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Premature Mortality From Non-Communicable Diseases in Latin America and The Caribbean: A Time-Series Analysis of Progress Toward SDG 3.4

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Abstract: Premature mortality from non-communicable diseases (NCDs) remains a major public health challenge in Latin America and the Caribbean, threatening progress toward Sustainable Development Goal (SDG) 3.4, which calls for a one-third reduction in premature NCD mortality. We examine trends and future trajectories of mortality from cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases among adults aged 30–70 years using monthly World Bank data from 2000 to 2024. The ARIMA modeling framework is employed to capture both long-run persistence and short-run fluctuations in mortality dynamics. Estimation results reveal strong persistence in premature NCD mortality, as evidenced by a positive and statistically significant autoregressive coefficient, alongside a negative and significant moving-average component indicating partial shock correction. Model diagnostics confirm stationarity and invertibility, supporting the reliability of forecasts. Projections indicate a gradual decline in premature NCD mortality, converging toward approximately 13.32% by 2046. While this trend reflects continued improvement, the projected level remains unacceptably high and insufficient to fully achieve SDG 3.4 targets. The findings underscore the urgency of strengthening NCD prevention, early diagnosis, and health-system capacity to accelerate mortality reductions in the region.

Keywords: *ARIMA, premature adult mortality, non-communicable diseases, Latin America, the Caribbean*

1. Introduction

Non-communicable diseases (NCDs), principally cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases have emerged as the leading cause of premature mortality globally, accounting for more than 70 percent of all deaths worldwide (WHO, 2023). The burden of NCDs is particularly acute in low- and middle-income regions, where demographic transitions, urbanization, lifestyle changes, and unequal access to quality healthcare interact to elevate mortality risks among working-age adults. In response to this growing challenge, Sustainable Development Goal (SDG) 3.4 commits countries to reducing premature mortality from NCDs by one-third by 2030 through prevention, treatment, and the promotion of mental health and well-being (United Nations, 2015).

Latin America and the Caribbean (LAC) have made notable progress in reducing communicable disease mortality; however, this success has been accompanied by a rapid epidemiological transition toward NCDs (PAHO, 2022). Despite improvements in life expectancy and health system coverage, premature mortality from NCDs among adults aged 30–70 years remains persistently high in the region. Cardiovascular diseases and cancers alone account for the majority of these deaths, often occurring during individuals' most productive years, thereby imposing substantial social and economic costs on households and national economies (Bloom et al., 2011; Nugent, 2016). The COVID-19 pandemic further disrupted NCD prevention, diagnosis, and management services, raising concerns about the sustainability of recent mortality gains (WHO, 2022).

While numerous studies have examined the determinants of NCD mortality in LAC using cross-sectional or panel data approaches (Barreto et al., 2012; Miranda et al., 2019), comparatively limited attention has been paid to the time-series dynamics of premature NCD mortality at the regional level. Existing research often emphasizes structural risk factors such as income inequality, behavioral risks, or health expenditure without adequately modeling the persistence, inertia, and shock responses inherent in mortality trends. This represents an important gap, as mortality outcomes typically evolve gradually and exhibit strong temporal dependence, implying that short-run interventions may have delayed or muted effects unless sustained over time (Box et al., 2015; Nahabwe & Maniple, 2025). Moreover, few studies explicitly link mortality forecasts to the feasibility of achieving SDG 3.4, limiting their direct relevance for medium- and long-term policy planning.

Against this backdrop, we address the research problem of persistently high premature mortality from NCDs in Latin America and the Caribbean by modeling its temporal behavior using a time-series framework. By applying an autoregressive integrated moving average (ARIMA) approach to World Bank data spanning 2000 to 2024, our study captures both long-run persistence and short-run fluctuations in mortality from cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases among adults aged 30–70 years. Unlike static or purely explanatory models, this approach enables robust forecasting of mortality trajectories and provides empirical evidence on whether current trends are consistent with the pace required to achieve SDG 3.4.

The rationale for this study is threefold. Firstly, understanding the dynamic properties of premature NCD mortality is essential for designing effective and sustained public health interventions. Secondly, credible long-term projections offer policymakers a benchmark against which to assess progress toward SDG 3.4 and identify potential shortfalls. Thirdly, by focusing on the LAC region as a whole, our study provides regionally relevant insights that complement country-specific analyses and support coordinated policy responses. In doing so, our research contributes to both the empirical literature on NCD mortality dynamics and the policy discourse on achieving global health targets in Latin America and the Caribbean.

2. Literature Review

Non-communicable diseases (NCDs) have dominated global mortality patterns over the past three decades, contributing to a significant share of premature deaths among adults aged 30–70 years (WHO, 2023).

Globally, cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases are estimated to account for more than 70% of all deaths, with a disproportionate burden afflicting low- and middle-income countries (LMICs) due to structural vulnerabilities, behavioral risk exposures, and limited access to early diagnosis and treatment (Zavalis et al., 2017; Naghavi et al., 2017; Nahabwe & Maniple, 2025). These mortality trends directly inform Sustainable Development Goal (SDG) 3.4, which mandates a one-third reduction in premature NCD mortality by 2030 relative to 2015 baselines (United Nations, 2015).

Empirical studies highlight that while high-income countries have made notable gains through comprehensive prevention and treatment strategies, many LMICs lag due to persistent health system bottlenecks and socio-economic inequities (Gakidou et al., 2017; Collaborators & Ärnlöv, 2020). This global evidence underscores the urgency of time-sensitive action and robust monitoring to achieve SDG 3.4.

Within Latin America and the Caribbean (LAC), the NCD burden has escalated alongside economic development and demographic transitions. Regional mortality patterns reveal high levels of premature deaths attributable primarily to cardiovascular diseases and cancers, with diabetes and chronic respiratory diseases also contributing substantially (PAHO, 2022; Martinez et al., 2020). These patterns are compounded by the high prevalence of modifiable risk factors including tobacco use, unhealthy diets, physical inactivity, and obesity (Gómez et al., 2019).

Although national health policies and surveillance systems have improved in many LAC countries, significant disparities persist between urban and rural populations as well as across socio-economic strata (Oliveira et al., 2020). Cross-country comparative studies suggest that variations in health system capacity, expenditure levels, and policy implementation influence the pace of NCD mortality decline, pointing to the need for coordinated regional policy frameworks that align with SDG priorities (Beaglehole et al., 2011; Miranda et al., 2019).

Despite growing awareness of the NCD crisis in the region, much of the existing research on LAC mortality trends has emphasized cross-sectional or explanatory risk factor analyses rather than longitudinal time-series perspectives. Where longitudinal studies exist, they often focus on country-specific trajectories (e.g., Brazil: Machado et al., 2020; Mexico: Barquera et al., 2016), leaving a gap in understanding regional temporal dynamics that integrate persistence and shock responses crucial to effective forecasting and policy evaluation.

At the national and sub-national levels, research has documented spatial and socio-economic inequalities in premature NCD mortality, often linked to disparities in health service access and prevention program coverage

(Oliveira et al., 2020; Robinson et al., 2012). For example, studies in Central American settings indicate that rural and lower-income populations experience elevated NCD mortality, reflecting barriers to early detection and ongoing management of chronic conditions (Garduño-Alanis et al., 2024). These local analyses enrich global and regional evidence by revealing the contextual and health system determinants of mortality patterns. However, few of these studies apply formal time-series methods to examine temporal dependencies and the trajectory of mortality trends limiting their utility for forecasting progress toward SDG targets.

The theoretical foundation for analyzing premature NCD mortality draws from the epidemiologic transition theory, which posits that societies undergoing economic development gradually shift from infectious to chronic disease dominance due to changes in lifestyle, aging, and environmental exposures (Omran, 1971; Frenk et al., 1991). In later stages of the transition, mortality improvements are influenced less by infectious disease control and more by prevention, early diagnosis, and effective long-term management of chronic conditions. Complementing this is the health systems theory, which emphasizes that sustained reductions in NCD mortality depend on comprehensive service delivery, financing, and governance arrangements that can adapt to changing disease burdens (Saltman et al., 2006). These theories collectively inform the expectation that mortality dynamics will exhibit persistence and respond to policy shocks over extended periods, thereby necessitating models such as ARIMA that explicitly account for temporal correlations in the data (Box et al., 2015; Nahabwe & Kagarura, 2025).

Conceptually, premature adult mortality from non-communicable diseases (NCDs) is specified as the dependent variable and measured as the probability (percentage) of death between ages 30 and 70 from cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases. This outcome reflects the combined and lagged effects of behavioral risks, socioeconomic conditions, health system performance, and demographic change in Latin America and the Caribbean. Rather than modeling these determinants explicitly, their influence is assumed to be embedded in the historical evolution of the mortality series. Autoregressive and moving-average components, therefore, capture persistence and short-term shocks, making the ARIMA framework appropriate for analyzing trends and forecasting progress toward SDG 3.4 (Box & Jenkins, 1976; Nahabwe & Maniple, 2025).

The cumulative review reveals three key gaps: Firstly, a scarcity of comprehensive time-series analyses of premature NCD mortality at the regional level; Secondly, limited integration of temporal dynamics in assessing SDG 3.4 progress; and thirdly, inadequate use of forecasting methodologies to guide long-term planning. Our study responds directly to these gaps by employing ARIMA modeling to capture the temporal structure of mortality trends and generate forecasts extending to 2046, thereby providing empirically grounded insights for regional policy agendas aligned with SDG targets.

3. Data and Method

We adopt a quantitative time-series research design to examine the dynamics and future trajectory of premature adult mortality from non-communicable diseases (NCDs) in Latin America and the Caribbean. A time-series approach is particularly appropriate given the study's objective of modeling temporal persistence, short-run shocks, and long-run trends in mortality outcomes, as well as assessing progress toward Sustainable Development Goal (SDG) 3.4. Unlike cross-sectional or panel designs, time-series analysis enables explicit modeling of inertia and innovation effects inherent in health outcomes that evolve gradually over time (Box et al., 2015; Enders, 2015; Nahabwe & Kagarura, 2025).

We utilize secondary monthly time-series data obtained from the World Bank's World Development Indicators (WDI) database (World Bank, 2024). The primary variable of interest is Mortality from cardiovascular diseases, cancer, diabetes, or chronic respiratory diseases between exact ages 30 and 70 (%), a core indicator used globally to monitor progress toward SDG 3.4 (United Nations, 2015; WHO, 2023).

The sample covers the period January 2000 to December 2024, yielding a total of 300 monthly observations. The shift from annual to monthly frequency enhances the statistical power of the analysis, improves the detection of short-run fluctuations, and allows for more precise estimation of dynamic adjustment processes in mortality trends (Harvey, 1990; Kagarura & Nahabwe, 2025). Our study focuses on Latin America and the

Caribbean region as an aggregate, reflecting the regional policy orientation of SDG monitoring and facilitating comparability with regional health assessments by the Pan American Health Organization (PAHO, 2022).

Given the complete availability of data for the study period, a census sampling approach is employed rather than probabilistic sampling. All observed monthly values within the specified timeframe are included, eliminating sampling bias and ensuring that the estimated dynamics fully reflect the historical mortality trajectory of the region (Kagarura et al., 2025).

Empirical analysis proceeds in several stages. Firstly, descriptive analysis is conducted to examine the level, trend, and variability of premature NCD mortality over time. Visual inspection and summary statistics are used to identify structural shifts and potential periods of increased volatility, such as during global health shocks.

Secondly, the stationarity properties of the series are assessed using standard unit root tests to determine the appropriate order of differencing. Consistent with time-series best practices, non-stationary behavior in levels necessitates differencing to achieve stationarity before model estimation (Dickey & Fuller, 1979; Enders, 2015; Nahabwe & Kagarura, 2025).

Thirdly, an autoregressive integrated moving average (ARIMA) framework is specified to capture both persistence (autoregressive effects) and transitory shocks (moving-average effects) in premature mortality dynamics. Model identification follows the Box–Jenkins methodology, guided by autocorrelation and partial autocorrelation diagnostics (Box et al., 2015; Kagarura & Nahabwe, 2025).

ARIMA (p, d, q) model specification is as follows:

$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ldots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$ …… (1)

Where;

Y_t is the value of the series at time t

μ is the mean of the series

ε_t is white noise

$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component

$\theta_1, \theta_2, \ldots \theta_q$ are the coefficients of the MA (q) component

p is the order of the autoregressive part, representing the number of past values considered

q is the order of the moving average part, indicating the number of past errors considered

d is the number of differences required to make the series stationary (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025)

Parameter estimation is conducted using Generalized Least Squares (GLS). GLS is preferred over ordinary least squares (OLS) because time-series data on mortality frequently exhibit serial correlation and heteroskedasticity, which violate classical OLS assumptions and lead to inefficient or biased inference (Greene, 2018; Nahabwe & Kagarura, 2025). By explicitly accounting for the error covariance structure, GLS yields more efficient and reliable parameter estimates, particularly in the presence of autoregressive and moving-average disturbances (Wooldridge, 2016; Nahabwe & Maniple, 2025).

Generalized least squares (GLS) estimation is selected for its ability to effectively handle time-series data that exhibits serial correlation and heteroscedasticity, thus providing more reliable and efficient parameter estimates compared to Ordinary Least Squares (OLS) in this context. The GLS procedure adjusts for potential correlations and non-constant variances in the error terms, which are common in time-series data (Greene 2018; Wooldridge 2016; Nahabwe & Kagarura, 2025). The GLS estimator for the regression coefficients is given by the following formula:

$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$

Where:

$\hat{\beta}$ is a column matrix of coefficients

X is the matrix of independent variables

y is the column vector of the dependent variable

Ω is the variance-covariance matrix of the error terms, accounting for both heteroscedasticity and autocorrelation in the residuals (Greene 2018; Hayashi 2000; Nahabwe & Maniple, 2025).

The robustness of the estimated model is evaluated through diagnostic tests for residual autocorrelation, stationarity, and invertibility. Once validated, the model is used to generate out-of-sample forecasts up to 2046, enabling an assessment of whether projected mortality trajectories are consistent with the pace required to achieve SDG 3.4.

4. Results and Discussion

Appendix 1 presents descriptive statistics for premature mortality from cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases among adults aged 30–70 years in Latin America and the Caribbean over the period January 2000 to December 2024. The mean mortality rate of 15.89% indicates a substantial burden of premature NCD mortality in the region, while the median value of 15.59% suggests that more than half of the observed months recorded mortality rates close to this high average level. The observed maximum (18.54%) and minimum (13.58%) values reveal a marked but gradual decline over time, consistent with long-term epidemiological transition dynamics reported in the region (PAHO, 2022; WHO, 2023).

The standard deviation of 1.23 indicates moderate variability in mortality rates, reflecting slow-moving structural changes rather than abrupt fluctuations, an expected feature of population-level health outcomes. The positive skewness value (0.32) suggests a longer right tail, implying that higher mortality episodes occurred more frequently in earlier periods of the sample. The kurtosis value (2.19) is below the Gaussian benchmark of 3, indicating a flatter distribution in levels. However, the Jarque–Bera statistic (13.17, $p = 0.0014$) rejects the null hypothesis of normality, reinforcing the need for robust time-series techniques that do not rely on strict normality assumptions (Enders, 2015; Wooldridge, 2016; Munyambonera et al., 2025).

Stationarity tests (Appendices 2 & 3) are conducted using the Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level ($p > 0.05$). After first difference, the series achieved stationarity ($p < 0.05$), justifying the use of the ARIMA model ($d = 1$) (Kagarura & Nahabwe, 2025). ARIMA(1,1,1) model is identified as the best, based on Akaike Information Criterion (AIC = -5.276310) and Schwarz Criterion (SC = -5.239181), Hannan-Quinn Criterion (H-QC) -5.261449.

Results are summarized as follows:

Results of the ARIMA(1,1,1) model (Appendix 4)

$$\widehat{Mortality\ from\ CVD, cancer, diabetes\ or\ CRD_t} = -0.017524 + 0.909354AR(1) - 0.614833MA(1) \quad \ldots\ldots (3)$$

Hence,

$$\hat{\beta} = \begin{bmatrix} -0.017524 \\ 0.909354 \\ -0.614833 \end{bmatrix}$$

The estimated ARIMA(1,1,1) model provides important insights into the temporal dynamics of premature NCD mortality. The constant term is negative and statistically significant (−0.017524), indicating an underlying downward drift in mortality over time. This finding reflects gradual improvements in prevention, treatment, and health system capacity in the region, albeit at a modest pace (Beaglehole et al., 2011; Miranda et al., 2019).

AR(1) coefficient (0.909354) is positive and statistically significant, implying strong persistence in premature mortality dynamics. This result indicates that current mortality levels are heavily influenced by past outcomes, such that shocks or policy interventions exert effects that unfold slowly over time. High persistence is characteristic of chronic disease mortality and aligns with epidemiological evidence that NCD outcomes respond gradually to sustained policy and behavioral changes rather than short-term interventions (Box et al., 2015; WHO, 2022).

Conversely, the MA(1) coefficient (–0.614833) is negative and statistically significant, suggesting that short-term innovations or shocks—such as temporary policy disruptions or health system stressors—are partially corrected in subsequent periods. This dynamic implies that while mortality trends are highly persistent, transitory deviations tend to dissipate rather than permanently alter the trajectory. Similar corrective patterns have been observed in time-series analyses of mortality and health expenditure dynamics (Akaike, 1974; Harvey, 1990; Kagarura & Nahabwe, 2025).

The adjusted R-squared value of 0.3171 indicates that approximately 32% of the variation in the differenced mortality series is explained by its own past values and error structure. Although modest, this explanatory power is consistent with univariate time-series models applied to complex health outcomes, where a large share of variation is driven by long-run structural determinants not explicitly modeled (Enders, 2015; Kagarura & Nahabwe, 2025; Nahabwe, 2025).

The Durbin–Watson statistic of 2.06 suggests the absence of first-order autocorrelation in the residuals, confirming that the ARIMA specification adequately captures the serial dependence in the data (Nahabwe & Kagarura, 2025; Kagarura et al., 2025).

Model diagnostics further validate the robustness of the estimated results. The histogram of residuals (Appendix 7) reports an exceptionally high kurtosis value (47.5, p = 0.0000), indicating leptokurtic residuals and the presence of extreme observations. While this departs from normality, such behavior is not uncommon in long health time-series and does not invalidate inference under GLS estimation, which remains consistent in the presence of non-normal disturbances (Greene, 2018; Wooldridge, 2016; Nahabwe & Kagarura, 2025).

Ljung–Box Q-statistic test (Appendix 5) yields a p-value of 0.511, leading to a failure to reject the null hypothesis of no residual autocorrelation. This result confirms that the model residuals resemble white noise, satisfying a key requirement for reliable forecasting (Box et al., 2015; Nahabwe & Kagarura, 2025; Kagarura et al., 2025).

Similarly, Breusch–Godfrey serial correlation LM test (Appendix 8) reports Prob. F(2,294) = 0.3679 and Prob. Chi-square(2) = 0.3630, indicating no evidence of higher-order serial correlation. AR and MA roots (Appendix 6) lie within the unit circle, confirming that the ARIMA(1,1,1) model is both covariance stationary and invertible, thereby reinforcing its suitability for inference and forecasting (Nahabwe & Kagarura, 2025; Nahabwe, 2025).

Model-based projections indicate a gradual decline in premature NCD mortality, converging toward approximately 13.32% by 2046. This projected trajectory suggests continued progress but at a decelerating pace. While the downward trend is consistent with regional improvements documented by PAHO (2022) and WHO (2023), the forecasted level remains substantially high, particularly given the SDG 3.4 target of a one-third reduction in premature mortality.

Compared with previous studies that report declining but uneven NCD mortality trends in Latin America and the Caribbean (Martinez et al., 2020; Oliveira et al., 2020), this study uniquely demonstrates that strong temporal persistence may constrain the speed of future mortality reductions. Unlike cross-sectional or panel analyses, the time-series approach highlights that without intensified and sustained interventions, existing trends alone may be insufficient to meet SDG 3.4 within the desired timeframe.

Our study makes three key contributions to the literature. Firstly, it provides one of the few monthly time-series analyses of premature NCD mortality at the regional level, offering a high-resolution view of mortality dynamics. Secondly, it empirically demonstrates the high persistence embedded in NCD mortality trends, underscoring the importance of long-term policy commitment. Thirdly, by linking forecasts directly to SDG 3.4, the study bridges the gap between econometric modeling and policy-relevant health planning, offering actionable insights for regional and global stakeholders.

Limitations

Despite its contributions, our study has several limitations that should be considered when interpreting the findings. Firstly, our research adopts a univariate time-series design, which focuses on the internal dynamics

of premature mortality from non-communicable diseases (NCDs) rather than explicitly modeling their socioeconomic, behavioral, and health-system determinants. While this approach is appropriate for assessing temporal persistence and forecasting progress toward SDG 3.4, it limits causal inference regarding the drivers of observed mortality trends (Enders, 2015; Wooldridge, 2016; Nahabwe & Kagarura, 2025). Consequently, the results should be interpreted as describing patterns and trajectories rather than identifying policy mechanisms.

Secondly, our study relies on aggregated regional data for Latin America and the Caribbean, which may mask substantial cross-country heterogeneity in NCD mortality profiles, health system capacity, and policy implementation. Countries in the region differ markedly in income levels, epidemiological transitions, and exposure to NCD risk factors, and these differences cannot be disentangled within a regional time-series framework (PAHO, 2022; WHO, 2023). As a result, the findings may not fully reflect country-specific progress or setbacks in achieving SDG 3.4.

Thirdly, the conversion of annual mortality estimates into monthly series, although methodologically justified to enhance temporal resolution and forecasting precision, may introduce measurement smoothing and interpolation bias. Monthly disaggregation assumes gradual intra-year variation in mortality, which may understate short-term shocks associated with epidemics, health system disruptions, or policy changes (Harvey, 1990; Box et al., 2015; Nahabwe & Kagarura, 2025). This limitation could affect the magnitude, though not the direction, of estimated dynamics.

Fourthly, although the Generalized Least Squares (GLS) based ARIMA framework is robust to autocorrelation and heteroskedasticity, it assumes parameter stability over time. Structural breaks such as major health reforms, economic crises, or the COVID-19 pandemic may alter mortality dynamics in ways not fully captured by the model (Greene, 2018; Nahabwe & Kagarura, 2025). Future research incorporating regime-switching or multivariate models could address this limitation.

5. Conclusion and Recommendations

Conclusion

Our study provides a rigorous time-series assessment of premature mortality from non-communicable diseases (NCDs) in Latin America and the Caribbean, offering critical insights into the region's trajectory toward achieving Sustainable Development Goal (SDG) 3.4. By modeling the internal dynamics of mortality over a long monthly horizon, the analysis demonstrates that progress toward reducing premature NCD mortality has been gradual and path-dependent, reflecting deep structural persistence in population health outcomes. Such persistence underscores the reality that NCD mortality responds slowly to interventions and remains strongly influenced by long-run demographic, behavioral, and health-system factors (WHO, 2023; PAHO, 2022).

Although the downward trajectory observed is encouraging, the projected stabilization of mortality at a level that remains epidemiologically significant suggests that current policy momentum may be insufficient to achieve the ambitious pace of reduction envisioned under SDG 3.4. This finding reinforces global evidence that incremental improvements, without sustained and coordinated prevention strategies, are unlikely to deliver transformative reductions in premature NCD deaths (Beaglehole et al., 2011; United Nations, 2015). The study thus highlights the importance of early, continuous, and system-wide policy action, particularly in addressing modifiable risk factors and strengthening primary health care systems.

Overall, our research contributes methodologically by demonstrating the value of high-frequency time-series modeling for monitoring SDG health targets and substantively by providing forward-looking evidence to inform regional health planning. Continued progress toward SDG 3.4 in Latin America and the Caribbean will require not only maintaining existing gains but also accelerating policy responses capable of disrupting entrenched mortality dynamics.

Recommendations

In light of the persistent and slowly declining trajectory of premature mortality from non-communicable diseases (NCDs) observed in this study, governments in Latin America and the Caribbean should intensify and recalibrate national NCD policies to accelerate progress toward SDG 3.4. The strong temporal persistence identified in mortality dynamics suggests that incremental policy adjustments are insufficient to disrupt entrenched health outcomes. Policymakers should therefore prioritize population-wide prevention strategies, including fiscal and regulatory measures targeting tobacco use, harmful alcohol consumption, unhealthy diets, and physical inactivity interventions consistently shown to yield the largest and most sustained mortality reductions (Beaglehole et al., 2011; WHO, 2023).

In addition, the projected stabilization of premature mortality at relatively high levels underscores the need to strengthen primary health care systems as the foundation of NCD prevention, early detection, and long-term management. Expanding universal health coverage with a focus on affordable access to essential NCD services is critical to preventing avoidable deaths among working-age adults (PAHO, 2022; United Nations, 2015).

At the program level, the findings point to the importance of long-term, continuous NCD interventions rather than short-lived or fragmented initiatives. Ministries of health should scale up integrated NCD programs that combine risk-factor reduction, routine screening, and sustained treatment adherence, particularly for cardiovascular diseases, cancers, diabetes, and chronic respiratory diseases. Given the inertia revealed by the time-series analysis, programs should be designed with multi-year horizons and protected financing to ensure durability and effectiveness (Bloom et al., 2011).

Furthermore, regional health institutions should enhance routine monitoring and evaluation systems, incorporating high-frequency mortality and morbidity indicators to track progress toward SDG 3.4 in near real time. Improved surveillance would enable earlier detection of deviations from desired trajectories and facilitate timely policy and program adjustments (WHO, 2023).

From a research perspective, our study highlights the need for complementary multivariate and country-specific analyses to unpack the structural drivers underlying persistent NCD mortality trends. Future studies could integrate socioeconomic, behavioral, environmental, and health-system variables to move beyond trajectory analysis toward causal explanation (Wooldridge, 2016; Enders, 2015; Nahabwe & Maniple, 2025). Such research would provide policymakers with clearer guidance on which levers are most effective in accelerating mortality reductions.

Additionally, further work could explore structural breaks and regime changes, including the long-term impacts of major shocks such as economic crises and pandemics, on NCD mortality dynamics. Expanding the use of high-frequency data and advanced time-series methods will strengthen evidence-based monitoring of SDG 3.4 and enhance accountability for health outcomes in the region (Nahabwe & Maniple, 2025).

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APPENDICES

Appendix 1: Descriptive statistics

	Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%)
Mean	15.89381
Median	15.58579
Maximum	18.54026
Minimum	13.57888
Std. Dev.	1.230697
Skewness	0.316421
Kurtosis	2.19182

Jarque-Bera	13.17054
Probability	0.001381
Sum	4768.143
Sum Sq. Dev.	452.8696
Observations	300

Appendix 2: Unit root test, Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%) **(in Level)**

Null Hypothesis: MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 14 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.965039	0.6174
Test critical values:	1% level	-3.990585	
	5% level	-3.425671	
	10% level	-3.135994	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD)
Method: Least Squares
Date: 01/03/26 Time: 11:45
Sample (adjusted): 2001M04 2024M12
Included observations: 285 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-1)	-0.008263	0.004205	-1.965039	0.0504
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-1))	0.295895	0.060031	4.928996	0.0000
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-2))	0.230894	0.061671	3.743953	0.0002
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-3))	0.108555	0.053742	2.019914	0.0444
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-4))	0.081349	0.054145	1.502433	0.1342
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-5))	0.060937	0.054366	1.120864	0.2633
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-6))	0.045841	0.054485	0.841359	0.4009
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-7))	0.034928	0.054541	0.640394	0.5225
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-8))	0.027342	0.054553	0.501191	0.6166
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-9))	0.022452	0.054522	0.411803	0.6808

D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-10))	0.019815	0.054429	0.364048	0.7161
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-11))	0.019141	0.054233	0.352935	0.7244
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-12))	-0.543042	0.053851	-10.08418	0.0000
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-13))	0.185231	0.061656	3.004258	0.0029
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-14))	0.153421	0.059949	2.559180	0.0110
C	0.143973	0.075674	1.902545	0.0582
@TREND("2000M01")	-0.000112	5.82E-05	-1.924773	0.0553

R-squared	0.509591	Mean dependent var	-0.015652
Adjusted R-squared	0.480312	S.D. dependent var	0.020849
S.E. of regression	0.015030	Akaike info criterion	-5.499763
Sum squared resid	0.060540	Schwarz criterion	-5.281895
Log likelihood	800.7162	Hannan-Quinn criterion.	-5.412425
F-statistic	17.40514	Durbin-Watson stat	2.029431
Prob(F-statistic)	0.000000		

Appendix 3: Unit root test, Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%) (in First difference)

Null Hypothesis: D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.805272	0.0176
Test critical values:	1% level	-3.990585	
	5% level	-3.425671	
	10% level	-3.135994	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD,2)
Method: Least Squares
Date: 01/03/26 Time: 11:46
Sample (adjusted): 2001M04 2024M12
Included observations: 285 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-1))	-0.294173	0.077307	-3.805272	0.0002
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-1),2)	-0.404553	0.084284	-4.799898	0.0000
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-2),2)	-0.173326	0.079098	-2.191264	0.0293
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-3),2)	-0.064209	0.079633	-0.806305	0.4208

D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-4),2)	0.016106	0.079513	0.202559	0.8396
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-5),2)	0.074799	0.079242	0.943937	0.3460
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-6),2)	0.117466	0.079007	1.486782	0.1382
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-7),2)	0.148482	0.078827	1.883640	0.0607
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-8),2)	0.171295	0.078614	2.178920	0.0302
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-9),2)	0.188659	0.078185	2.412993	0.0165
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-10),2)	0.202829	0.077216	2.626753	0.0091
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-11),2)	0.215713	0.075133	2.871067	0.0044
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-12),2)	-0.334306	0.070817	-4.720693	0.0000
D(MORTALITY_FROM_CVD__CANCER__DIABETES_OR_CRD(-13),2)	-0.149258	0.060229	-2.478160	0.0138
C	-0.004652	0.002444	-1.903759	0.0580
@TREND("2000M01")	2.78E-07	1.11E-05	0.025140	0.9800

R-squared	0.544804	Mean dependent var	6.84E-06
Adjusted R-squared	0.519422	S.D. dependent var	0.021796
S.E. of regression	0.015110	Akaike info criterion	-5.492475
Sum squared resid	0.061412	Schwarz criterion	-5.287423
Log likelihood	798.6777	Hannan-Quinn criterion.	-5.410275
F-statistic	21.46363	Durbin-Watson stat	2.026913
Prob(F-statistic)	0.000000		

Appendix 4: Results of the ARIMA(1,1,1) model

Dependent Variable: D(MORTALITY_FROM_CVD__CANCER__DIABETES_ OR_CRD)
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 01/03/26 Time: 11:51
Sample: 2000M02 2024M12
Included observations: 299
Convergence achieved after 19 iterations
Coefficient covariance computed using the outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.017524	0.004115	-4.258191	0.0000
AR(1)	0.909354	0.036463	24.93890	0.0000
MA(1)	-0.614833	0.068823	-8.933573	0.0000

R-squared	0.321647	Mean dependent var	-0.016593
Adjusted R-squared	0.317064	S.D. dependent var	0.020808
S.E. of regression	0.017196	Akaike info criterion	-5.276310
Sum squared resid	0.087529	Schwarz criterion	-5.239181
Log likelihood	791.8083	Hannan-Quinn criterion.	-5.261449
F-statistic	70.17554	Durbin-Watson stat	2.060306
Prob(F-statistic)	0.000000		

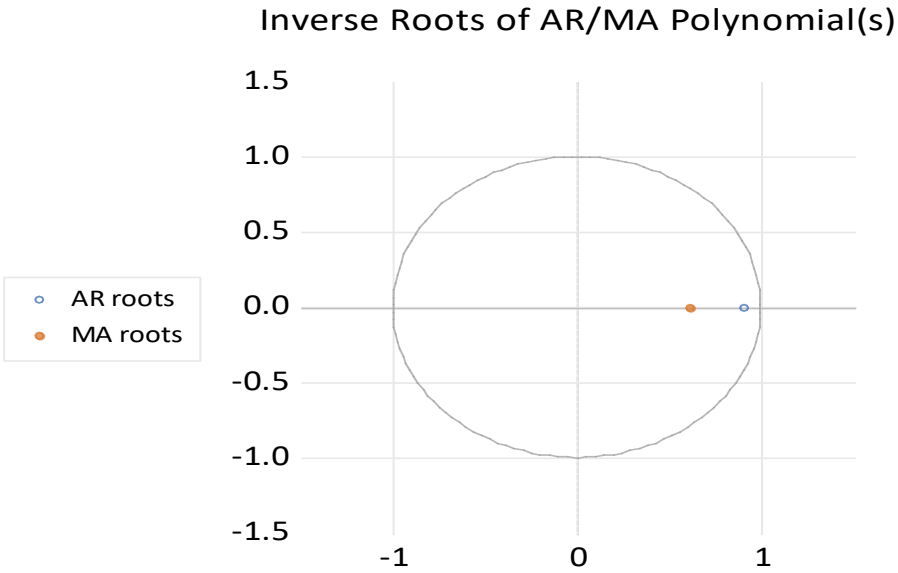
Inverted AR Roots	.91
Inverted MA Roots	.61

Appendix 5: Ljung-Box Q statistic/ test

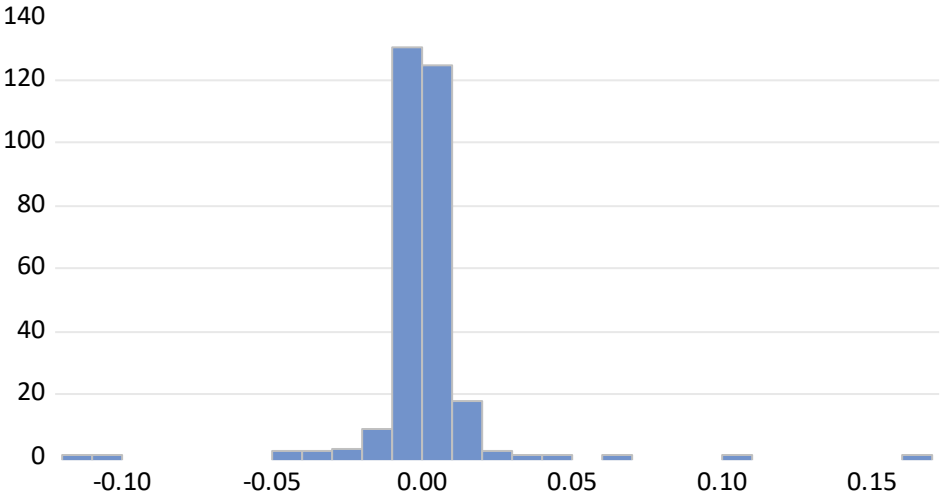
Date: 01/03/26 Time: 12:01
Sample (adjusted): 2000M02 2024M12
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.033	-0.033	0.3221	
.|. |	.|. |	2	0.001	-0.000	0.3222	
.|. |	.|. |	3	0.019	0.019	0.4321	0.511
.|. |	.|. |	4	0.028	0.029	0.6718	0.715
.|. |	.|. |	5	0.032	0.034	0.9774	0.807
.|. |	.|. |	6	0.032	0.034	1.2969	0.862
.|. |	.|. |	7	0.032	0.033	1.6099	0.900
.|. |	.|. |	8	0.032	0.033	1.9288	0.926
.|. |	.|. |	9	0.035	0.034	2.3048	0.941
.|. |	.|. |	10	0.042	0.041	2.8644	0.943
.|. |	.|. |	11	0.058	0.057	3.9327	0.916
****|. |	****|. |	12	-0.525	-0.533	90.452	0.000
.|. |	.|. |	13	0.051	0.022	91.271	0.000
.|. |	.|. |	14	0.028	0.033	91.512	0.000
.|. |	.|. |	15	0.013	0.037	91.565	0.000
.|. |	.|. |	16	0.004	0.037	91.570	0.000
.|. |	.|. |	17	-0.002	0.033	91.571	0.000
.|. |	.|. |	18	-0.006	0.028	91.583	0.000
.|. |	.|. |	19	-0.009	0.023	91.610	0.000
.|. |	.|. |	20	-0.012	0.018	91.655	0.000
.|. |	.|. |	21	-0.015	0.015	91.725	0.000
.|. |	.|. |	22	-0.018	0.014	91.836	0.000
.|. |	.|. |	23	-0.024	0.019	92.023	0.000
.|* |	**|. |	24	0.120	-0.245	96.763	0.000
.|. |	.|. |	25	-0.027	0.003	96.997	0.000
.|. |	.|. |	26	-0.022	0.005	97.157	0.000
.|. |	.|. |	27	-0.019	0.004	97.282	0.000
.|. |	.|. |	28	-0.018	0.003	97.389	0.000
.|. |	.|. |	29	-0.017	0.001	97.485	0.000
.|. |	.|. |	30	-0.016	-0.001	97.571	0.000
.|. |	.|. |	31	-0.015	-0.002	97.643	0.000
.|. |	.|. |	32	-0.012	-0.001	97.694	0.000
.|. |	.|. |	33	-0.008	0.003	97.717	0.000
.|. |	.|. |	34	-0.002	0.012	97.717	0.000
.|. |	.|. |	35	0.007	0.026	97.735	0.000
**|. |	****|. |	36	-0.326	-0.555	134.14	0.000

Appendix 6: ARIMA(1,1,1) structure



Appendix 7: Histogram of residuals



Series: Residuals
Sample 2000M02 2024M12
Observations 299

Mean	0.000221
Median	7.22e-05
Maximum	0.166774
Minimum	-0.114478
Std. Dev.	0.017137
Skewness	2.041881
Kurtosis	47.46298
Jarque-Bera	24837.36
Probability	0.000000

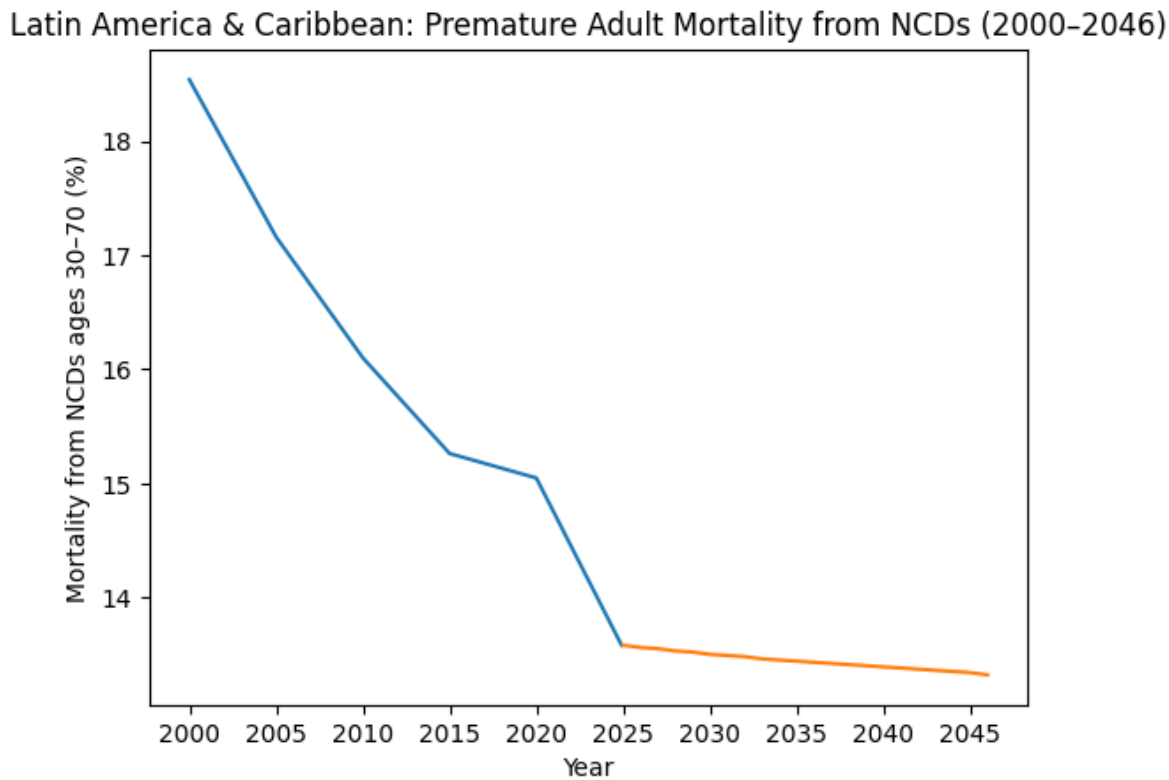
Appendix 8: Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	1.003246	Prob. F(2,294)	0.3679
Obs*R-squared	2.026783	Prob. Chi-Square(2)	0.3630

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/03/26 Time: 12:03
Sample: 2000M02 2024M12
Included observations: 299
Coefficient covariance computed using the outer product of gradients
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.06E-06	7.04E-05	-0.043481	0.9653
AR(1)	0.000653	0.000758	0.862026	0.3894
MA(1)	-0.004024	0.003115	-1.292072	0.1973
RESID(-1)	-0.233174	0.165163	-1.411782	0.1591
RESID(-2)	-0.110182	0.103915	-1.060316	0.2899

R-squared	0.006613	Mean dependent var	0.000221
Adjusted R-squared	-0.006903	S.D. dependent var	0.017137
S.E. of regression	0.017196	Akaike info criterion	-5.271710
Sum squared resid	0.086936	Schwarz criterion	-5.209829
Log likelihood	793.1206	Hannan-Quinn criterion.	-5.246942
F-statistic	0.489257	Durbin-Watson stat	2.003044
Prob(F-statistic)	0.743638		

Appendix 9: Graph showing Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%) ARIMA(1,1,1) Model Simulation