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The impact of public and private health investment expenditures on the health system in Türkiye: Causality analysis using the Toda-Yamamoto method for the period 2002-2022

Necati Kocakoc

Ondokuz Mayıs University, Institute of Graduate Studies, Department of Health Management, Samsun, Türkiye

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Abstract

Türkiye's healthcare system has undergone substantial changes since 2002, driven by public and private sector investments aimed at expanding capacity, improving service quality, and enhancing health outcomes. This study examined the causal effects of these investments on healthcare indicators such as hospital capacity, patient satisfaction, and mortality rates from 2002 to 2022 using data from the Ministry of Health, the World Bank, and TURKSTAT. Seventeen models were analyzed through the Toda-Yamamoto causality approach, focusing on variables like hospital beds, healthcare personnel, patient satisfaction, and economic factors such as GDP and the Consumer Confidence Index (CCI). Public health investments significantly increased beds in public hospitals (χ^2=10.14, p=0.04), while private investments had a strong impact on beds in private hospitals (χ^2=24.29, p<0.01). GDP also positively influenced the number of beds in both public (χ^2=56.13, p<0.01) and private hospitals (χ^2=59.01, p<0.01). Private investments were associated with increased healthcare personnel in the private sector (χ^2=39.34, p<0.01), whereas public investments had no significant impact on public-sector personnel (χ^2=1.06, p=0.59). GDP had a positive effect on patient satisfaction with public health services (χ^2=22.31, p<0.01), and private investments correlated with higher satisfaction in private healthcare (χ^2=24.29, p<0.01). Additionally, GDP significantly reduced infant mortality (χ^2=34.70, p<0.01) and under-five mortality (χ^2=41.55, p<0.01). Health investments were linked to lower mortality rates from cardiovascular disease, cancer, diabetes, and chronic kidney disease (χ^2=32.39, p<0.01). The findings highlight the essential role of both public and private investments in enhancing Türkiye's healthcare system. Private-sector investment is especially critical for expanding capacity and improving satisfaction. Policies integrating economic growth with healthcare improvements and continuous investments in infrastructure and human resources are vital for sustaining progress.

Keywords: Health investment, Türkiye, public health, private health, Toda-Yamamoto causality, health care outcomes

Introduction

Health investment expenditures are fundamental to the development and sustainability of a nation's healthcare system and play a critical role in improving the public health infrastructure, services, and outcomes [1]. These expenditures encompass a wide array of financial allocations aimed at expanding healthcare facilities, acquiring modern medical technologies, and ensuring the efficient delivery of healthcare services. Broadly, health investment expenditures can be categorized into two main types: public and private, each of which has distinct implications for the healthcare system [1-3].

Public health investment expenditures refer to the financial resources allocated by government bodies to enhance national healthcare infrastructure. This includes the construction and modernization of public hospitals, procurement of medical equipment, and funding for public health initiatives aimed at improving population health outcomes [3]. In Türkiye, public health investments are driven primarily by government policies and long-term strategic planning efforts. These investments are overseen by various institutions, including the Ministry of Health, which is responsible for setting healthcare priorities, developing national health plans, and coordinating the activities of public hospitals and healthcare facilities [4,5].

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Corresponding Author: Necati Kocakoc, Ondokuz Mayıs University, Institute of Graduate Studies, Department of Health Management, Samsun, Türkiye
Email: necatikocakoc@gmail.com

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The Turkish government's role in public health investment is critical, especially in ensuring that healthcare services are accessible to all citizens regardless of their geographical location or socioeconomic status. Public investments are often targeted at underserved areas, where private sector involvement is minimal. This helps reduce regional disparities in healthcare access and improves overall public health outcomes. Moreover, these investments are typically subject to rigorous planning and evaluation processes to ensure that they align with broader national health objectives such as improving health indicators and reducing mortality rates.

For instance, the government's investment in the "Health Transformation Program," which began in 2003, is an example of a large-scale public health investment aimed at improving the accessibility and quality of healthcare services across Türkiye. The program led to the construction of new healthcare facilities, upgrading existing ones, and enhancing the capabilities of the healthcare workforce [4].

Private health investment expenditures, on the other hand, involve financial contributions from private entities, including hospitals, clinics, pharmaceutical companies, and other healthcare service providers. These investments are primarily market driven, focusing on expanding private healthcare facilities, adopting advanced medical technologies, and enhancing the quality of services to meet the demands of a market-oriented healthcare system. Unlike public investments, private health investments are typically influenced by profitability considerations, although they are subject to governmental regulations and licensing requirements to ensure compliance with the national health standards.

In Türkiye, the role of the private sector in healthcare has expanded significantly over the past two decades, particularly in urban areas where there is a higher demand for specialized and high-quality healthcare services. This growth has been facilitated by government policies that encourage private sector participation in healthcare, such as public–private partnership (PPP) models, which have been used to develop large-scale healthcare projects, including the construction of city hospitals [6].

Private investments have not only contributed to the expansion of healthcare infrastructure but have also played a key role in introducing innovations in medical technology and healthcare delivery. For example, private hospitals in Türkiye often offer more specialized services and shorter wait times than their public counterparts, which has led to an increase in the demand for private healthcare services, particularly among middle- and upper-income populations.

Globally, the impact of health investment expenditures on health outcomes has been extensively studied, with a consensus that increased investments in healthcare lead to improved health indicators such as reduced mortality [7]. Similar studies have been conducted in Türkiye, although there is a need for more comprehensive research focusing on the specific impacts of public versus private health investment. The literature highlights the importance of strategic investment planning in achieving sustainable health outcomes and addressing inequalities in healthcare access and quality [8].

This study aims to analyze the effects of public and private health investment expenditures on Türkiye's health system during the period 2002-2022. Specifically, it investigates the causal impact of these expenditures on health care capacity, service quality, health indicators, and disease and mortality rates. By employing the Toda-Yamamoto causality analysis method, this study sought to provide empirical evidence on the distinct roles of public and private investments in shaping Türkiye's health care outcomes. The findings of this study are expected to contribute to the ongoing discourse on health investment strategies and their implications for public health policies in Türkiye.

Hypothetical Framework and Aim Questions for the Study

Health investment expenditures and their impact on capacity

1. What is the impact of public health investment expenditure on the number of beds in public hospitals?
2. How do private health investment expenditure affect the number of beds in private hospitals?
3. What is the relationship between health investment expenditures and the number of health personnel in the public and private sectors?

Health services quality

4. How do public and private health investment expenditures influence satisfaction levels with the healthcare services provided by public and private institutions?

Effects on health indicators (outcomes)

5. What impact do health investment expenditures have on key health indicators such as infant mortality and under-five mortality rates?
6. How does an increase in health investment expenditures influence life expectancy at birth?

Relationship with economic factors

7. How do health-related expenditures relate to Gross Domestic Product (GDP)?
8. How does the Confidence Index reflect the impact of health investment expenditure on healthcare services?

Causal relationships (potential for robust causal analysis with 20 years of data)

9. Does an increase in health investment expenditure causally contribute to improvements in health indicators?

These hypotheses are structured to guide the analysis and discussion of the study, ensuring a comprehensive examination of the effects of health investment expenditures on various aspects of Türkiye's health care system from 2002 to 2022.

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Material and Methods

Data Collection

This study examined the impact of public and private health investment expenditures on Türkiye's health system over the period 2002-2022. The analysis was based on data sourced from multiple authoritative institutions to ensure credible examination of the variables involved. The primary data sources included the Ministry of Health of Türkiye [9], World Bank [10], Central Bank of the Republic of Türkiye [11], and Turkish Statistical Institute (TURKSTAT) [12]. The data used were derived from the annual statistics provided by various public institutions. Specifically, the following data were obtained from the TURKSTAT:Türkiye's population figures, public health investment expenditures, private health investment expenditures, public health service satisfaction, private health service satisfaction, and life expectancy at birth (in years).

From the Ministry of Health of Türkiye's Statistical Yearbook, we collected data on the number of hospital beds in public hospitals, number of hospital beds in private hospitals, number of public healthcare personnel, number of private healthcare personnel, number of MRI machines in public hospitals, number of MRI machines in private hospitals, number of CT machines in public hospitals, number of CT machines in private hospitals, number of paid surgeries in public hospitals, number of surgeries in private hospitals, infant mortality rate, under-five mortality rate (‰), and crude death rate (per 1,000 people).

Additionally, we sourced data on mortality rates (percentage) caused by cardiovascular diseases, cancer, diabetes, or other chronic diseases between the ages of 30 and 70 years from the World Bank. Lastly, data on Gross Domestic Product (GDP), Consumer Confidence Index (CCI), and foreign exchange conversion rates were provided by the Central Bank of the Republic of Türkiye's Electronic Data Delivery System (EVDS) (Table 1).

Table 1. Variables

Code	Variables	Data Source
LNS1	Population of Türkiye	TurkStat
LNS2	Public health investment expenditure	TurkStat
LNS3	Private health investment expenditure	TurkStat
LNS4	Number of public hospital beds	MoH
LNS5	Number of private hospital beds	MoH
LNS6	Number of public health personnel	MoH
LNS7	Number of private health personnel	MoH
S8	Satisfaction with public health services	TurkStat
LNS9	Satisfaction with private health services	TurkStat
S10	Number of MRI machines in public hospitals	MoH
S11	Number of MRI machines in private hospitals	MoH
LNS12	Number of CT machines in public hospitals	MoH
LNS13	Number of CT machines in private hospitals	MoH
LNS14	Number of public sector surgeries	MoH
SQRTS15	Number of private sector surgeries	MoH
LNS16	Infant mortality rate	MoH
LNS17	Under-five mortality rate (‰)	MoH
LNS18	Life expectancy at birth (years)	TurkStat
LNS19	Crude death rate (per 1,000 people)	MoH
LNS20	Mortality rate between 30 and 70 years due to CVD, cancer, diabetes, or CRD (%)	WB
LNS21	Gross domestic product (GDP)	CBRT
LNS22	Consumer confidence index	CBRT

The dataset encompasses a wide range of variables including indicators of health investment expenditure, healthcare infrastructure (number of hospitals, beds, and healthcare personnel), healthcare service quality (patient satisfaction and health service accessibility), and health outcomes (mortality rates and disease incidence). Additionally, GDP and the Consumer Confidence Index (CCI) were incorporated as control variables to account for broader economic conditions influencing health system performance.

Seventeen models were developed to investigate the causal relationships between these variables, thereby providing a comprehensive understanding of the impact of health investments on the overall healthcare system.

Data Set and Transformations

The dataset used in this study included public and private health investments, hospital resources, mortality rates, and economic

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indicators in Türkiye. Before conducting the analysis, various transformations were applied to determine whether the series was stationary or not. The series, such as Satisfaction with Public Health Services, Number of MRI Machines in Public Hospitals, and Number of MRI Machines in Private Hospitals, did not exhibit a normal distribution after transformation; therefore, they were analyzed in their original form. For other variables, a natural logarithm (LN) transformation was applied to ensure normality. To achieve normality, a square-root transformation was applied to a series of surgeries in private hospitals.

Data Analysis

All financial data were standardized by converting them to U.S. dollars using the annual average exchange rates provided by the Central Bank of the Republic of Türkiye. This standardization ensures comparability across years and allows for a more accurate analysis of trends over time.

Data analysis was conducted using EViews version 12, a statistical software package specifically designed for econometric analyses.

Stationarity tests

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were applied to examine series stationarity and determine whether the variables used in the time-series analysis were stationary. Both tests assessed whether the series was stationary at levels (I(0)) and first differences (I(1)). The Schwarz Information Criterion (SIC) was used to determine lag lengths in the ADF test.

Stationarity in Time-Series Analysis

Stationarity is a critical concept in time series analyses. Ensuring stationarity of the data is essential for the validity and reliability of the analysis results. A stationary time series maintains constant properties such as the mean, variance, and autocovariance over time. If these structural features remain unchanged, the series is considered stationary. Failure to account for nonstationarity can lead to misleading results, such as identifying spurious relationships between variables that do not truly exist. For instance, regressions performed on non-stationary data might yield a high R^2 value owing to spurious correlations, potentially resulting in incorrect policy or business decisions.

If a time series is nonstationary, it can lead to invalid models and poor forecasting accuracy. The most common tests for checking stationarity in time series are the augmented Dickey (ADF) and Phillips (PP) tests. These tests assess whether a time series has a unit root, which indicates nonstationarity. ADF uses lagged differences to correct for autocorrelation, whereas PP is more flexible, addressing potential heteroskedasticity and serial correlation in error terms.

Logarithmic Transformation

Logarithmic and square root transformations are commonly applied to achieve normality and stabilize the variance in time-series analyses. These transformations are particularly useful in economic data analysis, where raw data may exhibit nonlinear relationships, outliers, or heteroscedasticity. Applying a logarithmic transformation helps normalize skewed distributions such as income or GDP and ensures that proportional changes are treated consistently. In this study, logarithmic transformations were applied to several variables, including health investment expenditures and mortality rates, to improve the model performance and ensure robust results.

Determination of optimal lag lengths

To correctly determine the lag length (k) used in the VAR model and obtain reliable results in the causality tests, the optimal lag lengths for each model were determined using various information criteria, including the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Quinn information criterion (HQ). The lag length with the lowest criterion value is selected as the optimal lag length.

Stationarity and Lag Length Determination

As noted, ensuring stationarity in the data is critical for a reliable time-series analysis. The results of our stationarity tests show that several variables became stationary only after the first differencing, which has implications for both the selection of lag lengths in the VAR models and the overall interpretation of the results. For instance, a nonstationary series can produce spurious results, leading to incorrect conclusions. Therefore, it is essential to differentiate non-stationary variables and make them stationary before proceeding with VAR models or causality tests such as the Toda-Yamamoto test. This process prevents misleading relationships and ensures that the models reflect the true economic interactions.

Lag Length Selection

In time-series analysis, selecting the appropriate lag length is crucial for obtaining accurate and reliable results. The optimal lag lengths for the VAR models in this study were determined using a combination of information criteria, including the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Quinn information criterion (HQ). These criteria help identify the model with the best fit by penalizing overfitting while balancing model complexity.

The final lag lengths were selected based on the criterion values, with the model receiving the most stars (*) across the criteria deemed the optimal lag length. These lag lengths were then combined with the maximum degree of integration (dmax) of the variables, ensuring that the Toda-Yamamoto method could handle nonstationary variables without requiring differencing.

Implications for Interpretation

The selection of lag length directly affects the results of the Toda-Yamamoto causality test. Choosing an incorrect lag length can result in biased estimates or missing causal relationships. In this study, by using appropriate lag lengths determined by multiple criteria, we minimized the risk of such errors, ensuring that the causality relationships identified were both accurate and reflective of true economic and health dynamics.

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Model stability evaluation

The structural stability of the models was assessed using Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMQ) tests. These graphical tests were instrumental in determining whether model parameters remained consistent over time.

Graphical Representation of Model Stability Using CUSUM and CUSUMQ Tests

Graphical representation of the CUSUM and CUSUMQ tests is critical for visually confirming the structural stability of the estimated models over the study period. These tests are particularly valuable in our analysis, as they help detect unexpected shifts or structural breaks in the regression coefficients and variance of the residuals, which could potentially impact the reliability of the causality findings.

Incorporation of Graphical Tests in the Analysis

The primary goal of including the CUSUM and CUSUMQ tests in this study is to ensure that the models used in the Toda-Yamamoto causality tests are structurally sound. These models, established via the Least Squares method and analyzed through Wald tests, are robust only if their underlying assumptions hold over time. Graphical tests (CUSUM for shifts in regression coefficients and CUSUMQ for shifts in variance) provide a straightforward method for visually inspecting these aspects. Any detected instability may suggest the presence of structural breaks due to external shocks, policy changes, or other pivotal events that could influence the estimated relationships.

Handling Structural Breaks

If structural breaks are identified, they are addressed by incorporating dummy variables into the models to account for these shifts, thus preserving the integrity of causality analysis. This approach not only enhances the robustness of the causality results, but also aligns with the rigorous standards required for academic scrutiny and policy implications.

Location of Graphical Results

Graphs illustrating the results of the CUSUM and CUSUMQ tests are presented in this section. These graphical representations provide readers with a clear visual confirmation of the model's stability, enhancing their understanding of the methodological rigor applied in the study.

Explanation of the Non-Application of the ARDL Model

It is important to clarify that although ARDL models frequently use CUSUM tests to verify model stability, our study did not apply ARDL modeling. Instead, we used VAR models to determine the optimal lag lengths required for the Toda-Yamamoto causality tests. As a result, impulse-response analysis, which is typically employed in VAR model assessments to examine the dynamic effects of shocks, was not relevant to our analysis. This clarification helps delineate the specific analytical framework and methodologies adopted in this study.

Causality testing

The Toda-Yamamoto causality test was employed to explore the potential cause-effect relationships between variables [13]. This method is particularly advantageous because it does not require the variables to be cointegrated, thereby allowing the analysis of nonstationary series that may be integrated with different orders. The Toda-Yamamoto approach ensures rigorous examination of the directional relationships between health investments and health outcomes.

Justification for the Toda-Yamamoto Method

The Toda-Yamamoto (TY) method offers several advantages when working with non-stationary data. In addition to its robustness to nonstationary series, the TY method provides reliable causal results across a wider range of economic and financial time series. Traditional methods such as the Granger causality test or VAR models often require stationary data. However, the TY method circumvents this requirement by using an augmented VAR model to test for causality, thus allowing it to work with nonstationary or even integrated data series. This flexibility is particularly advantageous when dealing with datasets that include mixed integration orders and structural breaks.

The TY method, developed by Toda and Yamamoto (1995), is particularly suitable for datasets in which variables may not be stationary at the same level or cointegrated. Traditional methods would either require transformations of the data (through differencing), which may lead to the loss of long-term information, or necessitate cointegration tests. The TY method, on the other hand, avoids these constraints by using level data directly. This preserves the integrity of the dataset, retaining both short- and long-term relationships between variables, which is critical for a comprehensive time-series analysis. Furthermore, the method reduces potential model specification errors by eliminating the need for differencing or pre-testing for co-integration, thus maintaining a more holistic approach to causality testing. These features make the Toda-Yamamoto method ideal for analyzing the complex interactions between health investments and economic factors in our study.

Model Stability with CUSUM and CUSUMQ Tests

The stability of the models in this study was evaluated using CUSUM and CUSUMQ tests. These tests offer insights into whether the coefficients and variances of the model parameters remain stable over time. The CUSUM test assesses the cumulative sum of residuals over time and identifies potential changes in model coefficients, whereas the CUSUMQ test examines changes in the variance of residuals. In our analysis, minor deviations in certain models, such as LNS6 the Number of Public Health Personnel) around 2017, may be indicative of structural breaks possibly linked to policy changes or economic crises, such as healthcare reforms or economic downturns. For instance, the COVID-19 pandemic could account for the instability observed around 2020 in some models, reflecting shifts in both public and private health care dynamics.

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Ethical Considerations

The data used in this study were obtained from publicly accessible databases, ensuring transparency and reproducibility of the research. Because the study did not involve the collection or use of personal or sensitive information, ethical committee approval was not required. The study strictly adhered to the ethical guidelines for the use of open-access data, ensuring that all procedures were conducted in an ethically responsible manner.

Results

Distribution of Health and Economic Indicators in Türkiye

The population of Türkiye (LNS1) averaged 18.14 million (range: 17.99-18.26), with a median of 18.14±0.09 million. Public health investment expenditure (LNS2) showed a mean of 7.33 (min: 5.68, max: 8.06) with a median of 7.53±0.60, indicating variability in government spending on healthcare. Private health investment expenditure (LNS3) had a mean of 6.08 (range: 5.03-7.26) and a median of 6.15±0.51, reflecting consistent investment levels in the private sector. The average number of hospital beds in public hospitals (LNS4) averaged 11.98 (range: 11.80-12.24), with minimal variation (median: 11.97±0.14), while private hospitals (LNS5) showed slightly more variability with a mean of 10.64 (range: 10.31-10.92) and a median of 10.71±0.20. The number of health personnel in the public sector (LNS6) and private sector (LNS7) averaged 12.42 and 11.08, respectively, with slightly higher variability in the private sector. Public satisfaction with health services (S8) demonstrated a mean satisfaction score of 65.92% (range: 39.00%-77.79%) and a median of 69.12±11.79, indicating moderate to high satisfaction levels. The number of MRI machines in public hospitals (S10) averaged 306.95 (range: 25–493), with substantial variation (median: 325.00±143.71), whereas private hospitals (S11) had a higher mean of 346.67 (range: 33–480) with similar variability. The number of CT machines in public hospitals (LNS12) and private hospitals (LNS13) averaged 6.07 and 5.99, respectively, with low variability. Surgical operations in public hospitals (LNS14) had a mean of 14.99 (range: 14.14-15.62) and a median of 14.98±0.34, while private hospitals (SQRTS15) showed greater variability with a mean of 1080.41 operations (range: 467.80-1303.22) and a median of 1202.76±255.47. The infant mortality rate (LNS16) averaged 2.58 per 1,000 live births (range: 2.17-3.45), and the under-five mortality rate (LNS17) was 2.80‰ (range: 2.37 â-3.69°), reflecting steady progress in child health. Life expectancy at birth (LNS18) averaged 4.32 years (range: 4.28-4.36) with low variability, indicating consistent improvements in longevity. The crude death rate (LNS19) was 1.66 per 1,000 people (range: 1.62-1.70), while the mortality rate due to major diseases (LNS20) averaged 2.83% (range: 2.71%–2.99%). The Gross Domestic Product (GDP, LNS21) had a mean of 13.43 (range: 12.39-13.77) and a median of 13.56 Â±0.37, reflecting economic stability, while the Consumer Confidence Index (LNS22) averaged 4.50 (range: 4.27-4.74) with a median of 4.52±0.11. Table 2 presents the descriptive statistics for the health and economic indicators in Türkiye over the study period.

Table 2. Distribution of health and economic indicators in Türkiye

Code	Mean	Median	Maximum	Minimum	Std. deviation	Skewness	Kurtosis	Jarque-bera	Probability	Number of observations
LNS1	18.1360	18.1413	18.2615	17.9902	0.0869	-0.1736	1.7830	1.4015	0.4962	21
LNS2	7.3331	7.5302	8.0633	5.6793	0.6031	-1.6056	4.7267	11.6312	0.0030	21
LNS3	6.0752	6.1478	7.2600	5.0284	0.5127	0.2127	3.3910	0.2922	0.8641	21
LNS4	11.9821	11.9661	12.2411	11.8036	0.1369	0.4805	2.0731	1.5596	0.4585	21
LNS5	10.6445	10.7079	10.9163	10.3146	0.2031	-0.4186	1.7479	1.9851	0.3706	21
LNS6	12.4154	12.4299	12.8834	12.0353	0.2724	0.2027	1.8477	1.3056	0.5206	21
LNS7	11.0765	11.1359	11.5371	10.5454	0.2924	-0.3134	2.0843	1.0775	0.5835	21
S8	65.9195	69.1200	77.7900	39.0000	11.7857	-1.1731	3.1212	4.8298	0.0894	21
LNS9	4.0409	4.0667	4.2062	3.7842	0.1283	-0.9053	2.7451	2.9256	0.2316	21
S10	306.9524	325.0000	493.0000	25.0000	143.7120	-0.4678	2.1438	1.4074	0.4948	21
S11	346.6667	425.0000	480.0000	33.0000	141.7379	-0.9956	2.6004	3.6093	0.1645	21
LNS12	6.0706	6.2324	6.6670	4.8283	0.5250	-0.8951	2.7853	2.8443	0.2412	21
LNS13	5.9900	6.2025	6.3008	5.0304	0.3944	-1.1647	2.9897	4.7480	0.0931	21
LNS14	14.9913	14.9821	15.6208	14.1373	0.3369	-0.3560	3.6237	0.7839	0.6757	21
SQRTS15	1080.4120	1202.7590	1303.2210	467.8002	255.4688	-1.2498	3.1260	5.4812	0.0645	21
LNS16	2.5780	2.4481	3.4500	2.1661	0.4013	0.9926	2.7360	3.5093	0.1730	21
LNS17	2.8014	2.6642	3.6889	2.3708	0.4258	0.9207	2.4997	3.1862	0.2033	21
LNS18	4.3231	4.3265	4.3628	4.2847	0.0224	-0.0648	1.9972	0.8946	0.6394	21
LNS19	1.6568	1.6601	1.6982	1.6174	0.0263	-0.0875	1.8007	1.1016	0.5765	18
LNS20	2.8316	2.8214	2.9907	2.7081	0.0792	0.2422	2.1709	0.8069	0.6680	21
LNS21	13.4291	13.5600	13.7715	12.3855	0.3714	-1.5830	4.5927	10.9904	0.0041	21
LNS22	4.5016	4.5177	4.7350	4.2684	0.1140	-0.1859	2.7840	0.1618	0.9223	21

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Stationarity Test Outcomes

The stationarity test results obtained through the ADF and PP tests provide insights into the stability of the time-series data used in the analysis (Table 3).

1. ***LNS2: Public Health Investment Expenditure***

ADF Test: The variable was non-stationary at the level (constant, p=0.03; constant and trend, p=0.22), but became stationary after first differencing (constant, p=0.004; constant and trend, p=0.008).

PP Test: Similar to the ADF test, the variable was stationary after the first differencing (constant, p=0.004; constant and trend, p=0.008).

2. ***LNS3: Private Health Investment Expenditure***

ADF Test: The variable was non-stationary at the level (constant, p=0.03; constant and trend, p=0.09), but was stationary after first differencing (constant, p=0.01; constant and trend, p=0.06).

PP Test: The variable was stationary after first differencing (constant, p=0.01; constant and trend, p=0.05).

3. ***LNS4: Number of Hospital Beds in Public Hospitals***

ADF Test: The variable was non-stationary at the level (constant, p=1.00; constant and trend, p=0.83), but became stationary after first differencing (constant, p=0.002; constant and trend, p=0.003).

PP Test: The variable was stationary after first differencing (constant, p=0.002; constant and trend, p=0.002).

4. ***LNS5: Number of Hospital Beds in Private Hospitals***

ADF Test: The variable was non-stationary at the level (constant, p=0.77; constant and trend, p=0.39), but became stationary after first differencing (constant, p=0.002; constant and trend, p=0.01).

PP Test: Consistent with the ADF results, it was stationary after first differencing (constant, p=0.001; constant and trend, p=0.001).

5. ***LNS6-Number of Health Personnel in Public Sector***

ADF Test: Non-stationary at the level (constant, p=1.00; constant and trend, p=0.38), but stationary after first differencing (constant, p=0.002; constant and trend, p=0.01).

PP Test: Stationary after first differencing (constant, p=0.002; constant and trend, p=0.01).

6. ***LNS7-Number of Health Personnel in Private Sector***

ADF Test: Non-stationary at the level (constant, p=0.67; constant and trend, p=0.43), but stationary after first differencing (constant, p=0.001; constant and trend, p=0.003).

PP Test: Stationary after first differencing (constant, p=0.001; constant and trend, p=0.002).

7. ***S8. Satisfaction with Public Health Services***

ADF Test: The variable was marginally non-stationary at a constant level (p=0.10) but became stationary after first differencing (constant, p=0.001; constant and trend, p=0.001).

PP Test: The variable was stationary at the level (constant, p=0.05) and significantly stationary after first differencing (constant, p=0.001; constant and trend, p<0.001).

8. ***LNS9: Satisfaction with Private Health Services***

ADF Test: The variable was non-stationary at the level (constant, p=0.11; constant and trend, p=0.43), but became stationary after first differencing (constant, p<0.001; constant and trend, p<0.001).

PP Test: The variable was stationary after first differencing (constant, p<0.001; constant and trend, p<0.001).

9. ***S10. Number of MRI Machines in Public Hospitals***

ADF Test: The variable was non-stationary at the level (constant, p=0.02; constant and trend, p=0.76), but became stationary after first differencing (constant, p=0.06; constant and trend, p=0.03).

PP Test: The variable was stationary at a constant level (p=0.02) and marginally stationary after the first differencing (constant, p=0.06).

10. ***LNS11: Number of MRI Machines in Private Hospitals***

ADF Test: Non-stationary at a constant level (p=0.10; constant and trend, p=0.34) and did not achieve stationarity after first differencing with trend (p=0.87).

PP Test: Stationary at the level with constant (p<0.001) but non-stationary with trend after differencing (p=0.38).

11. ***LNS12: Number of CT Machines in Public Hospitals***

ADF Test: The variable became stationary at the first difference (constant, p=0.001; constant and trend, p=0.000).

PP Test: Consistent results with the ADF test, achieving stationarity after first differencing.

12. ***LNS13: Number of CT Machines in Private Hospitals***

ADF Test: The variable became stationary at the first difference (constant, p=0.001; constant and trend, p=0.001).

PP Test: Consistent results with ADF, showing stationarity after first differencing.

13. ***LNS14: Number of Surgeries in Public Hospitals***

ADF Test: The variable became stationary at the first difference (constant, p=0.01; constant and trend, p=0.07).

PP Test: The variable became stationary after the first differencing (constant, p=0.02).

14. ***SQRTS15: Number of Surgeries in Private Hospitals***

ADF Test: The variable became stationary at the first difference (constant, p=0.03; constant and trend, p=0.04).

PP Test: Consistent results with ADF, achieving stationarity after first differencing.

15. ***LNS16-Infant Mortality Rate***

ADF Test: The variable was stationary at first differencing (constant, p=0.003).

PP Test: The variable became stationary at first differencing (constant, p=0.06; constant and trend, p=0.002).

16. LNS17-Under-Five Mortality Rate

ADF Test: The variable became stationary after the first differencing (constant, p=0.004; constant and trend, p<0.001).

PP Test: The variable was stationary after first differencing (constant, p=0.02; constant and trend, p<0.001).

17. LNS18: Life Expectancy at Birth

ADF Test: The variable became stationary after the first differencing (constant and trend, p=0.03).

PP Test: The variable was stationary after first differencing (constant and trend, p=0.000).

18. LNS19: Crude Death Rate

ADF Test: The variable became stationary after the first differencing (constant, p=0.04; constant and trend, p<0.001).

PP Test: Consistent results with ADF, showing stationarity after first differencing.

19. LNS20: Mortality Rate Due to Major Diseases

ADF Test: The variable was stationary at the first difference (constant, p=0.004; constant and trend, p=0.02).

PP Test: Results are consistent with ADF, showing stationarity after the first differencing (constant, p=0.02).

20. LNS21: Gross Domestic Product (GDP)

ADF Test: The variable became stationary after the first differencing (constant, p=0.001; constant and trend, p=0.07).

PP Test: Consistent with the ADF test, stationary after first differencing (constant, p=0.04; constant and trend, p=0.08).

21. LNS22-Consumer Confidence Index:

ADF Test: The variable became stationary at the first difference (constant, p=0.001; constant and trend, p=0.003).

PP Test: Results, consistent with ADF, showing stationarity after first differencing (constant, p=0.001; constant and trend, p=0).

Table 3. Stationarity test results for selected variables using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests

Test	Variable	I (0)				I (1)			
		Constant		Constant and with trend		Constant		Constant and with trend	
		Test statistic	p-value	Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
Augmented Dickey-Fuller	LNS2	-3.33	0.0271**	-2.7872	0.2171	-4.272	0.004***	-4.6396	0.0081***
	LNS3	-3.2562	0.0322**	-3.3107	0.0945*	-3.6695	0.014**	-3.5631	0.061*
	LNS4	1.3212	0.9977	-1.4015	0.8284	-4.6505	0.0018***	-5.1861	0.0029***
	LNS5	-0.8782	0.7736	-2.3494	0.3916	-4.7089	0.0016***	-4.6113	0.0086***
	LNS6	1.0996	0.9959	-2.3728	0.3807	-4.5565	0.0022***	-4.8256	0.0057***
	LNS7	-1.1697	0.6661	-2.2769	0.4262	-5.2647	0.0005***	-5.2237	0.0027***
	S8	-2.6552	0.0991*	-1.6584	0.7273	-5.1767	0.0006***	-5.8294	0.001***
	LNS9	-2.5901	0.1113	-2.2694	0.4299	-7.0351	0.0000***	-7.322	0.0001***
	S10	-3.4968	0.0192**	-1.5967	0.7576	-2.9636	0.0567*	-4.0493	0.025**
	S11	-2.6861	0.0967*	-2.4685	0.3367	-0.9973	0.7292	-1.2267	0.8709
	LNS12	-11.8752	0.0000***	-4.5469	0.0105**	-2.6442	0.1039	-15.937	0.0001***
	LNS13	-3.0732	0.0451**	-2.1613	0.4836	-4.9829	0.0009***	-6.035	0.0006***
	LNS14	-3.1276	0.0406**	-2.8409	0.2011	-3.6453	0.0147**	-3.4596	0.0731*
	SQRTS15	-3.0938	0.0433**	-1.9759	0.5785	-3.3817	0.0251**	-3.7849	0.0408**
	LNS16	-4.1199	0.0055***	-1.7294	0.6977	-1.6187	0.4493	-5.1121	0.0033***
	LNS17	-4.3755	0.0032***	-1.0055	0.919	-0.7331	0.8123	-6.4812	0.0002***
	LNS18	-1.7041	0.4125	-4.4797	0.0111**	-5.5606	0.0003***	-4.0738	0.0264**
	LNS19	-1.7459	0.3923	-3.9297	0.0358**	-4.1354	0.0072***	-3.9687	0.0355**
	LNS20	-0.7927	0.797	-3.714	0.0516*	-4.345	0.0037***	-4.1997	0.0199**
	LNS21	-5.0268	0.0007***	-3.2453	0.1041	-3.1468	0.0399**	-3.4738	0.0713*
	LNS22	-1.2712	0.6216	-2.4773	0.3341	-5.2735	0.0005***	-5.1464	0.0031***

Significance levels: ***1%, **5%, *10%. I(0): Level I(1): First Difference; The stationarity of the series was tested using the augmented Dickey (ADF) unit root test and the Phillips (PP) test; Lag lengths for the ADF test were determined using the Schwarz Information Criterion (SIC); The null hypothesis (H0) tests for the presence of a unit root indicate non-stationarity, whereas the alternative hypothesis (H1) indicates the stationarity of the series; Stationarity was evaluated using two models: with constant, and with constant and trend; The MRI series in private hospitals was found to be stationary at level, while most other series became stationary after first differencing; The maximum integration degree (dmax) was considered to be 1 for the series included in the models*

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Table 3. Stationarity test results for selected variables using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests

Test	Variable	I (0)				I (1)			
		Constant		Constant and with trend		Constant		Constant and with trend	
		Test statistic	p-value	Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
Phillips-Perron	LNS2	-3.7702	0.0108**	-2.9136	0.1791	-4.2772	0.004***	-4.6379	0.0082***
	LNS3	-2.5487	0.1197	-2.5118	0.3194	-3.9156	0.0084***	-3.7119	0.0467**
	LNS4	2.185	0.9998	-1.4015	0.8284	-4.6523	0.0018***	-5.4734	0.0017***
	LNS5	-0.7718	0.8054	-2.3494	0.3916	-5.2386	0.0005***	-5.6833	0.0011***
	LNS6	1.0996	0.9959	-2.3489	0.3919	-4.561	0.0022***	-4.8256	0.0057***
	LNS7	-1.5981	0.4651	-2.2166	0.4559	-5.2726	0.0005***	-5.2925	0.0023***
	S8	-3.0657	0.0458**	-0.5301	0.9723	-5.131	0.0007***	-21.7756	0.0001***
	LNS9	-2.5679	0.1158	-2.1164	0.5065	-7.0351	0.0000***	-7.906	0.0000***
	S10	-3.5617	0.0168**	-1.5813	0.7638	-2.9636	0.0567*	-4.0493	0.025**
	S11	-5.9041	0.0001***	-1.5048	0.7932	-1.2554	0.6275	-2.3697	0.3814
	LNS12	-1.7187	0.4072	-2.9031	0.182	-10.7696	0.0000***	-14.3376	0.0001***
	LNS13	-4.2216	0.0041***	-2.1389	0.495	-4.9829	0.0009***	-7.5978	0.0000***
	LNS14	-3.1091	0.0421**	-2.932	0.174	-3.607	0.0159**	-3.3724	0.0851*
	SQRTS15	-4.002	0.0066***	-2.0702	0.5301	-3.3725	0.0256**	-3.7221	0.0458**
	LNS16	-8.5484	0.0000***	-1.1498	0.8936	-2.9748	0.0555*	-5.5235	0.0015***
	LNS17	-4.2507	0.0039***	-0.7977	0.9488	-3.5032	0.0196**	-6.4812	0.0002***
	LNS18	-0.337	0.9026	-2.5972	0.2847	-1.0647	0.7072	0.4809	0.9982
	LNS19	-1.5758	0.4726	-3.1791	0.1212	-7.1979	0.0000***	-6.8555	0.0003***
	LNS20	-1.4894	0.5181	-2.9414	0.1715	-3.381	0.0251**	-2.8584	0.1959
	LNS21	-6.647	0.0000***	-4.0546	0.0237**	-3.1083	0.043**	-3.4179	0.0787*
	LNS22	-0.9822	0.7388	-2.4773	0.3341	-5.4951	0.0003***	-5.3257	0.0022***

Significance levels: ***1%, **5%, *10%. I(0): Level I(1): First Difference; The stationarity of the series was tested using the augmented Dickey (ADF) unit root test and the Phillips (PP) test; Lag lengths for the ADF test were determined using the Schwarz Information Criterion (SIC); The null hypothesis (H0) tests for the presence of a unit root indicate non-stationarity, whereas the alternative hypothesis (H1) indicates the stationarity of the series; Stationarity was evaluated using two models: with constant, and with constant and trend; The MRI series in private hospitals was found to be stationary at level, while most other series became stationary after first differencing; The maximum integration degree (dmax) was considered to be 1 for the series included in the models*

Optimal Lag Lengths for Causality Analysis Outcomes

For model LNS4=f(LNS2, LNS21, LNS22), the optimal lag length was determined to be 3 with the addition of the maximum integration degree (dmax), resulting in a total lag length of 4 (dmax+k=4). Similar procedures were followed for the other models, with optimal lag lengths of LNS5=f(LNS3, LNS21, LNS22), LNS6=f(LNS2, LNS21, LNS22), LNS7=f(LNS3, LNS21, LNS22), and S8=f(LNS2, LNS21, LNS22).

In all cases, the lag lengths identified by the criteria with the most stars (*) are selected as the optimal lags for the models. These optimal lags were then adjusted with the maximum integration degree (dmax), calculated as 1 for the series included in these models, to obtain the final lag lengths necessary for conducting the Toda-Yamamoto causality tests.

Table 4 presents the results for the optimal lag lengths determined for the models used in the causality analysis with the VAR model. The Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), Hannan-Quinn Information Criterion (HQ), and sequential modified LR test statistics were employed to identify the optimal lag length (k) for each model.

CUSUM and CUSUMQ Tests Outcomes

The CUSUM and CUSUMQ tests indicate that while many of the models maintain stable coefficients and variance over time, some models (notably LNS6, LNS9, LNS17, LNS18, LNS19, and LNS20) exhibit signs of structural breaks or instability during specific periods (Figure 1-6).

1. ***Model LNS4=f(LNS2, LNS21, LNS22)***

CUSUM (Figure 1A): This line remains within the significance boundaries, suggesting that the coefficients of the model are stable over time.

CUSUMQ (Figure 1B): The line remains within the boundaries, indicating stable variance in the residuals.

2. ***Model LNS5=f(LNS3, LNS21, LNS22)***

CUSUM (Figure 1C): The coefficients appear stable as the line remains within critical boundaries.

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CUSUMQ (Figure 1D): The variance of the residuals was stable with no significant structural breaks.

3. Model LNS6=f(LNS2, LNS21, LNS22)

CUSUM (Figure 1E): The line remained within the boundaries, indicating overall stability, although minor deviations suggest potential instability in 2017.

CUSUMQ (Figure 1F): A notable deviation occurred around 2017, indicating a structural break in the model parameters or variances during this period.

The CUSUMQ graph in Figure 1F, which represents the regression model where the dependent variable LNS6 is related to the independent variables LNS2, LNS21, and LNS22, shows that the blue line generally remains within the critical boundaries at the 5% significance level. However, it is observed that around the year 2017, the blue line crosses these critical boundaries. This deviation indicates a structural break or sudden change in the model in 2017. This suggests that the model's parameters did not remain stable over time and that a structural break occurred in the model. The reforms or updates made in the public health system around 2017 may have led to changes in employment or investment models. For instance, the transfer of military hospitals to the Ministry of Health could be one such example.

4. Model LNS7=f(LNS3, LNS21, LNS22).

CUSUM (Figure 2A): This line remained within the critical boundaries, suggesting stable coefficients.

CUSUMQ (Figure 2B): The variance was consistent over time, indicating no significant structural breaks.

5. Model S8=f(LNS2, LNS21, LNS22)

CUSUM (Figure 2C): The model showed stability with a line within critical boundaries.

CUSUMQ (Figure 2D): The variance of the residuals remained stable with no significant structural changes.

6. Model LNS9=f(LNS3, LNS21, and LNS22)

CUSUM (Figure 2E): This line shows stability within the boundaries until 2020, suggesting potential instability.

CUSUMQ (Figure 2F): The deviation around 2020 indicates a structural break, suggesting that the model parameters or variances may have changed during this period.

The CUSUMQ graph in Figure 2F, which represents the regression model where the dependent variable LNS9 is related to the independent variables LNS3, LNS21, and LNS22, shows that the blue line generally remains within the critical boundaries at the 5% significance level. However, it is observed that around the year 2020, the blue line crosses these critical boundaries. This deviation indicates a structural break or sudden change in the model in 2020. This suggests that the model's parameters did not remain stable over time and that a structural break occurred in the model. The structural break in 2020 likely highlights significant changes driven by major global events such as the COVID-19 pandemic.

7. Model S10=f(LNS2, LNS21, LNS22).

CUSUM (Figure 3A): The coefficients appear stable as the line remains within critical boundaries.

CUSUMQ (Figure 3B): The variance was stable with no significant structural breaks.

8. Model S11=f(LNS3, LNS21, and LNS22)

CUSUM (Figure 3C): The model remained stable within boundaries.

CUSUMQ (Figure 3D): Variance was consistent over time, indicating the absence of structural breaks.

9. Model LNS12=f(LNS2, LNS21, LNS22)

CUSUM (Figure 3E): The coefficients appear stable as the line remains within critical boundaries.

CUSUMQ (Figure 3F): The variance remained stable, with no significant structural changes.

10. Model LNS13=f(LNS3, LNS21, LNS22)

CUSUM (Figure 4A): The line remains within the boundaries, indicating overall stability.

CUSUMQ (Figure 4B): The variance remained stable, with no significant structural changes.

11. Model LNS14=f(LNS2, LNS21, LNS22)

CUSUM (Figure 4C): The coefficients appear stable as the line remains within critical boundaries.

CUSUMQ (Figure 4D): The variance remains stable with no significant structural breaks.

12. Model SQRTS15=f(LNS3, LNS21, LNS22),

CUSUM (Figure 4E): The line remains within the boundaries, indicating overall stability.

CUSUMQ (Figure 4F): The variance remained stable, with no significant structural changes.

13. Model LNS16=f(LNS2, LNS3, LNS21, LNS22).

CUSUM (Figure 5A): The line remains within the boundaries, indicating overall stability.

CUSUMQ (Figure 5B): The variance remained stable, with no significant structural changes.

14. Model LNS17=f(LNS2, LNS3, LNS21, LNS22).

CUSUM (Figure 5C): This line crossed the boundaries between 2019 and 2022, suggesting potential instability or structural breaks during this period.

CUSUMQ (Figure 5D): The structural break post-2019 indicates a change in the model parameters or variance.

In Figure 5C, which shows the CUSUM graph of the regression model where the dependent variable LNS17 is related to the independent variables LNS2, LNS3, LNS21, and LNS22, it is observed that the blue line crosses the critical boundaries, especially between 2019 and 2022. This deviation indicates a structural break or sudden change in the model after 2019. This suggests that the model's parameters did not remain stable over time and that a structural break occurred in the model. The structural break between 2019 and 2022 likely highlights a significant change driven by major global events such as the COVID-19 pandemic.

15. Model LNS18=f(LNS2, LNS3, LNS21, LNS22).

CUSUM (Figure 5E): The coefficients appear stable as the line remains within critical boundaries.

CUSUMQ (Figure 5F): The variance shows a structural break between 2016 and 2021, suggesting a significant change during this period.

In Figure 5F, which shows the CUSUMQ graph of the regression model where the dependent variable LNS18 is related to the independent variables LNS2, LNS3, LNS21, and LNS22, it is observed that the blue line crosses the critical boundaries, particularly between 2016 and 2021. This deviation indicates a structural break or sudden change in the model during this period. This suggests that the model's parameters did not remain stable over time and that a structural break occurred in the model. The structural break between 2016 and 2021 likely points to significant events such as major changes in health policies, economic conditions, or global crises like the pandemic, which have impacted the health system.

16. Model LNS19=f(LNS2, LNS3, LNS21, LNS22).

CUSUM (Figure 6A): The line deviates post-2019, indicating a structural break or instability.

CUSUMQ (Figure 6B): The variance suggests instability post-2019, indicating a significant change in the model parameters or variance.

In Figure 6D, which shows the CUSUMQ graph of the regression model where the dependent variable LNS19 is related to the independent variables LNS2, LNS3, LNS21, and LNS22, it is observed that the blue line crosses the critical boundaries, particularly between 2020 and 2021. This deviation indicates a structural break or sudden change in the model during this period. This suggests that the model's parameters did not remain stable over time and that a structural break occurred in the model. This deviation likely reflects the effects of the COVID-19 pandemic on healthcare services and mortality rates. The economic downturn caused by the pandemic appears to have affected GDP and consumer confidence.

17. Model LNS20=f(LNS2, LNS3, LNS21, and LNS22)

CUSUM (Figure 6C): This line shows the potential structural breaks between 2020 and 2021, suggesting instability during this period.

CUSUMQ (Figure 6D): This deviation indicates a structural break in the model parameters or the variance between 2020 and 2021.

In Figure 6C, which shows the CUSUM graph of the regression model where the dependent variable LNS20 is related to the independent variables LNS2, LNS3, LNS21, and LNS22, it is observed that the blue line crosses the critical boundaries, particularly after 2019. This deviation indicates a structural break or sudden change in the model after 2019. This suggests that the model's parameters did not remain stable over time and that a structural break occurred in the model. This deviation likely reflects the effects of the COVID-19 pandemic on healthcare services and mortality rates. The economic downturn caused by the pandemic appears to have affected GDP and consumer confidence.

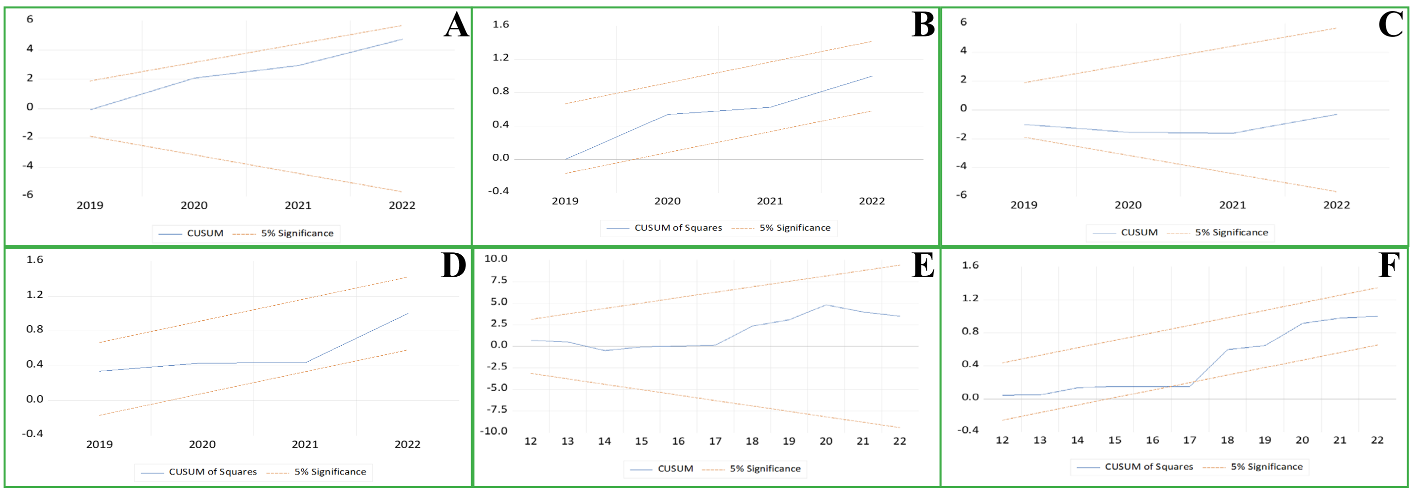

Figure 1. A. CUSUM graph of the LNS4=f(LNS2, LNS21, LNS22) model; **B.** CUSUMQ graph for the model LNS4=f(LNS2, LNS21, LNS22); **C.** CUSUM graph for the model LNS5=f(LNS3, LNS21, LNS22); **D.** CUSUMQ graph for the model LNS5=f(LNS3, LNS21, LNS22); **E.** CUSUM graph for the model LNS6=f(LNS2, LNS21, LNS22); **F.** CUSUMQ graph for the model LNS6=f(LNS2, LNS21, LNS22)

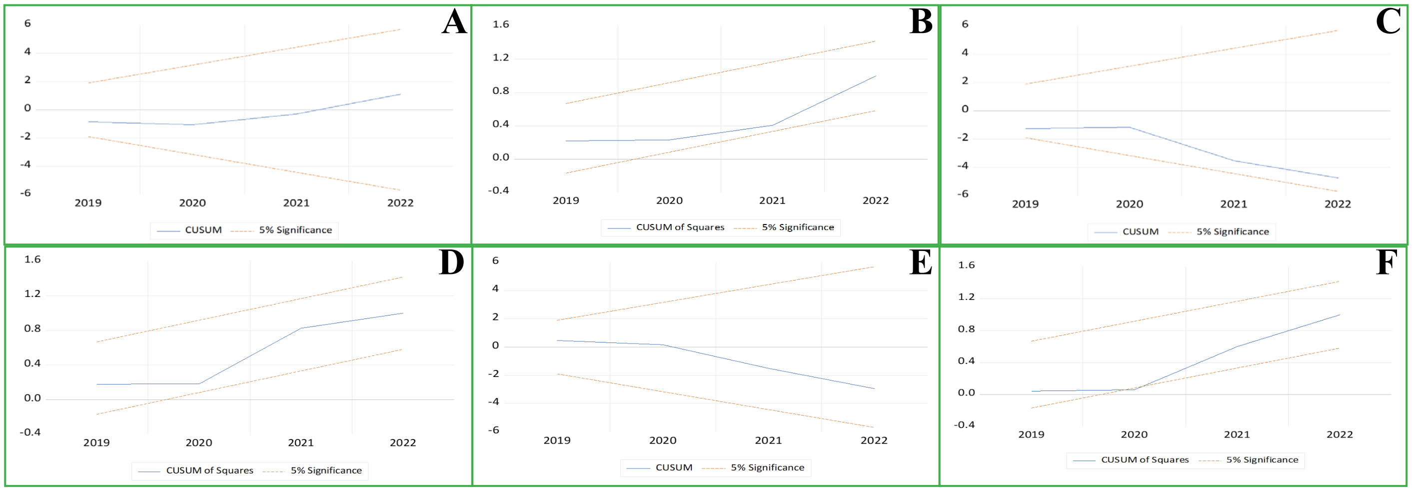

Figure 2. A. CUSUM graph for the model LNS7=f(LNS3, LNS21, LNS22); **B.** CUSUMQ graph for the model LNS7=f(LNS3, LNS21, LNS22; **C.** CUSUM graph for the model S8=f(LNS2, LNS21, LNS22); **D.** CUSUMQ graph for the model S8=f(LNS2, LNS21, LNS22); **E.** CUSUM graph for the model LNS9=f(LNS3, LNS21, LNS22); **F.** CUSUMQ graph for the model LNS9=f(LNS3, LNS21, LNS22)

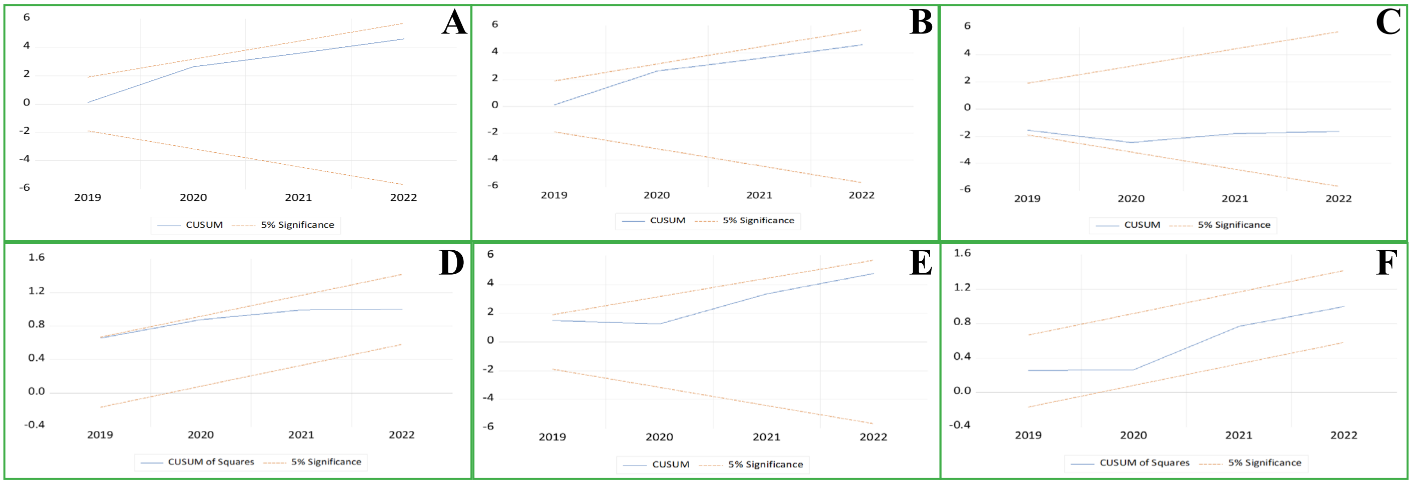

Figure 3. A. CUSUM graph for the model S10=f(LNS2, LNS21, LNS22); **B.** CUSUMQ graph for the model S10=f(LNS2, LNS21, LNS22); **C.** CUSUM graph for the model S11=f(LNS3, LNS21, LNS22); **D.** CUSUMQ graph for the model S11=f(LNS3, LNS21, LNS22); **E.** CUSUM graph for the model LNS12=f(LNS2, LNS21, LNS22); **F.** CUSUMQ graph for the model LNS12=f(LNS2, LNS21, LNS22)

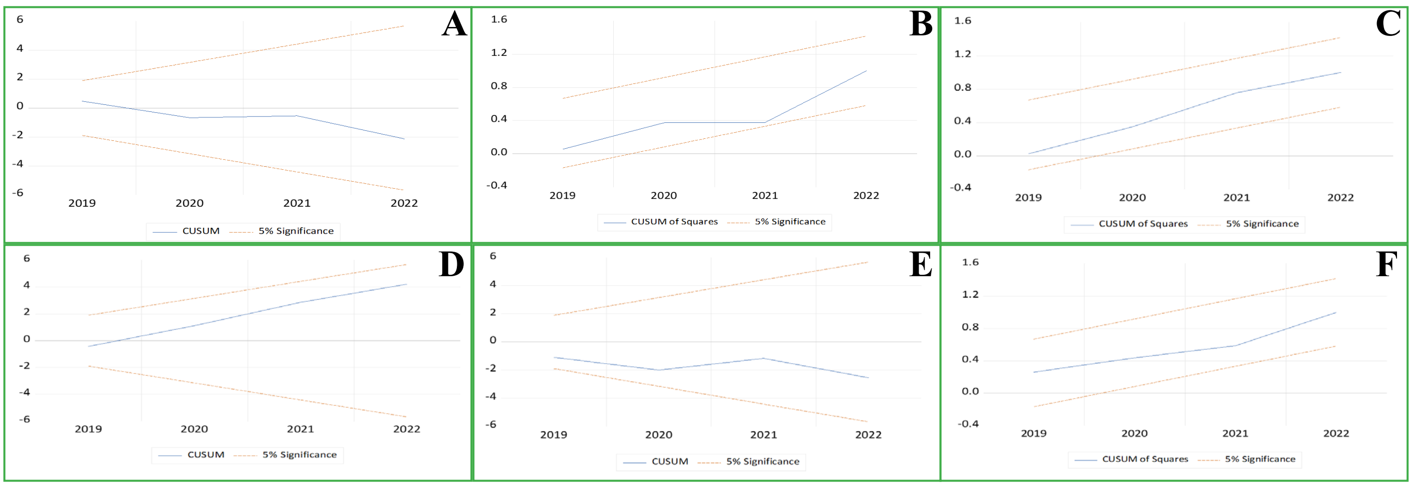

Figure 4. A. CUSUM graph for the model LNS13=f(LNS3, LNS21, LNS22); **B.** CUSUMQ graph for the model LNS13=f(LNS3, LNS21, LNS22); **C.** CUSUM graph for the model LNS14=f(LNS2, LNS21, LNS22); **D.** CUSUMQ graph for the model LNS14=f(LNS2, LNS21, LNS22)); **E.** CUSUM graph for the model LNS14=f(LNS2, LNS21, LNS22); **F.** CUSUMQ graph for the model LNS14=f(LNS2, LNS21, LNS22))

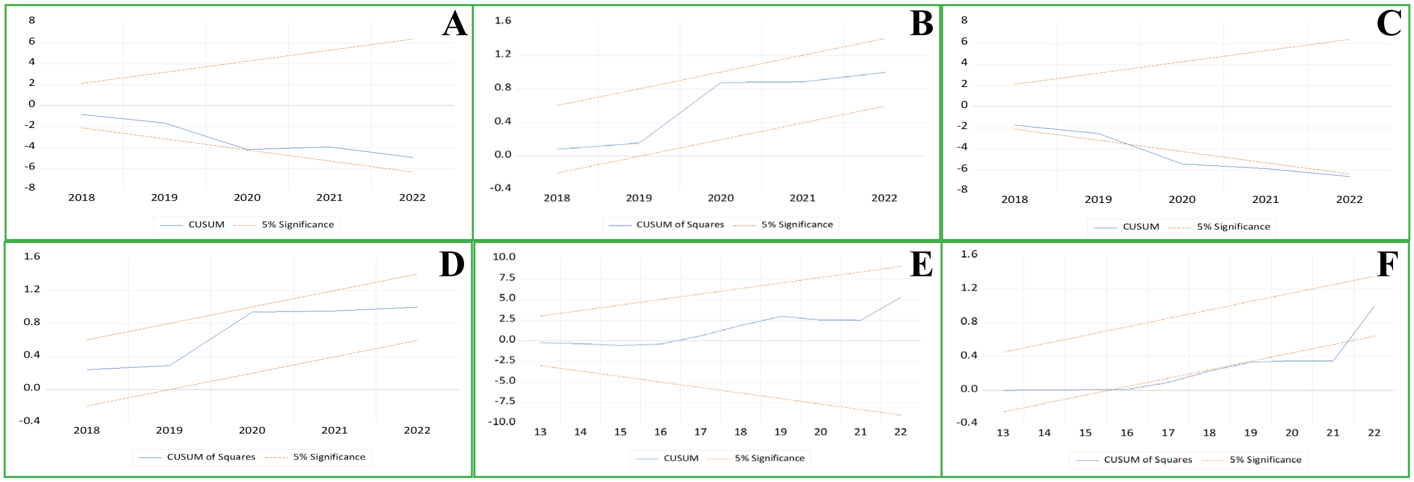

Figure 5. A. CUSUM graph for the model LNS16=f(LNS2, LNS3, LNS21, LNS22); **B.** CUSUMQ graph for the model LNS16=f(LNS2, LNS3, LNS21, LNS22); **C.** CUSUM graph for the model LNS17=f(LNS2, LNS3, LNS21, LNS22); **D.** CUSUMQ graph for the model LNS17=f(LNS2, LNS3, LNS21, LNS22); **E.** CUSUM graph for the model LNS18=f(LNS2, LNS3, LNS21, LNS22); **F.** CUSUMQ graph for the model LNS18=f(LNS2, LNS3, LNS21, LNS22)

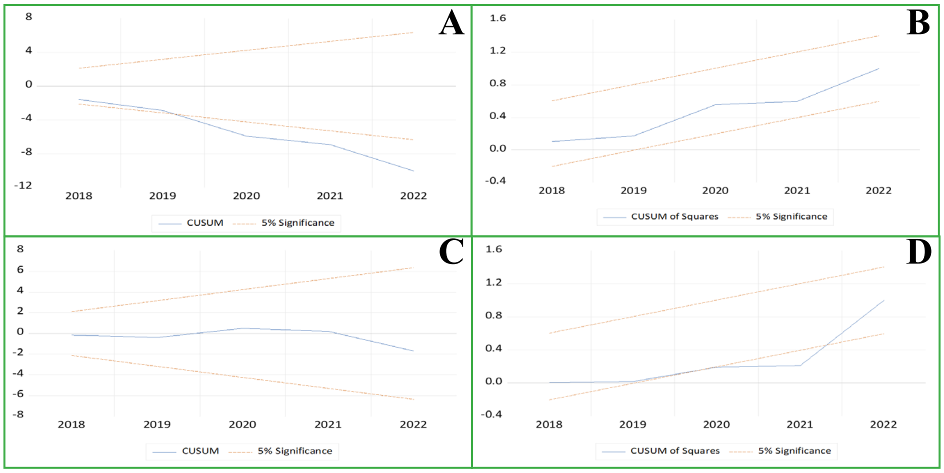

Figure 6. A. CUSUM graph for the model LNS20=f(LNS2, LNS3, LNS21, LNS22); **B.** CUSUMQ graph for the model LNS20=f(LNS2, LNS3, LNS21, LNS22); **C.** CUSUM graph for the model LNS19=f(LNS2, LNS3, LNS21, LNS22); **D.** CUSUMQ graph for the model LNS19=f(LNS2, LNS3, LNS21, LNS22)

Causality Testing Outcomes

The Toda-Yamamoto causality test was employed to assess the causal relationships between various health and economic indicators (Table 4).

Table 4. Identification of models to be examined for causality and determination of optimal lag lengths

	Lag	LogL	LR	FPE	AIC	SC	HQ	Optimal lag length (k)	d_{max}+k
LNS9=f(LNS3, LNS21, LNS22)	0	36.22941	NA	0.00000	-3.58105	-3.38319	-3.55376	3	4
	1	79.93974	63.13714*	0.00000	-6.65997	-5.67067	-6.52356		
	2	103.673	23.73330	0.00000	-7.51923	-5.73848	-7.27369		
	3	138.5877	19.39703	3.57e-09*	-9.620853*	-7.048668*	-9.266184*		
S10=f(LNS2, LNS21, LNS22)	0	-68.6515	NA	0.03768	8.07239	8.27025	8.09967	3	4
	1	-5.72612	90.89227*	0.00022	2.85846	3.84776	2.99487		
	2	14.88998	20.61609	0.00018	2.34556	4.12630	2.59110		
	3	41.95416	15.03566	0.000164*	1.116204*	3.688389*	1.470874*		

ADF: Augmented Dickey-Fuller, PP: Phillips-Perron, VAR: Vector Autoregression, SC: Schwarz Information Criterion, HQ: Hannan-Quinn Information Criterion, AIC: Akaike Information Criterion, LR: Likelihood Ratio, FPE: Final Prediction Error, dmax: Maximum Integration Degree, GDP: Gross Domestic Product, CKD: Chronic Kidney Disease, LNS: Logarithm of the Series, S: Series

Table 4. Identification of models to be examined for causality and determination of optimal lag lengths

	Lag	LogL	LR	FPE	AIC	SC	HQ	Optimal lag length (k)	d_{max}+k
S11=f(LNS3, LNS21, LNS22)	0	-76.2354	NA	0.08751	8.91505	9.11291	8.94233	3	4
	1	-11.7211	93.18742*	0.00042	3.52456	4.51387	3.66098		
	2	10.14127	21.86235	0.00031	2.87319	4.65394	3.11873		
	3	56.79243	25.91731	3.16e-05*	-0.532492*	2.039693*	-0.177823*		
LNS12=f(LNS2, LNS21, LNS22)	0	34.80162	NA	0.00000	-3.42240	-3.22454	-3.39512	3	4
	1	72.78909	54.87079	0.00000	-5.86545	-4.87615	-5.72904		
	2	89.70362	16.91453	0.00000	-5.96707	-4.18633	-5.72153		
	3	138.0042	26.83366*	3.80e-09*	-9.556023*	-6.983838*	-9.201353*		
LNS13=f(LNS3, LNS21, LNS22)	0	27.61558	NA	0.00000	-2.62395	-2.42609	-2.59667	3	4
	1	76.85476	71.12326	0.00000	-6.31720	-5.32789	-6.18078		
	2	109.7185	32.86370*	4.83e-09*	-8.19094	-6.41020	-7.94540		
	3	133.311	13.10697	0.00000	-9.034557*	-6.462372*	-8.679887*		
LNS14=f(LNS2, LNS21, LNS22)	0	33.90368	NA	0.00000	-3.32263	-3.12477	-3.29535	3	4
	1	74.82424	59.10747*	0.00000	-6.09158	-5.10228	-5.95517		
	2	91.17594	16.35170	0.00000	-6.13066	-4.34992	-5.88512		
	3	125.8329	19.25389	1.47e-08*	-8.203661*	-5.631475*	-7.848991*		
SQRTS15=f(LNS3, LNS21, LNS22)	0	-83.6957	NA	0.20047	9.74396	9.94182	9.77124	3	4
	1	-30.5124	76.82031	0.00342	5.61249	6.60179	5.74890		
	2	3.568028	34.08039*	0.00064	3.60355	5.38430	3.84909		
	3	36.59705	18.34946	0.000298*	1.711439*	4.283624*	2.066109*		
LNS16=f(LNS2, LNS3, LNS21, LNS22)	0	33.27188	NA	0.00000	-2.97599	-2.72745	-2.93393	2	3
	1	109.8203	104.75040	0.00000	-8.40214	-6.91092	-8.14976		
	2	169.5276	50.27984*	9.07e-12*	-12.05554*	-9.321634*	-11.59285*		
LNS17=f(LNS2, LNS3, LNS21, LNS22)	0	32.17854	NA	0.00000	-2.86090	-2.61236	-2.81884	2	3
	1	119.1153	118.9661*	0.00000	-9.38056	-7.88934	-9.12819		
	2	159.2337	33.78387	2.68e-11*	-10.97197*	-8.238063*	-10.50928*		
LNS18=f(LNS2, LNS3, LNS21, LNS22)	0	81.19698	NA	0.00000	-8.02073	-7.77220	-7.97867	1	2
	1	142.0925	83.33072*	5.78e-12*	-11.79921	-10.30799*	-11.54684		
	2	169.943	23.45307	0.00000	-12.09927*	-9.36536	-11.63658*		
LNS19=f(LNS2, LNS3, LNS21, LNS22)	0	62.0159	NA	0.00000	-7.12699	-6.88555	-7.11463	2	3
	1	115.6289	67.01625	0.00000	-10.70361	-9.25501	-10.62943		
	2	202.8082	54.48706*	3.09e-14*	-18.47602*	-15.82025*	-18.34003*		
LNS20=f(LNS2, LNS3, LNS21, LNS22)	0	55.79709	NA	0.00000	-5.34706	-5.09853	-5.30500	2	3
	1	138.2692	112.8565*	0.00000	-11.39675	-9.905533*	-11.14438		
	2	172.8711	29.13846	6.38e-12*	-12.40748*	-9.67358	-11.94480*		

ADF: Augmented Dickey-Fuller, PP: Phillips-Perron, VAR: Vector Autoregression, SC: Schwarz Information Criterion, HQ: Hannan-Quinn Information Criterion, AIC: Akaike Information Criterion, LR: Likelihood Ratio, FPE: Final Prediction Error, dmax: Maximum Integration Degree, GDP: Gross Domestic Product, CKD: Chronic Kidney Disease, LNS: Logarithm of the Series, S: Series

Public Hospital Beds: There is significant causal relationship between GDP (chi-square=56.13, p=0.00) and the Consumer Confidence Index (chi-square=24.31, p=0.00) with the number of public hospital beds. Public health investment expenditures also showed a significant causal effect (chi-square=10.14, p=0.04).

Private Hospital Beds: Both GDP (chi-square=59.01, p=0.00) and the Consumer Confidence Index (chi-square=18.63, p=0.00) had significant impacts on the number of private hospital beds. Similarly, private health investment expenditure had a significant influence (chi-square=24.29, p=0.00).

Health Personnel: The number of public health personnel was significantly influenced by Private Health Investment Expenditure (chi-square=39.34, p=0.00), GDP (chi-square=58.37, p=0.00),

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and Consumer Confidence Index (chi-square=23.39, p=0.00). However, public health investment expenditure did not show a significant causal relationship with the number of public health personnel (chi-square=1.06, p=0.59).

Satisfaction with Health Services: The Satisfaction with public health services was significantlytable influenced by GDP (chi-squared=22.31, p=0.00), whereas the Consumer Confidence Index showed a trend towards significance (chi-squared=7.71, p=0.10). Satisfaction with private health services was significantly affected by Private Health Investment Expenditure (chi-square=24.29, p=0.00), GDP (chi-square=835.81, p=0.00), and the Consumer Confidence Index (chi-square=1148.24, p=0.00).

MRI and CT Machines: The number of MRI machines in public hospitals was significantly influenced by GDP (chi-square=161.97, p=0.00) and Consumer Confidence Index (chi-square=48.34, p=0.00). The number of MRI machines in private hospitals was significantly influenced by GDP (chi-square=53.15, p=0.00) and Consumer Confidence Index (chi-square=9.34, p=0.05). For CT machines in public hospitals, GDP (chi-square=58.67, p=0.00) and the Consumer Confidence Index (chi-square=23.75, p=0.00) were significant predictors, whereas in private hospitals, only GDP (chi-square=10.27, p=0.04) showed a significant effect.

Surgeries: The number of surgeries in public hospitals was significantly influenced by Public Health Investment Expenditure (chi-square=9.99, p=0.04), whereas in private hospitals, significant effects were observed for Private Health Investment Expenditure (chi-square=63.01, p=0.00), GDP (chi-square=16.49, p=0.00), and Consumer Confidence Index (chi-square=62.37, p=0.00).

Mortality and Life Expectancy: GDP significantly influenced the infant mortality rate (chi-square=34.70, p=0.00), under-five mortality rate (chi-square=41.55, p=0.00), and mortality rate due to cardiovascular diseases, cancer, diabetes, and CKD (chi-square=96.65, p=0.00). The Consumer Confidence Index also showed a significant influence on under-five (chi-square=20.95, p=0.00) and infant mortality rates (chi-square=8.77, p=0.03). No significant causal relationships were observed between the studied factors and life expectancy at birth (Table 5).

Table 5. Toda-Yamamoto causality test results

Causal relationship	Chi-square test statistic	Degrees of freedom	p-value
Public health investment expenditure → Number of public hospital beds	10.1412	4	**0.0381**
GDP → Number of public hospital beds	56.1341	4	**0.0000**
Consumer confidence index → Number of public hospital beds	24.3068	4	**0.0001**
Private health investment expenditure → Number of private hospital beds	24.2866	4	**0.0001**
GDP → Number of private hospital beds	59.0146	4	**0.0000**
Consumer confidence index → Number of private hospital beds	18.6274	4	**0.0009**
Public health investment expenditure → Number of public health personnel	1.0608	2	0.5884
GDP → Number of public health personnel	0.7055	2	0.7028
Consumer confidence index → Number of public health personnel	4.1881	2	0.1232
Private health investment expenditure → Number of private health personnel	39.3383	4	**0.0000**
GDP → Number of private health personnel	58.3716	4	**0.0000**
Consumer confidence index → Number of private health personnel	23.3900	4	**0.0001**
Public health investment expenditure → Satisfaction with public health services	4.0055	4	0.4053
GDP → Satisfaction with public health services	22.3055	4	**0.0002**
Consumer confidence index → Satisfaction with public health services	7.7056	4	0.1030
Private health investment expenditure → Satisfaction with private health services	24.2892	4	**0.0001**
GDP → Satisfaction with private health services	835.8093	4	**0.0000**
Consumer confidence index → Satisfaction with private health services	1148.2350	4	**0.0000**
Public health investment expenditure → Number of MRI machines in public hospitals	9.0823	4	0.0591
GDP → Number of MRI machines in public hospitals	161.9695	4	**0.0000**
Consumer confidence index → Number of MRI machines in public hospitals	48.3437	4	**0.0000**
Private health investment expenditure → Number of MRI machines in private hospitals	3.9194	4	0.4170
GDP → Number of MRI machines in private hospitals	53.1505	4	**0.0000**
Consumer confidence index → Number of MRI machines in private hospitals	9.3437	4	0.0531
Public health investment expenditure → Number of CT machines in public hospitals	6.7586	4	0.1492
GDP → Number of CT machines in public hospitals	58.6687	4	**0.0000**

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Table 5. Toda-Yamamoto causality test results

Causal relationship	Chi-square test statistic	Degrees of freedom	p-value
Consumer confidence index → Number of CT machines in public hospitals	23.7481	4	**0.0001**
Private health investment expenditure → Number of CT machines in private hospitals	2.3982	4	0.6630
GDP → Number of CT machines in private hospitals	10.2729	4	**0.0361**
Consumer confidence index → Number of CT machines in private hospitals	2.4800	4	0.6482
Public health investment expenditure → Number of surgeries in public hospitals	9.9927	4	**0.0406**
GDP → Number of surgeries in public hospitals	2.8772	4	0.5786
Consumer confidence index → Number of surgeries in public hospitals	3.7544	4	0.4403
Private health investment expenditure → Number of surgeries in private hospitals	63.0078	4	**0.0000**
GDP → Number of surgeries in private hospitals	16.4872	4	**0.0024**
Consumer confidence index → Number of surgeries in private hospitals	62.3706	4	**0.0000**
Public health investment expenditure → Infant mortality rate	3.5051	3	0.3201
Private health investment expenditure → Infant mortality rate	1.2219	3	0.7477
GDP → Infant mortality rate	34.7005	3	**0.0000**
Consumer confidence index → Infant mortality rate	8.7659	3	**0.0326**
Public health investment expenditure → Under-five mortality rate (‰)	1.4756	3	0.6879
Private health investment expenditure → Under-five mortality rate (‰)	6.9186	3	0.0745
GDP → Under-five mortality rate (‰)	41.5528	3	**0.0000**
Consumer confidence index → Under-five mortality rate (‰)	20.9531	3	**0.0001**
Public health investment expenditure → Life expectancy at birth (years)	3.1762	2	0.2043
Private health investment expenditure → Life expectancy at birth (years)	0.1155	2	0.9439
GDP → Life expectancy at birth (years)	3.5072	2	0.1732
Consumer confidence index → Life expectancy at birth (years)	0.4061	2	0.8162
Public health investment expenditure → Crude death rate (per 1,000 people)	1.3597	3	0.7150
Private health investment expenditure → Crude death rate (per 1,000 people)	0.2075	3	0.9764
GDP → Crude death rate (per 1,000 people)	0.6106	3	0.8940
Consumer confidence index → Crude death rate (per 1,000 people)	1.5937	3	0.6608
Public health investment expenditure → Mortality rate due to cardiovascular diseases, cancer, diabetes, or CKD (%)	32.3909	3	**0.0000**
Private health investment expenditure → Mortality rate due to cardiovascular diseases, cancer, diabetes, or CKD (%)	3.5857	3	0.3098
GDP → Mortality rate due to cardiovascular diseases, cancer, diabetes, or CKD (%)	96.6515	3	**0.0000**
Consumer confidence index → Mortality rate due to cardiovascular diseases, cancer, diabetes, or CKD (%)	3.8673	3	0.2762

Discussion

This study aimed to analyze the impact of public and private health investment expenditures on various health system indicators in Türkiye from 2002 to 2022. Toda-Yamamoto causality analysis was utilized to explore the causal relationships between these expenditures and several health outcomes, including hospital capacity, health personnel numbers, patient satisfaction, and mortality rates.

The analysis of our study demonstrated a significant causal relationship between both public and private health investment expenditures and the number of beds in public and private hospitals. Specifically, public health investment expenditure significantly influenced the number of public hospital beds (χ^2=10.14, p=0.04), whereas private health investment expenditure had a significant impact on the number of beds in private hospitals (χ^2=24.29, p=0.00). These findings align with the existing literature, which underscores the critical role of health investment in expanding healthcare infrastructure. For instance, previous studies have documented that increased public health investment is strongly associated with enhanced hospital capacity and reduced regional disparities in access to healthcare services [1]. Our results are consistent with Esen and Çelik Keçili's (2021) analysis, which found that public investments in health infrastructure significantly contributed to an increase in hospital bed capacity across Türkiye during the early 2000s [4]. Furthermore, the significant influence of private investment on the capacity of private hospitals mirrors the findings from studies in other developing countries, which show that private health expenditures are pivotal in meeting the demand for specialized and high-quality healthcare services in urban areas [2].

The results also indicated that private health investment expenditure significantly influenced the number of health personnel in both public and private sectors. Private investment had a marked effect on the number of private (χ^2=39.34, p=0.00) and public health personnel (χ^2=58.37, p=0.00). However, public health investment expenditures did not show a significant causal relationship with the number of public health personnel (χ^2=1.06, p=0.59). This could be due to the relatively rigid structure of public sector employment compared with the private sector, where investment is more directly linked to personnel recruitment and retention. This divergence might reflect the efficiency and demand-driven nature of private healthcare investments, which are often more flexible and responsive to market needs than public sector investments [3]. The finding that private health investment expenditure significantly influences the number of health personnel in both the public and private sectors aligns with broader discussions on the role of private investment in healthcare. However, a systematic review by Basu et al. (2012) on the comparative performance of private and public healthcare systems in low- and middle-income countries challenges the assumption that private sector involvement consistently improves healthcare outcomes [14]. Along with the study by West et al., this review highlights that while the private sector may increase the availability and number of healthcare personnel, this does not always translate into better patient outcomes or efficiency [15]. In fact, the private sector often prioritizes profit over patient care, leading to issues such as unnecessary treatment and poorer medical standards. This suggests that, while private investment can enhance certain aspects of healthcare capacity, such as staffing, it does not necessarily ensure better quality or more effective healthcare delivery, particularly in environments where regulatory oversight is limited. This dichotomy underscores the importance of balancing the private and public sector roles in health system development to optimize both access and quality of care.

This study found that GDP and CCI had a significant influence on public satisfaction with health services, with GDP being a particularly strong predictor (χ^2=22.31, p=0.00). Satisfaction with private health services was significantly affected by private health investment expenditures (χ^2=24.29, p=0.00), GDP, and CCI. The significant impact of private investment on patient satisfaction with private health services, as highlighted in this study, aligns with the global trends observed in the healthcare sector. Private healthcare systems are often preferred by individuals seeking personalized and timely care, a preference supported by evidence from other regions as well. For instance, the findings of Rajamani and RamaRao (2019) in their report on enhancing customer satisfaction with health services emphasize that private healthcare providers often employ customer experience (CX) models that focus on creating tailored experiences, which significantly contribute to higher levels of patient satisfaction [16]. This is also consistent with the work of Ozyilmaz et al. (2022), who observed that private healthcare facilities tend to score higher on patient satisfaction owing to shorter wait times and better service quality, particularly in urban settings [6]. This global trend underscores the importance of private investment in healthcare infrastructure, where the emphasis on patient-centered care and the ability to rapidly respond to patient needs foster an environment of trust and satisfaction, further solidifying the role of private healthcare in modern health systems.

When examining the influence of health investments on mortality rates, our study found that GDP had a significant impact on reducing infant mortality (χ^2=34.70, p=0.00) and under-five mortality rates (χ^2=41.55, p=0.00), underscoring the critical role of economic stability in improving child health outcomes. However, public health investment did not show a significant direct effect on these mortality rates, which could indicate that other factors, such as healthcare quality and accessibility, might play a more substantial role in this context. To understand the role of healthcare expenditure in shaping health outcomes in Pakistan, Saleem et al.'s study highlights the significant impact of health investment on the expansion of healthcare infrastructure, providing key insights for policy enhancement. The results indicate that the under-5 mortality rate in Pakistan has risen, attributed to insufficient government spending on education, current health expenses, and the prevalence of infectious diseases [17]. Monady et al. investigated the effects of public health expenditure on various proximate and ultimate health outcomes across 28 Indian states during 2005-2016 using panel fixed-effects models and found that per capita public healthcare expenditure has an adverse impact on infant and child mortality rates [18]. This finding is also supported by international research, where similar trends have been observed: countries with higher GDP and robust economic growth generally experience lower mortality rates owing to better healthcare infrastructure and services [7].

The breaking points found in our analyses were the stability of public health personnel influenced by public health investments showing signs of instability, particularly around 2017; the crude death rate model suggests instability post-2019, the satisfaction with private health services model indicates a potential structural break around 2020, and structural breaks between 2019 and 2022, suggesting instability in the under-five mortality rate model during this period; and the life expectancy model showed instability between 2016 and 2021. These breakpoints suggest periods during which significant changes occurred within Türkiye’s health system.

The instability in public health personnel models in 2017 could be associated with changes in government policies or economic conditions that affected public sector employment. This period coincides with Türkiye's efforts to centralize and restructure its public health system, which might have led to fluctuations in staffing and resource allocation. The instability observed in public health personnel models around 2017 reflects that global trends are economic, and policy shifts impact healthcare employment. For instance, Raghupathi and Raghupathi (2020) highlight how financial crises and austerity measures in Europe resulted in reduced healthcare workforce capacity, leading to service delivery challenges [19]. Similarly, Türkiye's restructuring of its health system during this period likely contributed to fluctuations in staffing levels, as has been observed in other countries undergoing health sector reforms [20].

The potential structural break in satisfaction with private health services around 2020 likely reflects the COVID-19 pandemic's impact. The pandemic disrupted healthcare services globally, leading to significant shifts in patient satisfaction, particularly in the private sector, where the demand for services may have increased due to the strain on public hospitals. The structural break in satisfaction with private health services around 2020 can be linked to the COVID-19 pandemic, which has had a profound impact on health care systems worldwide. Studies have documented how the pandemic led to increased demand for private healthcare services owing to overwhelming public hospitals, which in turn affected patient satisfaction levels [21]. This trend was observed globally, where the private sector became a crucial alternative for those seeking immediate care, albeit with varying levels of satisfaction [14,22].

The structural breaks observed in models related to under-five mortality rates and life expectancy, the 2019-2022 Instability, may indicate the long-term effects of the COVID-19 pandemic or economic downturns during these years. The pandemic could have influenced child health outcomes and overall life expectancy, reflecting the broader systemic challenges in healthcare delivery during crises. The instability in the under-five mortality rates and life expectancy models between 2019 and 2022 can be attributed to the combined effects of the COVID-19 pandemic and economic downturn. Saleem et al. (2021) found that health crises and economic recessions often exacerbate child mortality and reduce life expectancy, particularly in low-income and middle-income countries [17]. The observed trends in Türkiye are consistent with global findings that suggest that the pandemic has had a deleterious effect on vulnerable populations, thereby affecting key health indicators [4,22].

The breakpoints identified in these models emphasize the critical need for health systems to be resilient in the face of economic shocks, policy changes, and public health emergencies. This is in line with findings from studies conducted by the World Bank (2020) and others, which advocate the integration of economic and health planning to mitigate the adverse effects of such breaking points [23]. The need for continuous monitoring and adaptive health policies is further supported by the work of the WHO (2020), which stresses the importance of flexibility in health system planning to maintain stability in healthcare outcomes [24].

The findings of this study reveal several important insights into the relationship between health investments and healthcare system capacity in Türkiye. Notably, while public health investment significantly influenced the number of hospital beds in public hospitals, it did not have a significant impact on the number of healthcare personnel in the public sector. This lack of significant influence could be attributed to structural rigidities within the public healthcare sector, where staffing levels are often determined by long-term government policies and regulations rather than being directly linked to investment flows. Public sector employment tends to be less flexible compared to the private sector, where investments can be more swiftly translated into personnel recruitment and retention. This suggests that public health investment may be more effective in expanding infrastructure (e.g., hospital beds) than in adjusting workforce levels.

This finding has important policy implications. In particular, it indicates that increasing public health investment alone may not be sufficient to address workforce shortages in the public sector. Policymakers may need to consider complementary strategies, such as reforms in hiring practices or workforce planning, to ensure that investments in infrastructure are matched by an adequate increase in healthcare personnel. Additionally, this highlights the potential need for public-private partnerships (PPPs) to help meet staffing demands, especially in areas where public sector recruitment is slow or constrained by budgetary limitations. However, the significant impact of private health investment on both hospital capacity and healthcare personnel reflects the market-driven nature of private healthcare in Türkiye. Private sector investments are typically more responsive to market demand and profitability considerations, allowing for quicker adjustments in staffing levels and service capacity. This suggests that private health investments are crucial in regions with growing healthcare demands, particularly in urban areas, where the need for specialized services is high. Moreover, the significant influence of GDP on various health outcomes, such as patient satisfaction and reduced mortality rates, underscores the importance of broader economic stability in driving improvements in the health care sector. Higher GDP likely translates into increased public spending, better healthcare services, and improved accessibility, thereby positively affecting health outcomes. This indicates that economic growth and stability are essential for sustaining improvements in health care and service quality.

The lack of a direct causal relationship between public health investments and public sector healthcare personnel highlights the need for targeted policy interventions. To effectively scale up healthcare services, investments must be accompanied by strategic workforce planning and operational reforms. Future policies should focus on ensuring that public sector investments in health infrastructure are aligned with human resource strategies, enabling a more balanced development of both physical and human capital in Türkiye's healthcare system.

Conclusion

This study provides critical insights into the impact of public and private health investment expenditure on the Turkish healthcare system from 2002 to 2022. The findings demonstrate that both public and private investments play significant roles in shaping health care outcomes, although the magnitude and direction of their impacts vary across different indicators.

1. **Capacity Expansion:** This study confirmed that public health investments have a significant causal effect on increasing the number of beds in public hospitals, while private investments similarly affect the number of beds in private hospitals. This underscores the importance of continued investment in expanding healthcare infrastructure to meet the growing demand.
2. **Human Resources:** Private health investments were found to be more effective in increasing the number of health personnel in both the public and private sectors, highlighting the flexibility and market responsiveness of the private sector in addressing workforce needs.
3. **Service Quality and Patient Satisfaction:** The analysis revealed that GDP and Consumer Confidence Index significantly influence patient satisfaction with healthcare services. Private investments were particularly effective in enhancing satisfaction with private healthcare services, which aligns with the trend of patients preferring private facilities for better service quality and shorter waiting times.
4. **Health Outcomes:** This study identified GDP as a critical factor in reducing infant and under-five mortality rates, indicating that broader economic stability plays a vital role in improving health outcomes. Public health investments, however, did not show a significant direct effect on these mortality rates, suggesting that other factors, such as healthcare quality, accessibility, and socioeconomic conditions, might be more influential.
5. **Economic Growth and Healthcare:** The significant relationships between health investment expenditures, GDP, and Consumer Confidence Index emphasize the interconnectedness of economic growth, consumer confidence, and the effectiveness of health investments. This finding highlights the need for integrated economic and health policies to sustain and improve health outcomes.

Overall, this study provides valuable evidence for the ongoing discourse on health care investment strategies in Türkiye. This highlights the importance of balanced public and private sector involvement in healthcare to address capacity, workforce, and service quality challenges, thereby improving health outcomes across the population. With these findings, we hope to provide a foundation for policymakers to design targeted interventions that enhance the efficiency and effectiveness of health investments in Türkiye's dynamic health care landscape.

Conflict of Interests
The authors declare that there is no conflict of interest in the study.

Financial Disclosure
The authors declare that they have received no financial support for the study.

Ethical Approval
The study did not involve the collection or use of personal or sensitive information, ethical committee approval was not required. The study strictly adhered to the ethical guidelines for the use of open-access data, ensuring that all procedures were conducted in an ethically responsible manner.

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