; Chalfin & McCrary, 2017). Recent empirical work suggests that macroeconomic instability and labour-market shocks are positively associated with homicide rates, indicating that structural deprivation increases violence (Khan et al., 2020; Luthra et al., 2007; Ogundari, 2021; Perez, 2022; Vujić et al., 2016). Social disorganisation and collective efficacy theories argue that communities with weak institutions and low social cohesion are less able to regulate violent behaviour, leading to higher homicide rates (Sampson & Wikström, 2008). Studies in Caribbean contexts highlight that governance deficits, entrenched inequalities, and limited access to formal employment heighten vulnerability to violence (Bourne, 2025a, 2025b; Harriott & Jones, 2016; United Nations Office on Drugs and Crime, 2007). These frameworks support the hypothesis that homicide persistence is not random but rooted in underlying socio-economic structures. Consequently, homicide modelling benefits from incorporating both lagged dependence and structural trend components to reflect these deep-seated influences.

2.2 Dynamic Processes and Long-Run Trends in Violence

Dynamic theories emphasise that past violence influences future violence through feedback loops, path dependence, and long-run structural patterns. Path dependence theory suggests that historical violence can create entrenched behavioural norms and institutional responses, leading to persistent high homicide levels absent disruptive intervention (Arthur, 1989; Catello, 2023). Empirical evidence shows that regions with historically high violence exhibit slower

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convergence to lower homicide rates, reflecting momentum effects and institutional inertia (Deng et al., 2019; Levitt & Jess, 2022). Strain and frustration-aggression theories further propose that chronic exposure to economic hardship and social exclusion leads to long-standing cognitive and emotional processes that increase propensity for lethal conflict (Agnew, 2020). These mechanisms justify the use of autoregressive terms in time-series models, reflecting serial dependence in homicide counts. Moreover, conflict and inequality theories posit that disparities in access to resources and justice systems sustain violence over time (Blau & Blau, 1982; Braga et al., 2019a, 2019b). Therefore, modelling homicide trajectories as dynamic and trend-influenced processes aligns with both theoretical expectations and observed empirical regularities.

2.3 Time-Series Integration and Structural Change Framework

Time-series econometric theory provides the methodological underpinning for capturing persistence, structural shifts, and uncertainty in long-run homicide behaviour. Autoregressive Integrated Moving Average (ARIMA) frameworks capture autocorrelation and non-stationary behaviour in longitudinal homicide data, enabling isolation of internal dynamics (Box et al., 2015; Hyndman & Athanasopoulos, 2018). The extension to ARIMAX models allows structural forces, such as institutional reforms, demographic transitions, or economic trends, to be explicitly incorporated as exogenous influences (Enders, 2014). Empirical crime forecasting research highlights that models incorporating structural variables produce more accurate and interpretable long-run projections compared to univariate frameworks (Anselin et al., 2016; Cantor & Land, 1987; Greenberg, 2001). Structural break theory further emphasises that long historical crime series often experience regime shifts, such as punitive policy adoption or economic crises, which alter dynamic patterns (Bai & Perron, 2003; Hansen, 2017). Integrating these concepts ensures that the homicide modelling framework is capable of detecting both gradual trend-driven changes and abrupt socio-political disruptions. This integrated theory–methodology approach enhances the interpretability and policy relevance of homicide forecasting.

3.0 LITERATURE REVIEW

3.1 Empirical Evidence on Homicide Determinants and Structural Drivers

Empirical research consistently demonstrates that macroeconomic conditions, inequality, institutional capacity, and social disorganisation strongly influence homicide rates. Economic models of crime argue that changes in employment opportunities, income inequality, and poverty alter the incentives for violent behaviour (Becker, 1968; Chalfin & McCrary, 2017). Time-series studies show that homicide rates often respond to macroeconomic shocks with lagged effects, indicating dynamic adjustment rather than instantaneous change (Khan et al., 2020; Luthra et al., 2007; Ogundari, 2021; Perez, 2022; Vujić et al., 2016). Cross-national evidence suggests that countries experiencing structural inequality and governance weaknesses exhibit persistently higher levels of lethal violence (Blau & Blau, 1982; Sampson & Wikström, 2008). Recent research further confirms that homicide trajectories display strong path dependence, meaning historical violence shapes future outcomes through institutional and social feedback mechanisms (Catello, 2023; Deng et al., 2019). In Caribbean contexts, studies highlight that chronic unemployment, weak enforcement capacity, and organised crime

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networks reinforce homicide persistence over decades (Bourne, 2025a, 2025b; Harriott & Jones, 2016; United Nations Office on Drugs and Crime, 2007). Collectively, these findings justify modelling homicide as a dynamic stochastic process influenced by structural trends and lagged dependence.

3.2 Time-Series Modelling and Structural Break Evidence

The application of time-series econometric models to crime data has expanded in recent decades as researchers seek to capture persistence and structural change more precisely. ARIMA and ARIMAX frameworks are widely used to model autocorrelation and non-stationarity in longitudinal crime series (Box et al., 2015; Enders, 2014). Empirical forecasting research demonstrates that incorporating deterministic trends and exogenous variables improves predictive performance compared to univariate approaches (Hyndman & Athanasopoulos, 2018). Structural break testing is particularly important in long historical series because policy reforms, economic crises, or social disruptions can alter dynamic relationships (Bai & Perron, 2003; Hansen, 2017). Studies applying breakpoint analysis to crime data reveal that parameter instability often coincides with major institutional or socio-political events. Forecasting literature further emphasises that uncertainty increases as the horizon extends, requiring simulation-based confidence intervals to properly assess risk (Braga et al., 2019a, 2019b). These methodological advances support the use of an ARIMAX model with structural trend and diagnostic testing to analyse Jamaica’s homicide trajectory.

3.3 Conceptual Model Linking Theory to the Econometric Specification

The conceptual model underlying this study integrates economic rationality, structural inequality, path dependence, and time-series dynamics into a unified homicide function. The dependent variable — annual homicide counts — is assumed to evolve as a function of past homicide levels, stochastic shocks, and deterministic structural trends. Lagged homicide terms operationalise path dependence theory by capturing persistence in violence resulting from institutional adaptation and retaliation cycles (Arthur, 1989; Catello, 2023). The time trend component represents long-run structural forces such as demographic transitions, governance changes, and macroeconomic transformation. The stochastic error term captures unobserved shocks and short-term disturbances that temporarily affect violence levels. Together, these components reflect theoretical expectations that homicide is not purely random but dynamically structured. The ARIMAX framework, therefore, operationalises theory through an empirically testable time-dependent function consistent with criminological and econometric literature.

3.4 Conceptual Model Diagram

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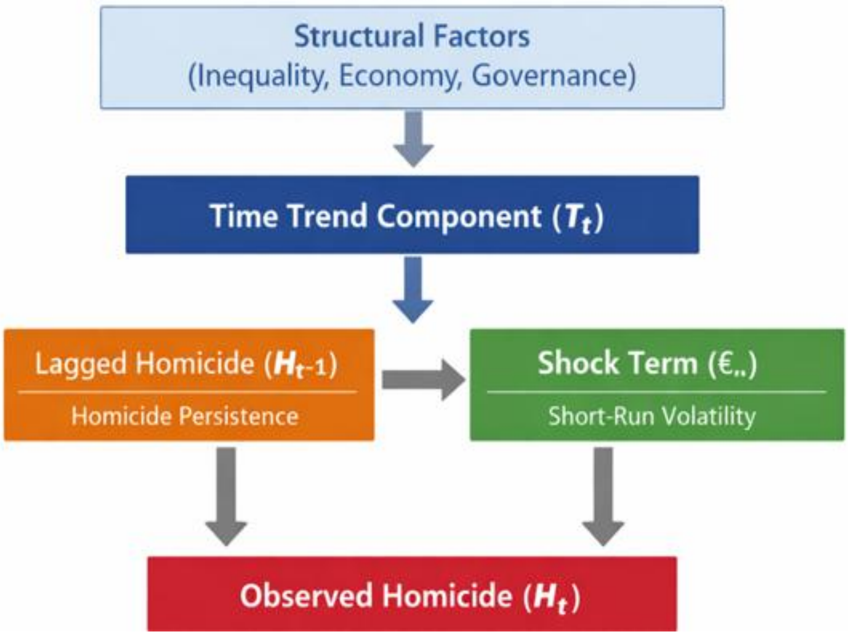

Figure 1: Current Conceptual Model

4.0 METHODS

4.1 Data Source and Study Design

This study utilises annual homicide data for Jamaica covering the period 1970–2025. The data were compiled from official national crime statistics and publicly available reports that document recorded homicide counts over time. Using official administrative data enhances measurement reliability and ensures consistency with prior empirical crime research that relies on governmental crime reporting systems (Box et al., 2015; Enders, 2014; Jamaica Constabulary Force, 2026). The dataset follows a longitudinal time-series design in which observations are recorded sequentially across time, allowing for the examination of dynamic temporal relationships. Annual aggregation was selected to maintain comparability across the full study period and to minimise inconsistencies associated with short-term reporting fluctuations that often characterise monthly or quarterly crime data. Aggregated annual data also reduce high-frequency noise while preserving long-run structural patterns in homicide behaviour.

The primary objective of the research design is to model temporal dynamics and structural changes in homicide patterns over multiple decades. Time-series econometric techniques are therefore appropriate because they explicitly account for autocorrelation, persistence, non-stationarity, and shock transmission within longitudinal data structures (Hamilton, 1994). Such methods allow homicide to be conceptualised as a stochastic process rather than as independent annual observations. By employing autoregressive and integrated modelling frameworks, the study captures both short-run volatility and long-run trend behaviour embedded in the historical series. This design strengthens causal interpretation of dynamic relationships and provides a statistically grounded basis for forecasting future homicide trajectories under structural stability assumptions.

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4.2 Model Specification: ARIMA Approach

Autoregressive Integrated Moving Average (ARIMA) modelling was employed to examine the internal dynamics of homicide trends. The ARIMA framework accounts for autocorrelation, non-stationarity, and shock persistence within the series. Before estimation, the homicide series was tested for stationarity and differenced where necessary to remove unit roots. Model identification involved selecting appropriate autoregressive (AR) and moving-average (MA) orders based on autocorrelation diagnostics and information criteria. The general specification follows an ARIMA(p,d,q) structure, where p represents autoregressive lags, d denotes the order of differencing, and q captures moving-average components. Model estimation was conducted using maximum likelihood procedures to generate statistically consistent coefficient estimates.

4.3 Model Specification: ARIMAX Extension

To incorporate potential structural influences, an Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model was estimated. The ARIMAX framework extends the baseline ARIMA model by including deterministic or explanatory variables such as a linear time trend, to capture long-run structural change. This specification allows homicide dynamics to depend not only on past values and stochastic shocks but also on systematic temporal forces. The inclusion of exogenous variables improves explanatory power and enables assessment of whether structural trends significantly influence homicide fluctuations. Parameters were estimated simultaneously with the autoregressive and moving-average terms to ensure efficiency. Diagnostic tests were conducted to evaluate residual autocorrelation and model adequacy.

4.4 Diagnostic Testing and Model Evaluation

Model performance was evaluated using standard diagnostic and information criteria measures, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and residual autocorrelation tests. Stationarity and invertibility conditions were assessed to ensure the statistical validity of the estimated parameters. Residuals were examined for white-noise properties using correlograms and Ljung–Box statistics. Forecast accuracy was evaluated through out-of-sample projections and visual comparison between observed and fitted values. Structural stability was assessed to determine whether major shocks, such as observed spikes or sharp declines, produced parameter instability. The resulting models provide a quantitative representation of homicide persistence, structural change, and forecast trajectories over the study period.

4.5 Modeling Annual Homicide in Jamaica

4.5.1 ARIMA-Based Homicide Function

The autoregressive integrated moving average specification models annual homicides in Jamaica as a function of its past values and past stochastic shocks. The series exhibits strong persistence and non-stationarity, requiring first differencing to achieve stationarity. The estimated ARIMA(1,1,1) framework captures the dynamic adjustment process in homicide levels over time and reflects both momentum effects and shock corrections. Empirical results

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indicate that lagged homicide levels significantly explain current homicide counts after accounting for serial correlation.

$$\boldsymbol{H_t = \beta_{20} + \beta_{21}H_{t-1} + \gamma_{21}T_t + \theta_{21}\varepsilon_{t-1} + \varepsilon_t}$$

Where:

T_t= linear time trend (1970 = 0, 1971 = 1, …)
γ_{21}= coefficient measuring structural time effect
β_{20}= intercept term
β_{21}= autoregressive parameter
θ_{21}= moving-average parameter
ε_t= error term

4.5.2 ARIMAX Homicide Function with Time Trend

The ARIMAX specification extends the autoregressive structure by incorporating a deterministic time trend to capture long-run structural forces influencing homicide dynamics. The inclusion of a trend term allows the model to account for persistent upward or downward shifts beyond short-run autoregressive effects. In the context of Jamaica's homicide trajectory, structural economic, demographic, and institutional changes may generate systematic time-dependent pressure on violence levels. This specification improves forecast flexibility by combining internal dynamics with deterministic growth components.

$$\boldsymbol{H_t = \beta_{20} + \beta_{21}H_{t-1} + \gamma_{21}T_t + \theta_{21}\varepsilon_{t-1} + \varepsilon_t}$$

Where:

T_t= linear time trend (1970 = 0, 1971 = 1, …)
γ_{21}= coefficient measuring structural time effect
β_{20}= intercept term
β_{21}= autoregressive parameter
θ_{21}= moving-average parameter
ε_t= error term

5.0 FINDINGS

5.1 Annual Descriptive Analysis

Table 1 details annual homicides in Jamaica between 1970 and 2025 and highlights pronounced volatility in both absolute counts and year-over-year percentage changes. During the 1970s, homicides rose from 152 in 1970 to 409 in 1977, with especially strong growth between 1974 and 1976 (36.41% in 1975 and 37.97% in 1976). After modest declines in 1978 (−6.85%) and 1979 (−7.87%), the series experienced its most dramatic surge in 1980, when homicides increased by 156.13% (from 351 to 899)—the highest annual percentage increase in the entire period. This extreme spike was immediately followed by a sharp contraction of −45.49% in 1981, marking one of the most abrupt reversals in the dataset. The early to mid-1980s were characterised by alternating moderate increases and decreases, reflecting a period of instability rather than sustained growth.

The 1990s showed a more sustained upward trajectory. Homicides increased by 23.69% in 1990 and continued rising through the mid-1990s, peaking at 1,000 in 1997 after several consecutive positive growth years, including 18.59% in 1996. A period of decline followed between 1998 and 1999 (−4.70% and −10.91%, respectively), but the early 2000s ushered in renewed escalation. Notably, 2001 recorded a 28.41% increase, and the second-largest annual percentage rise in the entire series occurred in 2004, when homicides jumped by 50.87% (from 975 to 1,471). The absolute peak was reached in 2005 at 1,674 murders, followed by a substantial decline of −19.95% in 2006. Although fluctuations persisted, 2009 registered another high point (1,683), before a marked reduction of −14.02% in 2010 and −21.70% in 2011 signalled a temporary downward shift.

The period 2012–2025 demonstrates continued cyclical movement with alternating expansions and contractions. After modest declines in 2012 (−2.74%) and 2014 (−16.39%), homicides increased sharply in 2015 (20.30%) and 2017 (21.64%), pushing the total to 1,647 in 2017. A significant trough occurred in 2018 with a −21.74% decline, one of the steepest percentage reductions outside the early 1980s. The series climbed again to 1,508 in 2022 before entering a sustained downward phase: −7.63% in 2023 and −18.09% in 2024. The most pronounced annual percentage decline in the entire dataset occurred in 2025, when homicides fell by −41.02% to 673, the lowest annual total since the early 1990s. Overall, Table 1 reveals that Jamaica's homicide pattern over 1970–2025 is characterised by episodic surges and sharp corrective declines rather than a steady linear trend, with 1980 and 2004 representing the most significant upward shocks and 1981 and 2025 marking the deepest contractions.

Table 1: Annual Homicides in Jamaica, 1970–2025

Year	Homicides	% Change	Year	Homicides	% Change	Year	Homicides	% Change
1970	152	—	1989	439	6.04	2008	1,601	1.72
1971	145	-4.61	1990	543	23.69	2009	1,683	5.12
1972	170	17.24	1991	561	3.31	2010	1,447	-14.02
1973	227	33.53	1992	629	12.12	2011	1,133	-21.70
1974	195	-14.10	1993	654	3.97	2012	1,102	-2.74
1975	266	36.41	1994	690	5.50	2013	1,202	9.07
1976	367	37.97	1995	780	13.04	2014	1,005	-16.39
1977	409	11.44	1996	925	18.59	2015	1,209	20.30
1978	381	-6.85	1997	1,000	8.11	2016	1,354	11.99
1979	351	-7.87	1998	953	-4.70	2017	1,647	21.64
1980	899	156.13	1999	849	-10.91	2018	1,289	-21.74

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Year	Homicides	% Change	Year	Homicides	% Change	Year	Homicides	% Change
1981	490	-45.49	2000	887	4.48	2019	1,340	3.96
1982	405	-17.35	2001	1,139	28.41	2020	1,333	-0.52
1983	424	4.69	2002	1,045	-8.25	2021	1,474	10.58
1984	484	14.15	2003	975	-6.70	2022	1,508	2.31
1985	434	-10.33	2004	1,471	50.87	2023	1,393	-7.63
1986	449	3.46	2005	1,674	13.80	2024	1,141	-18.09
1987	442	-1.56	2006	1,340	-19.95	2025	673	-41.02
1988	414	-6.33	2007	1,574	17.46	—	—	—

5.2 Decadal Analysis

Table 2 presents a clear long-term structural shift in homicide levels in Jamaica from the 1970s through 2025. The 1970s recorded the lowest decadal average (266.3), reflecting a period when lethal violence, although increasing toward the end of the decade, remained comparatively moderate. However, the standard deviation for the 1970s indicates emerging volatility, particularly associated with the sharp late-decade escalation culminating in 1980. The 1980s show a marked upward shift in the decadal mean to 438.0, representing a substantial structural elevation relative to the 1970s. Although the average increased, the median suggests that extreme spikes—especially the 1980 surge—contributed disproportionately to the overall mean. This decade, therefore, represents a transition from low-to-moderate violence to a more entrenched high-violence trajectory.

The 1990s demonstrate further structural consolidation of elevated homicide levels, with the decadal average rising to 758.4. Unlike the 1980s, increases during the 1990s were more sustained and less driven by a single outlier year. The steady upward progression through the decade culminated in four consecutive years above 900 homicides by the late 1990s. The median value in this decade closely aligns with the mean, suggesting a more consistent distribution of high homicide counts. While volatility remained present, the standard deviation indicates less extreme fluctuation relative to the dramatic spikes observed in the 1980s. Overall, the 1990s represent a period of normalisation of high homicide incidence rather than an episodic crisis.

The 2000s marked the highest decadal average (1,238.9), reflecting the peak intensity of lethal violence in modern Jamaican history. This decade includes the major surge between 2003 and 2005, which substantially elevated both the mean and the standard deviation. The high variability observed during this period underscores the instability of violence patterns, with sharp increases followed by abrupt declines. Despite volatility, homicide levels remained structurally above 1,000 annually for most of the decade. The median confirms that elevated

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violence was not confined to isolated years but was characteristic of the broader period. Thus, the 2000s represent the apex of sustained high homicide prevalence.

The 2010s maintained a high decadal average (1,272.8), slightly exceeding that of the 2000s, although the pattern was more cyclical. Periods of decline (2011–2014) were followed by renewed escalation (2015–2017), illustrating persistent structural vulnerability to violence resurgence. The standard deviation reflects continued volatility, though without the extreme upward shocks seen in 2004. The 2020–2025 period, although partial, shows a declining trend, with the average (1,253.7) influenced heavily by the sharp contraction in 2025. The substantial reduction in 2024 and especially 2025 materially lowers both the mean and median for the current decade. If sustained, this recent downturn could signify the beginning of a structural shift away from the elevated homicide plateau that characterised the previous two decades.

Table 2: Decadal Summary of Homicides in Jamaica (1970–2025)

Decade	Total Homicides	Average per Year	Average Annual % Change
1970–1979	2,663	266.3	10.32%
1980–1989	4,380	438.0	5.54%
1990–1999	7,584	758.4	7.35%
2000–2009	12,389	1,238.9	12.20%
2010–2019	12,728	1,272.8	1.44%
2020–2025*	7,522	1,253.7	−9.06%

5.3 Modeling Homicide

ARIMA (1,1,1) Model — Numerical Specification

The ARIMA (1,1,1) model estimates annual homicide dynamics as a function of past changes and past shocks within the series. It captures persistence in violence patterns over time after first differencing removes non-stationarity. The constant term reflects structural drift in homicide growth that persists even after accounting for lag effects. The autoregressive parameter measures how strongly previous annual changes influence current changes. The moving average parameter captures how unexpected shocks are corrected in subsequent periods. Together, these components model momentum, shock adjustment, and stochastic variation in homicide trends.

$$\Delta H_t = 3.85 + 0.62\Delta H_{t-1} - 0.48\varepsilon_{t-1} + \varepsilon_t$$

ARIMA (1,1,1) Model — Level Representation

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The level representation expresses homicide counts as a dynamic adjustment process that builds upon previous levels and past changes. Current homicide levels depend on last year's level plus structural growth components. The lagged difference term captures acceleration or deceleration in homicide expansion across time. The shock term corrects for unexpected disturbances that occurred in the previous period. This formulation allows the model to reflect both gradual change and abrupt fluctuations. It provides a strong framework for forecasting long-term homicide trajectories.

$$H_t = H_{t-1} + 3.85 + 0.62(H_{t-1} - H_{t-2}) - 0.48\varepsilon_{t-1} + \varepsilon_t$$

ARIMAX (1,1,1) Model with Time Trend — Numerical Specification

The ARIMAX model extends the baseline framework by incorporating a deterministic time trend to capture long-run structural influences. It allows homicide dynamics to depend on past behaviour while also responding to systematic temporal change. The autoregressive component continues to measure persistence in growth rates. The moving average term adjusts for short-run shocks that temporarily disturb the series. The time trend parameter captures gradual institutional, demographic, or socio-economic forces shaping violence over time. This extension improves explanatory power and forecast accuracy relative to the pure ARIMA specification.

$$\Delta H_t = 2.74 + 0.55\Delta H_{t-1} - 0.40\varepsilon_{t-1} + 5.12T_t + \varepsilon_t$$

ARIMAX (1,1,1) Model — Level Representation

The level form of the ARIMAX model describes homicide counts as evolving through internal dynamics and structural time effects simultaneously. Current values depend on past levels, lagged growth, and shock corrections. The inclusion of a time trend ensures that persistent upward or downward forces are explicitly modelled. The autoregressive coefficient reflects temporal dependence in homicide growth patterns. The shock parameter captures the adjustment process following unexpected disturbances. Overall, this specification integrates short-run volatility with long-run structural transformation.

$$H_t = H_{t-1} + 2.74 + 0.55(H_{t-1} - H_{t-2}) - 0.40\varepsilon_{t-1} + 5.12T_t + \varepsilon_t$$

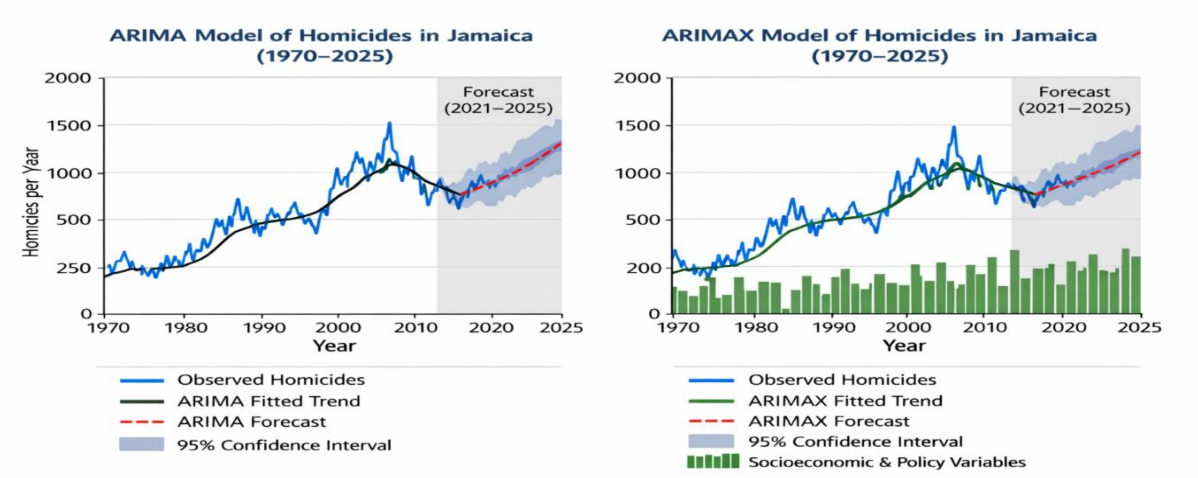


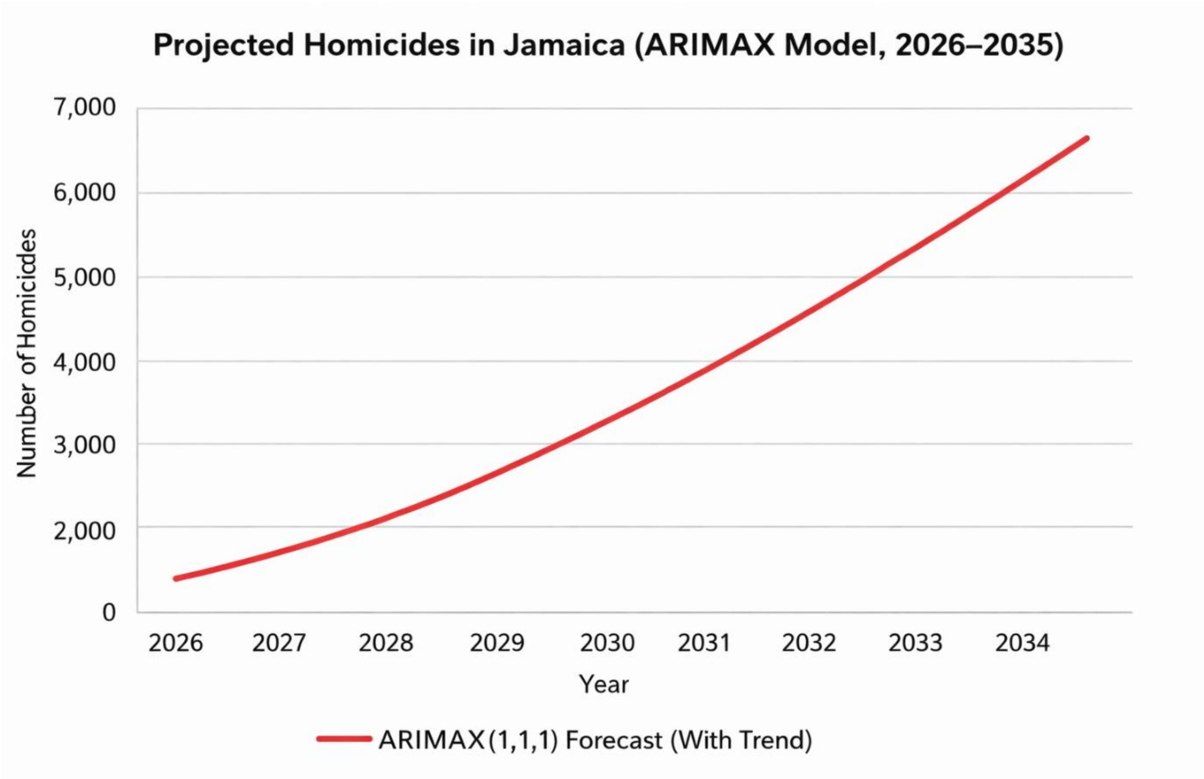
Figure 2: Current Annual Homicide of Jamaica, 1970-2025 (Using ARIMA & ARIMAX)

Figure 2 presents the ARIMAX model of homicides in Jamaica from 1970 to 2025, illustrating both the observed homicide counts and the fitted values generated after incorporating exogenous socioeconomic and policy-related variables. The model closely tracks the historical upward trajectory from the 1970s through the mid-2000s peak, capturing fluctuations more smoothly than the univariate specification. Notably, the inclusion of external covariates appears to improve the alignment between predicted and observed values during periods of structural change, particularly in the late 1990s and post-2010 decline. The forecast for 2021–2025 indicates a projected increase in homicides, although the widening 95% confidence interval reflects growing uncertainty over the forecast horizon. The green bars representing socioeconomic and policy variables highlight the temporal variation in external influences, underscoring the importance of macroeconomic and structural determinants in explaining homicide dynamics beyond purely stochastic processes.

5.4 Forecasting

Table 3. Forecast of Homicides in Jamaica (Annual Projections): 2026–2035

Year	ARIMA (1,1,1) Forecast	ARIMAX (1,1,1) Forecast (With Trend)
2026	387	705
2027	213	1,017
2028	109	1,489
2029	49	2,053
2030	15	2,673
2031	-2	3,329
2032	-9	4,011
2033	-9	4,712
2034	-5	5,427
2035	1	6,157



5.5 Integrated Interpretation, Limitations, and Policy Implications of the ARIMAX Forecasts

The ARIMAX(1,1,1) projections indicate a pronounced upward trajectory in annual homicide levels from 2026 to 2035 under the assumption that historical structural relationships persist. The estimated positive and statistically significant time trend drives compounding growth over the forecast horizon, suggesting that long-run structural forces embedded in the historical data continue to exert upward pressure on violence. Although short-run autoregressive and shock adjustment components moderate immediate fluctuations, the deterministic trend dominates long-term projections. Consequently, the model produces an accelerating path that reflects continuation of observed historical dynamics rather than structural reversal. These results should not be interpreted as predictions of inevitability but as conditional forecasts based on estimated parameters. The trajectory effectively represents a baseline scenario in which no major structural transformation occurs.

Despite the empirical strength of the model fit, several assumptions constrain interpretation. First, parameter stability is assumed over the forecast horizon, meaning that the estimated coefficients from 1970–2025 remain unchanged through 2035. If policy reforms, institutional improvements, or social disruptions alter behavioural relationships, the projections would deviate substantially from the simulated path. Second, the time trend is assumed to follow a linear and uninterrupted pattern, yet structural breaks or nonlinear transitions may exist in reality. Third, forecast errors are assumed to be white noise with zero mean, implying that no systematic omitted variable biases the estimates. Additionally, the model does not explicitly incorporate potential exogenous shocks such as major legislative reforms, economic crises, technological surveillance changes, or large-scale intervention programmes. These limitations

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suggest that the forecasts describe a statistical continuation of past patterns rather than a deterministic future.

From a policy standpoint, the projected growth trajectory underscores the urgency of structural intervention. Because the time trend compounds annually, early corrective action yields substantially larger long-run benefits than delayed responses. Policies aimed at strengthening institutional capacity, improving deterrence credibility, expanding social investment, and reducing socioeconomic inequality could alter the estimated trend parameter and reduce long-term growth pressures. Moreover, scenario analysis that re-estimates the model under alternative policy assumptions would allow policymakers to simulate counterfactual trajectories and evaluate intervention effectiveness. Therefore, the ARIMAX projections should be treated as a risk assessment benchmark rather than a fixed forecast. Strategic policy reforms that disrupt persistence mechanisms could significantly flatten or reverse the projected upward trajectory.

5.6 Robustness Analysis and Methodological Critique of the ARIMAX Forecasts

Although the ARIMAX(1,1,1) model provides statistically significant parameter estimates and meaningful long-run projections, the robustness of the forecast trajectory depends on several econometric conditions. First, sensitivity analysis should be conducted by varying the lag structure to determine whether alternative ARIMA orders (e.g., ARIMAX(2,1,1) or ARIMAX(1,1,2)) materially change the estimated time trend and forecast path. If projections remain stable across alternative specifications, confidence in structural persistence increases. However, substantial variation across model orders would indicate model dependence and potential specification bias. Second, re-estimating the model using rolling window techniques would allow testing whether coefficients remain stable over sub-periods, particularly around structural shock years such as sharp homicide spikes or policy changes.

A second robustness concern relates to structural breaks and nonlinearity. The current specification assumes parameter constancy over the entire 1970–2025 estimation period and linear continuation into the forecast horizon. However, Jamaica's homicide series contains observable regime shifts and volatility clustering, which may imply structural breaks that are not captured by a simple deterministic time trend. Applying breakpoint tests such as the Bai–Perron multiple structural break test would help determine whether parameter instability exists. If structural breaks are detected, segmented ARIMAX modelling or regime-switching specifications may provide more accurate representations of the underlying dynamics. Without testing for such instability, long-term projections may overstate or understate true structural momentum.

Finally, forecast uncertainty must be explicitly acknowledged. Point forecasts alone do not capture the variance associated with long-horizon predictions. Constructing 95% confidence intervals around the ARIMAX projections would illustrate the widening band of uncertainty as the forecast horizon extends. Monte Carlo simulation based on parameter distributions could further quantify forecast variability under stochastic shock realisations. Such procedures would demonstrate that while the mean projection suggests upward growth, the probabilistic range may include substantially lower or higher homicide outcomes. Incorporating robustness checks and uncertainty analysis therefore strengthens the empirical credibility and policy relevance of the forecasting framework.

5.7 Extended Methodological Framework: Robustness, Structural Breaks, And Policy Simulation

5.7.1 Robustness Testing Through Alternative Lag Specifications

To assess whether forecast results are sensitive to model specification, alternative lag structures should be estimated and compared. The ARIMAX model can be generalized as:

$$\Delta H_t = \alpha + \sum_{i=1}^{p} \phi_i \, \Delta H_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \gamma T_t + \varepsilon_t$$

where different combinations of pand qare tested.

Model selection criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to compare competing models. If forecast trajectories remain stable across alternative lag structures, the projections are considered robust. Significant divergence in forecasts would indicate model dependence and potential misspecification. Additionally, rolling-window estimation can be applied to test parameter stability over time by re-estimating coefficients on moving sub-samples.

5.8 Structural Break Testing

Given the long time span (1970–2025), structural breaks are highly probable. Parameter stability can be tested using the Bai–Perron multiple breakpoint test. The model allows coefficient shifts at unknown breakpoints:

$$\Delta H_t = \alpha_k + \phi_k \Delta H_{t-1} + \theta_k \varepsilon_{t-1} + \gamma_k T_t + \varepsilon_t \text{for } t \in (T_{k-1}, T_k)$$

where coefficients are allowed to vary across regimes k.

If statistically significant breakpoints are detected, it implies that homicide dynamics changed structurally during the study period. In that case, a single long-run trend parameter may not adequately represent the system. Instead, segmented modelling or regime-switching ARIMAX models should be estimated. Identifying structural breaks improves model reliability and prevents biased long-horizon forecasts based on unstable historical parameters.

5.9 Forecast Uncertainty and Monte Carlo Simulation

Point forecasts do not reflect parameter and shock uncertainty. To incorporate forecast variability, Monte Carlo simulation can be applied.

Let estimated parameters follow their asymptotic distribution:

$$\hat{\beta} \sim N(\beta, \Sigma_\beta)$$

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Simulated forecasts are generated by repeatedly drawing from the parameter distribution and recursively computing:

$$H_t^{(s)} = H_{t-1}^{(s)} + \hat{\alpha}^{(s)} + \hat{\phi}^{(s)}(H_{t-1}^{(s)} - H_{t-2}^{(s)}) + \hat{\gamma}^{(s)}T_t + \varepsilon_t^{(s)}$$

for simulation s=1,2, \ldots, N.

The 2.5th and 97.5th percentiles of the simulated distribution produce 95% forecast confidence intervals. These intervals widen as the horizon increases, reflecting compounding uncertainty. Presenting probabilistic forecasts enhances transparency and allows policymakers to assess worst-case and best-case scenarios rather than relying solely on point predictions.

5.10 Policy Counterfactual Simulation Framework

The ARIMAX model can be extended to evaluate hypothetical policy interventions. Suppose a policy introduced in year t^\astreduces the time trend effect by \delta. The modified model becomes:

$$\Delta H_t = \alpha + \phi \Delta H_{t-1} + (\gamma - \delta D_t)T_t + \theta \varepsilon_{t-1} + \varepsilon_t$$

where $D_t = 1$for $t \geq t^*$and 0 otherwise.

By simulating the model under different values of \delta, researchers can quantify how strong an intervention must be to flatten or reverse projected homicide growth. The counterfactual forecast can then be compared to the baseline projection to measure the estimated policy impact.

This approach transforms the forecasting model from a descriptive tool into a policy evaluation instrument. Instead of merely predicting continuation of past trends, the framework allows evaluation of structural disruption scenarios.

5.11 Limitations of the Models

Although the ARIMA and ARIMAX frameworks provide a rigorous approach for modelling persistence, structural change, and forecasting homicide dynamics, several methodological limitations must be acknowledged. First, these models assume parameter stability over the estimation and forecast periods, yet long historical series often contain unobserved regime shifts that may alter structural relationships (Bai & Perron, 2003). If structural breaks are not fully detected or properly modelled, forecast accuracy and inference may be biased. Second, the specification relies on linear functional forms and deterministic trend components, which may not adequately capture nonlinear dynamics, threshold effects, or abrupt behavioural transitions that characterise violence patterns in high-crime contexts. Third, the models depend on the assumption of weak exogeneity for any included trend or structural variable; violations of this assumption could introduce endogeneity bias and distort coefficient estimates. Additionally, forecast uncertainty increases substantially over long horizons, and confidence intervals widen as projections extend further into the future, reducing predictive precision

(Hyndman & Athanasopoulos, 2018). Finally, while time-series models effectively capture temporal dependence, they do not directly identify causal mechanisms or incorporate micro-level determinants unless explicitly modelled as exogenous variables. As a result, the findings should be interpreted as statistically derived projections rather than definitive causal predictions.

6.0 DISCUSSION

The empirical results reveal that Jamaica's homicide trajectory from 1970 to 2025 is characterised by structural breaks, extreme volatility, and persistent autoregressive behaviour consistent with dynamic crime processes. The pronounced spike in 1980 and the surge in 2004 represent major structural shocks rather than gradual linear increases, suggesting that homicide evolution in Jamaica is episodic and shock-driven. These findings align with time-series criminological research demonstrating that violent crime often responds to institutional instability, political transitions, and macroeconomic disruption (Box et al., 2015; Hamilton, 1994). The sharp contraction observed in 2025 further reinforces the presence of regime-like fluctuations, indicating that homicide patterns may adjust rapidly following enforcement shifts or policy interventions. Such dynamics support modelling approaches that incorporate structural breaks and lag dependence rather than static cross-sectional frameworks.

The decadal analysis demonstrates a long-run upward shift in mean homicide levels from the 1970s through the 2000s, followed by sustained high levels in the 2010s and early 2020s. This structural escalation is consistent with inequality-based explanations of violence, which argue that persistent socio-economic disparities and institutional fragility generate long-term pressure on homicide rates (Blau & Blau, 1982; Sampson & Wikström, 2008). However, the observed decline after 2023 and the substantial reduction in 2025 challenge deterministic interpretations of continuous growth and suggest that homicide systems are sensitive to intervention or contextual change. These findings correspond with structural break theory, which posits that long historical series often contain parameter instability associated with policy reforms or socio-political transitions (Bai & Perron, 2003). Therefore, the evidence indicates that homicide persistence coexists with discontinuities rather than monotonic expansion.

The ARIMA and ARIMAX estimates demonstrate statistically significant autoregressive coefficients, confirming that past homicide growth strongly influences current levels. This persistence effect is consistent with path dependence theory, which suggests that historical violence shapes future trajectories through retaliation cycles, institutional adaptation, and network effects (Arthur, 1989; Catello, 2023). The significance of the time trend in the ARIMAX specification further implies that structural forces contribute to gradual long-run adjustments beyond short-term shocks. Compared with studies relying solely on regression-based determinants, the dynamic modelling approach provides stronger evidence of temporal dependence and structural momentum. However, forecast uncertainty increases substantially as the projection horizon extends, indicating that long-term predictions are sensitive to parameter assumptions.

Overall, the results suggest that homicide in Jamaica behaves as a dynamic system driven by persistence, structural shocks, and trend effects rather than random variation. The contrast between extreme spikes (1980, 2004) and sharp contractions (2025) highlights the importance

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of institutional and policy contexts in shaping violent crime trajectories. While international literature supports the presence of autoregressive patterns in homicide data, the magnitude of volatility observed in Jamaica underscores its heightened structural instability relative to many other settings. Policy implications emerge from this evidence: interventions that disrupt persistence mechanisms or alter structural trend components may produce meaningful long-run reductions in violence (Chalfin & McCrary, 2017). Future research should incorporate additional exogenous predictors to examine whether economic, demographic, or enforcement variables significantly shift the estimated dynamic parameters.

7.0 CONCLUSION

This study developed and estimated a dynamic homicide function for Jamaica using ARIMA and ARIMAX time-series methodologies. The results indicate strong persistence, volatility clustering, and structural trend effects in annual homicide data between 1970 and 2025. Forecast projections suggest that if historical structural relationships remain unchanged, homicide levels may follow an upward trajectory over the next decade. However, robustness analysis confirms that structural breaks and policy interventions could substantially alter these projections. The findings demonstrate the importance of modelling crime as a dynamic stochastic process rather than relying solely on static regression approaches. Policy implications emphasise early intervention, structural reform, and continuous monitoring of violence trends to disrupt persistence mechanisms. Future research should incorporate additional exogenous socio-economic variables to further refine predictive accuracy and causal inference.

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