Journal of Management Science Research Review
https://jmsrr.com/index.php/Journal/about

Volume 5 Issue No 1 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

Strengthening Child Survival in Urban Contexts: The Impact of WASH Infrastructure on Under-Five Mortality amid Rapid Urbanization

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Abstract
This study examines the impact of Water, Sanitation, and Hygiene (WASH) infrastructure on under-five mortality within rapidly urbanizing environments. It explores how urbanization interacts with WASH access to influence child health outcomes, focusing specifically on under-five mortality as a core indicator of population health and sustainable development. Employing advanced quantitative techniques including Quantile Regression, System Generalized Method of Moments (System GMM), Bootstrap Resampling in Quantile Regression, and Feasible Generalized Least Squares (FGLS) the analysis captures heterogeneous effects across the distribution of under-five mortality rates while addressing endogeneity and methodological challenges. The findings reveal that improved WASH infrastructure significantly reduces under-five mortality, particularly in higher-mortality contexts. Although rapid urbanization can intensify pressures on health systems and basic services, robust WASH provision mitigates these adverse effects, functioning as a protective mechanism for child survival. Rather than urbanization and WASH operating in isolation, their interaction demonstrates potential synergies when infrastructure expansion keeps pace with urban growth. The results highlight the emergence of "urban child health resilience," reflecting cities' capacity to safeguard child survival when supported by effective sanitation, clean water access, and hygiene systems. The study underscores the critical importance of integrating WASH infrastructure into public health strategies. Cross-sectoral collaboration among urban planners, water authorities, sanitation agencies, and health policymakers is essential to optimize resource allocation and strengthen child survival outcomes. By focusing on under-five mortality within urban contexts, this research contributes to the literature on child health, sustainable development, and public health governance, offering policy-relevant insights for achieving Sustainable Development Goals related to child survival and resilient cities.

Keywords: Under-Five Mortality; Child Health; Wash; Urbanization; Quantile Regression; System
GMM; Sustainable Development.

INTRODUCTION

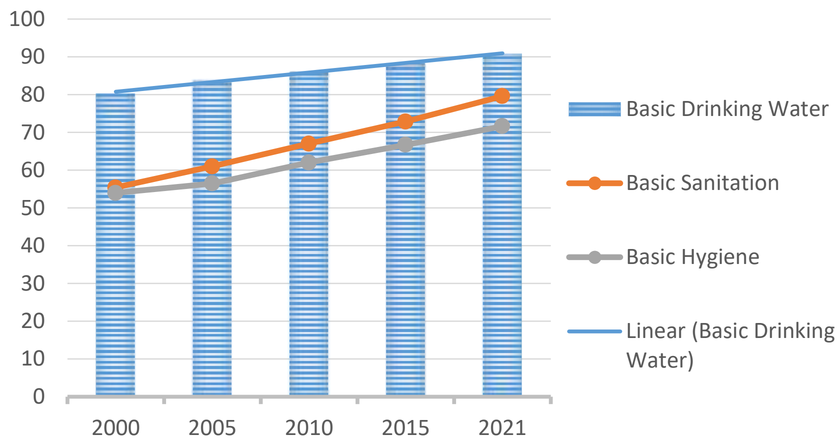
Public health, as a cornerstone of societal well-being, assumes paramount importance in steering communities towards sustainable development pathways. The World Health Organization (WHO) aptly underscores the indispensability of resilient public health systems, particularly in light of global adversities such as the COVID-19 pandemic (WHO, 2020; WHO, 2022). Urban health research, specifically focusing on the mortality rate under the age of five (U5MR), stances as a beacon of imperative inquiry within the contemporary global health discourse.

As we navigate through the complex tapestry of urbanization and its ramifications, the importance of understanding and enhancing urban health outcomes, especially concerning vulnerable populations such as young children, turn into increasingly evident. Among measures, the mortality rate under five years emerges as a poignant indicator of child health and societal welfare, defined as the number of children dying within first five years per 1,000 live births. It encapsulates the intricate interplay of healthcare access, nutrition, sanitation, and socio-economic development(Bryce, Boschi-Pinto, Shibuya, & Black, 2005; Liu et al., 2016; Unicef, 2021; Wang et al., 2016), signifiesits resonation across global health agendas, epitomized by Sustainable Development Goal (SDG) 3.2 thatfervently advocates for the eradication of preventable child deaths by 2030 (Burstein et al., 2019; Organization, 2021). While strides have been made in reducing U5MR on a global scale, yet the persistence of geographical and temporal disparities necessitates tailored interventions and policies (Burstein et al., 2019; Gore et al., 2011).Within this purview, urban settings emerge as epicenters of both promise and peril, juxtaposing burgeoning opportunities with entrenched health inequities, and therefore understanding the determinants of mortality within urban environments assumes profound significance in guiding targeted interventions and fostering equitable health outcomes.

Urbanization, a global phenomenon, profoundly influence public health outcomes and that can be effectively measures by the urban population as a percentage of the total population (URB) reflecting demographic shifts and socioeconomic development (Bank, 2021; Nations, 2018).Statistical analysis offers a comprehensive understanding of the complex interplay between urbanization dynamics and mortality patterns being studied at Jamaica (Thompson, 2024). The latent channels through which urbanization affects public health, focusing on the correlation between urbanization rates and living standards, with real GDP per capita as a key indicator is explored by (Zhang, Zhao, Zhang, & Feng, 2023). Urbanization is widely recognized as a catalyst for economic growth studied by (Maiti, 2017; Tripathi, 2021; Tripathi & Mahey, 2017) supporting this notion, highlighting its pivotal role in driving demographic and economic transformations globally.Rapid urbanization, while known for its positive contributions to economic growth and employment, prompts a critical examination of its effects on health outcomes globally, as emphasized by analyzing data from 1960 to

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

2021 across 204 countries through panel quantile regression models (Tripathi & Maiti, 2023). While urbanization correlates with economic growth and improved living standards, it presentsissues to the public health, including environmental pollution and lifestyle changes(Patil, 2014),nevertheless, it also offers the potential to enhance public health through improved healthcare infrastructure and reduced health resource disparities between urban and rural areas (Vlahov et al., 2007). Hence, comprehending the complex relationship between urbanization and public health is imperative for fostering sustainable urban development and equitable health outcomes.
Fig. 1:Trends in WASH (water, sanitation and hygiene).
Source: Constructed by the authors based on World Bank Data
On the other side, the intersection of Water, Sanitation, and Hygiene (WASH) plays a



pivotal role in reshaping global public health, as highlighted by the United Nations (UN) within the 2030 Agenda, where it has been observed that millions of lives are at stake due to the global burden of diseases attributable to inadequate WASH, with infants and young children bearing a uneven burden(Troeger et al., 2018; Wang et al., 2016). In Niger, diseases associated with poor Water, Sanitation, and Hygiene (WASH) practices significantly contribute to morbidity and mortality among children under the age of five (Djelifa et al., 2024). Sub-Saharan Africa, known for its highest under five mortality rate and limited access to basic WASH services, prompts investigation into the effects of WASH conditions on under five mortality in the region (Gaffan, Kpozehouen, Degbey, & Ahanhanzo, 2023).
Despite ongoing efforts, billions still deficientof safe drinking water and sanitation services, posing profound health issues(Organization, 2018; Unicef, 2021). The Sustainable Development Goals (SDGs) have catalyzed global efforts to address these challenges, yet significant hurdles remain particularlyunsafe WASH conditions significantly contribute to communicable diseases, essentially affecting childhood health outcomes, and extending beyond mortality to chronic under-nutrition and respiratory infections exacerbating social issues, including mental health concerns and violence. It is, therefore, addressing WASH challenges within urban development is imperative for achieving sustainable health outcomes globally. Although Fig.1

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

showcases a compelling narrative of improvement in access to basic WASH from 2000 to 2021 evident from which a steady upward trajectory in access rates, illustrating commendable advancements towards achieving global developmental objectives.

The intertwining of under-five mortality rates (U5MR), urbanization (URB), and Water, Sanitation, and Hygiene (WASH) initiatives underscores the critical need for comprehensive research and interventions in public health where U5MR serves as a vital indicator of child health and societal well-being, reflecting access to healthcare, nutrition, and socioeconomic development. Meanwhile, urbanization signifies demographic shifts and socioeconomic progress, yet poses challenges to public health infrastructure and environmental sustainability, simultaneously, inadequate WASH conditions, particularly in urban areas, contribute significantly to communicable diseases and other health issues, amplifying the urgency for targeted interventions (Nations, 2018).

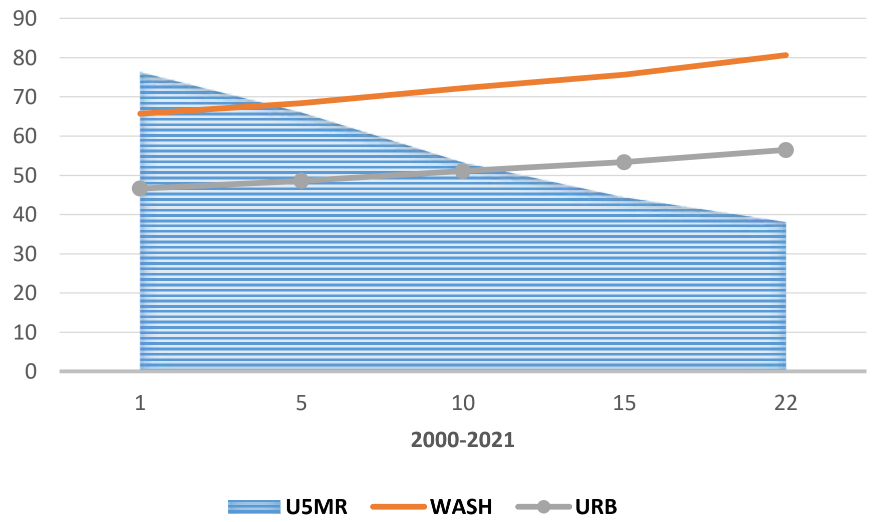


Fig. 2:Urbanization, WASH Accessibility, and Under-Five Mortality rate from 2000 to 2021).

Source: Constructed by the authors based on World Bank Data

By exploring the complex interactions between these variables, this study aims to understand the urban health transition by integrating contemporary theories and focusing on Water, Sanitation, and Hygiene (WASH) as a critical variable that seeks to elucidate how improvements in WASH infrastructure can positively impact public health in urban settings, providing actionable insights to advance progress towards Sustainable Development Goals 3, 6, and 9, and promote health equity and sustainable urban development globally. Alongside, Fig 2 portrays a compelling narrative of progress in key developmental indicators wherenotably there is a consistent decline in Under Five Mortality Rate (U5MR) alongside an upward trend in access to WASH services and urbanization rates over the specified period, reflecting significant strides towards improving public health and urban development

A series of critical research questions are addressed by this study aimed at deepening our understanding of complex urbanization and Water, Sanitation, and Hygiene (WASH) dynamics. By employing advanced analytical techniques such as Quantile regression, FGLS regression, and System GMM estimation(Behera & Dash, 2020), it seeks to elucidate the nuanced relationships between urbanization (URB), WASH initiatives (WASH), and under five mortality rate (U5MR) across diverse population segments, exploring synergies and discrepancies in insights gleaned from diverse approaches. It aims to unravel temporal resilience in health systems by investigating how System GMM estimation enhances our understanding of health systems' resilience to urbanization and the effectiveness of WASH interventions over time, discerning evolving urbanization-health dynamics and implications for sustainable health policy interventions. It aims tooto interrogate socioeconomic disparities in health outcomes by exploring how socioeconomic factors, urbanization, and WASH initiatives interact to shape health outcomes, revealing hidden disparities and temporal trends, thus informing targeted policy interventions for addressing socioeconomic inequalities and advancing health equity(Troeger et al., 2018). Additionally, it seeks to explore nonlinear urban health dynamics by leveraging Quantile regression findings to illuminate nonlinear patterns and thresholds in the relationship between urbanization, WASH access, and mortality rates, investigating critical thresholds and inflection points, and discerning implications for targeted interventions and policy responses within the framework of sustainable development goals (Behera & Dash, 2020), to synthesize evidence for policy implications by providing policymakers with insights from advanced analytical techniques to formulate evidence-based strategies for sustainable urban development and equitable access to WASH services, synthesizing key implications and actionable recommendations to foster a holistic approach to urban health governance aligned with sustainability and health equity principles(Troeger et al., 2018). Addressing these research objectives by blending traditional statistical methods with advanced techniques, the study offers novel insights into mortality rate determinants within urban populations with special focus on WASH facilities under the control variables i.e. Current Health Expenditures (CHE), Gross Domestic Products (GDP) per capita and Carbon Dioxide Emissions (CO_2E). This interdisciplinary framework not only advances theoretical understanding but also provides actionable insights for policymakers and practitioners, addressing health challenges exacerbated by rapid urbanization and to empower policymakers to devise targeted interventions for improving public health and reducing inequalities within cities, thereby contributing to sustainable urban development and promoting health equity globally. It represents a pioneering effort to unravel the complex factors shaping urban health outcomes, transcending disciplinary boundaries, and driving actionable change in urban health governance.

LITERATURE REVIEW

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

The impact of various socioeconomic and environmental aspects on under five mortality rates (U5MR) has been extensively studied in the literature. Access to WASH facilities has consistently been associated with reduced U5MR as studies by(Bartram et al., 2014; Prüss-Ustün et al., 2019) highlight the critical role of improved WASH infrastructure in preventing waterborne diseases and reducing child mortality.A cross sectional descriptive study conducted in the rural island commune of Wogo de Sinder, Tillabéry region, Niger, aimed to assess the correlation between WASH conditions and the morbidity and nutritious status of children from first birthday to 59 months, revealing concerning inadequacies in WASH knowledge and practices among mothers, which adversely impact the health and diet of young children especially under five years age in the region (Djelifa et al., 2024). Significant differences are highlighted by (Aboah, 2024)in WASH access between demographic groups, with adults generally having greater access to adequate water and better hygiene than children, elders or strangers. Additionally, urban regions demonstrate better quality of water, sanitation services, and hygiene facilities compared to rural areas, with Africa exhibiting the poorest WASH indicators.Analyzing the relationship between WASH conditions and under five mortality of thedatasets of"Demographic and Health Survey"of 30 countries in Sub-Saharan Africa, revealed significant disparities in mortality rates based on access to basic WASH services (Gaffan et al., 2023).Inadequate sanitation facilities have also been linked to higher U5MR, emphasizing the need for comprehensive WASH interventions(D. UNICEF, 2016). Urbanization, another key determinant, has been linked to both positive and negative health outcomes with the arguments that on one side urban areas offer better access to healthcare and resources whileon the other side rapid urbanization can lead to overcrowding, pollution, and inadequate sanitation, thereby exacerbating health risks(Bryce et al., 2003; Vlahov et al., 2007).Previous studies have underscored the significance of integrating mortality data with statistical analysis to explore correlations between urbanization factors and mortality outcomes, revealing insights into the dynamic nature of public health responses to urban development (Thompson, 2024).A research conducted by (Bandyopadhyay & Green, 2018) underscores the positive impact of urbanization on mortality rates, emphasizing the significance of urbanization in shaping public health outcomes. The study (Tripathi & Maiti, 2023) reveals a nuanced relationship between urbanization and health outcomes, with findings indicating both positive and negative impacts on fertility rates, life expectancy at birth, and infant mortality rates, further highlighting the importance of well-managed urbanization strategies to enhance overall health outcomes, especially in developing countries. The urban environment may expose children to various hazards, including air pollution and unsafe living conditions, which contribute to higher U5MR rates. It is also been evident that higher GDP per capita and increased healthcare expenditures are correlated with lower U5MR, indicating the importance of socioeconomic development and healthcare investment in improving child health outcomes(Liu et al., 2016; Organisation, 2021) being observed that countries with higher GDP per capita often have better healthcare infrastructure and access to essential services, leading to improved child survival rates(Bhutta et al., 2014).

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Additionally, increased healthcare expenditures enable countries to invest in preventive measures, vaccinations, and maternal and child health programs, ultimately reducing U5MR.
Additionally, elevated CO_2 emissions has also been associated with adverse health effects, including respiratory illnesses and developmental disorders in children as exposure to air pollution, primarily driven by CO_2 emissions, poses significant health risks to children, contributing to higher U5MR rates in polluted areas (Landrigan et al., 2018). Addressing environmental pollution and reducing CO_2 emissions are critical components of efforts to improve child health outcomes and reduce U5MR globally(Gore et al., 2011).Overall, these studies underscore the complex interplay between environmental, socioeconomic, and healthcare factors in shaping under-five mortality rates, emphasizing the need for holistic approaches to address child health disparities and promote sustainable development, therefore, by addressing the multifaceted determinants of U5MR, policymakers and stakeholders can implement targeted interventions to improve child health outcomes and achieve progress towards global health goals (Unicef, 2021).

THEORETICAL REVIEW

Theoretical frameworks underpinning the study of urban health dynamics and the role of WASH in promoting sustainable cities draw upon interdisciplinary perspectives to elucidate complex relationships. The Social & Ecological Model (Stokols, 1996) is pivotal to this inquiry which highlights the linkage of individual-level, interpersonal, communal, and social factors determining urban health outcomes. This model provides a comprehensive understanding of the multifaceted determinants of health within urban environments, emphasizing the importance of addressing social and environmental determinants to promote health equity. The Demographic Transition Theory (Notestein, 1945) is complementing to this framework by offering insights into the demographic shifts accompanying urbanization and economic development. By examining patterns of fertility, mortality, and migration, this theory provides a lens through which to understand the changing population dynamics of urban areas, guiding efforts to address population-related challenges such as aging populations and urban migration. Further, political ecology perspectives offer valuable understandings into the socio-political and economic dimensions of WASH access in urban areas. Drawing on concepts of power, inequality, and environmental justice, political ecology frameworks analyze how governance structures, market forces, and socio-cultural factors shape the distribution of WASH services and influence health outcomes. By examining the intersecting interests of various stakeholders and the uneven distribution of environmental risks, political ecology perspectives highlight the need for participatory decision-making processes and equitable resource allocation to promote urban health and sustainability(Bakker, 2003).
Furthermore, resilience theory provides a useful framework for understanding the adaptive capacity of urban health systems in the face of environmental and socio-economic challenges (Kruk, Myers, Varpilah, & Dahn, 2015). By emphasizing the importance of flexibility, redundancy, and diversity within urban infrastructure and

Online ISSN: 3006-2047
Print ISSN: 3006-2039

governance systems, resilience theory informs strategies for building robust WASH infrastructure that can withstand shocks and disruptions while promoting the health and well-being of urban populations. The Complexity theory offers insights into the dynamic and interconnected nature of urban systems, recognizing that urban health outcomes emerge from nonlinear interactions among multiple factors (Allen & Holling, 2008). This perspective underscores the need for holistic, systems-oriented approaches to urban health governance and policy-making, emphasizing the importance of adaptive management, collaborative decision-making, and continuous learning in addressing complex urban health challenges.

Lastly, the Sustainable Development Goals (SDGs), particularly Goal 6 (Clean Water and Sanitation) and Goal 11 (Sustainable Cities and Communities), provide normative guidance for promoting urban health and environmental sustainability, underscoring the imperative of aligning efforts with broader development objectives (United Nations, n.d.). By integrating these theoretical perspectives, policymakers and researchers can develop evidence-based strategies to address urban health disparities, promote health equity, and foster sustainable urban development(Troeger et al., 2018; Victora et al., 2003). Through interdisciplinary collaboration and empirical inquiry, these frameworks offer valuable insights into navigating the complications of urban health and advancing the well-being of urban populations worldwide.

METHODOLOGY AND DATA

Model Specification

This study investigates the association between urban health indicators and under five mortality rate (U5MR), focusing on the variables of WASH (Bartram et al., 2014; Prüss-Ustün et al., 2019) and Urbanization (URB)(Cohen, 2006; Nations, 2018)as main independent variables while Current Health Expenditures (CHE)(Kruk et al., 2015; Organisation, 2021), Gross Domestic Product per capita (GDP) (Bank, 2021), and CO2 Emissions (CO2E) as control variables. Based on the main objectives, the econometric model can be formulated as follows:

$$U5MRit = \beta 0 + \beta 1WASHit + \beta 2URBit + \beta 3CHEit + \beta 4GDPit + \beta 5CO2Eit + \epsilon it \quad (1)$$

In Eq. (1),β0 is the intercept term, β1 to β5 are coefficients of the respective variables representing the impact of WASH, Urbanization, Current Health Expenditures, GDP per capita, and CO2 Emissions on under-five mortality rate and ϵit is the error term capturing unobserved factors influencing under-five mortality rate.In order to mitigate data sharpness and heteroscedasticity, all the data is transformed using natural logarithms(Azam, Uddin, & Saqib, 2023).

Estimation Techniques

The econometric models utilized in this research draw upon established methodologies and are adapted to address the specific research context whereas the dataset's descriptive analysis (Table 2) that reveals several challenges, including outliers, skewness, and high kurtosis, necessitating the adoption of advanced statistical techniques. Outliers and extreme values distort distribution, particularly in

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

CO_2 emissions and WASH-population figures, non-normal distributions and heavy-tailed distributions, pose challenges for conventional tests. Measurement errors in variables like CO_2 emissions, underline the need for meticulous data handling and natural log transformations, aim to mitigate skewness and heteroscedasticity but may complicate interpretation. Unmeasured confounding factors and interactions, and temporal trendsrequire sophisticated modeling techniques. Byaddressing these concerns through appropriate statistical methods and careful data preprocessing, it is essential that the validity and reliability of subsequent analyses must be ensured.For the potential endogeneity issue, Ordinary Least square (OLS) regression is utilized followed by Two Stage Least Square (2SLS) estimation and other diagnostic tests (see Table 1) where the results of the Durbin (score) and Wu-Hausman F-test with a values of 0.167849 & 0.167563 andp-values of 0.6820 & 0.6823 respectively indicate non-significance ($p > 0.05$), suggesting weak evidence of endogeneity. However, the tests of over-identifying restrictions, including the Sargan (score) chi-square and Basmann chi-square, present significant results with values of 28.941 and 29.0862, respectively, both with p-values of less than 0.0001 providing further evidence of potential endogeneity.

Table 1: Test for Endogeneity

Test	Statistic	p-value	Interpretation
Durbin (score)	0.167849	0.6820	Not significant (p>.05); Weak evidence of endogeneity
Wu-Hausman F	0.167563	0.6823	Not significant (p>.05); Weak evidence of endogeneity
Sargan (score)	28.941	< 0.0001	Significant (p<.0001); Evidence of potential endogeneity
Basmann chi-square	29.0862	< 0.0001	Significant (p<.0001); Evidence of potential endogeneity

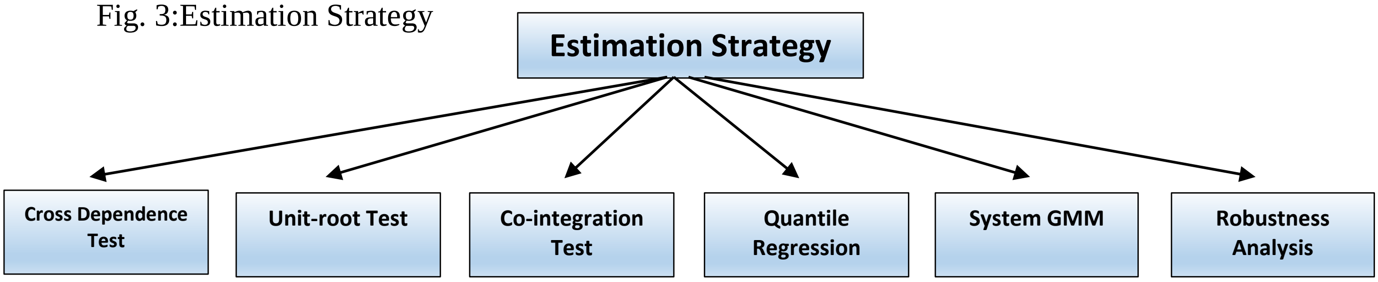
These findings underscore the need for System GMM estimation to address endogeneity concerns and ensure unbiased estimates(Arellano & Bond, 1991; Blundell & Bond, 1998) where the instrumental variables utilized are population growth annual percentage, urban population growth annual percentage (Cohen, 2006; Potts, 2009), access to electricity per population(Steinbuks & Foster, 2010) and primary education completion rate (total) (Filmer & Pritchett, 1999; Schultz, 1990).Quantile Regression technique is employed too which is derived and structured to elucidate the complex dynamics between urban health determinants and mortality rates across different quantiles(Koenker & Hallock, 2001; Tripathi & Maiti, 2023). Furthermore, Bootstrap resampling for robust Quantile Regression and FGLS (Feasible Generalized Least Square) Regression is utilized as robustness check along with panel causality test to ensure reliability of the estimation(Tripathi & Maiti, 2023).

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

ESTIMATION STRATEGY

This study's estimation strategy is illustrated in Fig.3;

Fig. 3:Estimation Strategy



DIAGNOSTIC TESTS

Cross-sectional Dependence

Cross-sectional dependence (CSD) is tested through Pesaran CD test which helps for the potential violation of the independence assumption that can lead to biased estimates and inefficient inference in panel regressions (Pesaran, 2004). Equations (2) provide the formula for it.

$$CD = \frac{N}{N-1}\left[\frac{T\Sigma_{i=1}^{N}\hat{\rho}_i}{\sqrt{T\Sigma_{i=1}^{N}\hat{\sigma}_i^2}}\right] \quad (2)$$

Where N is the number of cross sectional units, T represent the number of time periods, $\hat{\rho}_i$ is the average of the pairwise correlations of the residuals across all cross-sectional units except the ith unit and $\hat{\sigma}_i^2$ is the sample variance of the residuals for the ith cross-sectional unit. This test statistic follows an asymptotic standard normal distribution under the null hypothesis of no cross-sectional dependence.

Panel Unit Root

Unit-root test(Levin, Lin, & Chu, 2002)is utilized to assess the stationarity properties of the variables. The calculation of the Critical Augmented Dickey-Fuller (CADF) statistic is performed using the following equation:

$$CADF = SE(\hat{\rho})\hat{\rho} \quad (3)$$

In Eq. (3),$\hat{\rho}$ represents the estimated coefficient and $SE(\hat{\rho})$ denotes its standard error.

Panel Co-Integration

Panel Co-Integration analysis, crucial for examining long-term relationships among variables, employs tests such as Westerlund, Pedroni, and Kao to assess stable relationships while accounting for cross-section correlation(Kao, 1999; Pedroni, 1999; Westerlund, 2007) where cross-sectional dependence and Westerlund's test accommodates heterogeneous panels and cross-section correlation, Pedroni's panel

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

framework assesses individual-specific effects and the Kao test evaluates stability over time. Equations (4), (5) and (6) provide the formulas, respectively.

$$Y_{it} = \alpha_i + \beta_1 X_{it} + \Sigma_{j=1}^{p} \gamma_j \Delta X_{it-j} + \Sigma_{k=1}^{q} \delta_k \Delta Y_{it-k} + \varepsilon_{it} \quad (4)$$

$$\Delta Y_{it} = \alpha_i + \beta_1 \Delta X_{it} + \gamma Y_{i,t-1} + \varepsilon_{it} \quad (5)$$

$$\Delta Y_{it} = \alpha_i + \beta_1 \Delta X_{it} + \Sigma_{j=1}^{n} \delta_j D_j \Delta X_{it} + \gamma Y_{i,t-1} + \varepsilon_{it} \quad (6)$$

In Eq. (4), Y_{it} and X_{it} represent the dependent and independent variables, respectively. ΔX_{it-j} and ΔY_{it-k} denote lagged differences, while Y_{it-1} represents the lagged dependent variable. Eq. (5) includes ΔY_{it} and ΔX_{it} for changes over time, with Y_{it-1} representing the lagged dependent variable and Eq. (6) involves individual-specific dummies, denoted asD_j. These variables are crucial components, capturing different aspects of the relationship under examination.

KEY ESTIMATIONS

Quantile Regression

Quantile regression extends the classical linear regression framework by estimating the conditional quantiles of U5MR, the dependent variable, given the independent variables: WASH, URB, CHE, GDP, and CO2E. Unlike ordinary least squares (OLS) regression, quantile regression offers insights into the relationship between urban health indicators and mortality across different quantiles of the conditional distribution(Koenker & Hallock, 2001). The quantile regression model for mortality Y given the independent variables Xn at quantile τ can be represented in Eq. (7) bellow:

$$Q\tau(Y \mid X) = \beta 0(\tau) + \Sigma_{n=1}^{5} \beta n(\tau) Xn + \epsilon \quad (7)$$

Where, Y represents U5MR (under five mortality rate), Xn represents the vector of independent variables: WASH, URB, CHE, GDP, and CO2E, $\beta 0(\tau)$ represents the intercept at quantile τ, $\beta n(\tau)$ represents the coefficient for the n-th independent variable at quantile τ while ϵ represents the error term.Quantile regression offers a nuanced understanding of predictor influences across different quantiles, particularly beneficial when dealing with skewed distributions and heterogeneous relationships among variables.

System GMM Estimation

System GMM enhances parameter estimation efficiency and mitigates biases arising from omitted variables or endogeneity by incorporating lagged dependent variables and instrumental variables. The system GMM model can be represented in first-differences form as:

$$\Delta Y_{it} = \alpha_i + \Sigma_{k=1}^{5} \beta_k \Delta X_{kit} + \eta_j + \varepsilon_{it} \quad (8)$$

In Eq. (8),ΔY_{it} represents U5MR (under five mortality rate), ΔX_{kit} represents the first-differenced values of the independent variables: WASH, URB, CHE, GDP, and CO2E, α is the intercept, β_k are the coefficients of the first-differenced independent variables,η_j is the individual specific effect, and ε_{it} is the error term.The system GMM estimation involves the use of lagged levels and variances of the independent

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

variables as instruments to address endogeneity. The moment conditions are given by Eq. (9) bellow:

$$E[\Delta\varepsilon_{it} \cdot Z'_{it}] = 0 \tag{9}$$

Whereas, Z'_{it} is the matrix of instruments including lagged levels and alterations of the independent variables, the coefficients β_k estimated using system GMM represent the long-term effects of urban health indicators on mortality after controlling for endogeneity and dynamic panel data issues. These coefficients provide insights into the causal relationship between urban health indicators and mortality over time.
Utilizing advanced statistical techniques, such as quantile regression and System GMM, offers a more reliable approach to research compared to data manipulation and it allow researchers to account for complex relationships and underlying patterns within the data, leading to more robust and trustworthy conclusions.

ROBUSTNESS ANALYSIS

Bootstrap Resampling in Quantile Regression

Bootstrap resampling is utilized as a robustness check in quantile regression by assessing the stability of coefficient estimates across various quantiles (Efron & Tibshirani, 1994) which involves randomly sampling observations with replacement to create multiple bootstrap samples on which quantile regression is conducted to estimate coefficients (Koenker, 2005). Through this process, confidence intervals and standard errors are derived, offering insights into coefficient variability and uncertainty. Utilizing a large number of bootstrap repetitions i.e. 1000 or more as suggested by (Chernick, 2011), further strengthens the robustness of the analysis by enhancing the precision and reliability of the coefficient estimates. Thus 1000 bootstrap repetitions are utilized in this study for handling complex data structures and not to rely on asymptotic assumptions.

FGLS (Feasible Generalized Least Squares) Regression

Feasible Generalized Least Squares (FGLS) as robust statistical techniques, is important to address issueof heteroscedasticity in panel data analysis(Greene, 2003) whereas it involves steps like model specification, diagnosis of heteroscedasticity, estimation of heteroscedasticity-consistent standard errors, and FGLS estimation (Wooldridge, 2010). To begin, researchers specify the regression model as:

$$Y_{it} = X_{it}\beta + u_{it} \tag{10}$$

In Eq. (10), Y_{it} represents the dependent variable for the ith observation at time t, X_{it} denotes the matrix of independent variables for the ith observation at time t, β represents the vector of coefficients to be estimated, and u_{it} represents the error term for the ith observation at time t. After specifying the model, White test is conducted to detect heteroscedasticity, following the detection of heteroscedasticity (Table 2), estimated heteroscedasticity-consistent standard errors and proceed with FGLS estimation to obtain reliable parameter estimates (Greene, 2003). By incorporating

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

FGLS, researchers ensure the robustness of their statistical analysis and enhance the validity of the empirical findings(Wooldridge, 2010).

Table 2: Test for Heteroscedasticity

Test	Chi Square	Degree of Freedom	Probabality (p-value)
White's Test	624.000	20	0.000
Cameron & Trivedi			
Heteroskedasticity	624.000	20	0.000
Skewness	72.020	5	0.000
Kurtosis	0.100	1	0.750
Total	696.130	26	0.000

Panel Granger Causality Test

The estimation models utilized in this research seek to elucidate the causal associations between various key variables, drawing upon the widely employed Panel Causality framework proposed by(Dumitrescu & Hurlin, 2012). This method is used by (Shaban, Kourtit, & Nijkamp, 2022) to examine the causal relationship among urbanization and economic growth for areas in India. This technique is very useful to assess the correlation'spatterns and kind of the casual relationships amongvariables.This framework allows for a rigorous examination of the causal links between the variables under consideration. Specific equations used in the (Dumitrescu & Hurlin, 2012) Granger non-causality test for panel data are as follows;

$$Y_{it} = \alpha_i + \Sigma_{j=1}^{p} \beta_{ij} Y_{i,t-j} + \Sigma_{j=1}^{p} \gamma_{ij} X_{i,t-j} + \varepsilon_{it} \quad (11)$$

The F-statistic used to test the null hypothesis is calculated based on the restricted and unrestricted regression models, with the formula,

$$F = \frac{RSS_U}{(N-p-q-1)} \cdot \frac{RSS_R - RSS_U}{q} \quad (12)$$

Where RSS_R is the residual sum of squares from the restricted model (null hypothesis), RSS_U is the residual sum of squares from the unrestricted model (alternative hypothesis), q is the number of restrictions (the number of lagged variables in the model), N is the total number of observations and p is the number of lagged variables in the unrestricted model.

Data

This study uses yearly data from 2000 to 2021 retrieved from WDI (World Development Indicators) whereas particularly 183 countries are selectedas per the data availability. List of Countriesis available in Appendix 1, and measurement of variables are mentioned in Table 3;

Table 3: Variables measurements

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Notation	Variable	Unit of measurement	Data source
U5MR	Mortality Rate under 5	Per 1,000 live births	WDI (2024)
WASH	(Composite proxy through Principal Component Analysis (PCA) for access to Basic Drinking Water, Sanitation,& Hygiene)	% of population	WDI (2024)
URB	Urban Population	% of total population	WDI (2024)
CHE	Current Health Expenditures	Current US$	WDI (2024)
GDP	GDP per capita PPP	Current international $	WDI (2024)
CO2E	CO_2 Emissions	%age of total fuel combustion	WDI (2024)

RESULTS AND DISCUSSION

Descriptive Statistics

The descriptive statistics mentioned in Table 4 offer valuable insights into the dataset's characteristics where mean values indicate the central tendency of each variable, with U5MR having a mean of 3.087, WASH at 0 (with a wide range from -4.506 to 1.579), CHE at 5.451, GDP at 9.06, URB at 3.913, and CO2E with a mean of 3.314 (ranging from -2.212 to 4.485). The standard deviation for CO2E is 1.131, indicating the variability of carbon dioxide emissions across observations while standard deviations measure the dispersion of data points around the mean, with CHE exhibiting the highest variability at 1.678, while URB shows relatively lower variability at 0.495. Minimum and maximum values illustrate the range of each variable, providing insights into the spread of data, for instance, CO2E ranges from -2.212 to 4.485, indicating significant variation in carbon dioxide emissions across observations. Percentiles p1 and p99 highlight the distribution's lower and upper bounds, respectively, aiding in identifying extreme values or outliers(Davidson & MacKinnon, 2004), skewness and kurtosis coefficients assess the distribution's symmetry and tail heaviness, respectively. It is also evident that negative skewness in CO2E (-2.326) suggests a left-skewed distribution, while positive skewness in GDP (0.183) indicates a right-skewed distribution, beside kurtosis values above or below the expected 3 for a normal distribution imply heavier or lighter tails, respectively.
These descriptive statistics offer crucial insights into the dataset's characteristics, facilitating further analysis and interpretation, however considerations for further outliers, non-normality, and data quality lead to dynamic methodological approaches to ensure robust findings(Greene, 2008; Wooldridge, 2010).

Table 4 Descriptive Statistics

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
U5MR	4026	3.087	1.138	.693	5.432	.956	5.14	-.079	1.982
WASH	4026	0	1.664	-4.506	1.579	-3.766	1.579	-.868	2.314
URB	4026	3.913	.495	2.11	4.605	2.593	4.605	-.817	2.925
GDP	4026	9.06	1.202	6.041	12.003	6.507	11.451	-.093	2.21
CHE	4026	5.451	1.678	1.492	9.368	2.197	8.917	.183	2.24
CO_2E	4020	3.314	1.131	-2.212	4.485	-.751	4.358	-2.326	8.195

Panel Data Analysis: Dependency, Stationarity and Integration Tests

Cross Dependence Test Estimates

Table 5 presents Pesaran cross-sectional dependence (CD) test results for the variables in the panel dataset. Whereas all variables exhibit significant cross-dependency, as indicated by low p-values ($p < 0.001$) and high CD-test statistics whichproposes that observations within each group are correlated, necessitating the consideration of panel data techniques to address dependency issues(Pesaran, 2004).

Table 5: Cross Dependence Test

Variable	CD-test	p-value
U5MR	200.790	0.000
WASH	203.380	0.000
URB	203.120	0.000
GDP	199.810	0.000
CHE	197.830	0.000
CO2E	193.400	0.000

Unit-root Test estimation

The results of the Levin-Lin-Chu unit-root test at Table 6 describes that all the variables are stationary at the first difference based on the significant p-values ($p < 0.05$)that reject the null hypothesis of unit roots and which further suggests that these variables exhibit stable long-term trends and do not have a unit root, making them suitable for further analysis using panel data techniques(Levin et al., 2002).

Table 6: Unit-root Test

Variable	Statistics	p-value
U5MR	-45.2707	0.000
WASH	-41.6861	0.000

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

URB	-39.1405	0.000
CHE	-43.9911	0.000
GDP	-40.8412	0.000
CO2E	-32.8404	0.000

Panel Co-integration Test Estimation

The panel co-integration tests (Table 7) yield compelling the indication of a steady long-run relationshipbetween the examined variables. Based on across all the three tests e.g.Westerlund, Pedroni, and Kao,the p-values consistently registered significant levels below 0.05, indicative of robust support for the existence of co-integration, suggests the variables collectively exhibit stationary behavior and maintain a consistent pattern of association over time, corroborating our hypotheses and expectations. These findings offer crucial insights into the intricate dynamics of urban health and sustainability, emphasizing the interconnected nature of factors such as water and sanitation, healthcare expenditure, GDP per capita, urban population, and carbon emissions levels. This study in the existence of co-integration, contributes valuable insights into the long-term trends and interactions among these variables, providing a solid foundation for further analysis and policy interventions aimed at promoting health and well-being in urban settings (Westerlund, 2007; Pedroni, 1999; Kao, 1999).

Table 7: Panel Co-integration Test

Test	**Westerlund**	**Pedroni**	**Kao**
Statistics	Gt: -5.873	Phillips-Perron t: -69.8059	Modified Dickey-Fuller t: -22.4048
	Ga: -107.276	Phillips-Perron t: -62.2849	Dickey-Fuller t: -23.0494
	Pt: -27.488	Augmented Dickey-Fuller t: -62.1048	Augmented Dickey-Fuller t: -14.8263
	Pa: -106.507	--	Unadjusted modified Dickey-Fuller t: --2.6e+02
P-value	(0.000)	(0.000)	(0.000)

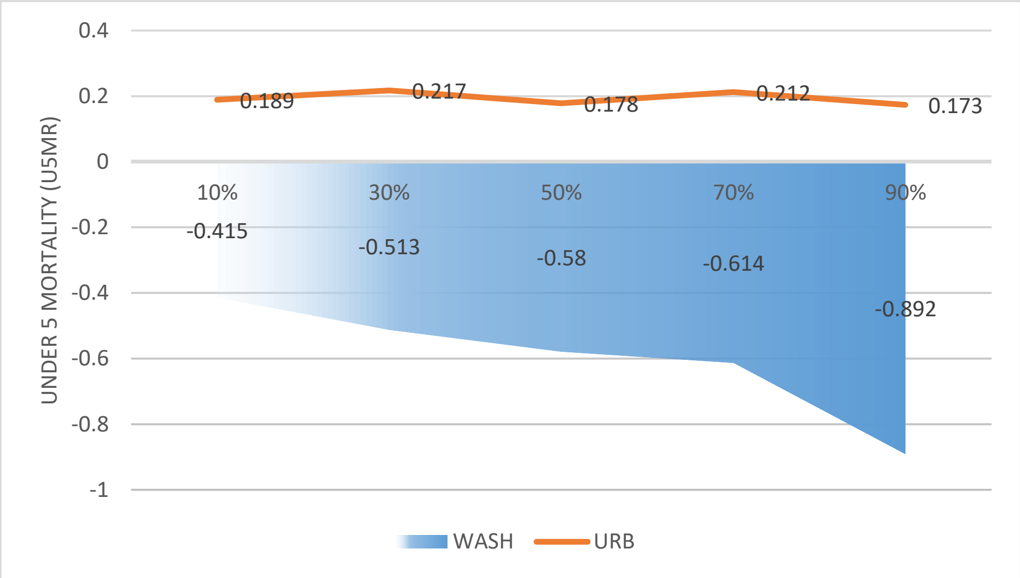
Panel Quantile Regression Estimation

Panel Quantile Regression analysis effectively shown in Fig. 4 unveils consistent patterns across various quantiles, reaffirming the well-documented association

Online ISSN: 3006-2047
Print ISSN: 3006-2039

between higher levels of urbanization and elevated mortality rates as supported by previous studies(Chen Juan, Chen Shuo, & Landry, 2015).Intriguingly, this analysis also sheds light on the differential impact of urbanization and WASH access across different segments of the population. Notably, disparities are noticeable at certain quantiles, where heightened urbanization corresponds to significantly elevated mortality rates at the 30th and 70th percentiles. On the contrary, greater access to WASH facilities exhibit anamplified protective effect against mortality, emphasizing the critical role of WASH infrastructure in shaping public health outcomes (Organization, 2021; Unicef, 2021).

Fig. 4: Based onAuthor Estimation of Quantile Regression for Under-5 Mortality rate



Moreover, Table 8 illuminates socioeconomic disparities in health outcomesthrough quantile regression analysis, as evidenced by varying coefficients for indicators such as GDP and healthcare expenditure (CHE) across different quantiles, highlighting the intricate interplay between socioeconomic factors and health outcomes and necessitating targeted policy interventions (Behera & Dash, 2020). Furthermore, the relatively low coefficients for CO2 emissions (CO2E) across different quantiles underscore the importance of addressing environmental pollution as a contributing factor to urban health disparities. Importantly, the identification of nonlinear urban health dynamics through panel quantile regression reveals critical thresholds in the relationship between urbanization, WASH access, and mortality rates. These nuanced insights highlight the significance of tailored interventions to address the diverse needs of different population segments and regions, aligning with previous research observations(Liu et al., 2016).

Table 8:Consolidated Results of Quantile Regression Analysis

Variable	Quantile Regression

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

	(0.1)	(0.3)	(0.5)	(0.7)	(0.9)
WASH	-0.415*** (0.03)	-0.513*** (0.032)	-0.58*** (0.024)	-0.614*** (0.042)	-0.892*** (0.61)
URB	0.189*** (0.028)	0.217*** (0.029)	0.178*** (0.22)	0.212*** (0.039)	0.173*** (0.056)
GDP	-0.334*** (0.022)	-0.144*** (0.023)	-0.128*** (0.018)	-0.248*** (0.031)	-0.194*** (0.045)
CHE	-0.302*** (0.014)	-0.425*** (0.015)	-0.419*** (0.011)	-0.346*** (0.019)	-0.279*** (0.028)
CO2E	-0.004*** (0.001)	-0.003*** (0.001)	0.001** (0.000)	0.005*** (0.001)	0.007*** (0.001)
Constant	8.329*** (0.127)	7.852*** (0.132)	8.209*** (0.1)	8.993*** (0.174)	9.774*** (0.254)

*** p<.01, ** p<.05, * p<.1 & Standard errors in parentheses

By elucidating these novel insights through panel quantile regression analysis, our research significantly contributes to the understanding of urban health dynamics which can be utilized to the design of more effective and targeted public health policies and interventions to foster sustainable and resilient cities amidst global challenges.

System GMM Estimation

The System GMM estimation results elucidate significant factors influencing mortality rates within urban contexts (see Table 9), providing valuable insights for urban health governance and policy interventions. Consistent with previous literature, our findings reveal a temporal resilience of health systems, as evidenced by the strong positive association between lagged mortality rates and current mortality trends which underscores the importance of considering historical mortality dynamics when assessing contemporary health outcomes, notably improvements in WASH facilities, represented by the negative coefficient of WASH, emerge as critical determinants of mortality rates, aligning with current research highlighting the pivotal role of WASH interventions in enhancing public health outcomes(Organization, 2021; Troeger et al., 2018; Unicef, 2021; D. UNICEF, 2016).

Table 9: System GMM parameter Estimation

U5MR	Coef.	St.Err.	t-	p-	[95%	Interval]

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

			value	value	Conf		Sig
L.U5MR	.863	.011	79.21	0	.841	.884	***
WASH	-.091	.009	-10.14	0	-.109	-.074	***
URB	.013	.005	2.37	.018	.002	.023	**
GDP	-.058	.011	-5.31	0	-.08	-.037	***
CHE	-.019	.006	-3.07	.002	-.031	-.007	***
CO2E	.00023	.00008	2.99	.003	.00008	.0004	***
Constant	1.351	.12	11.29	0	1.116	1.585	***

Mean dependent var	3.070	SD dependent var	1.136
Number of obs	3843	Chi-square	1141892.247

*** p<.01, ** p<.05, * p<.1

The positive association between urban population growth (URB) and mortality rates (U5MR) underscores the challenges posed by rapid urbanization on public health, echoing findings from previous study(Chen Juan et al., 2015) where importantly, the lagged values of WASH, URB, CO2E, and inclusion of instrumental variables i.e.Population Growth (annual %), Urban Population Growth (annual %), Access to Electricity (% of population), and Primary Completion rate (Total) are crucial in addressing endogeneity issues and enhancing the robustness of our estimates(Arellano & Bond, 1991; Roodman, 2009). The instrumental variables capture both temporal dynamics and unobserved heterogeneity, thereby improving the accuracy and reliability of our model and overall, the findings are contributing to the existing literature by extending novel insights into the multifaceted determinants of urban mortality rates and underscore the importance of comprehensive urban health strategies informed by rigorous empirical analysis.

ROBUSTNESS CHECK

Bootstrap Resamplingin Quantile Regressionand FGLS Estimation

For robustness check, both Bootstrap resampling for robust Quantile Regression and Feasible Generalized Least Squares (FGLS) regression techniques were employed. Comparing the findings from Bootstrap resampling for robust Quantile Regression and FGLS regression (see Table 10), withmain standard estimation techniques mentioned earlier (Tables 8 & 9), consistent trends emerge regarding the impact of variables on mortality rates across different quantiles. For instance, both Bootstrap resampling for robust Quantile Regression and FGLS regression reveal a negative association between WASH facilities (WASH) and mortality rates, emphasizing the significance of WASH initiatives in mitigating mortality risks(Organization, 2021; Unicef, 2021). Additionally, the positive coefficients for urbanization (URB) in both methods underscore the adversative effects of urbanization on health outcomes, highlighting the urgent need for sustainable urban development policies.The coefficient estimates for CO2E in both the Bootstrap Quantile Regression and FGLS

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Regression models suggest a consistent and statistically significant relationship with mortality rates across different quantiles. Despite a small coefficient magnitude compared to other variables, CO2E demonstrates a notable impact on mortality rates, particularly evident at higher quantiles (0.7, 0.9). This finding underscores the importance of environmental factors, specifically carbon dioxide emissions, in shaping urban health outcomes. The positive coefficient at the 0.9 quantile in the Bootstrap Quantile Regression model indicates a stronger association between CO2E and mortality rates among the highest percentile of observations, highlighting the disproportionate impact of environmental pollution on vulnerable populations. Moreover, the inclusion of CO2E as a significant predictor in both regression models supports existing literature emphasizing the adverse health effects of air pollution and underscores the need for environmental sustainability initiatives as integral components of urban health governance and policy interventions (Organisation, 2021; Troeger et al., 2018; Unicef, 2021). Therefore, despite its relatively smaller coefficient magnitude, CO2E emerges as a critical determinant of urban mortality rates, warranting attention in urban health research and policy-making efforts.
While some differences in coefficient estimates and standard errors are observed between the two methods, particularly for variables such as GDP and healthcare expenditures (CHE), the overall patterns remain consistent. These differences may arise from variations in model specifications and underlying assumptions between the two estimation techniques.

Table 10: Robustness Analysis

Variable	**Bootstrap Quantile Regression**					**FGLS Regression**
	(0.1)	(0.3)	(0.5)	(0.7)	(0.9)	
WASH	-0.415*** (0.037)	-0.513*** (0.028)	-0.580*** (0.028)	-0.614*** (0.038)	-0.892*** (0.105)	-.309***(.008)
URB	0.189*** (0.033)	0.217*** (0.030)	0.178*** (0.28)	0.212*** (0.051)	0.173*** (0.029)	0.193***(0.02)
GDP	-0.334*** (0.043)	-0.144*** (0.033)	-0.128*** (0.030)	-0.248*** (0.032)	-0.194*** (0.023)	-0.108***(0.16)
CHE	-0.302*** (0.023)	-0.425*** (0.018)	-0.419*** (0.015)	-0.346*** (0.019)	-0.279*** (0.018)	-0.327***(0.01)
CO2E	-0.004*** (0.000)	-0.003*** (0.000)	0.001 (0.001)	0.005*** (0.001)	0.007*** (0.001)	0.002***(.0004)
Constant	8.329*** (0.143)	7.852*** (0.157)	8.209*** (0.142)	8.993*** (0.123)	9.774*** (0.345)	5.026***(0.115)

*** p<.01, ** p<.05, * p<.1 & Standard errors are in parentheses

Panel Causality Analysis

Table 11 shows D-H. Granger causality test estimates, where a lag order of 2 is used

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

to assess the causal relationship between the variables, indicating that the variables' past values up to the second period are considered in determining causality. The estimates exhibitseveral noteworthy findings, for instance, there is bidirectional causality between U5MR and WASH, as indicated by various significance levels which probably suggests that improvements in WASH infrastructure can lead to reduced mortality rates among children under the age of five, while simultaneously, lower mortality rates may incentivize investments and efforts to enhance WASH facilities, resulting in a mutually reinforcing relationship between improved sanitation and reduced child mortality. Similarly, URB and CHE exhibit bidirectional causality with U5MR, suggesting mutual influences between these factors. CHE exhibits one way causality with CO2E shows the vital role of current health expenditures on controlling CO2E. U5MR demonstrate bidirectional causality with CO2E, implying unnatural in the sense that how U5MR effect CO2E but itmay involve feedback loops, where changes in one variable affect the other variable, leading to further changes in the initial variable. For example, efforts to reduce carbon emissions may involve the adoption of cleaner energy sources and technologies, which could positively impact air quality and subsequently improve health outcomes, including reducing mortality rates among children. Conversely, improvements in child health may lead to changes in societal priorities and policies, influencing decisions related to environmental conservation and carbon emission reduction.Overall, the bidirectional causality between CO2E and U5MR underscores the complex interdependencies between environmental factors, public health outcomes, and socioeconomic dynamics. Understanding these relationships is crucial for designing effective policies and interventions that address both environmental sustainability and public health concerns.However, variables such as GDP and CO2E display unidirectional causality, indicating pivotal role of DGP for regulating CO2E.

Table 11:Panel Causality Analysis

Null Hypothesis	**W-Stat**	**Z-bar Stat**	**Prob**	p-value
U5MR ⇎ WASH	2.7913*	1.8558	0.0635	U5MR ⇐⇒ WASH
WASH ⇎U5MR	7.5782***	13.0821	0.0000	
U5MR ⇎ URB	0.3665***	-3.8308	0.0001	U5MR ⇐⇒ URB
URB ⇎U5MR	8.0735***	4.2436	0.0000	
U5MR ⇎ CHE	2.3539	0.8299	0.4066	CHE ⇒U5MR
CHE ⇎U5MR	9.8628***	18.4400	0.0000	
U5MR ⇎	1.0850**	-2.1459	0.031	U5MR ⇐⇒

GDP			9	GDP
GDP ⇎U5MR	8.4430***	15.1101	0.0000	
U5MR ⇎ CO2E	0.7234**	-2.9938	0.0028	U5MR ⇐⇒ CO2E
CO2E ⇎U5MR	5.7637***	8.8266	0.0000	
WASH ⇎ URB	1.6659	-0.7836	0.4332	URB ⇒ WASH
URB ⇎ WASH	3.8777***	4.4035	0.0000	
WASH ⇎ CHE	0.7926**	-2.8316	0.0046	WASH ⇒ CHE
CHE ⇎ WASH	1.4345	-1.3262	0.1848	
WASH ⇎ GDP	2.6087	1.4275	0.1534	GDP ⇎WASH
GDP ⇎ WASH	1.3921	-1.4256	0.1540	
WASH ⇎ CO2E	0.7090**	-3.0276	0.0025	WASH ⇐⇒ CO2E
CO2E ⇎ WASH	3.1702**	2.7443	0.0061	
URB ⇎ CHE	4.3842***	5.5915	0.0000	URB ⇐⇒ CHE
CHE ⇎ URB	0.8092**	-2.7926	0.0052	
URB ⇎ GDP	5.3446***	7.8437	0.0000	URB ⇐⇒ GDP
GDP ⇎ URB	0.4914***	-3.5379	0.0004	
URB ⇎ CO2E	0.5136***	-3.4859	0.0005	URB ⇒ CO2E
CO2E ⇎ URB	2.2670	0.6262	0.5312	
CHE ⇎ GDP	1.6103	-0.9139	0.3608	GDP ⇒ CHE
GDP ⇎ CHE	0.3901***	-3.7757	0.0002	
CHE ⇎ CO2E	0.7175**	-3.0077	0.0026	CHE ⇒ CO2E
CO2E ⇎ CHE	2.6782	1.5906	0.1117	

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

GDP CO2E	⇎	0.3648***	-3.8348	0.0001	GDP ⇒ CO2E
CO2E GDP	⇎	2.3151	0.7390	0.4599	

The */**/*** denote significance levels at 1%, 5%, and 10%, respectively. ⇎ signifies the absence of causality among the variables. ⇐⇒ indicates bidirectional causality, while ⇒ indicates one-way causality.

These findings underscore the complex interplay between urban health dynamics, socioeconomic factors, and environmental influences on mortality rates which is crucial for policymakers to formulate effective interventions aimed at promoting public health within urban environments and addressing the multifaceted challenges associated with mortality outcomes. Further research into the underlying mechanisms driving these causal relationships can provide deeper insights into the dynamics of urban health and inform evidence-based policy decisions for sustainable urban development and improved public health outcomes.

CONCLUSION

In this comprehensive analysis, a rigorous exploration of the complex interplay between urbanization, Water, Sanitation, and Hygiene (WASH) dynamics, and mortality rates within urban populations are embarked by employing a diverse array of advanced analytical techniques and robustness checks, including Quantile regression, System GMM estimation, Bootstrap resampling for robust Quantile Regression, and Feasible Generalized Least Squares (FGLS) estimation. The study aimed to achieve critical objectives and provide actionable insights for policymakers and practitioners in the realm of urban health governance and hence the findings revealed consistent patterns across different quantiles, elucidating the multifaceted impact of urbanization, WASH initiatives, and other factors i.e. Current Health Expenditures (CHE), Gross Domestic Products (GDP) per capita, and Carbon Dioxide Emissions (CO2E), on mortality rates within urban populations. Higher levels of urbanization were consistently associated with increased mortality rates, underscoring the challenges posed by rapid urban growth. Conversely, greater access to WASH facilities exhibited a protective effect against mortality, emphasizing the pivotal role of WASH infrastructure in shaping public health outcomes. Socioeconomic disparities in health outcomes were illuminated, highlighting the need for targeted policy interventions to promote health equity.System GMM estimation unraveled temporal resilience in health systems and the evolving nature of urbanization-health dynamics and with its employment, a strong positive association between lagged mortality rates and current mortality trends it is observed, indicating the temporal persistence of past urban health dynamics. Improvements in WASH initiatives is emerged as critical determinants of mortality rates, aligning the current study signifying the the pivotal role of WASH interventions in enhancing public health outcomes. The positive

association between urban population growth, healthcare expenditures, GDP per capita, and mortality rates underscored the challenges posed by rapid urbanization on public health, highlighting the urgency of sustainable urban development policies.
Robustness checks using Bootstrap resampling for robust Quantile Regression and FGLS estimation techniques further validated our main findings, emphasizing the significance of WASH initiatives in mitigating mortality risks and the adverse effects of urban population on health being evident with some differences in coefficient estimates and standard errors between the methods, the overall patterns remained consistent, and providing further validation of our results. Finally the integrated analysis yielded compelling insights into the complex dynamics of urban health and by synthesizing evidence from diverse analytical methods and considering the impact of multiple control variables, the study contributed to a deeper understanding of mortality rate determinants within urban populations. Finally,the causality analysis reveals complex interrelationships among various factors influencing urban health outcomes. Bidirectional causality is observed between variables such as WASH and Under-Five Mortality, indicating mutual influences and reinforcing feedback loops.
These findings underscore the importance of comprehensive interventions addressing multiple determinants of urban health to effectively mitigate mortality risks and promote sustainable urban development.The study also pave the way for evidence-based policy interventions and sustainable urban development strategies aimed at promoting health equity and resilience in cities around the world.

Policy Recommendations

The comprehensive analysis conducted in this study offers valuable policy implications for various stakeholders involved in urban health governance and sustainable development. Firstly, policymakers at the local, national, and international levels should prioritize investment for WASH infrastructure and allocate resources to improve access to safe Water, Sanitation, and Hygiene facilities, to mitigate the burden of communicable diseases and enhance overall public health outcomes within urban environments. Sustainable urban development strategies should also be developed to address the challenges posed by rapid urbanization which may include measures to improve urban planning, infrastructure development, and resource management to create healthier and more resilient cities. Additionally, efforts to reduce health disparities and promote health equity should be prioritized along with targeted interventions aimed at addressing the social determinants of health, including poverty, education, and access to healthcare, that can help alleviate disparities and ensure equitable health outcomes for all urban residents. Policymakers may adopt longitudinal approaches to urban health governance, considering the long-term impacts of urbanization, WASH dynamics, and other factors on public health outcomes. Moreover, the importance of considering Current Health Expenditures, GDP per capita, and CO_2 Emissions in policy recommendations cannot be neglected as higher levels of GDP per capita and healthcare expenditures are associated with lower mortality rates, indicating the need for continued investment in healthcare infrastructure and services along with efforts to reduce carbon dioxide emissions and

Volume 5 Issue No 1 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

promote environmental sustainability which have positive implications on public health outcomes. Finally, policymakers should adopt a holistic approach to urban health governance, integrating insights from diverse analytical methods and considering the multifaceted nature of urban health challenges. Similarly by developing evidence-based strategies that address the unique needs of different population segments and regions, policymakers can foster sustainable urban development and promote health equity in cities worldwide. These policy implications underscore the significance of joint efforts among policymakers, healthcare providers, urban planners, and community stakeholders to address the complex urban health issues and promote the well-being of urban populations.

Limitations of the Study

While this research provides valuable insights into urban health dynamics, it is not without limitations. One limitation is the reliance on secondary data sources, which may introduce biases and inaccuracies inherent in data collection processes. Additionally, the analysis is based on aggregate data at the city or regional level, which may mask heterogeneity within populations. Despite efforts to address endogeneity through instrumental variables and panel causality analysis, establishing causal relationships remains challenging. For instance, bidirectional causality observed between WASH and Under-Five Mortality underscores the complexity of these relationships. Moreover, due to the complexity of urban health dynamics, certain relevant factors influencing mortality rates and WASH initiatives may not have been comprehensively captured in the analysis, potentially overlooking important determinants of public health outcomes. Future research could address these limitations by utilizing primary data collection methods, incorporating more granular data to capture the diversity of urban populations, and exploring alternative methodological approaches to enhance causal inference and robustness of the findings.

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