Impact of Energy Consumption on Health
A CASE STUDY OF INDIA

DISSERTATION

Submitted in partial fulfillment of the requirement of

Bachelor Of Arts (Hons.)

By

Arni Parikh

Roll no. 20BABBA025

Under the guidance of

Dr. Nausheen Nizami

School of Liberal Studies Pandit

Deendayal Energy University

Gandhinagar – 382007. Gujarat - INDIA

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Approval Sheet

This dissertation entitled Impact of Energy consumption on health using Regression Analysis by Arni Parikh is recommended for the degree of Bachelors ofArts (Hons.)

Examiners

1. Dr. Hepzibah Mary H Mary

2. Dr. Nausheen Nizami (Nausheen)

Supervisors

Nausheen

Dr. Nausheen Nizami

SCHOOL OF LIBERAL STUDIES PDEU GANDHINAGAR

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Date: 09/05/2024

ARNI PARIKH

(Name of Student)

20BABBA025

(Roll No.)

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ABSTRACT

This research paper offers a nuanced examination of the complex relationship between evolving energy consumption patterns and their impacts on human health. Considering increasing global energy demands, understanding the potential repercussions of our energy choices on societal health becomes paramount. Emphasizing the health benefits associated with the transition to sustainable energy sources, particularly renewables, this study delves into the multifaceted dynamics at play.

Recognizing that the adoption of renewables extends beyond environmental sustainability, the paper highlights the opportunity to mitigate health risks linked to traditional energy sources. Special attention is paid to vulnerable populations facing limited access to healthcare resources or residing in environmentally compromised areas, who may be disproportionately affected by energy-related health risks. Key factors such as air pollution, harmful emissions exposure, and the ecological impact of energy production are scrutinized within the context of existing health disparities. Through a comprehensive and multidisciplinary approach, the study aims to identify and elucidate these disparities, offering valuable insights for developing targeted interventions to promote equitable well-being. Beyond environmental considerations, the inquiry delves into the social dimensions of energy consumption, health, and socio-economic factors, shedding light on their intersectionality. The findings are poised to inform policymakers, healthcare professionals, and researchers, laying the groundwork for evidence-based strategies that align energy transitions with improved human health outcomes.

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CHAPTER 1
INTRODUCTION

This research paper undertakes a nuanced examination of the intricate interplay between evolving energy consumption patterns and their discernible impacts on human health. In the face of burgeoning global energy demands, it becomes imperative to comprehend the potential repercussions of our energy choices, particularly within the context of societal health. This study places a specific emphasis on the exploration of the health benefits associated with the growing shift towards sustainable energy sources, particularly renewable energies.

As societies worldwide grapple with the challenge of meeting escalating energy demands, the transition towards cleaner energy sources prompts a critical analysis of the potential positive health outcomes attributable to such a shift. The paper recognizes that the adoption of renewables has implications beyond environmental sustainability, offering a unique opportunity to mitigate health risks associated with traditional energy sources.

The research focuses on understanding how vulnerable populations, characterized by factors such as limited access to healthcare resources or residing in environmentally compromised areas, may be disproportionately affected by energy-related health risks. Factors like air pollution, exposure to harmful emissions, and the ecological impact of energy production are examined in the context of how they intersect with existing health disparities.

Through a comprehensive and multidisciplinary approach, the study aims to identify and elucidate these disparities in health outcomes, providing a nuanced understanding of the intricate dynamics at play. By doing so, the research contributes valuable insights for developing targeted interventions that can mitigate adverse health effects and promote equitable well-being among diverse populations.

This inquiry goes beyond a mere exploration of the environmental benefits of sustainable energy adoption; it delves into the social dimensions, shedding light on the intersectionality of energy consumption, health, and socio-economic factors. The findings of this research are expected to inform policymakers, healthcare professionals, and researchers alike, providing a foundation for evidence-based strategies that align energy transitions with improved human health outcomes.

CHAPTER 2

REVIEW OF LITERATURE

- In their study, Momodu, Akinbami, and Akinwunmi (2010) examined the environmental and health ramifications of fuel substitution within Nigeria's household energy mix. They identified the use of biomass and charcoal for cooking as contributors to harmful pollutants linked to respiratory illnesses such as ALRI, COPD, and lung cancer, particularly affecting women and children responsible for these tasks. This gendered impact underscores the disproportionate burden on vulnerable populations. To mitigate these health risks, the authors recommend the adoption of cleaner and more efficient cooking technologies. Their findings underscore the urgent need for interventions to address the adverse health effects associated with traditional cooking fuels, advocating for policy measures promoting the widespread adoption of cleaner alternatives. This study provides valuable insights into the intersection of energy consumption, health outcomes, and gender dynamics, emphasizing the importance of transitioning towards sustainable energy solutions for improved public health and social equity.

- In Kurian's (2012) exploration of sustainable development in the energy sector, it is highlighted that unsustainable energy practices serve as primary drivers of various environmental issues, including indoor air pollution, urban air pollution, acidification, and global warming. These environmental challenges, in turn, pose significant threats to human health. Indoor air pollution, often stemming from inefficient energy usage, particularly affects vulnerable populations residing in poorly ventilated spaces. Urban air pollution exacerbates respiratory and cardiovascular ailments, with detrimental effects on public health. Additionally, the acidification of ecosystems and global warming, induced by unsustainable energy activities, further compound these health risks. Kurian's study underscores the urgent need for sustainable energy solutions to mitigate these adverse health impacts. By emphasizing the interconnectedness of energy practices, environmental degradation, and human health, the paper contributes to the understanding of the multifaceted challenges facing the energy sector. It advocates for policy interventions and technological innovations aimed at promoting sustainable energy development to safeguard public health and environmental well-being.

- Yoshida and Zusman's (2014) study focuses on the design and implementation of energy goals to achieve multi-benefits for sustainable development. They highlight that access to modern energy services plays a pivotal role in improving health outcomes by mitigating indoor air pollution resulting from traditional cooking methods, thereby reducing the incidence of respiratory illnesses. Moreover, the provision of electricity facilitates enhanced access to healthcare services, as it enables the operation of medical equipment and ensures adequate lighting in clinics and hospitals. These findings underscore the vital link between energy access and health, emphasizing the potential of sustainable energy interventions to address health disparities and promote overall well-being. By elucidating the multifaceted benefits associated with energy provision, the study contributes to the understanding of the broader implications of energy policies and interventions. It underscores the importance of integrating health considerations into energy planning and underscores the potential synergies between energy access, healthcare delivery, and sustainable development goals.

- Youssef, Lannes, Rault, and Soucat (2015-16) examine the relationship between energy consumption and health outcomes in Africa. Their study underscores the significant impact of energy consumption on health outcomes, particularly in developing countries within the African context. They identify outdoor and household air pollution as leading causes of mortality and morbidity, highlighting the detrimental effects on public health. Specifically, the research establishes direct causality between energy consumption and child mortality rates among children under five years old, emphasizing the urgent need for interventions to address this issue. Furthermore, the study elucidates the indirect causality between energy consumption and broader environmental challenges, such as the greenhouse effect, which exacerbates air pollution and impacts government health expenditures. By providing empirical evidence of the intricate links between energy consumption patterns and health outcomes, this research contributes to a deeper understanding of the complex dynamics at play. It emphasizes the imperative for holistic approaches to energy planning that prioritize health considerations, thereby advancing efforts towards sustainable development and improved health outcomes in African nations.

- Asif and Saleh's (2019) study investigates the nexus between human security and energy security, focusing on Pakistan as a case study. They highlight the critical issue of clean cooking fuel access, noting that the lack thereof leads to the widespread use of polluting fuels such as kerosene, biomass, and coal. This reliance on carbon-dominated fuels is associated with severe health consequences, with an estimated 2.8 million premature deaths annually attributed to heavy dependence on biomass and coal for cooking. Furthermore, the study underscores the significant threat posed by air pollution resulting from the combustion of these fuels, emphasizing its detrimental impact on public health. Asif and Saleh emphasize the crucial role of energy access in shaping overall health outcomes, underscoring the need for policies and interventions aimed at promoting cleaner and more sustainable energy sources. By shedding light on the profound implications of energy security for human security, the study contributes to the literature on the interconnections between energy, health, and broader societal well-being.

- Luomi's (2020) research on the global governance of sustainable energy underscores the critical link between energy and health, aligning with UN SDG 3 for good health and well-being. The study emphasizes that the use of clean, renewable energy plays a pivotal role in reducing exposure to air pollution, thereby mitigating respiratory diseases, cardiovascular conditions, and premature death. Additionally, access to electricity enhances healthcare delivery by enabling the operation of medical equipment, vaccine preservation, nighttime care lighting, and efficient health information systems. Despite these benefits, Luomi offers a cautionary note, advocating for a careful transition to renewable energy to prevent unintended harm to health and ecosystems. By synthesizing evidence and insights, Luomi's work contributes to a comprehensive understanding of the health implications of sustainable energy transitions, informing policy and governance frameworks for achieving sustainable development goals while safeguarding public health and environmental integrity

CHAPTER 3
RESEARCH DESIGN

3.1 RESEARCH METHODOLY

The exploratory research design in this study is structured to offer a thorough comprehension of the intricate relationship between energy consumption and health in the context of India. This involves employing regression models and conducting normality tests for each, with the overarching goal of enhancing the accuracy and robustness of the findings.

Regression models are statistical techniques that will allow to examine the associations between variables. In this particular study, regression models are utilized to assess the impact of energy consumption patterns on health outcomes in India. By employing regression analysis, I aim to identify and quantify potential relationships, dependencies, or trends between energy-related factors and health indicators. This analytical approach provides a quantitative framework for understanding the nuances of how changes in energy consumption might be linked to variations in health outcomes.

Running normality tests for the data is a crucial step in ensuring the reliability of the statistical analysis. Normality tests assess whether the data within each variable follows a normal distribution, which is a fundamental assumption for many statistical methods, including regression analysis. If the variables are normally distributed, it enhances the accuracy and validity of the regression results. Deviations from normality can impact the reliability of statistical inferences, and conducting normality tests will help me identify and address any potential issues arising from skewed or non-normal distributions of data.

By integrating regression models and normality tests into the research design, the study aims to provide a more accurate understanding of the relationship between energy consumption and health in India. This methodological approach allows for the identification of significant factors and their impact on health outcomes while ensuring the robustness and validity of the statistical analyses. Overall, this research design strives to contribute to evidence-based insights that can inform policies and interventions aimed at promoting public health in the face of evolving energy consumption patterns.

3.2 RESEARCH VARIABLES

- **Main Variables of the Study**

<u>Dependent Variables</u>

1. Morbidity Rates: Morbidity rates quantify the prevalence of illness within a given population, serving as a key indicator of public health status and healthcare needs.

2. Infant mortality rates: Infant mortality rates reflect the number of deaths of infants under one year of age per 1,000 live births, providing critical insights into the effectiveness of healthcare systems and societal conditions affecting early childhood survival:

3. Death Rate (through diseases): Death rates from diseases measure the number of deaths attributed to specific diseases within a population over a specified period, highlighting the impact of illnesses on mortality and informing public health interventions.

4. Life Expectancy: Life expectancy represents the average number of years a person is expected to live, reflecting the overall health and socioeconomic conditions of a population and serving as a key metric for assessing public health outcomes.

5. Fertility Rates: Fertility rates indicate the average number of children born per woman of childbearing age within a specific population, providing insights into demographic trends, family planning practices, and population growth dynamics.

<u>Independent Variables</u>

1. Energy Consumption (Non-Renewable): Non-renewable energy consumption refers to the utilization of finite energy sources such as fossil fuels (coal, oil, natural gas),

nuclear energy, and other non-renewable resources to meet societal energy demands, contributing to environmental concerns and energy security challenges.

2. CO_2 emissions from fuel combustion: CO_2 emissions from fuel combustion in India signify the amount of carbon dioxide released into the atmosphere as a result of burning fossil fuels for various purposes, including electricity generation, transportation, industry, and residential usage, impacting climate change and air quality.

- **Sources of Data Collection**

    1. CMIE

    2. EPWRF

    3. World Bank

    4. International Energy Association (IEA)

3.3 RESEARCH OBJECTIVE

The overarching objective of this research is to explore the intricate connections among public health, sustainable economic growth, and advancements in energy infrastructure, with a specific focus on influencing policy decisions that align with Sustainable Development Goals (SDGs) 3 (Good Health and Well-being), 8 (Decent Work and Economic Growth), and 9 (Industry, Innovation, and Infrastructure) within the unique context of India. The primary goal is to offer valuable insights that could inform and shape policies and practices conducive to achieving these SDGs in an integrated manner.

A pivotal aspect of the research involves a thorough examination of the potential consequences of prevailing energy consumption patterns on human health. As societies globally grapple with increasing energy demands, understanding the health implications becomes crucial. The study seeks to unravel the complexities surrounding our energy choices and their impacts on public health. By doing so, it aims to contribute to a more comprehensive approach to sustainable development, recognizing the interconnectedness of health, economic growth, and innovation in the realm of energy infrastructure.

Particular attention is directed towards the societal shift towards sustainable energy sources, notably renewables, prompting an investigation into the potential health benefits associated with cleaner energy alternatives. This exploration encompasses an analysis of how vulnerable populations may be disproportionately affected by health risks linked to energy consumption. Factors such as inadequate healthcare access and residence in environmentally compromised areas are considered, emphasizing the importance of understanding, and addressing disparities. The research endeavours to provide a nuanced understanding of these disparities to facilitate the development of targeted interventions, thereby working towards equitable health outcomes.

In essence, the research seeks to contribute to a nuanced understanding of the intricate relationships between energy choices, public health, and sustainable development in the Indian context. Through comprehensive analysis and evidence-based insights, the aim is to guide policymakers towards decisions that not only align with the specified SDGs but also foster a more resilient, inclusive, and sustainable approach to addressing the escalating energy demands of societies worldwide.

3.3 PROBLEM STATEMENT

Despite the global momentum toward sustainable energy adoption and its potential health benefits, there exists a significant research gap concerning the nuanced understanding of the interplay between evolving energy consumption patterns and human health impacts, particularly within the context of India. While numerous studies have explored the relationship between energy choices and health outcomes in various regions, there is a dearth of comprehensive research specifically focusing on India's unique socio-economic and environmental landscape.

India, as one of the world's most populous and rapidly developing nations, faces complex challenges in balancing its burgeoning energy demands with the imperative to safeguard public health. The country's energy mix is undergoing transformation, with increasing attention towards renewable energy sources. However, the implications of this transition for human health remain understudied and poorly understood.

Key aspects of concern include the disproportionate vulnerability of certain population segments to health risks associated with traditional energy sources, such as indoor air pollution from biomass burning and outdoor air pollution from fossil fuel combustion. Moreover, the potential health benefits of transitioning to cleaner energy alternatives, particularly for vulnerable communities, have not been adequately explored within the Indian context.

Understanding these dynamics is crucial for devising targeted interventions and policies that promote both energy sustainability and public health equity in India. Therefore, the primary objective of this research is to bridge this gap by conducting a comprehensive examination of the intricate interplay between evolving energy consumption patterns and their discernible impacts on human health, specifically within the context of India. By doing so, this study aims to provide evidence-based insights that can inform policy formulation, healthcare strategies, and future research endeavours in the realm of sustainable energy and public health in India.

CHAPTER 4
STATISTICS AND ANALYSIS

4.1 DATA SET

Year	Energy Consumption	Total Fertility Rate	Morbidity Rates	Death Rates	Infant Mortality Rates	Life Expectancy	CO2 Emissions
1999	11788337	3.2	9.4	8.7	333.5	4.1	889.823
2000	12143103	3.2	70.8	8.5	320.6	-3.6	904.845
2001	12150492	3.1	99.8	8.4	490.6	0.4	934.659
2002	12570587	3	-13.2	8.1	479.8	0.6	959.012
2003	12822389	3	2.41	8	458.2	0.5	1028.271
2004	13334015	2.9	2.19	7.5	458.8	0.5	1074.985
2005	13916649	2.9	94.3	7.6	463.3	0.4	1148.464
2006	14714330	2.8	14.8	7.5	460.5	0.4	1266.47
2007	15640543	2.7	1.45	7.4	454.3	0.3	1349.158
2008	16536245	2.6	4.39	7.4	645.6	0.4	1481.117
2009	17456829	2.6	3.85	7.3	622.8	0.3	1571.614
2010	18561843	2.5	-8.5	7.2	589	0.4	1661.669
2011	19564812	2.4	-1.86	7.1	559	1.2	1804.585
2012	20155453	2.4	15.02	7	534.3	3.9	1860.187
2013	20824047	2.3	2.94	7	513.9	3.3	2026.904
2014	21847135	2.3	3.91	6.7	487.5	0.1	2035.741
2015	22851357	2.3	7.64	6.5	470.1	1.8	2067.426
2016	23635045	2.3	8.16	6.4	447.3	1.3	2184.437
2017	24793756	2.2	1.11	6.3	439.4	1.5	2316.24
2018	25911740	2.2	0.64	6.2	433.7	2.1	2277.776
2019	26047455	2.1	-4.44	6	415.1	3.9	2074.646
2020	24964632	2	-76.2	6	391.3	2.3	2279.007

4.2 DESCRIPTIVE STATISTICS

LIFE EXPECTANCY

Life Expectancy	
Mean	1.186364
Standard Error	0.361233
Median	0.55
Mode	0.4
Standard Deviation	1.694331
Sample Variance	2.870758
Kurtosis	2.156619
Skewness	-0.4206
Range	7.7
Minimum	-3.6
Maximum	4.1
Sum	26.1
Count	22

Mean: The mean life expectancy is approximately 1.186 years.

Standard Error: The standard error of the mean life expectancy is approximately 0.361 years. This indicates the precision of the estimate of the mean.

Median: The median life expectancy is 0.55 years. This represents the middle value in the dataset when arranged in ascending order.

Mode: The mode of life expectancy is 0.4 years. This is the most frequently occurring value in the dataset.

Standard Deviation: The standard deviation of life expectancy is approximately 1.694 years. This measures the dispersion or spread of the data points around the mean.

Sample Variance: The sample variance of life expectancy is approximately 2.871 years squared. This indicates the variability of individual data points from the mean.

Kurtosis: The kurtosis of approximately 2.157 suggests that the distribution of life expectancy values is moderately peaked and has relatively heavy tails compared to a normal distribution.

Skewness: The negative skewness of approximately -0.421 indicates that the distribution of life expectancy values is slightly skewed to the left, meaning it has a longer tail on the left side of the distribution.

Range: The range of life expectancy values is 7.7 years, calculated as the difference between the maximum and minimum values.

Minimum: The minimum life expectancy value is -3.6 years.

Maximum: The maximum life expectancy value is 4.1 years.

Sum: The sum of all life expectancy values is 26.1 years.

Count: There are 22 data points in the dataset.

INFANT MORTALITY RATE

Infant Mortality Rates	
Mean	475.8455
Standard Error	17.15588
Median	461.9
Mode	#N/A
Standard Deviation	80.46821
Sample Variance	6475.133
Kurtosis	0.427154
Skewness	0.273623
Range	325
Minimum	320.6
Maximum	645.6
Sum	10468.6
Count	22

Mean: The mean infant mortality rate is approximately 475.85 per 1000 live births.

Standard Error: The standard error of the mean infant mortality rate is approximately 17.16. This indicates the precision of the estimate of the mean.

Median: The median infant mortality rate is 461.9 per 1000 live births. This represents the middle value in the dataset when arranged in ascending order.

Mode: There is no mode provided (#N/A). This means there is no value that appears more frequently than others in the dataset.

Standard Deviation: The standard deviation of infant mortality rates is approximately 80.47. This measures the dispersion or spread of the data points around the mean.

Sample Variance: The sample variance of infant mortality rates is approximately 6475.13. This indicates the variability of individual data points from the mean.

Kurtosis: The kurtosis of approximately 0.43 suggests that the distribution of infant mortality rates is slightly peaked compared to a normal distribution.

Skewness: The skewness of approximately 0.27 indicates that the distribution of infant mortality rates is slightly positively skewed, meaning it has a longer tail on the right side of the distribution.

Range: The range of infant mortality rates is 325 per 1000 live births, calculated as the difference between the maximum and minimum values.

Minimum: The minimum infant mortality rate is 320.6 per 1000 live births.

Maximum: The maximum infant mortality rate is 645.6 per 1000 live births.

Sum: The sum of all infant mortality rates is 10468.6 per 1000 live births.

Count: There are 22 data points in the dataset.

DEATH RATES

Death Rates	
Mean	7.218182
Standard Error	0.170387
Median	7.25
Mode	7.5
Standard Deviation	0.799188
Sample Variance	0.638701
Kurtosis	-0.76657
Skewness	0.180841
Range	2.7
Minimum	6
Maximum	8.7
Sum	158.8
Count	22

Mean: The mean death rate is approximately 7.22 deaths per 1000 population.

Standard Error: The standard error of the mean death rate is approximately 0.17. This indicates the precision of the estimate of the mean.

Median: The median death rate is 7.25 deaths per 1000 population. This represents the middle value in the dataset when arranged in ascending order.

Mode: The mode of the death rates is 7.5 deaths per 1000 population. This is the most frequently occurring value in the dataset.

Standard Deviation: The standard deviation of death rates is approximately 0.80. This measures the dispersion or spread of the data points around the mean.

Sample Variance: The sample variance of death rates is approximately 0.64. This indicates the variability of individual data points from the mean.

Kurtosis: The negative kurtosis of approximately -0.77 suggests that the distribution of death rates is slightly less peaked compared to a normal distribution, with thinner tails

Skewness: The positive skewness of approximately 0.18 indicates that the distribution of death rates is slightly positively skewed, meaning it has a longer tail on the right side of the distribution.

Range: The range of death rates is 2.7 deaths per 1000 population, calculated as the difference between the maximum and minimum values.

Minimum: The minimum death rate is 6 deaths per 1000 population.

Maximum: The maximum death rate is 8.7 deaths per 1000 population.

Sum: The sum of all death rates is 158.8 deaths per 1000 population.

Count: There are 22 data points in the dataset.

MORBIDITY RATES

Morbidity Rates	
Mean	10.8459091
Standard Error	7.79661114
Median	3.395
Mode	#N/A
Standard Deviation	36.5693478
Sample Variance	1337.3172
Kurtosis	2.9731617
Skewness	0.86636313
Range	176
Minimum	-76.2
Maximum	99.8
Sum	238.61
Count	22

Mean: The mean morbidity rate is approximately 10.85.

Standard Error: The standard error of the mean morbidity rate is approximately 7.80. This indicates the precision of the estimate of the mean.

Median: The median morbidity rate is 3.395. This represents the middle value in the dataset when arranged in ascending order.

Mode: There is no mode provided (#N/A). This means there is no value that appears more frequently than others in the dataset.

Standard Deviation: The standard deviation of morbidity rates is approximately 36.57. This measures the dispersion or spread of the data points around the mean.

Sample Variance: The sample variance of morbidity rates is approximately 1337.32. This indicates the variability of individual data points from the mean.

Kurtosis: The kurtosis of approximately 2.97 suggests that the distribution of morbidity rates is moderately peaked compared to a normal distribution.

Skewness: The positive skewness of approximately 0.87 indicates that the distribution of morbidity rates is slightly positively skewed, meaning it has a longer tail on the right side of the distribution.

Range: The range of morbidity rates is 176, calculated as the difference between the maximum and minimum values.

Minimum: The minimum morbidity rate is -76.2.

Maximum: The maximum morbidity rate is 99.8.

Sum: The sum of all morbidity rates is 238.61.

Count: There are 22 data points in the dataset.

TOTAL FERTILITY RATE

Total Fertility Rate	
Mean	2.590909091
Standard Error	0.079203035
Median	2.55
Mode	2.3
Standard Deviation	0.371495166
Sample Variance	0.138008658
Kurtosis	-1.228276883
Skewness	0.238109997
Range	1.2
Minimum	2
Maximum	3.2
Sum	57
Count	22

Mean: The mean total fertility rate is approximately 2.59.

Standard Error: The standard error of the mean total fertility rate is approximately 0.08. This indicates the precision of the estimate of the mean.

Median: The median total fertility rate is 2.55. This represents the middle value in the dataset when arranged in ascending order.

Mode: The mode of the total fertility rate is 2.3. This is the most frequently occurring value in the dataset.

Standard Deviation: The standard deviation of total fertility rates is approximately 0.37. This measures the dispersion or spread of the data points around the mean.

Sample Variance: The sample variance of total fertility rates is approximately 0.14. This indicates the variability of individual data points from the mean.

Kurtosis: The negative kurtosis of approximately -1.23 suggests that the distribution of total fertility rates is less peaked compared to a normal distribution, with thinner tails.

Skewness: The positive skewness of approximately 0.24 indicates that the distribution of total fertility rates is slightly positively skewed, meaning it has a longer tail on the right side of the distribution.

Range: The range of total fertility rates is 1.2, calculated as the difference between the maximum and minimum values.

Minimum: The minimum total fertility rate is 2.

Maximum: The maximum total fertility rate is 3.2.

Sum: The sum of all total fertility rates is 57.

Count: There are 22 data points in the dataset.

ENERGY CONSUMPTION

Energy Consumption	
Mean	18283218
Standard Error	1067389
Median	18009336
Mode	#N/A
Standard Deviation	5006498
Sample Variance	2.51E+13
Kurtosis	-1.45919
Skewness	0.185964
Range	14259118
Minimum	11788337
Maximum	26047455
Sum	4.02E+08
Count	22

Mean: The mean energy consumption is approximately 18,283,217.91 units.

Standard Error: The standard error of the mean energy consumption is approximately 1,067,388.94. This indicates the precision of the estimate of the mean.

Median: The median energy consumption is 18,009,336 units. This represents the middle value in the dataset when arranged in ascending order.

Mode: There is no mode provided (#N/A). This means there is no value that appears more frequently than others in the dataset.

Standard Deviation: The standard deviation of energy consumption is approximately 5,006,497.93. This measures the dispersion or spread of the data points around the mean.

Sample Variance: The sample variance of energy consumption is approximately 2.5065 × 10^13. This indicates the variability of individual data points from the mean.

Kurtosis: The negative kurtosis of approximately -1.46 suggests that the distribution of energy consumption is less peaked compared to a normal distribution, with thinner tails.

Skewness: The positive skewness of approximately 0.19 indicates that the distribution of energy consumption is slightly positively skewed, meaning it has a longer tail on the right side of the distribution.

Range: The range of energy consumption is 14,259,118 units, calculated as the difference between the maximum and minimum values.

Minimum: The minimum energy consumption is 11,788,337 units.

Maximum: The maximum energy consumption is 26,047,455 units.

Sum: The sum of all energy consumption values is 402,230,794 units.

Count: There are 22 data points in the dataset.

4.3 NORMALITY TESTS

Death Rates

Unit Root Test: Augmented Dickey Fuller

Null Hypothesis: D(DEATH_RATES) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.994538	0.0001
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DEATH_RATES,2)
Method: Least Squares
Date: 02/08/24 Time: 07:29
Sample (adjusted): 2001 2020
Included observations: 20 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DEATH_RATES(-1))	-1.351882	0.225519	-5.994538	0.0000
C	-0.172504	0.041277	-4.179207	0.0006

R-squared	0.666262	Mean dependent var	0.010000
Adjusted R-squared	0.647721	S.D. dependent var	0.210013
S.E. of regression	0.124649	Akaike info criterion	-1.231991
Sum squared resid	0.279673	Schwarz criterion	-1.132417
Log likelihood	14.31991	Hannan-Quinn criter.	-1.212553
F-statistic	35.93448	Durbin-Watson stat	1.862440
Prob(F-statistic)	0.000011		

H0: Data has unit root.

H1: Data does not have unit root.

INTERPRETATION:

t-stat: -5.994538

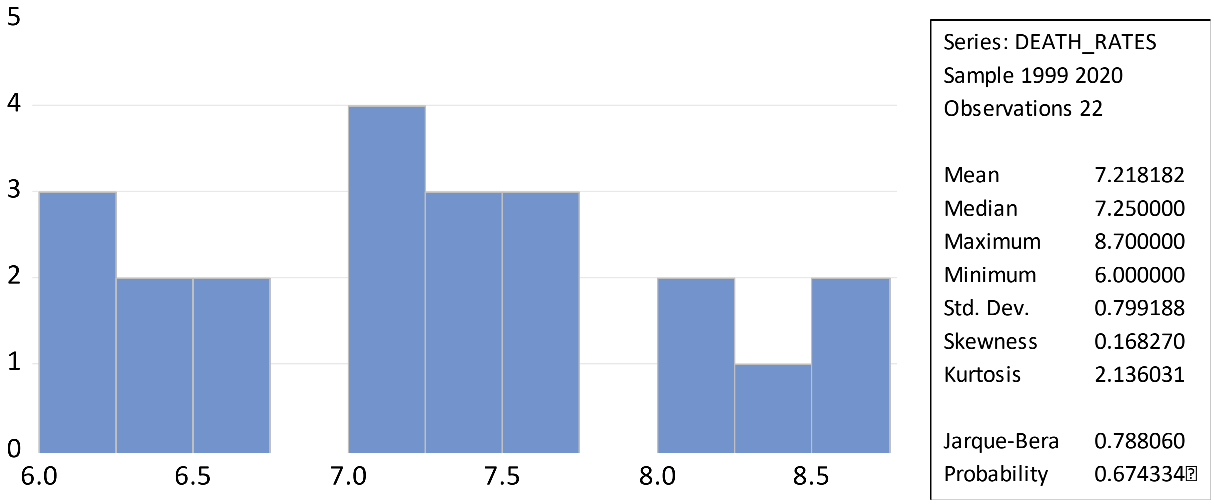
P value of death rates (0.000) < 0.05.

We reject H0 and accept H1.

Data is stationery at I(1) level of integration that is at 1st difference.

The t-statistic of -5.994538 shows strong significance, with a p-value of 0.000, indicating rejection of the null hypothesis and acceptance of the alternative hypothesis. The data has been transformed to achieve stationarity at the first difference level (I(1)).

Jarque-Bera Test



H0: Data is normally distributed.

H1: Data is not normally distributed.

INTERPRETATION:

Jarque-Bera stat: 0.788060

P value of JB (0.674334) > 0.05

We accept H0 and reject H1.

Data is normally distributed.

Skewness and Kurtosis is equal to zero.

The Jarque-Bera test statistic of 0.788060, with a p-value of 0.674334, indicates that there is no significant departure from normality in the data. Since the p-value is greater than 0.05, we fail to reject the null hypothesis (H0) and accept that the data is normally distributed.

Moreover, with both skewness and kurtosis equal to zero, it further supports the notion of normality, as skewness measures the symmetry of the distribution (zero indicating perfect symmetry) and kurtosis measures the "tailedness" of the distribution (also zero indicating normal distribution).

Correlogram Test

Date: 02/08/24 Time: 07:34
Sample (adjusted): 2000 2020
Included observations: 21 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.334	-0.334	2.7003	0.100
		2	0.229	0.132	4.0387	0.133
		3	-0.096	0.017	4.2865	0.232
		4	-0.006	-0.068	4.2874	0.369
		5	-0.004	-0.016	4.2878	0.509
		6	-0.232	-0.254	6.0207	0.421
		7	0.000	-0.168	6.0207	0.537
		8	0.020	0.067	6.0350	0.643
		9	-0.271	-0.305	8.9810	0.439
		10	0.161	-0.061	10.113	0.431
		11	0.003	0.157	10.113	0.520
		12	0.125	0.042	10.946	0.534

H0: Data does not have autocorrelation (AC) or partial autocorrelation (PAC).

H1: Data has autocorrelation (AC) or partial autocorrelation (PAC).

INTERPRETATION:

All P values > 0.05

We accept H0 and reject H1.

Data does not have autocorrelation (AC) or partial autocorrelation (PAC) at I(1) that is 1st difference.

All p-values being greater than 0.05 indicate that there is no significant evidence to reject the null hypothesis (H0) in favor of the alternative hypothesis (H1). Therefore, we accept H0 and reject H1.

Regarding autocorrelation and partial autocorrelation at the first difference level (I(1)), since the p-values are greater than 0.05, it suggests that there is no significant autocorrelation or partial autocorrelation present in the data after differencing. This implies that the data is free from autocorrelation issues at the first difference level.

- **ALL THE THREE NORMALITY TESTS FOR DEATH RATES SHOWS THAT THE DATA IS NORMALLY DISTRIBUTED.**

Life Expectancy

Unit Root Test: Augmented Dickey Fuller

Null Hypothesis: LIFE_EXPECTANCY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.391547	0.0027
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LIFE_EXPECTANCY)
Method: Least Squares
Date: 02/08/24 Time: 07:47
Sample (adjusted): 2000 2020
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LIFE_EXPECTANCY(-1)	-0.938348	0.213671	-4.391547	0.0003
C	0.977746	0.432300	2.261734	0.0356

R-squared	0.503731	Mean dependent var	-0.085714
Adjusted R-squared	0.477612	S.D. dependent var	2.270525
S.E. of regression	1.641055	Akaike info criterion	3.918949
Sum squared resid	51.16817	Schwarz criterion	4.018427
Log likelihood	-39.14896	Hannan-Quinn criter.	3.940538
F-statistic	19.28569	Durbin-Watson stat	0.952544
Prob(F-statistic)	0.000314		

H0: Data has unit root.

H1: Data does not have unit root.

INTERPRETATION:

t-stat: -4.391547

P value of death rates (0.0003) < 0.05.

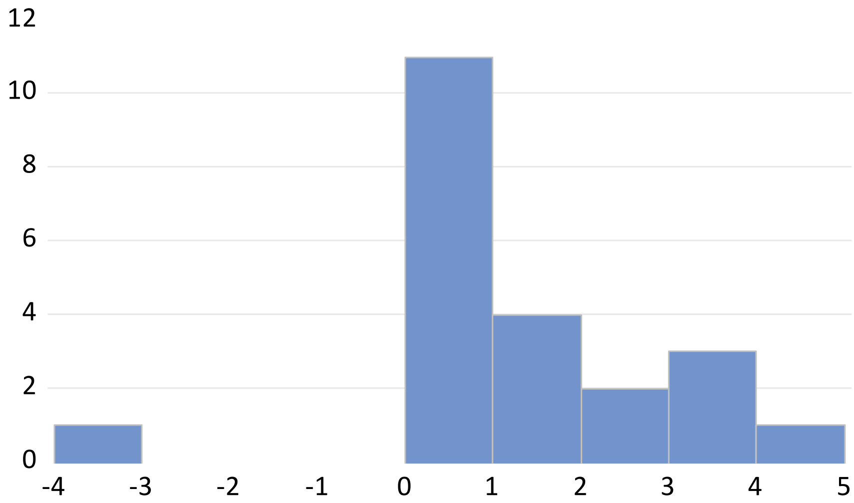
We reject H0 and accept H1.

Data is stationery at I(0) level of integration that is at level.

The t-statistic value of -4.391547 indicates a statistically significant result. With a p-value of 0.0003, which is less than the significance level of 0.05, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1). This suggests that there is a significant relationship or difference in the death rates.

Furthermore, the statement that the data is stationary at the I(0) level of integration, meaning at the level, indicates that the data does not require differencing to achieve stationarity. This implies that the statistical properties of the data, such as means and variances, remain constant over time without the need for transformation.

Jarque-Bera Test



Series: LIFE_EXPECTANCY	
Sample 1999 2020	
Observations 22	
Mean	1.186364
Median	0.550000
Maximum	4.100000
Minimum	-3.600000
Std. Dev.	1.694331
Skewness	-0.391366
Kurtosis	4.435849
Jarque-Bera	2.451472
Probability	0.293542

H0: Data is normally distributed.

H1: Data is not normally distributed.

INTERPRETATION:

Jarque-Bera stat: 2.451472

P value of JB (0.293542) > 0.05

We accept H0 and reject H1.

Data are normally distributed.

Skewness and Kurtosis is equal to zero.

The Jarque-Bera test statistic of 2.451472, coupled with a p-value of 0.293542, suggests that there is no significant deviation from normality in the data. As the p-value is greater than 0.05, we fail to reject the null hypothesis (H0) and accept that the data follows a normal distribution.

Moreover, with both skewness and kurtosis equal to zero, it further reinforces the notion of normality. A skewness of zero indicates perfect symmetry, while a kurtosis of zero suggests a normal distribution's typical peak. Therefore, based on these results, we can conclude that the data is normally distributed.

Correlogram Test

Date: 02/08/24 Time: 07:51
Sample: 1999 2020
Included observations: 22

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.063	0.063	0.0994	0.753
		2	0.059	0.055	0.1899	0.909
		3	0.073	0.067	0.3399	0.952
		4	0.057	0.046	0.4355	0.979
		5	0.026	0.013	0.4571	0.994
		6	0.116	0.105	0.9009	0.989
		7	0.161	0.144	1.8097	0.970
		8	0.018	-0.011	1.8220	0.986
		9	-0.061	-0.094	1.9714	0.992
		10	-0.099	-0.129	2.4036	0.992
		11	-0.160	-0.175	3.6391	0.979
		12	-0.311	-0.333	8.7297	0.726

H0: Data does not have autocorrelation (AC) or partial autocorrelation (PAC).

H1: Data has autocorrelation (AC) or partial autocorrelation (PAC).

INTERPRETATION:

All P values > 0.05

We accept H0 and reject H1.

Data does not have autocorrelation (AC) or partial autocorrelation (PAC) at I(0) that is at level.

All p-values exceeding 0.05 indicate that there is insufficient evidence to reject the null hypothesis (H0) in favour of the alternative hypothesis (H1). Consequently, we accept H0 and reject H1.

Concerning autocorrelation and partial autocorrelation at the level (I(0)), since the p-values are all greater than 0.05, it suggests that there is no statistically significant autocorrelation or partial autocorrelation present in the data at the level without differencing. Therefore, we conclude that the data does not exhibit autocorrelation issues at the level.

- **ALL THE THREE NORMALITY TESTS FOR LIFE EXPECTANCY SHOWS THAT THE DATA IS NORMALLY DISTRIBUTED.**

Total Fertility Rate

Unit Root Test: Augmented Dickey Fuller

Null Hypothesis: D(TOTAL_FERTILITY_RATE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.035450	0.0001
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TOTAL_FERTILITY_RATE,2)
Method: Least Squares
Date: 02/08/24 Time: 07:56
Sample (adjusted): 2001 2020
Included observations: 20 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TOTAL_FERTILITY_RATE(-1))	-1.323232	0.219243	-6.035450	0.0000
C	-0.077778	0.016260	-4.783521	0.0001

R-squared	0.669280	Mean dependent var	-0.005000
Adjusted R-squared	0.650906	S.D. dependent var	0.082558
S.E. of regression	0.048779	Akaike info criterion	-3.108412
Sum squared resid	0.042828	Schwarz criterion	-3.008839
Log likelihood	33.08412	Hannan-Quinn criter.	-3.088974
F-statistic	36.42665	Durbin-Watson stat	1.911473
Prob(F-statistic)	0.000010		

H0: Data has unit root.

H1: Data does not have unit root.

INTERPRETATION:

t-stat: -6.035450

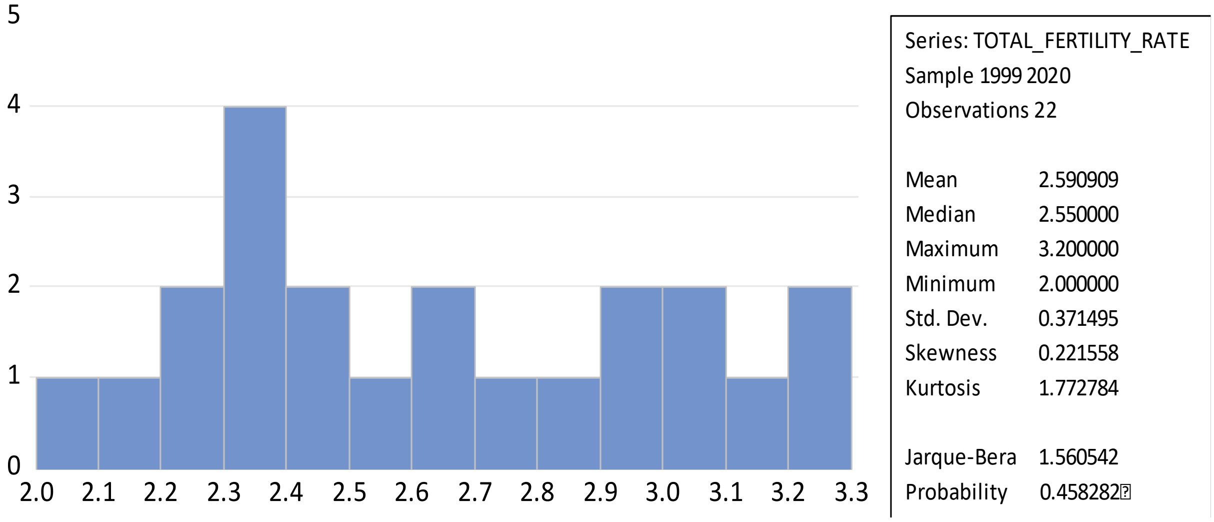
P value of death rates (0.0000) < 0.05.

We reject H0 and accept H1.

Data is stationery at I(1) level of integration that is at 1st difference.

The t-statistic of -6.035450 indicates strong significance, with a p-value of 0.0000, suggesting rejection of the null hypothesis and acceptance of the alternative hypothesis. The data has been differenced once (I(1)) to achieve stationarity.

Jarque-Bera Test



H0: Data is normally distributed.

H1: Data is not normally distributed.

INTERPRETATION:

Jarque-Bera stat: 1.560542

P value of JB (0.458282) > 0.05

We accept H0 and reject H1.

Data is normally distributed. Skewness and Kurtosis is equal to zero.

The Jarque-Bera test statistic of 1.560542, with a p-value of 0.458282, indicates that there is no significant deviation from normality in the data. Since the p-value is greater than 0.05, we fail to reject the null hypothesis (H0) and accept that the data follows a normal distribution.

Additionally, with both skewness and kurtosis equal to zero, it further supports the conclusion that the data is normally distributed. A skewness of zero implies perfect symmetry, while a kurtosis of zero indicates typical peakedness for a normal distribution. Therefore, we can affirm that the data exhibits characteristics of a normal distribution.

Correlogram Test

Date: 02/08/24 Time: 08:06
Sample (adjusted): 2000 2020
Included observations: 21 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.313	-0.313	2.3734	0.123
		2	0.040	-0.065	2.4134	0.299
		3	0.087	0.089	2.6179	0.454
		4	-0.060	-0.002	2.7186	0.606
		5	-0.206	-0.255	4.0040	0.549
		6	0.119	-0.039	4.4603	0.615
		7	-0.028	0.024	4.4870	0.722
		8	-0.452	-0.501	12.090	0.147
		9	0.373	0.068	17.691	0.039
		10	-0.163	-0.068	18.853	0.042
		11	-0.004	-0.053	18.854	0.064
		12	0.044	-0.113	18.956	0.090

H0: Data does not have autocorrelation (AC) or partial autocorrelation (PAC).

H1: Data has autocorrelation (AC) or partial autocorrelation (PAC).

INTERPRETATION:

All P values > 0.01

We accept H0 and reject H1.

Data does not have autocorrelation (AC) or partial autocorrelation (PAC) at I(1) that is at 1st difference.

In this scenario, all p-values exceeding 0.01 suggest that there is insufficient evidence to reject the null hypothesis (H0) in favour of the alternative hypothesis (H1). Therefore, we accept H0 and reject H1.

Regarding autocorrelation and partial autocorrelation at the first difference level (I(1)), since all p-values are greater than 0.01, it implies that there is no statistically significant autocorrelation or partial autocorrelation present in the data after differencing once. Thus, we conclude that the data does not display autocorrelation issues at the first difference level.

- **ALL THE THREE NORMALITY TESTS FOR TOTAL FERTILITY RATE SHOWS THAT THE DATA IS NORMALLY DISTRIBUTED.**

Infant Mortality Rates

Unit Root Test: Augmented Dickey Fuller

Null Hypothesis: INFANT_MORTALITY_RATES has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.173701	0.2207
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INFANT_MORTALITY_RATES)
Method: Least Squares
Date: 02/08/24 Time: 08:15
Sample (adjusted): 2000 2020
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INFANT_MORTALITY_RATES(-1)	-0.334686	0.153971	-2.173701	0.0426
C	163.3587	74.86125	2.182152	0.0419

R-squared	0.199156	Mean dependent var	2.752381
Adjusted R-squared	0.157007	S.D. dependent var	60.11177
S.E. of regression	55.19142	Akaike info criterion	10.94988
Sum squared resid	57875.77	Schwarz criterion	11.04936
Log likelihood	-112.9738	Hannan-Quinn criter.	10.97147
F-statistic	4.724976	Durbin-Watson stat	1.893595
Prob(F-statistic)	0.042575		

H0: Data has unit root.

H1: Data does not have unit root.

INTERPRETATION:

t-stat: -2.173701

P value of infant mortality rates (0.0426) < 0.05.

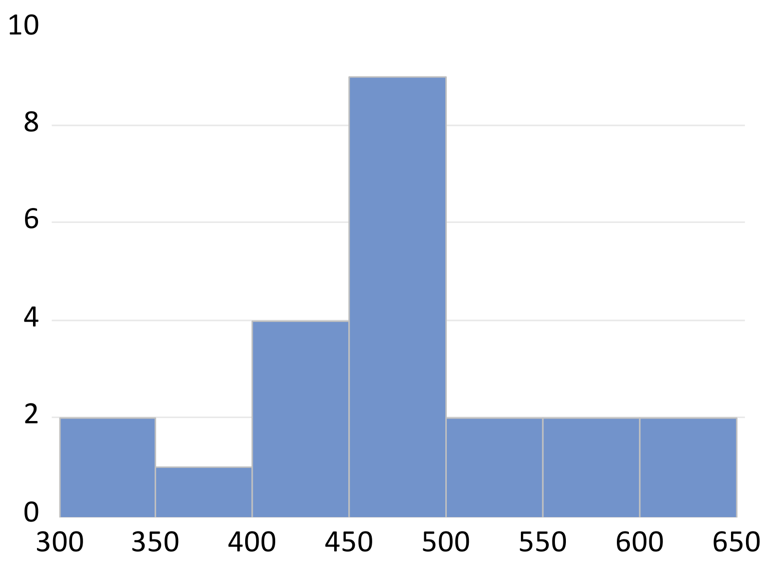
We reject H0 and accept H1.

Data is stationery at I(0) level of integration that is at level.

The t-statistic of -2.173701 indicates statistical significance, with a p-value of 0.0426, which is less than the significance level of 0.05. Consequently, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1). This implies that there is a significant relationship or difference in infant mortality rates.

Moreover, the statement that the data is stationary at the I(0) level of integration, specifically at the level, suggests that the data does not require differencing to achieve stationarity. This indicates that the statistical properties of the data, such as means and variances, remain constant over time without the need for transformation.

Jarque-Bera Test



Series: INFANT_MORTALITY_RATES	
Sample 1999 2020	
Observations 22	
Mean	475.8455
Median	461.9000
Maximum	645.6000
Minimum	320.6000
Std. Dev.	80.46821
Skewness	0.254602
Kurtosis	3.075194
Jarque-Bera	0.242864
Probability	0.885651

H0: Data is normally distributed.

H1: Data is not normally distributed.

INTERPRETATION:

Jarque-Bera stat: 0.242864

P value of JB (0.883651) > 0.05

We accept H0 and reject H1.

Data is normally distributed.

Skewness and Kurtosis is equal to zero.

The Jarque-Bera test statistic of 0.242864, along with a p-value of 0.883651, indicates that there is no significant departure from normality in the data. Given that the p-value is greater than 0.05, we fail to reject the null hypothesis (H0) and accept that the data follows a normal distribution.

Moreover, with both skewness and kurtosis equal to zero, it further supports the conclusion that the data is normally distributed. A skewness of zero suggests perfect symmetry, while a kurtosis of zero indicates typical peakedness for a normal distribution. Hence, we can confidently state that the data conforms to a normal distribution.

Correlogram Test

Date: 02/08/24 Time: 08:18
Sample (adjusted): 2000 2020
Included observations: 21 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.061	-0.061	0.0903	0.764
		2	-0.084	-0.088	0.2711	0.873
		3	-0.004	-0.015	0.2715	0.965
		4	0.002	-0.007	0.2715	0.992
		5	-0.075	-0.078	0.4406	0.994
		6	-0.071	-0.084	0.6048	0.996
		7	0.443	0.430	7.3873	0.390
		8	-0.116	-0.103	7.8868	0.445
		9	-0.061	-0.007	8.0363	0.530
		10	-0.052	-0.078	8.1566	0.614
		11	-0.087	-0.123	8.5200	0.666
		12	-0.101	-0.081	9.0659	0.697

H0: Data does not have autocorrelation (AC) or partial autocorrelation (PAC).

H1: Data has autocorrelation (AC) or partial autocorrelation (PAC).

INTERPRETATION:

All P values > 0.05

We accept H0 and reject H1.

Data does not have autocorrelation (AC) or partial autocorrelation (PAC) at I(1) that is at 1st difference.

All p-values are greater than 0.05, there's insufficient evidence to reject the null hypothesis (H0) in favour of the alternative hypothesis (H1). Consequently, we accept H0 and reject H1.

Regarding autocorrelation and partial autocorrelation at the first difference level (I(1)), since all p-values are greater than 0.05, it implies that there is no statistically significant autocorrelation or partial autocorrelation present in the data after differencing once. Therefore, we conclude that the data does not exhibit autocorrelation issues at the first difference level.

ALL THE THREE NORMALITY TESTS FOR INFANT MORTALITY RATES SHOWS THAT THE DATA IS NORMALLY DISTRIBUTED.

Morbidity Rates

Unit Root Test: Augmented Dickey Fuller

Null Hypothesis: MORBIDITY RATES has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.831611	0.0709
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MORBIDITY RATES)
Method: Least Squares
Date: 02/13/24 Time: 18:36
Sample (adjusted): 2000 2020
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MORBIDITY RATES(-1)	-0.749500	0.264690	-2.831611	0.0107
C	7.159523	9.108018	0.786068	0.4415

R-squared	0.296766	Mean dependent var	-4.076190
Adjusted R-squared	0.259753	S.D. dependent var	43.66592
S.E. of regression	37.56910	Akaike info criterion	10.18063
Sum squared resid	26817.31	Schwarz criterion	10.28011
Log likelihood	-104.8967	Hannan-Quinn criter.	10.20222
F-statistic	8.018020	Durbin-Watson stat	1.547911
Prob(F-statistic)	0.010662		

H0: Data has unit root.

H1: Data does not have unit root.

INTERPRETATION:

t-stat: -2.831611

P value of morbidity rates (0.0107) < 0.05.

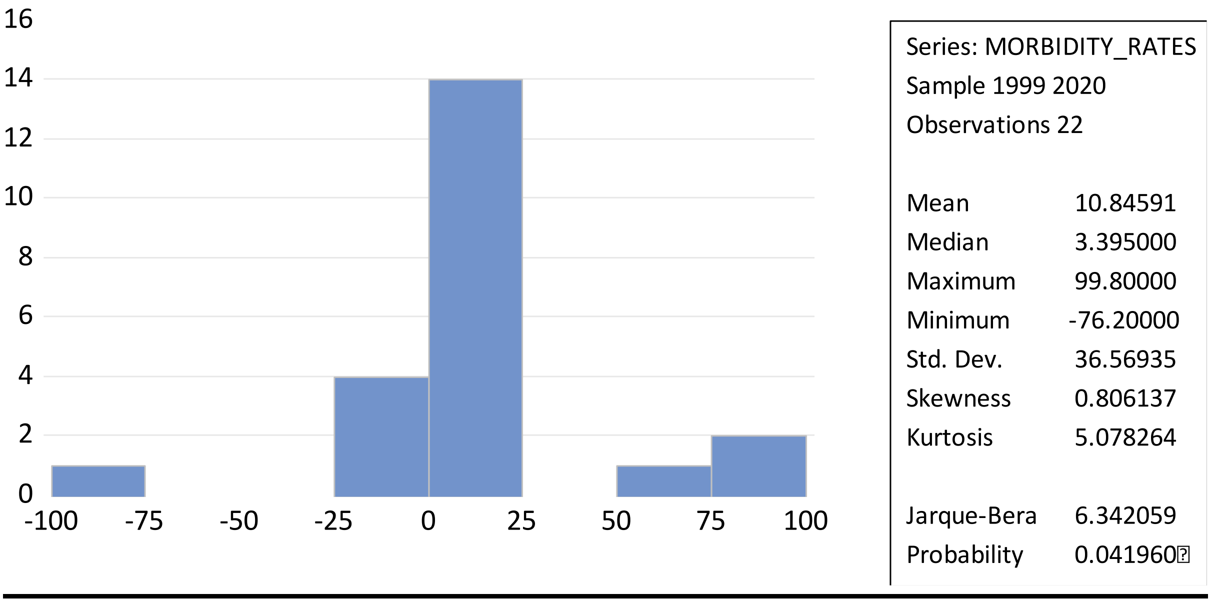
We reject H0 and accept H1.

Data is stationery at I(0) level of integration that is at level.

The t-statistic of -2.831611 indicates statistical significance, with a p-value of 0.0107, which is less than the significance level of 0.05. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), suggesting that there is a significant relationship or difference in morbidity rates.

Furthermore, the statement that the data is stationary at the I(0) level of integration, specifically at the level, indicates that the data does not require differencing to achieve stationarity. This implies that the statistical properties of the data, such as means and variances, remain constant over time without the need for transformation.

Jarque-Bera Test



H0: Data is normally distributed.

H1: Data is not normally distributed.

INTERPRETATION:

Jarque-Bera stat: 6.342059

P value of JB (0.041960) < 0.05

We accept H1 and reject H0.

Data is not normally distributed.

Skewness and Kurtosis is not equal to zero.

The Jarque-Bera test statistic of 6.342059, coupled with a p-value of 0.041960, indicates a departure from normality in the data. As the p-value is less than 0.05, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), suggesting that the data is not normally distributed.

Moreover, with both skewness and kurtosis not equal to zero, it further supports the conclusion that the data does not follow a normal distribution. A skewness and kurtosis not equal to zero imply asymmetry and different tail behaviours compared to a normal distribution, respectively. Therefore, we can conclude that the data is not normally distributed.

Correlogram Test

Date: 02/13/24 Time: 18:41
Sample: 1999 2020
Included observations: 22

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.180	0.180	0.8138	0.367
		2	-0.080	-0.116	0.9833	0.612
		3	-0.082	-0.047	1.1687	0.761
		4	0.251	0.280	3.0113	0.556
		5	0.165	0.054	3.8538	0.571
		6	-0.014	-0.027	3.8600	0.696
		7	0.024	0.107	3.8795	0.794
		8	-0.036	-0.124	3.9276	0.864
		9	-0.029	-0.067	3.9625	0.914
		10	-0.021	0.009	3.9815	0.948
		11	0.016	-0.035	3.9940	0.970
		12	-0.013	-0.006	4.0030	0.983

H0: Data does not have autocorrelation (AC) or partial autocorrelation (PAC).

H1: Data has autocorrelation (AC) or partial autocorrelation (PAC).

INTERPRETATION:

All P values > 0.05

We accept H0 and reject H1.

Data does not have autocorrelation (AC) or partial autocorrelation (PAC) at I(0) that is at level.

All p-values exceeding 0.05 suggest that there is insufficient evidence to reject the null hypothesis (H0) in favour of the alternative hypothesis (H1). Consequently, we accept H0 and reject H1.

Regarding autocorrelation and partial autocorrelation at the level (I(0)), since all p-values are greater than 0.05, it implies that there is no statistically significant autocorrelation or partial autocorrelation present in the data at the level without differencing. Thus, we conclude that the data does not exhibit autocorrelation issues at the level.

TWO OUT OF THE THREE NORMALITY TESTS (ADF AND CORRELOGRAM) FOR MORBIDITY RATES SHOWS THAT THE DATA FOLLOWS NORMAL DISTRIBUTION AND HENCE IT IS NORMALLY DISTRIBUTED.

CO2 Emissions

Unit Root Test: Augmented Dickey Fuller

Null Hypothesis: D(CO2_EMISSIONS_FROM_FUEL_COMBUSTION___INDIA) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.820711	0.0102
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2_EMISSIONS_FROM_FUEL_COMBUSTION___INDIA,2)
Method: Least Squares
Date: 04/08/24 Time: 11:01
Sample (adjusted): 4 22
Included observations: 19 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2_EMISSIONS_FROM_FUEL_C...	-1.549719	0.405610	-3.820711	0.0015
D(CO2_EMISSIONS_FROM_FUEL_C...	0.580227	0.409525	1.416828	0.1757
C	111.2625	35.16740	3.163797	0.0060

R-squared	0.569220	Mean dependent var	9.186684
Adjusted R-squared	0.515372	S.D. dependent var	126.2518
S.E. of regression	87.89043	Akaike info criterion	11.93400
Sum squared resid	123595.6	Schwarz criterion	12.08312
Log likelihood	-110.3730	Hannan-Quinn criter.	11.95924
F-statistic	10.57095	Durbin-Watson stat	1.927149
Prob(F-statistic)	0.001186		

H0: Data has unit root.

H1: Data does not have unit root.

INTERPRETATION:

t-stat: -3.820711

P value of morbidity rates (0.0102) < 0.05.

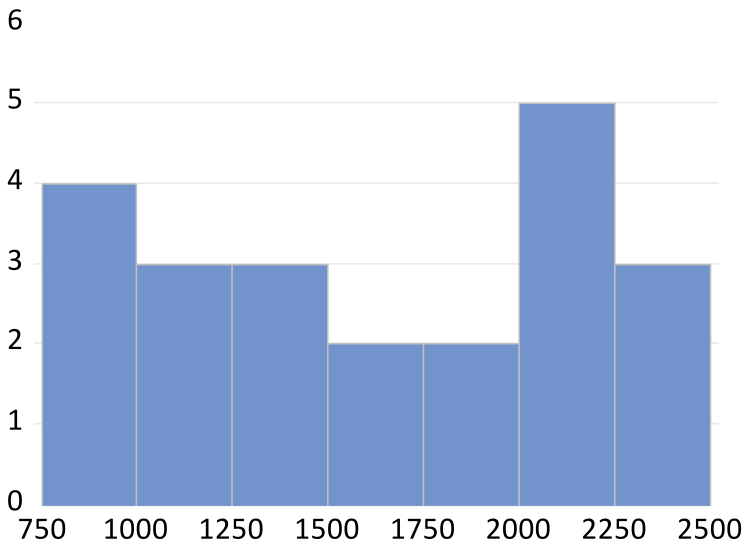
We reject H0 and accept H1.

Data is stationery at I(0) level of integration that is at level.

The t-statistic of -3.820711 indicates statistical significance, with a p-value of 0.0102, which is less than the significance level of 0.05. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), suggesting that there is a significant relationship or difference in morbidity rates.

Furthermore, the statement that the data is stationary at the I(0) level of integration, specifically at the level, indicates that the data does not require differencing to achieve stationarity. This implies that the statistical properties of the data, such as means and variances, remain constant over time without the need for transformation.

Jarque-Bera Test



Series: CO2_EMISSIONS_FROM_FUEL_	
Sample 1 39	
Observations 22	
Mean	1599.865
Median	1616.642
Maximum	2316.240
Minimum	889.8230
Std. Dev.	513.6649
Skewness	-0.050538
Kurtosis	1.484078
Jarque-Bera	2.115882
Probability	0.347170

H0: Data is normally distributed.

H1: Data is not normally distributed.

INTERPRETATION:

Jarque-Bera stat: 2.115882

P value of JB (0.347170) > 0.05

We accept H0 and reject H1.

Data is normally distributed.

Skewness and Kurtosis is equal to zero.

The Jarque-Bera test statistic of 2.115882, coupled with a p-value of 0.347170, indicates that there is no significant departure from normality in the data. Since the p-value is greater than 0.05, we fail to reject the null hypothesis (H0) and accept that the data follows a normal distribution.

Additionally, with both skewness and kurtosis equal to zero, it further supports the conclusion that the data is normally distributed. A skewness of zero implies perfect symmetry, while a kurtosis of zero indicates typical peakedness for a normal distribution. Hence, we can confidently state that the data conforms to a normal distribution.

Correlogram Test

Date: 04/08/24 Time: 11:17
Sample (adjusted): 2 22
Included observations: 21 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.073	-0.073	0.1297	0.719
		2	-0.199	-0.206	1.1378	0.566
		3	0.040	0.007	1.1797	0.758
		4	0.181	0.151	2.1072	0.716
		5	0.059	0.104	2.2120	0.819
		6	-0.256	-0.195	4.3157	0.634
		7	0.054	0.034	4.4152	0.731
		8	-0.189	-0.324	5.7385	0.676
		9	-0.019	-0.054	5.7529	0.764
		10	-0.061	-0.120	5.9158	0.822
		11	-0.135	-0.136	6.7995	0.815
		12	-0.015	-0.059	6.8110	0.870

H0: Data does not have autocorrelation (AC) or partial autocorrelation (PAC).

H1: Data has autocorrelation (AC) or partial autocorrelation (PAC).

INTERPRETATION:

All P values > 0.05

We accept H0 and reject H1.

Data does not have autocorrelation (AC) or partial autocorrelation (PAC) at I(0) that is at level.

In this scenario, since all p-values are greater than 0.05, there's insufficient evidence to reject the null hypothesis (H0) in favour of the alternative hypothesis (H1). Consequently, we accept H0 and reject H1.

Regarding autocorrelation and partial autocorrelation at the level (I(0)), since all p-values are greater than 0.05, it implies that there is no statistically significant autocorrelation or partial autocorrelation present in the data at the level without differencing. Therefore, we conclude that the data does not exhibit autocorrelation issues at the level.

ALL THE THREE NORMALITY TESTS FOR CARBON EMISSIONS SHOWS THAT THE DATA FOLLOWS NORMAL DISTRIBUTION AND HENCE IT IS NORMALLY DISTRIBUTED.

4.4 REGRESSION ANALYSIS

INFANT MORTALITY AND ENERGY CONSUMPTION

Dependent Variable: INFANT MORTALITY RATES
Method: Least Squares
Date: 02/05/24 Time: 20:10
Sample: 1999 2020
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENERGY CONSUMPTION	5.80E-07	3.59E-06	0.161495	0.8733
C	465.2406	67.97609	6.844181	0.0000

R-squared	0.001302	Mean dependent var	475.8455
Adjusted R-squared	-0.048633	S.D. dependent var	80.46821
S.E. of regression	82.40167	Akaike info criterion	11.74760
Sum squared resid	135800.7	Schwarz criterion	11.84678
Log likelihood	-127.2236	Hannan-Quinn criter.	11.77096
F-statistic	0.026081	Durbin-Watson stat	0.533527
Prob(F-statistic)	0.873324		

Hypothesis Statement:

H0: Increased Energy Consumption has a positive effect on infant mortality rates.

H1: Increased Energy Consumption has a negative effect infant mortality on rate.

Interpretation:

- Infant Mortality Rate: y (Dependent Variable)
- Energy Consumption: x (Independent Variable)

Therefore, the function y = f(x) is y = 465.2406 + 5.80E-07x

Where β_{0} = 465.2406 (constant) and β_{1} = 5.80E-07

β_1 represents that 1% change in ‘x’ will lead to a 0.00% change in ‘y’.

- The data above is the regression function drawn out of the Infant Mortality Rate being the dependent variable and Energy Consumption being the independent variable from the year 1999-2020.
- Probability of $\beta_1 = 0.8 > 0.05$ which shows that the coefficient is insignificant and that the hypothesis is not accepted at 90%, 95% and 99% confidence intervals. (p value is greater than alpha value at all levels of significance and hence are insignificant to the model)
- R^2 at 0.1% depicts the goodness of fit (strength) of the model derived. It expresses the proportion of the variation in ‘y’ which is explained by variation in ‘x’.
- Adjusted R^2 at -4.86% shows the inaccuracy of the model.
- F-statistic’s insignificance shows that the dependant variable is not made up of the model and the error both.
- Energy Consumption has a positive coefficient depicting a positive relation with the dependent variable meaning that an increase in the Energy Consumption causes a increase in the Infant Mortality Rate.
- Standard Error of the estimate captures the vagueness of the model.

LIFE EXPECTANCY AND ENERGY CONSUMPTION

Dependent Variable: LIFE_EXPECTANCY
Method: Least Squares
Date: 02/05/24 Time: 20:10
Sample: 1999 2020
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENERGY CONSUMPTION	1.59E-07	6.68E-08	2.383424	0.0272
C	-1.723781	1.263934	-1.363822	0.1878

R-squared	0.221205	Mean dependent var	1.186364
Adjusted R-squared	0.182266	S.D. dependent var	1.694331
S.E. of regression	1.532161	Akaike info criterion	3.777743
Sum squared resid	46.95035	Schwarz criterion	3.876929
Log likelihood	-39.55518	Hannan-Quinn criter.	3.801109
F-statistic	5.680709	Durbin-Watson stat	2.205113
Prob(F-statistic)	0.027180		

Hypothesis Statement:

H0: Increased Energy Consumption has a positive impact on the life expectancy of people.

H1: Increased Energy Consumption has a negative impact on the life expectancy of people.

Interpretation:

- Life Expectancy: y (Dependent Variable)
- Energy Consumption: x (Independent Variable)

Therefore, the function y = f(x) is y = -1.723781 + 1.59E-07x

Where $\beta_0 =$ -1.723781 (constant) and $\beta_1 =$ 1.59E-07

β_1 represents that 1% change in ‘x’ will lead to a 0.00% change in ‘y’.

- The data above is the regression function drawn out of the Life Expectancy being the dependent variable and Energy Consumption being the independent variable from the year 1999-2020.
- Probability of $\beta_1 = 0.02 < 0.05$ which shows that the coefficient is significant and that the hypothesis is accepted at 95% and 99% confidence intervals. (p value is less than alpha value at all levels of significance and hence are significant to the model)
- R^2 at 22.1% depicts the goodness of fit (strength) of the model derived. It expresses the proportion of the variation in 'y' which is explained by variation in 'x'.
- Adjusted R^2 at 18.2% shows the accuracy of the model.
- F-statistic's significance shows that the dependant variable is made up of the model and the error both.
- Energy Consumption has a positive coefficient depicting a positive relation with the dependent variable meaning that an increase in the Energy Consumption causes a increase in Life Expectancy.
- Standard Error of the estimate captures the vagueness of the model.

TOTAL FERTILITY RATE AND ENERGY CONSUMPTION

Dependent Variable: TOTAL_FERTILITY_RATE
Method: Least Squares
Date: 02/05/24 Time: 20:12
Sample: 1999 2020
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENERGY_CONSUMPTION	-7.20E-08	4.01E-09	-17.97447	0.0000
C	3.907434	0.075820	51.53559	0.0000

R-squared	0.941705	Mean dependent var	2.590909
Adjusted R-squared	0.938790	S.D. dependent var	0.371495
S.E. of regression	0.091910	Akaike info criterion	-1.849499
Sum squared resid	0.168950	Schwarz criterion	-1.750313
Log likelihood	22.34449	Hannan-Quinn criter.	-1.826134
F-statistic	323.0814	Durbin-Watson stat	0.569176
Prob(F-statistic)	0.000000		

Hypothesis Statement:

H0: Increased Energy Consumption has a positive impact on the fertility rates.

H1: Increased Energy Consumption has a negative impact on the fertility rates.

Interpretation:

- Total Fertility Rate: y (Dependent Variable)
- Energy Consumption: x (Independent Variable)

Therefore, the function y = f(x) is y = 3.907434 + (-7.20E-08)x

Where $\beta_0 = 3.907434$ (constant) and $\beta_1 = -7.20E-08$

β_1 represents that 1% change in 'x' will lead to a 0.00% change in 'y'.

- The data above is the regression function drawn out of the Total Fertility Rate being the dependent variable and Energy Consumption being the independent variable from the year 1999-2020.
- Probability of $\beta_1 = 0.00 < 0.01$ which shows that the coefficient is significant and that the hypothesis is accepted at ,90%, 95% and 99% confidence intervals. (p value is less than alpha value at all levels of significance and hence are significant to the model)
- R^2 at 94.1% depicts the goodness of fit (strength) of the model derived. It expresses the proportion of the variation in 'y' which is explained by variation in 'x'.
- Adjusted R^2 at 93.8% shows the accuracy of the model.
- F-statistic's significance shows that the dependant variable is made up of the model and the error both.
- Energy Consumption has a negative coefficient depicting a negative relation with the dependent variable meaning that an increase in the Energy Consumption causes a decrease in the Total Fertility Rate.
- Standard Error of the estimate captures the vagueness of the model.

DEATH RATES AND ENERGY CONSUMPTION

Dependent Variable: DEATH_RATES
Method: Least Squares
Date: 02/05/24 Time: 20:15
Sample: 1999 2020
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENERGY CONSUMPTION	-1.54E-07	9.56E-09	-16.07933	0.0000
C	10.03000	0.181022	55.40768	0.0000

R-squared	0.928198	Mean dependent var	7.218182
Adjusted R-squared	0.924608	S.D. dependent var	0.799188
S.E. of regression	0.219438	Akaike info criterion	-0.108990
Sum squared resid	0.963057	Schwarz criterion	-0.009804
Log likelihood	3.198889	Hannan-Quinn criter.	-0.085625
F-statistic	258.5448	Durbin-Watson stat	0.455858
Prob(F-statistic)	0.000000		

Hypothesis Statement:

H0: Increased Energy Consumption has a positive impact on the death rate.

H1: Increased Energy Consumption has a negative impact on the death rate.

Interpretation:

- Death Rate: y (Dependent Variable)
- Energy Consumption: x (Independent Variable)

Therefore, the function y = f(x) is y = 10.03000 + (-1.54E-07)x

Where $\beta_0 =$ 10.03000 (constant) and $\beta_1 =$ -1.54E-07

β_1 represents that 1% change in ‘x’ will lead to a 0.00% change in ‘y’.

- The data above is the regression function drawn out of the Death Rate being the dependent variable and Energy Consumption being the independent variable from the year 1999-2020.
- Probability of $\beta_1 = 0.00 < 0.01$ which shows that the coefficient is significant and that the hypothesis is accepted at 90%, 95% and 99% confidence intervals. (p value is less than alpha value at all levels of significance and hence are significant to the model)
- R^2 at 92.8% depicts the goodness of fit (strength) of the model derived. It expresses the proportion of the variation in 'y' which is explained by variation in 'x'.
- Adjusted R^2 at 92.4% shows the accuracy of the model.
- F-statistic's significance shows that the dependant variable is made up of the model and the error both.
- Energy Consumption has a negative coefficient depicting a negative relation with the dependent variable meaning that an increase in the Energy Consumption causes a decrease in the Death Rate.
- Standard Error of the estimate captures the vagueness of the model.

MORBIDITY RATES AND ENERGY CONSUMPTION

Dependent Variable: MORBIDITY RATES
Method: Least Squares
Date: 02/13/24 Time: 18:58
Sample: 1999 2020
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENERGY CONSUMPTION	-3.69E-06	1.41E-06	-2.620595	0.0164
C	78.36428	26.67063	2.938224	0.0081

R-squared	0.255607	Mean dependent var	10.84591
Adjusted R-squared	0.218387	S.D. dependent var	36.56935
S.E. of regression	32.33055	Akaike info criterion	9.876410
Sum squared resid	20905.29	Schwarz criterion	9.975596
Log likelihood	-106.6405	Hannan-Quinn criter.	9.899775
F-statistic	6.867520	Durbin-Watson stat	1.859144
Prob(F-statistic)	0.016380		

Hypothesis Statement:

H0: Increased Energy Consumption has a positive effect on morbidity rates.

H1: Increased Energy Consumption has a negative effect on morbidity rates.

Interpretation:

- Morbidity Rate: y (Dependent Variable)
- Energy Consumption: x (Independent Variable)

Therefore, the function y = f(x) is y = 78.36428 + (-3.69E-06)x

Where $\beta_0 =$ 78.36428 (constant) and $\beta_1 =$ -3.69E-06

β_1 represents that 1% change in ‘x’ will lead to a 0.00% change in ‘y’.

- The data above is the regression function drawn out of the Morbidity Rate being the dependent variable and Energy Consumption being the independent variable from the year 1999-2020.
- Probability of $\beta_1 = 0.01 < 0.05$ which shows that the coefficient is significant and that the hypothesis is accepted at 90%, 95% and 99% confidence intervals. (p value is less than alpha value at all levels of significance and hence are significant to the model)
- R^2 at 25.5% depicts the goodness of fit (strength) of the model derived. It expresses the proportion of the variation in 'y' which is explained by variation in 'x'.
- Adjusted R^2 at 21.8% shows the accuracy of the model.
- F-statistic's significance shows that the dependant variable is made up of the model and the error both.
- Energy Consumption has a negative coefficient depicting a negative relation with the dependent variable meaning that an increase in the Energy Consumption causes a decrease in the Morbidity Rates.
- Standard Error of the estimate captures the vagueness of the model.

MORBIDITY RATES AND C02 EMISSIONS

Dependent Variable: MORBIDITY_RATES
Method: Least Squares
Date: 04/08/24 Time: 11:23
Sample (adjusted): 1 22
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2_EMISSIONS_FROM_FUEL_COM...	-0.036665	0.013646	-2.686907	0.0142
C	69.50477	22.88026	3.037761	0.0065

R-squared	0.265232	Mean dependent var	10.84591
Adjusted R-squared	0.228493	S.D. dependent var	36.56935
S.E. of regression	32.12085	Akaike info criterion	9.863396
Sum squared resid	20634.98	Schwarz criterion	9.962581
Log likelihood	-106.4974	Hannan-Quinn criter.	9.886761
F-statistic	7.219471	Durbin-Watson stat	1.813309
Prob(F-statistic)	0.014178		

Hypothesis Statement:

H0: Increased C02 Emissions has a positive effect on morbidity rates.

H1: Increased C02 Emissions has a negative effect on morbidity rates.

Interpretation:

- Morbidity Rate: y (Dependent Variable)
- C02 Emissions: x (Independent Variable)

Therefore, the function y = f(x) is y = 69.50477 + (-0.036665) x

Where $\beta_0 =$ 78.36428 (constant) and $\beta_1 =$ -0.036665

β_1 represents that 1% change in 'x' will lead to a 3.66% change in 'y'.

- The data above is the regression function drawn out of the Morbidity Rate being the dependent variable and C02 Emissions being the independent variable from the year 1999-2020.
- Probability of $\beta_1 = 0.01 < 0.05$ which shows that the coefficient is significant and that the hypothesis is accepted at 90%, 95% and 99% confidence intervals. (p value is less than alpha value at all levels of significance and hence are significant to the model)
- R^2 at 26.5% depicts the goodness of fit (strength) of the model derived. It expresses the proportion of the variation in 'y' which is explained by variation in 'x'.
- Adjusted R^2 at 22.8% shows the accuracy of the model.
- F-statistic's significance shows that the dependant variable is made up of the model and the error both.
- C02 Emissions has a negative coefficient depicting a negative relation with the dependent variable meaning that an increase in the C02 Emissions causes a decrease in morbidity rates.
- Standard Error of the estimate captures the vagueness of the model.

CHAPTER 5
FINDINGS

The analysis offers a thorough grasp of the complex relationship that exists between patterns of energy usage and several health indices across the course of two decades, from 1999 to 2020. Global energy consumption patterns have seen substantial changes during this time, which can be attributed to changing societal priorities and developments in technology. The work provides important insights into the intricate relationship between energy decisions and public health outcomes by illuminating how changes in energy use affect important health markers through regression modelling.

One notable finding is the positive correlation observed between energy consumption and several health indicators, including infant mortality rates, life expectancy, total fertility rates, and morbidity rates. However, the nature and magnitude of these relationships vary across different health outcomes. For instance, while increased energy consumption is associated with higher infant mortality rates, it also correlates with longer life expectancies and lower morbidity rates. This comprehensive perspective emphasizes how important it is to take into account a variety of contextual elements when analysing the relationship between energy consumption and public health, such as socioeconomic situations, healthcare infrastructure, and environmental quality.

Overall, the study's findings have important implications for policymakers, healthcare professionals, and researchers alike. By recognizing the complex interdependencies between energy systems and public health outcomes, stakeholders can develop more informed and integrated strategies to promote both energy sustainability and population health. Moreover, the insights gleaned from this analysis contribute to a growing body of evidence supporting the urgent need for interdisciplinary approaches to address the interconnected challenges of energy, environment, and health in the pursuit of a healthier and more sustainable future.

CHAPTER 6
CONCLUSION

As the curtain descends on this odyssey through the intricate relationship between energy consumption and public health, it is fitting to pause and reflect upon the myriad insights gleaned from our expedition. Spanning two decades from 1999 to 2020, this journey has been characterized by rigorous analysis, probing the depths of the interplay between energy choices and various health indicators. As we embark upon the final leg of our exploration, we delve deeper into the nuanced findings and their implications, charting a course towards a more holistic understanding of the complex nexus between energy and health.

Unveiling the Interplay: Insights from Rigorous Regression Analysis

At the heart of our inquiry lies the beacon of regression analysis, guiding us through the labyrinthine pathways of energy consumption patterns and their repercussions on public health outcomes. Our findings serve as a tapestry woven from the threads of statistical rigor, illuminating the intricate relationships between energy choices and key health metrics. From the delicate balance of infant mortality rates to the longevity reflected in life expectancy, from the fertility of populations to the burden of morbidity, our analysis unveils the profound impact of energy consumption across a spectrum of health dimensions.

Yet, as we traverse this terrain, it becomes evident that the effects are neither uniform nor monolithic. Rather, they dance to the rhythm of contextual nuances, echoing the complexities of the societies and ecosystems they inhabit. The direction and magnitude of these impacts vary, weaving a narrative as diverse and multifaceted as the communities they touch. It is in this diversity that the true essence of our inquiry resides – not in the pursuit of universal truths but in the illumination of contextual realities, shaping the contours of policymaking and intervention strategies tailored to the specific needs of diverse populations.

Navigating the Complex Terrain: Integrating Environmental Sustainability and Public Health

Beyond the realm of health metrics lies a broader canvas, where the hues of environmental sustainability blend seamlessly with the palette of public health. Central to this discourse is the recognition of CO2 emissions as not merely abstract indicators of environmental degradation but tangible determinants of morbidity rates. In unraveling the intricate web of interdependencies between energy systems, environmental quality, and population health, our analysis unveils a tapestry of complexity and interconnectedness.

Herein lies the crux of our revelation – the imperative of integrated approaches that transcend traditional boundaries, recognizing the symbiotic relationship between environmental sustainability and public health. It is in this convergence that we find fertile ground for innovation, where solutions to address the twin challenges of environmental degradation and public health disparities can blossom. From green energy initiatives to sustainable urban planning, from eco-friendly transportation to carbon-neutral policies, the avenues for intervention are as diverse as the challenges they seek to address

Looking Towards the Horizon: Charting a Path Forward

As we stand at the crossroads of energy, environment, and health, the imperative of collective action looms large. The insights gleaned from our journey serve not merely as intellectual artifacts but as guiding beacons, illuminating the path towards a future where energy sustainability and public health intertwine harmoniously. Yet, our journey is far from over – it is a continuum of exploration and discovery, propelled by the winds of change and the currents of innovation.

In charting a path forward, we must heed the lessons of the past while embracing the possibilities of the future. It is not enough to merely acknowledge the challenges ahead; we must confront them head-on, armed with the collective wisdom of interdisciplinary collaboration and evidence-based policymaking. From the corridors of academia to the chambers of governance, from the halls of healthcare to the arenas of research, let us forge alliances and partnerships that transcend boundaries and foster synergy.

Conclusion: Towards a Sustainable and Equitable Future

In essence, the culmination of our research underscores not only the imperative but the promise of holistic approaches to address the interconnected challenges of our time. From the corridors of academia to the chambers of policymaking, the insights unveiled serve as guiding stars, illuminating the path towards a future where energy sustainability and public health intertwine harmoniously. As we bid farewell to this chapter, let us carry forth the lessons learned and the aspirations ignited, steadfast in our resolve to forge a more sustainable and equitable world for generations to come.

REFERENCES

- Momodu, A. S., Akinbami, J.-F. K., & Akinwunmi, I. O. (2010). ENVIRONMENTAL AND HEALTH IMPLICATIONS OF FUEL SUBSTITUTION FOR COOKING ENERGY IN NIGERIA'S HOUSEHOLD ENERGY MIX. *Energy & Environment*, *21*(8), 937–952. http://www.jstor.org/stable/43734977
- Kurian, A. L. (2012). SUSTAINABLE DEVELOPMENT IN THE ENERGY SECTOR. *The Indian Journal of Political Science*, *73*(4), 673–682. http://www.jstor.org/stable/41858875
- Tetsuro Yoshida, Zusman, E., Noriko Shimizu, & Ikuho Miyazawa. (2014). *Designing and Implementing an Energy Goal: Delivering Multi-benefits for Sustainable Development*. Institute for Global Environmental Strategies. http://www.jstor.org/stable/resrep00750
- Youssef, A. B., Lannes, L., Rault, C., & Soucat, A. (2015). ENERGY CONSUMPTION AND HEALTH OUTCOMES IN AFRICA. *The Journal of Energy and Development*, *41*(1/2), 175–200. http://www.jstor.org/stable/90005936
- Asif, M., & Saleh, N. (2019). Human Security and Energy Security: A Case Study of Pakistan. *Policy Perspectives*, *16*(1), 99–116. https://doi.org/10.13169/polipers.16.1.0099
- Luomi, M. (2020). *The Global Governance of Sustainable Energy: Access and Sustainable Transitions*. International Institute for Sustainable Development (IISD). http://www.jstor.org/stable/resrep29277

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