

RESEARCH ARTICLE

THE IMPACT OF HEALTH WORKERS ON HEALTH OUTCOMES DURING THE COVID-19 PANDEMIC IN G20 COUNTRIES

Fuad SELAMZADE *

ABSTRACT

The COVID-19 pandemic has highlighted the critical importance of healthcare systems and workforce efficiency on global health outcomes. This study investigates the impact of the number of physicians and nurses and midwives on health outcomes in G20 countries during the pandemic, utilizing Stochastic Frontier Analysis (SFA) in combination with Least Squares (LS) and Maximum Likelihood estimation (ML) methods. The study aims to evaluate the impact of variations in health human resources among G20 countries in 2020 on key health indicators such as life expectancy at birth, the share of health expenditures in GDP, and COVID-19-related mortality rates. By applying Stochastic Frontier Analysis (SFA), the study identifies whether inefficiencies in healthcare systems stem from technical factors or random errors. A limitation of the study is the difficulty in obtaining data for some countries for the analysis year 2020, which necessitated the use of data from the closest available years. Furthermore, restricting the sample to G20 countries may partially limit the generalizability of the findings on a global scale. Empirical analysis reveals that an increase in the number of physicians and nurses and midwives is positively associated with improvements in life expectancy and reductions in mortality rates. Specifically, the study finds that while technical inefficiencies significantly affect health outcomes in some models, random errors predominantly influence others. The results indicate that a higher healthcare workforce density correlates with better health outcomes, underscoring the essential role of healthcare human resources in managing and mitigating the impacts of a global health crisis. The findings provide valuable insights for policymakers and healthcare administrators, suggesting that enhancing the number of healthcare professionals could be a critical factor in improving health outcomes and preparing for future public health emergencies. This study contributes to the broader discourse on health policy and offers recommendations for strengthening healthcare systems in the face of global challenges.

Keywords: G20, COVID-19, Health Outcomes, Stochastic Frontier Analysis, Least Squares, Maximum Likelihood

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G20 ÜLKELERİNDE SAĞLIK ÇALIŞANLARININ COVID-19 PANDEMİSİ DÖNEMİNDE SAĞLIK ÇIKTILARI ÜZERİNDEKİ ETKİSİ

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ÖZ

COVID-19 pandemisi, sağlık sistemleri ve iş gücü verimliliğinin küresel sağlık sonuçları üzerindeki kritik önemini vurgulamıştır. Bu çalışma, G20 ülkelerinde pandeminin etkisi altında, hekim ve hemşire ile ebe sayısının sağlık sonuçları üzerindeki etkisini araştırmakta, Stokastik Sınır Analizi (SFA) ile birlikte En Küçük Kareler (LS) ve Maksimum Olabilirlik (ML) tahmin yöntemlerini kullanmaktadır. Araştırma, G-20 ülkelerinin 2020 yılında sağlık insan kaynaklarındaki varyasyonların, doğumda beklenen yaşam süresi, GSYİH'deki sağlık harcamalarının payı ve COVID-19 ile ilişkili ölüm oranları gibi anahtar sağlık göstergeleri üzerindeki etkisini değerlendirmeyi amaçlamaktadır. SFA uygulanarak, sağlık sistemlerindeki verimsizliğin teknik faktörlerden veya rastgele hata kaynaklı olduğunu belirlenmiştir. Bazı ülkelerin verilerinin analiz yılı olan 2020 yılı için elde edilmesinde sıkıntıların yaşanması ve yerinde en yakın yılların verilerin kullanılması çalışmanın sınırlılığı olarak görülmektedir. Ayrıca, G20 ülkeleriyle sınırlı bir örneklem kullanılması, sonuçların küresel ölçekte genellenebilirliğini kısmen sınırlayabilmektedir. Ampirik analiz, hekim, hemşire ve ebe sayısındaki artışın, doğumda beklenen yaşam süresinin iyileşmesi ve ölüm oranlarının azalması ile olumlu bir ilişki içerisinde olduğunu ortaya koymaktadır. Özel olarak, çalışma, bazı modellerde teknik verimsizliklerin sağlık sonuçlarını önemli ölçüde etkilediğini, diğerlerinde ise rastgele hataların öncelikli olarak etkili olduğunu bulmaktadır. Sonuçlar, daha yüksek sağlık iş gücü yoğunluğunun daha iyi sağlık sonuçları ile ilişkilendirildiğini göstererek, sağlık insan kaynaklarının küresel bir sağlık krizinin yönetilmesi ve etkilerinin azaltılmasında hayati bir rol oynadığını vurgulamaktadır. Bulgular, politika yapıcılar ve sağlık yöneticileri için değerli içgörüler sunmakta ve sağlık profesyonellerinin sayısının artırılmasının, sağlık sonuçlarının iyileştirilmesi ve gelecekteki kamu sağlığı acil durumlarına hazırlık açısından kritik bir faktör olabileceğini önermektedir. Bu çalışma, sağlık politikası konusundaki daha geniş tartışmalara katkıda bulunmakta ve küresel zorluklarla başa çıkma konusunda sağlık sistemlerinin güçlendirilmesi için önerilerde bulunmaktadır.

Anahtar Kelimeler: G20, COVID-19, Sağlık Çıktıları, Stokastik Sınır Analizi En Küçük Kareler, Maksimum Olabilirlik

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I. INTRODUCTION

The COVID-19 pandemic has served as an extraordinary global crisis that tested the resilience of health systems and highlighted the critical role of healthcare human resources in ensuring service continuity. During this period, the availability of physicians, nurses, and midwives played a vital role not only in managing the disease burden but also in reducing preventable deaths. In this context, investigating the impact of the number of healthcare workers on health outcomes is not only academically relevant but also of high practical value for shaping health policies (Korkmazer, Selamzade, and Bostan, 2020). Analyzing this relationship within the context of G20 countries, which comprise both high- and middle-income nations, offers the potential to generate generalizable findings for global health security. Therefore, this study aims to make a significant contribution by evaluating how healthcare human resources affected key health indicators such as mortality and life expectancy during the pandemic (Selamzade et al., 2020).

The G20 countries represent a substantial portion of the global population and a significant segment of the world economy. The effectiveness of healthcare systems in these countries can directly influence both national and global health outcomes. Among the methods used to evaluate healthcare system performance, Stochastic Frontier Analysis (SFA), in conjunction with regression analyses, holds a prominent place. SFA provides technical efficiency and productivity analyses, which can be instrumental in developing strategies to improve health outcomes.

This study analyzes the impact of the number of physicians and nurses and midwives on health outcomes in G20 countries using Stochastic Frontier Analysis (SFA), alongside Least Squares (LS) and Maximum Likelihood estimation (ML) methods. The objective of the study is to determine the role of healthcare human resources during the COVID-19 pandemic and to correlate them with health outcomes. In this context, the study examines the effects of the number of physicians and nurses and midwives on indicators such as life expectancy at birth, the share of health expenditures in GDP, COVID-19-related mortality rates, and other health metrics.

The study aims to evaluate the performance of healthcare systems in G20 countries and understand the impact of healthcare workforce on health outcomes during the pandemic. It also seeks to provide insights and recommendations for policymakers, highlighting how the findings can be utilized to strengthen healthcare systems and prepare for future crises. The study's results are expected to contribute to the literature on health policy and international health management.

The structural and functional differences in the healthcare systems of G20 countries, which include both developed and developing nations, have made a significant contribution to shaping this study and have enabled comparisons of the distribution and efficiency levels of health human resources across countries. This diversity has allowed for a broader perspective in evaluating the effects of both health expenditures and workforce density on health outcomes. Consequently, the findings offer policy recommendations not only for uniform healthcare system practices but also for countries with varying economic and socio-cultural contexts.

II. LITERATURE REVIEW

In contemporary times, the performance measurement analyses of various economic unions or communities, particularly in the service sector and especially within the healthcare sector, are often conducted using parametric methods such as Stochastic Frontier Analysis and/or non-parametric methods like Data Envelopment Analysis. This study references several domestic and international research works that have investigated the efficiency of healthcare systems using Stochastic Frontier Analysis methods.

In a study by Bedir (2016), the link between income and healthcare expenditures from 1995 to 2013 was analyzed using Stochastic Frontier Analysis for developing countries across Europe, the

Middle East, Africa, and Asia. The findings indicated that income plays a crucial role in explaining the disparities in healthcare expenditures among these nations. Aboubacar and Xu (2017) explored the connection between healthcare expenditures and economic growth in Sub-Saharan Africa from 1995 to 2014, utilizing the Generalized Method of Moments (GMM). Their research revealed a positive and statistically significant relationship between the two variables.

Jakovljevic et al. (2020) examined the relationship between healthcare expenditures and real GDP growth before, during, and after the 2008 Global Crisis in G7 and Emerging Markets Seven (EM7) countries. They concluded that EM7 countries were more resilient to the crisis's effects compared to G7 economies. The study also estimated that the 2008 economic crisis adversely impacted healthcare expenditure patterns in both groups. Mumba (2020) conducted a study on the determinants of local public healthcare expenditures within the Southern African Development Community (SADC) using annual panel data from 2000 to 2016. By applying the Autoregressive Distributed Lag (ARDL) approach and the Pooled Mean Group Estimator, the study found that GDP per capita, infant mortality rate, and aging population negatively and significantly influenced local public healthcare expenditures in the long term. Nassar et al. (2020) assessed the technical efficiency of healthcare systems in 21 selected middle-income countries from 2000 to 2017 using the Random Effects Model of Stochastic Frontier Analysis. The study concluded that persistent inefficiency in the healthcare systems of these countries was lower than transient inefficiency. It suggested that less efficient nations, such as South Africa and Russia, could enhance their healthcare systems by adopting strategies from more efficient countries. Efficient countries like Vietnam, Mexico, and China were noted for their nearly universal social health insurance systems. Yesilyurt and Selamzade (2020) evaluated the efficiency of healthcare systems in the Commonwealth of Independent States using Stochastic Frontier Analysis with data from 2010 and 2015. The study discovered that an increase in the number of physicians per thousand people was significantly associated with reductions in under-five mortality rates and tuberculosis cases. Welfens (2020) estimated the macroeconomic and healthcare impacts of the COVID-19 pandemic in the European Union, the United States, and selected countries using Stochastic Frontier Analysis with 2018 data. The study found that the global pandemic had a considerably negative effect on both the economies and healthcare metrics of these countries.

Alexiou and Trachanas (2021) examined the influence of government political orientation on infant mortality rates in 15 G20 countries from 2000 to 2018. Their analysis showed that the political orientation of the ruling party significantly affected infant mortality rates. The study suggested that left-wing governments, compared to right-wing and centrist parties, contributed more positively to health outcomes, especially in conjunction with government healthcare spending. Meng (2021) tested the convergence clustering hypothesis in G20 countries using daily data from March 1, 2020, to October 10, 2020, based on COVID-19 pandemic spread measures. The study identified three clusters for income per capita and two clusters each for new cases and total cases per million people. It also revealed that G20 countries implemented similar measures against pandemic deaths per million people, as only one and two clusters were identified for new deaths and total deaths per million people, respectively. Selamzade and Yeşilyurt (2021) analyzed the effects of health status indicators on healthcare expenditures in OECD countries using Stochastic Frontier Analysis with 2016 data. The findings indicated that inefficiencies were largely due to random errors. The study found positive significant relationships between healthcare expenditures and life expectancy at birth, as well as the number of nurses, while a negative significant relationship was identified with infant mortality rates.

Kocadağlı et al. (2022) assessed the impact of demographic structure, socio-economic development, government measures against COVID-19, and health practices on the transmission rate until the first peak days (plateaus) in G20 and EU countries using Multivariate Analysis. The study concluded that the first COVID-19 plateaus varied between developed and developing countries, with some developed nations showing similar trends due to their higher proportions of the population over 65 and higher Human Development Index (HDI) ratios. Taylan et al. (2022) sought to reveal the hidden economic models of G20 countries, analyze the complexity of relevant economic factors, and evaluate the economic responses of policymakers during the COVID-19 pandemic recession (2019-

2020). They employed parametric non-classification tree and hierarchical clustering approaches, along with data mining techniques, to analyze variables such as GDP per capita, industrial production, government spending, COVID-19 cases per population, patient recovery, COVID-19 death cases, number of hospital beds per 1000 people, and the percentage of the vaccinated population. The study concluded that GDP per capita and COVID-19 patient recovery rates were the most significant factors for G20 countries.

Bhattacharyya and Paul (2023) aimed to identify disparities in healthcare facility expenditures in 14 selected low- and high-income countries during two periods, 2009-2019 and 2020-2021, using the Generalized Entropy (GE) method. Their study concluded that the COVID-19 shock and heterogeneity in healthcare expenditures, particularly during the pandemic, did not support the convergence trend. Ngami and Ventelou (2023) examined the impact of environmental quality on health system outcomes in OECD countries using Stochastic Frontier Analysis with data from 2007-2016, as measured by life expectancy at birth. Their study concluded that environmental quality is critically important in addressing public health challenges.

III. METHODOLOGY

3.1. Least Squares method

One of the most frequently used methods in regression analysis, the Least Squares (LS) method, was developed by the German mathematician C. F. Gauss in the 18th century (Kutlar, 2012). The choice of Stochastic Frontier Analysis (SFA) was driven by its ability to separate inefficiency effects from random statistical noise, providing more nuanced insights into the technical efficiency of healthcare systems (Techi et al. 2025). Compared to other parametric methods, SFA offers a structured framework for modeling production frontiers under stochastic conditions; however, it relies on specific distributional assumptions for inefficiency and error terms, which may affect the robustness of the results if these assumptions are violated (Cooper and Tone, 1997). When contrasted with non-parametric techniques such as Data Envelopment Analysis (DEA), SFA has the advantage of accounting for measurement errors, yet it is less flexible in handling complex, multi-input and multi-output settings and can be sensitive to model specification. These considerations highlight that while SFA is a powerful tool, its findings should be interpreted in light of these methodological constraints (Selamzade and Yeşilyurt, 2021).

To ensure simplicity, classical economic calculations often use the Cobb-Douglas production function, where the maximization of a single output "Y" using inputs X_1 and X_2 is formulated as follow (Meeusen and van den Broeck, 1977; Cooper and Tone, 1997):

$$Y_i = \alpha X_{i1}^{\beta_1} X_{i2}^{\beta_2} e^{v_i} \quad (1)$$

When this exponential equation is linearized (log-linearized), it can be expressed as (Cooper and Tone, 1997):

$$\ln Y_i = \ln \alpha + \beta_1 \ln X_{i1} + \beta_2 \ln X_{i2} + v_i = \beta_0 + \beta_1 \ln X_{i1} + \beta_2 \ln X_{i2} + v_i \quad (2)$$

Here, the β serve as estimators for the actual production function parameters. In logarithmic equations, the estimated parameters do not provide the slope, as in linear regression equations, but rather elasticity coefficients (Cooper and Tone, 1997). The statistical errors in the regression (also known as residual values) are denoted by v . These statistical error terms can later be added to each Y value through sampling from the distribution $v_i \sim \text{iid } N(0, \sigma_v^2)$ by sampling (iid - independent, identically distributed). The residuals are independent and have a zero mean and constant variance distribution. Since equation (2) cannot be observed directly, a sample regression equation is used instead, which can be written as (Selamzade and Yeşilyurt, 2021):

$$\ln Y_i = \tilde{\beta}_0 + \tilde{\beta}_1 \ln X_{i1} + \tilde{\beta}_2 \ln X_{i2} + v_i = \ln \tilde{Y}_i + \tilde{v}_i \quad (3)$$

$$\tilde{v}_i = \ln Y_i - \ln \tilde{Y}_i \quad (4)$$

Here, $\ln Y_i$ represents the actual output, while $\ln \tilde{Y}_i$ represents the estimated output values. Since the sum of the residuals for N observations equals zero, the LS criterion is applied (Selamzade and Yeşilyurt, 2021):

$$\min \sum \tilde{v}_i^2 = \sum (\ln Y_i - \ln \tilde{Y}_i)^2 \quad (5)$$

To minimize the sum of squared residuals, the partial derivatives with respect to the independent variables (elasticity parameters $\tilde{\beta}_0, \tilde{\beta}_1, \tilde{\beta}_2$) are taken (Khan, 2017). The standard error of the estimated residuals is the square root of the variance σ^2 , which is considered the conditional variance of Y_i and u_i given X_i . In addition to the standard errors of the estimated parameters, the coefficient of determination R^2 and the adjusted $\bar{R}^2$ are used to measure the goodness-of-fit of the regression results. The values of R^2 and $\bar{R}^2$ indicate the proportion of the variation in Y_i that can be explained by the changes in X_i , and are expressed as follows (Kumar, 2020):

$$R^2 = 1 - \frac{\sum \tilde{u}_i^2}{\sum y_i^2}; \quad \bar{R}^2 = 1 - \frac{\sum \tilde{u}_i^2 / (n-k)}{\sum y_i^2 / (n-1)} \quad (6)$$

The reliability of the estimated parameters in the regression equation is also assessed by calculating the t-distribution. The t-statistic, developed before the 1960s by R. A. Fisher, J. R. Newman, and P. Pearson, indicates whether the obtained estimates confirm or refute the null hypothesis (Perezgonzalez and Fisher, 2015). The t-value is obtained by dividing the difference between the estimator and the actual parameter by the standard error of the estimator (Perezgonzalez and Fisher, 2015):

$$t = \frac{\tilde{\beta} - \beta}{sh(\tilde{\beta})} \quad (7)$$

To find the confidence interval for β , the significance level α is divided by two, and the desired significance level is obtained from the t-statistic table at $t_{\alpha/2}$, with $n-k$ degrees of freedom. The P-value is calculated as follows (Pfanzagl and Sheynin, 1996):

$$P(-t_{\alpha/2} \leq t(= \frac{\tilde{\beta} - \beta}{sh(\tilde{\beta})}) \leq t_{\alpha/2} = 1 - \alpha \quad (8)$$

$$P(\tilde{\beta} - t_{\alpha/2} * sh(\tilde{\beta}) \leq \beta \leq \tilde{\beta} + t_{\alpha/2} * sh(\tilde{\beta}) = 1 - \alpha \quad (9)$$

When the degrees of freedom exceed 2 and the significance level is set at 0.05, the null hypothesis is rejected if the absolute value of the t-statistic exceeds ± 2 . In such cases, the estimator is considered significantly different from zero. When evaluating the results of statistical tests, the P-value, which indicates the lowest probability level at which the null hypothesis can be rejected, is considered. If the P-value from the regression result does not exceed the given significance level, the result is considered significant; otherwise, it is deemed non-significant.

In multiple regression analyses, the t-test can be misleading. In such cases, variance analysis is performed using the F-statistic, which only pertains to the parameters of the variables and does not involve any testing related to the constant term. The F-statistic is calculated as follows (Kutlar, 2012):

$$F = \frac{R^2 / (k-1)}{(1-R^2) / (n-k)} \quad (10)$$

Here, k denotes the number of parameters, and n represents the number of observations, with $k-1$ as the numerator and $n-k$ as the denominator degrees of freedom. If the F-statistic value exceeds the

critical value at the significance level α given in the F table, the null hypothesis is rejected; otherwise, it is accepted. Stochastic frontier analysis regressions rely on key assumptions for model success. These assumptions include the absence of perfect multicollinearity among independent variables, heteroscedasticity in the u_i term, and autocorrelation among the disturbance terms. The presence of any of these issues complicates or even makes it impossible to obtain reliable regression parameter estimates.

To investigate the possibility of heteroscedasticity, the White Test was applied in the analysis. The following hypotheses were tested (Kutlar and Salamov, 2018):

H_0 : The residuals do not have heteroscedasticity.

H_1 : The residuals have heteroscedasticity.

During the test, the square of the residuals is regressed on the constant, X_i and X_i^2 variables. The value obtained by multiplying the R^2 value from the regression by the number of observations will be checked for consistency with the χ^2 distribution at a 5% significance level under the null hypothesis of homoscedasticity (Kumar, 2020). When a linear relationship is present and significant among the inputs in the analysis, it is likely that multicollinearity exists among the independent variables. To detect multicollinearity, the Variance Inflation Factor (VIF) equation was used. When the relationship among the independent variables is close to zero, the VIF value equals 1. If the relationship among the independent variables exceeds 95% ($VIF > 5$), it is considered that there is significant near-perfect collinearity (Kutlar and Salamov, 2018).

In econometric analyses, relationships between successive observations arranged in cross-sections and time series indicate autocorrelation or serial dependence. One of the assumptions accepted in the OLS method is the independence of successive values of the random variable u_i , meaning that the value taken by u_i is not influenced by previous periods. To determine whether there is serial dependence in the analysis, the Durbin-Watson d-statistic is used, which is expressed as the ratio of the sum of the squares of the first differences of successive observations of the stochastic variable to the sum of its squared values (Perezgonzalez and Fisher, 2015). In the Durbin-Watson d statistic analysis, the following hypotheses are tested:

H_0 : There is no positive or direct autocorrelation.; H_1 : There is no negative or inverse autocorrelation.

As d approaches 0, positive autocorrelation is assumed, while as d approaches 4, negative autocorrelation is assumed. If d is approximately around 2, it is concluded that there is no autocorrelation (Kutlar, 2012).

3.2. Maximum Likelihood (ML) Method

The Maximum Likelihood method is employed to characterize a sample used in analysis with a set of parameter values that most likely describe the data. The ML estimate of the parameter vector is simply the specific vector of β values that maximizes the likelihood of observing the given data (Kennedy, 2000).

When estimating a multiple regression model using the ML method, the joint probability density function for the normally and independently distributed Y_i outcome, considering the mean and variance, is represented by the following formula in a regression equation with k variables (Kutlar and Salamov, 2018):

$$f(Y_1, Y_2, \dots Y_n | \beta_0 + \beta_1 X_{1i} + \dots + \beta_k X_{ki}, \sigma^2) \quad (11)$$

When this function is expressed as the product of n individual densities, it takes the following form (Kimsey, 2009):

$$f(Y_i) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{1}{2} \frac{(Y_i - \beta_0 - \beta_1 X_{1i} - \dots - \beta_k X_{ki})^2}{\sigma^2}\right\} \quad (12)$$

The resulting equation (12) represents the density function of a normally distributed variable. This value, derived separately for each Y_i , is expressed by n equations (Kutlar, 2012; Kutlar and Salamov, 2018). To facilitate Stochastic Frontier analysis, we can represent the inefficiency formula based on the Cobb-Douglas function as follows (Kimsey, 2009):

$$\ln D_{0i} = \beta_0 + \sum_{m=1}^M \beta_m \ln y_{mi} + \sum_{n=1}^N \beta_n \ln x_{ni} + v \quad (13)$$

Generally, each v_i random variable is assumed to be independently distributed from each u_i random variable, and both error terms are assumed to be uncorrelated with the explanatory variables. In Stochastic Frontier analysis, the following assumptions are made for the random variable (Kennedy, 2000):

$$E(v_i | X_i) = 0 \quad (14)$$

This implies that, given the values of x , the mean of the disturbance term is zero. When v_i is homoscedastic, the variance of v_i is constant and positive for each X_i , expressed as (Akimova, 2014):

$$\text{variance}(v_i | X_i) = E[v_i - E(v_i) | X_i]^2 = E(v_i^2 | X_i) = \sigma_v^2 \quad (15)$$

The following distributional assumptions are used to obtain the ML estimates of the Stochastic Production Frontier (Aigner, Knox-Lovell and Schmidt, 1977). These assumptions include the distributions $v_i \sim \text{iid } N(0, \sigma_v^2)$ and $u_i \sim \text{iid } N^+(0, \sigma_u^2)$. The variance σ^2 is equal to the sum of σ_v^2 , the variance of the random variable, and σ_u^2 , the variance of technical inefficiency. When $\sigma_u^2 = 0$, the ML analysis regression equation reduces to the OLS method (Coelli, 1996).

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \quad (16)$$

The value of γ , which measures the significance of the Stochastic Frontier estimate, is equal to σ_u^2/σ^2 and indicates the source of the inefficiency (Coelli, 1996).

IV. DATAS

In the study, data obtained from the World Bank (2020), Worldometers Coronavirus database (2020) and the European Centre for Disease Prevention and Control (ECDC) (2024a; 2024b) website database for G20 countries for 2020 were used. Since physician and nurse data for Brazil and South Africa could not be accessed for 2020, the most recent 2021 data was used. Another variable used in the study, Covid-19 mortality rates, was obtained for December 30-31, 2020. The Covid-19 mortality rates of the European Union were calculated by the authors using data obtained from the ECDC website in the Excel program. Regression analyses were performed using Eviews7 and StataMP13 programs.

The unavailability of physician and nurse data for Brazil and South Africa for the year 2020, and the subsequent use of data from 2021 instead, may introduce a certain degree of bias or measurement error in the regression analyses. This issue is particularly relevant given that sudden changes in healthcare human resources during the peak periods of the pandemic may not be accurately captured. The use of 2021 data carries the risk that the corresponding coefficients might overestimate or underestimate the true effect, depending on whether the number of healthcare workers in these countries increased or decreased under pandemic conditions. Although this limitation affects only a limited number of countries, acknowledging this data discrepancy is essential for the interpretation of

the overall model results, necessitating a more cautious and context-sensitive evaluation of the findings (Mac-Seing, Gidey, & Di Ruggiero, 2023; Nair, 2023).

The dependent variables used in this study—life expectancy, COVID-19 mortality rate, health expenditures as a share of GDP, and neonatal, infant, and under-five mortality rates—are widely recognized by institutions such as the WHO and the World Bank as essential indicators of public health performance. The independent variables, the number of physicians and nurses/midwives per 1,000 population, represent core inputs reflecting the quality and capacity of healthcare delivery systems (Şener & Yiğit, 2024; Bhaskar, 2023; Ersezer, 2024; Ersezer & Ülgen, 2024). Child mortality indicators, in particular, are sensitive and direct reflections of a country's healthcare effectiveness and are strongly associated with the availability of skilled health personnel (Aras, 2023; Akbulut & Çeçen 2025;). For example, Yesilyurt and Selamzade (2020) empirically demonstrated that increased nurse density significantly contributes to reducing child mortality. During the COVID-19 pandemic, the presence of healthcare workers was critical in maintaining essential services, providing preventive care, and managing emergency responses. Therefore, the statistically significant negative association between healthcare workforce density and child mortality observed in this study underscores the essential role of human resources in mitigating the adverse effects of a strained health system during a pandemic (Kant & Clark, 2023; Kaya & Naldöken, 2023; Türkoğlu, & Abiş 2024).

Table 1. Variables Used in the Study and Definitions

Variables	Definitions
Physicians	Generalist and specialist medical practitioner physicians, per 1,000 people.
Nurses	Includes nurses and midwives of all categories working in health institutions and organizations per 1,000 people.
LifeExp	Life expectancy at birth- represents the number of years a newborn can live assuming that the prevalent mortality rates in the country at the time of birth remain the same throughout its life.
CovidDeath	The Covid-19 death rate shows the number of people who died from the COVID-19 pandemic during the year divided by the number of deaths per 100.000 populations.
NeonMort	Neonatal Mortality Rate: The number of newborns dying before reaching 28 days of age, per 1,000 live births in a given year.
InfantMort	Infant Mortality Rate: The number of infants dying before reaching one year of age, per 1,000 live births in a given year.
Under5Mort	Under-Five Mortality Rate: The probability per 1,000 that a newborn will die before reaching the age of five, given the age-specific mortality rates of the specified year.
ExpGDP	Current Health Expenditure as a Percentage of GDP: The level of health expenditure expressed as a percentage of the Gross Domestic Product (GDP).

All data except CovidDeath are obtained from World Bank Development Indicators for 2020 year <https://data.worldbank.org>
The data for CovidDeath are extracted from Worldometers Coronavirus Data and European Centre for Disease Prevention and Control (2020)
<https://www.worldometers.info/coronavirus/>
<https://www.ecdc.europa.eu/en/publications-data/archive-historical-data-testing-volume-covid-19>
<https://www.ecdc.europa.eu/en/publications-data/download-historical-data-20-june-2022-weekly-number-new-reported-covid-19-cases>

The hypotheses investigated in the study were created as follows:

$H_0: \beta_0 = \beta_1 = \beta_2 = \beta_3 = 0$; H_1 : At least one parameter $\neq 0$

The following regression equations were created in the calculation of the efficiency estimates:

$$1. \ln \text{LifeExp} = \beta_0 + \beta_1 \ln \text{Physicians} + \beta_2 \ln \text{Nurses} + v_i - u_i$$

$$2. \ln \text{ExpGDP} = \beta_0 + \beta_1 \ln \text{Physicians} + \beta_2 \ln \text{Nurses} + v_i - u_i$$

$$3. \ln\text{CovidDeath} = \beta_0 + \beta_1 \ln\text{Physicians} + \beta_2 \ln\text{Nurses} + v_i - u_i$$

$$4. \ln\text{NeonMort} = \beta_0 + \beta_1 \ln\text{Physicians} + \beta_2 \ln\text{Nurses} + v_i - u_i$$

$$5. \ln\text{InfantMort} = \beta_0 + \beta_1 \ln\text{Physicians} + \beta_2 \ln\text{Nurses} + v_i - u_i$$

$$6. \ln\text{Under5Mort} = \beta_0 + \beta_1 \ln\text{Physicians} + \beta_2 \ln\text{Nurses} + v_i - u_i$$

The statistics of the data used in the study analyzing the health systems of G20 countries are presented in Table 2. The independent variables used in the study are: Germany is the country with the maximum number of Physicians, Indonesia is the country with the minimum number; Australia is the country with the maximum number of Nurses, India is the country with the minimum number; Japan is the country with the maximum number of LifeExp, and South Africa is the country with the minimum number.

Table 2. Statistics of Variables

	Physicians	Nurses	LifeExp	CovidDeath
Max	4.459	16.40	84.560	328.4
Min	0.627	1.728	65.252	1.736
Average	2.793	7.687	77.090	71.865
Std. Dev.	1.166	4.078	5.602	75.994
	NeonMort	InfantMort	Under5Mort	ExpGDP
Max	20.200	28.100	35.300	18.756
Min	0.800	1.800	2.400	3.340
Average	5.188	8.381	9.938	9.291
Std. Dev.	4.750	8.034	9.603	3.749

The dependent variables used in the study are: The country with the maximum CovidDeath number is China, the country with the minimum is the Republic of South Korea; the country with the maximum NeonMort and InfantMort numbers is India, the country with the minimum is Japan; the country with the maximum Under5Mort number is South Africa, the country with the minimum is Japan; the country with the maximum ExpGDP is USA, the country with the minimum is India.

V. RESULTS

In the study, the Least Squares (LS) and Maximum Likelihood (ML) methods of stochastic frontier analysis were used to create Cobb-Douglas production function regression equations. Before the calculations were made, it was examined whether there was multicollinearity, heteroscedasticity and serial dependency between the disturbing terms and between the independent variables in the regressions.

Table 3 presents the analysis of assumptions regarding the accuracy of the model resulting from the stochastic frontier analysis regression. The analysis revealed that the Variance Inflation Factor (VIF) values obtained from the regressions were less than 5, indicating the absence of multicollinearity issues. Furthermore, the results of the White test, which assesses the presence of heteroscedasticity in regression analyses, showed that the F-statistic values were smaller than those from the F-table and were statistically insignificant, suggesting that there were no issues with variable variance.

Table 3. Accuracy Tests of Regressions

	Model 1		Model 2		Model 3	
VIF		1.6966		1.6966		1.6966
Heteroskedasticity Test: White	N	p	N	p	N	p
F-statistic	0.407	0.836	1.670	0.206	1.614	0.220
Obs*R ²	2.538	0.771	7.472	0.188	7.313	0.198
Scaled explained SS	1.388	0.926	3.510	0.622	3.351	0.646
Durbin-Watson Test	1.750		1.542		1.896	
	No autocorrelation		No autocorrelation		No autocorrelation	
	Model 4		Model 5		Model 6	
VIF		1.6966		1.6966		1.6966
Heteroskedasticity Test: White	N	p	N	p	N	p
F-statistic	0.580	0.714	0.863	0.530	0.586	0.711
Obs*R ²	3.436	0.633	4.711	0.452	3.460	0.630
Scaled explained SS	1.786	0.878	3.501	0.623	1.770	0.880
Durbin-Watson Test	1.549		1.122		1.571	
	No autocorrelation		No Decision		No autocorrelation	

The results of the Durbin-Watson test conducted to detect autocorrelation issues in the regressions indicate that, except for Model 5, all other regressions are at an acceptable level. In Model 5, the Durbin-Watson test value is 1.122, making it indeterminate whether an autocorrelation problem exists. Given that the obtained value is close to those indicating no autocorrelation, it is considered acceptable in the study. Various models have been developed to identify factors affecting the health status indicators of G20 countries. Models that do not exhibit the aforementioned issues have been included in the study.

Table 4 presents the LS method results for the impact of the number of physicians and nurses on life expectancy, the rate of health expenditures in GDP, and the mortality rate per 100,000 people during the COVID-19 pandemic in G20 countries. Predictions were made using three different models. In all three models, the t-values of the β coefficients for the independent variables were observed to be greater than $|\pm 2|$ and were statistically significant at the 1% and 5% levels. According to the regression results, a 1% increase in $\ln\text{Physicians}$ and $\ln\text{Nurses}$ is predicted to increase $\ln\text{LifeExp}$ by approximately 0.053% and 0.55%, respectively. Additionally, an increase in $\ln\text{Physicians}$ and $\ln\text{Nurses}$ is predicted to have a positive significant effect on $\ln\text{ExpGDP}$. A 1% increase in the $\ln\text{Physicians}$ is expected to result in a 0.203% increase in health expenditures, while a 1% increase in $\ln\text{Nurses}$ is expected to result in a 0.521% increase. Moreover, a 1% increase in $\ln\text{Physicians}$ is associated with a 1.508% decrease in $\ln\text{CovidDeath}$, whereas a 1% increase in $\ln\text{Nurses}$ is associated with a 1.304% decrease. The R^2 values of 0.610 and 0.771 for Models 1 and 2 suggest that approximately 61% and 77.1% of the total variation in the dependent variable is explained by the variation in the independent variables, which are considered sufficiently high values. In contrast, Model 3 yielded a significantly lower R^2 value of 23.9%. The high F-statistic values and their significance at the 1% level in all three models also indicate that the regression models are accurately predicting the outcomes.

As shown in Table 5, the normal/semi-normal ML model for Model 1 and Model 3 indicates that the entire inefficiency is attributed to technical inefficiency. This conclusion is derived from the γ parameter taking a value of 1. The σ_u value of 0.078 in Model 1 and 1.905 in Model 2 indicates the level of technical inefficiency.

Table 4. OLS Estimation Results (Model 1, Model 2 and Model 3)

Variables	Model 1	Model 2	Model 3
	Dep.Var: lnLifeExp	Dep.Var: lnExpGDP	Dep.Var: lnCovidDeath
C	4.190***	0.973***	4.683***
lnPhysicians	0.053**	0.203*	- 1.508**
lnNurses	0.055**	0.521***	-1.304*
R ²	0.610	0.771	0.239
Adjusted R ²	0.564	0.744	0.149
S.E. of Reg.	0.049	0.229	1.341
Sum squared resid	0.041	0.894	30.559
Log likelihood	33.524	2.695	-32.618
F-statistic	13.287***	28.662***	2.662***
Mean dep. var	4.342	2.141	3.580
S.D. dep. var	0.074	0.454	1.453
Akaike info crit.	-3.052	0.031	3.562
Schwarz criterion	-2.903	0.180	3.711
Hannan-Quinn crit.	-3.023	0.060	3.591

*p ≤ 0.10; **p ≤ 0.05; ***p ≤ 0.01.

The ML analysis for Model 2 yielded $\gamma=0$, indicating that the inefficiency is entirely due to stochastic errors. In the ML regression results, the p-value for the lnPhysicians independent variable in Model 1 is greater than 10%, suggesting that the significance level is not acceptable. In Model 2, it is positive and significant at the 1% level, while in Model 3, it is negative and significant. The coefficient values for lnPhysicians are estimated to be 0.203 and 1.3, respectively.

Table 5. ML Estimation Results (Stochastic frontier normal/half-normal model)

Variables	Model 1	Model 2	Model 3
	Dep.Var: lnLifeExp	Dep.Var: lnExpGDP	Dep.Var: lnCovidDeath
C	4.236***	0.976	6.060***
lnPhysicians	0.047	0.203***	-1.300***
lnNurses	0.068***	0.522***	-1.168***
$\ln\sigma_v^2$	-37.670	-3.107	-31.69909
$\ln\sigma_u^2$	-5.101***	-11.494***	1.289***
σ_v	0.000	0.212	0.000
σ_u	0.078	0.003	1.905
σ^2	0.006	0.044	3.628
γ	1.000	0.000	1.000
λ	1.18E+07	0.151	1.46E+07
Wald X^2	7.09E+08	67.44	6.25E+08
Log likelihood	36.492***	2.695***	-27.403***
Likelihood-ratio test of $\sigma_u = 0$			
chibar2	5.93***	0.000	10.43***

*p ≤ 0.10; **p ≤ 0.05; ***p ≤ 0.01.

In table 5 for the lnNurses independent variable, the coefficient values are significant at the 1% level in all three models. lnNurses is positively significant in Model 1 and Model 2, where the dependent variable is lnLifeExp and lnExpGDP, respectively. However, in Model 3, where the dependent variable is lnCovidDeath, it is negatively significant. The sufficiently high and statistically significant Wald X^2 values across all models indicate that the regression predictions are reliable.

Table 6 presents the results of the LS estimations where the dependent variables are "lnNeonMort," "lnInfantMort," and "lnUnder5Mort." It is observed that for both independent variables, the β coefficients have t-values greater than $|\pm 2|$ and are negatively significant at the 5% level. According to the regression results, a 1% increase in lnPhysicians and lnNurses is predicted to significantly reduce the mortality rates for newborns, children under one year old, and children under five years old. In the regression analyses for Model 4, Model 5, and Model 6, the R^2 values indicate that the changes in the independent variables explain approximately 74.7%, 65.7%, and 76.4% of the total variation in the dependent variables, respectively. The sufficiently high F-statistic values, which are statistically significant at the 1% level, further confirm that the regression equations are accurately estimated.

Table 6. OLS Estimation Results (Dependent Variables: Child Mortality Rates)

Variables	Model 4	Model 5	Model 6
	Dep.Var: lnNeonMort	Dep.Var: lnInfantMort	Dep.Var: lnUnder5Mort
C	3.507***	3.026***	3.663***
lnPhysicians	-0.750***	-0.599**	-0.760***
lnNurses	-0.556**	-0.614**	-0.540**
R^2	0.747	0.657	0.764
Adjusted R^2	0.717	0.617	0.736
S.E. of Reg.	0.431	0.496	0.410
Sum squared resid	3.152	4.178	2.856
Log likelihood	-9.902	-12.719	-8.915
F-statistic	25.049***	16.315***	27.454***
Mean dep. var	1.783	1.328	1.959
S.D. dep. var	0.809	0.801	0.797
Akaike info crit.	1.290	1.572	1.192
Schwarz criterion	1.440	1.721	1.341
Hannan-Quinn crit.	1.319	1.601	1.221

* $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$.

Upon examining Table 7, the following observations can be made: In the ML estimation performed for Model 4, where the dependent variable is lnNeonMort, the parameter γ equals 1. This indicates that 100% of the inefficiency is attributable to technical inefficiency. For Model 5, where the dependent variable is lnInfantMort, the ML analysis yields $\gamma=0.646$. This implies that approximately 65% of the inefficiency is due to technical inefficiency, with the remaining 35% attributable to random error. In Model 6, where the dependent variable is lnUnder5Mort, the ML analysis results in $\gamma=0.588$. This suggests that around 59% of the inefficiency is caused by technical inefficiency, while 41% is due to random error. These findings demonstrate that the proportion of inefficiency attributed to technical inefficiency decreases as the age range of the dependent variable increases, while the contribution of random error increases.

Table 7. ML Estimation Results (Dependent Variables: Child Mortality Rates)

Variables	Model 4 Dep.Var: lnNeonMort	Model 5 Dep.Var: lnInfantMort	Model 6 Dep.Var: lnUnder5Mort
C	-0.682***	-0.760***	-0.775***
lnPhysicians	-0.672***	-0.534***	-0.518***
lnNurses	3.841***	3.808***	3.926***
$\ln\sigma_v^2$	-35.730	-2.353**	-2.360*
$\ln\sigma_u^2$	-0.489	-1.751	-2.007
σ_v	0.000	0.308	0.307
σ_u	0.783	0.417	0.367
σ^2	0.614	0.269	0.229
Γ	1.000	0.646	0,588
Λ	4.49E+07	1.351	1.193
Wald X^2	4.65E+09	59.99	65.33
Log likelihood	-9.631***	-9.841***	-8.882***
Likelihood-ratio test of $\sigma_u = 0$			
chibar2	6.18***	0.12	0.07
*p ≤ 0.10; **p ≤ 0.05; ***p ≤ 0.01			

Compared to OLS Estimations, the ML analyses reveal a statistically significant positive relationship at the 1% level between lnNurses and the dependent variables in all three models. The high and statistically significant Wald X^2 values further validate the accuracy of the regression predictions.

VI. DISCUSSION AND CONCLUSION

The healthcare sector, being labor-intensive, derives its strength from the number and professionalism of physicians and nurses. Although rapid technological advancements have positively impacted the healthcare sector, the COVID-19 pandemic has revealed that countries need more health manpower rather than just technological advancements. During the COVID-19 pandemic, the inadequacy of healthcare systems was observed in both developed and developing countries. The uniqueness of each country's healthcare system, shaped by its economic, socio-cultural policies, and other factors, complicates the implementation of a uniform healthcare policy across countries. Even among countries with similar characteristics, different policies can be applied.

The G20 (Group of 20) countries, which together account for approximately two-thirds of the world's population and about 90% of the global economy (Larionova, 2022), include both developed and developing nations. The G20 countries, which account for around 78% of global health expenditures (Kaya and Naldöken, 2023), have drawn significant attention in the scientific community regarding the effectiveness of their healthcare systems and the impact of critical health inputs, such as physicians and nurses, on health status indicators like life expectancy at birth and mortality rates.

Data for this study was obtained from the World Bank, the European Centre for Disease Prevention and Control, and the Worldometer internet data sites, which collect COVID-19 data. Parametric Stochastic Frontier Analysis (SFA) was conducted using LS and ML methods. The study analyzed six different regression models using physician and nurse counts per 1,000 people as independent variables, with dependent variables including life expectancy at birth, the share of health expenditures in GDP, mortality rates per 100,000 populations during the COVID-19 pandemic, neonatal mortality rates per 1,000 live births, infant mortality rates under one year, and under-five mortality rates. To address issues such as perfect multicollinearity, variance heterogeneity, and serial correlation, VIF tests, White tests, and the Durbin-Watson test were performed. The analyses confirmed that these issues were not present in the regression models.

The empirical findings reveal a statistically significant positive relationship between the number of physicians and nurses per 1,000 people and both life expectancy at birth and the share of health expenditures in GDP. Furthermore, the ML analysis showed that inefficiency in the regression where life expectancy at birth was the dependent variable was due to technical inefficiency, while inefficiency in the regression where the share of health expenditures in GDP was the dependent variable was attributed to random error. It was found that changes in the independent variables explained approximately 61% and 77% of the variation in the dependent variables, respectively. The regression analysis of mortality rates per 100,000 populations during the COVID-19 pandemic revealed that both the number of physicians and nurses per 10,000 people had a significant effect on reducing these mortality rates. ML analysis indicated that inefficiency in the model where the dependent variable was neonatal mortality was entirely due to technical inefficiency, while in the other models, it was due to technical inefficiency by 65% and 59%, respectively.

By focusing on data from the year 2020, this study provides a direct assessment of the health outcomes during the initial and most severe phase of the COVID-19 pandemic. The results reveal a statistically significant negative relationship between the number of healthcare professionals and COVID-19-related mortality rates, indicating that healthcare workforce availability was a crucial determinant of health system resilience during the pandemic. While the exclusive use of 2020 data limits the ability to compare pre- and post-pandemic periods, the findings still provide valuable insights into how healthcare systems functioned under pressure. Future research could benefit from employing panel data to explore the evolution of these relationships over time. Nevertheless, the present results suggest that technical inefficiency in healthcare systems became more pronounced during the pandemic and that healthcare workforce density played a key mitigating role.

The findings of this study are largely consistent with previous research in the literature. For example, Selamzade and Yeşilyurt (2021) found that an increase in the number of nurses significantly reduced infant mortality rates and improved life expectancy in OECD countries. This aligns with the current study's results, which demonstrate a significant negative relationship between the number of physicians and nurses and all forms of child mortality. Similarly, Welfens (2020) identified that the COVID-19 pandemic had a substantial impact on healthcare systems and mortality rates in the European Union, emphasizing the systemic strain caused by the pandemic. Our finding that the number of healthcare workers significantly reduced COVID-19-related mortality confirms this conclusion. Additionally, Alexiou and Trachanas (2021) demonstrated that government policies and access to healthcare services were significant determinants of infant mortality, further supporting the idea that healthcare workforce capacity must be considered not only from a technical but also from a socio-political perspective.

Like other studies evaluating the technical efficiency of healthcare systems using Stochastic Frontier Analysis, this study has limitations. One challenge in measuring efficiency is the lack of statistical data or difficulty in obtaining it on a country-by-country basis. In this study, while data from 2020 was used, physician and nurse counts for Brazil and South Africa were missing, and 2021 data were utilized instead. The independent variables used in this study were selected based on their impact on health production, as commonly used in the literature.

This study's scope is limited to G20 countries, which may not fully capture the diversity and complexity of global health human resources, especially in low- and middle-income countries outside this group. Furthermore, the reliance on secondary data sources introduces potential biases due to variations in data collection methods, reporting standards, and data completeness across countries. The absence of 2020 data for some countries, replaced by 2021 figures, may also affect the accuracy of the temporal analysis, particularly given the significant disruptions caused by the COVID-19 pandemic during this period. These factors collectively limit the generalizability of the findings and suggest that results should be interpreted with caution.

Future research should aim to broaden the scope of analysis beyond the G20 countries to include a wider range of health systems, particularly those in low- and middle-income countries. Such an expansion would enable comparative assessments across diverse economic and socio-political contexts and provide a more comprehensive understanding of global health workforce dynamics. In addition to geographic expansion, future studies would benefit from incorporating longitudinal data that capture trends over an extended period. This would allow for the examination of temporal shifts in workforce distribution, the long-term effects of health policies, and the sustained impact of global crises such as pandemics on human resources for health.

Moreover, researchers should strive to improve data quality and consistency by advocating for standardized reporting systems and by leveraging new data collection methodologies, including digital health records, big data analytics, and real-time workforce tracking platforms. These approaches could reduce data gaps, improve accuracy, and facilitate more robust analytical models. Methodologically, future work could adopt mixed-method or multi-level approaches, integrating quantitative analyses with qualitative insights obtained through interviews, surveys, or case studies. Such triangulation would enrich interpretations and uncover context-specific factors that quantitative data alone may not reveal.

Finally, future investigations might explore the role of emerging technologies—such as artificial intelligence, telemedicine, and digital workforce management tools—in shaping the allocation, training, and retention of health professionals. Examining how these innovations influence efficiency, equity, and workforce resilience would offer valuable implications for policymakers and global health planners.

This study demonstrates that health inputs, such as the number of physicians and nurses, are significant determinants of health outcomes, particularly mortality rates, in the G20 countries. Increasing the number of healthcare workers in countries could improve health outcomes and positively contribute to human capital. Given that human capital plays a crucial role in economic development, there is a need for increased emphasis on healthcare spending, particularly on enhancing the quality and quantity of the healthcare workforce. Health expenditures, which directly impact quality of life, should be organized equitably regardless of individuals' age, gender, economic, and social status. Especially in developing G20 countries, there is a need to increase the share of health spending. Health services should not only aim to treat diseases but also to improve individuals' quality of life through preventive health services. In conclusion, for effective health status and optimal use of health inputs in G20 countries, especially in developing nations, policies should focus on reducing neonatal, infant, and child mortality rates, increasing per capita health spending, and improving life expectancy at birth. Reliable parametric efficiency estimates are crucial for health policy decisions. Researchers and policymakers should be aware of the limitations and inaccuracies of parametric techniques in comparing healthcare efficiency. However, meticulous quantitative international comparisons can provide valuable evidence for policy-making.

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REFERENCES

- Aboubacar, B., & Xu, D. Y. (2017). The impact of health expenditure on the economic growth in Sub-Saharan Africa. *Theoretical Economics Letters*, 7, 615–622. <https://doi.org/10.4236/tel.2017.73046>
- Aigner, D., Knox-Lovell, C. A., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function methods. *Journal of Econometrics*, 6, 21–37.
- Akbulut, F., & Çeçen, Z. (2025). Apec Ülkelerinin Sağlık Harcamalarının Etkinliğinin Veri Zarflama Analizi ve Malmquist İndex Yöntemleriyle İncelenmesi. *Gümüşhane Üniversitesi Sosyal Bilimler Dergisi*, 16(1), 119-133.
- Akimova, A. (2014). *Analysis of the BRIC countries technical efficiency patterns using stochastic frontier approach* (Doctoral dissertation). <http://scholarworks.uark.edu/etd/2263>
- Alexiou, C., & Trachanas, E. (2021). Politics, government health expenditure and infant mortality: Does political party orientation matter? *International Journal of Social Economics*, 48(12), 1810–1825.
- Aras, İ. A. (2023). Gelir gruplarına göre COVID-19 pandemisinde sağlık sistem performansı etkinliğinin ölçülmesi. *Dicle Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 13(26), 731-746.
- Bedir, S. (2016). Healthcare expenditure and economic growth in developing countries. *Advances in Economics and Business*, 4, 76–86. <https://doi.org/10.13189/aeb.2016.040202>
- Bhaskar, S. (2023). G20 policy for health systems: promoting holistic outcomes and addressing vulnerabilities in healthcare. *T20 policy brief*. Task Force 6 Accelerating SDGs: Exploring New Pathways to the 2030 Agenda, https://t20ind.org/wp-content/uploads/2023/07/T20_PB_TF-6_684_Health-Systems.pdf
- Bhattacharyya, R., & Paul, A. (2023). Divergences of health expenditures and role of the government in response to COVID-19 pandemic in selected nations—An investigation. In R. Bhattacharyya, R. C. Das, & A. Ray (Eds.), *COVID-19 pandemic and global inequality*. (pp. 153-172). Springer. https://doi.org/10.1007/978-981-99-4405-7_10
- Coelli, T. J. (1996). *A guide to Frontier Version 4.1: A computer program for stochastic frontier production and cost function estimation* (CEPA Working Papers, 7/96).
- Cooper, W. W., & Tone, K. (1997). Measures of inefficiency in data envelopment analysis and stochastic frontier estimation. *European Journal of Operational Research*, 99, 72–88.
- Ersezer, Ö. (2024). İnsani gelişmişlik endeksi ile sağlık çıktıları arasındaki ilişki: G20 ülkeleri üzerine bir inceleme. *Uluslararası Akademik Birikim Dergisi* 7(2), 93-103.
- Ersezer, Ö., & Ülgen, G. (2024). The impact of health expenditures on health outcomes in G20 countries. *Dicle Akademi Dergisi*, 4(2), 251-267.
- European Centre for Disease Prevention and Control. (2024a). *Publications data: Archive historical data testing volume COVID-19*. <https://www.ecdc.europa.eu/en/publications-data/archive-historical-data-testing-volume-covid-19>

- European Centre for Disease Prevention and Control. (2024b). *Publications data: Download historical data 20 June - 2022 weekly number new reported COVID-19 cases*. <https://www.ecdc.europa.eu/en/publications-data/download-historical-data-20-june-2022-weekly-number-new-reported-covid-19-cases>
- Jakovljevic, M., Timofeyev, Y., Ranabhat, C., et al. (2020). Real GDP growth rates and healthcare spending—Comparison between the G7 and the EM7 countries. *Global Health*, 16, 64. <https://doi.org/10.1186/s12992-020-00590-3>
- Kant, A., & Clark, H. (2023). The G20 must act now for the health and wellbeing of women, children, and adolescents around the world. *BMJ*, 382. <https://doi.org/10.1136/bmj.p1897>
- Kaya, M. V., & Naldöken, Ü. (2023). Comparative examination and evaluation of health systems in G20 countries. *Afyon Kocatepe University Journal of Social Sciences*, 25(1), 244–256. <https://doi.org/10.32709/akusosbil.1053949>
- Kaya, M. V., & Naldöken, Ü. (2023). G20 ülkelerinin sağlık sistemleri açısından karşılaştırmalı olarak incelenmesi ve değerlendirilmesi. *Afyon Kocatepe Üniversitesi Sosyal Bilimler Dergisi*, 25(1), 244-256.
- Kennedy, P. (2000). *Handbook of econometrics* (M. Sarımeşeli, Trans.). Gazi Kitabevi.
- Khan, A. (2017). *Cost and optimization in government: An introduction to cost accounting, operations management, and quality control* (2nd ed.). Routledge. <https://doi.org/10.4324/9781315207674>
- Kimsey, L. G. (2009). *How efficient are military hospitals? A comparison of technical efficiency using stochastic frontier analysis* (Doctoral dissertation, University of Kentucky).
- Kocadağlı, O., et al. (2022). Important factors affecting the transmission rate of COVID-19 in G20 and EU. *Sigma Journal of Engineering and Natural Sciences*, 40(1), 208–218. <https://doi.org/10.14744/sigma.2022.00017>
- Korkmazer, F., Selamzade, F., & Bostan, S. (2020). A study to measure the perceptions of Azerbaijani healthcare workers towards the COVID-19 pandemic. *Turkish Studies*, 15(4), 691-702. <https://dx.doi.org/10.7827/TurkishStudies.43464>
- Kumar, K. N. R. (2020). *Econometrics* (1st ed.). CRC Press. <https://doi.org/10.1201/9781003079651>
- Kutlar, A. (2012). *Introduction to econometrics* (2nd ed.). Nobel.
- Kutlar, A., & Salamov, F. (2018). Analysis of the Azerbaijani regional public hospitals by stochastic frontier methods. *Balkan and Near Eastern Journal of Social Sciences*, 4(2), 55–64.
- Larionova, M. (2022). A brief history of the G20 institutional dynamics (2008–21). *International Organisations Research Journal*, 17(2), 250–274. <https://doi.org/10.17323/1996-7845-2022-02-11>
- Mac-Seing, M., Gidey, M., & Di Ruggiero, E. (2023). COVID-19-related global health governance and population health priorities for health equity in G20 countries: a scoping review. *International Journal for Equity in Health*, 22(1), 232. doi.org/10.1186/s12939-023-02045-8
- Meeusen, W., & van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18(2), 435–444. <http://www.jstor.org/stable/2525757>

- Meng, T. (2021). Clusters in the spread of the COVID-19 pandemic: Evidence from the G20 countries. *Frontiers in Public Health*, 8, 628789. <https://doi.org/10.3389/fpubh.2020.628789>
- Mumba, P. N. (2020). *An investigation of the determinants of public health expenditure in SADC* (Doctoral dissertation, University of Namibia).
- Nair, P. (2023). *Healthcare Systems Moving Toward Data Governance-Centered Model: India's G20 Presidency in the Wake of Covid*. Pradeep Nair. Healthcare Systems Moving Toward Data Governance-Centered Model: India's G20 Presidency in the Wake of COVID. Qeios. <https://doi.org/10.32388/5DUZSE>.
- Nassar, H., Sakr, H., Ezzat, A., & Fikry, P. (2020). Technical efficiency of health-care systems in selected middle-income countries: An empirical investigation. *Review of Economics and Political Science*, 5(4), 267–287. <https://doi.org/10.1108/REPS-03-2020-0038>
- Ngami, A., & Ventelou, B. (2023). Respective healthcare system performances taking into account environmental quality: What are the re-rankings for OECD countries? *Health Research Policy and Systems*, 21, 57. <https://doi.org/10.1186/s12961-023-01005-6>
- Perezgonzalez, J. D. (2015). Fisher, Neyman-Pearson or NHST? A tutorial for teaching data testing. *Frontiers in Psychology*, 6, 223. <https://doi.org/10.3389/fpsyg.2015.00223>
- Pfanzagl, J., & Sheynin, O. (1996). Studies in the history of probability and statistics XLIV: A forerunner of the t-distribution. *Biometrika*, 83(4), 891–898. <https://doi.org/10.1093/biomet/83.4.891>
- Selamzade, F. et al. (2020). The effect of COVID-19 pandemic on society: A case of Azerbaijan. *Türkiye Klinikleri J Health Sci*. 5(2) 278-87. <https://doi.org/10.5336/healthsci.2020-75559>
- Selamzade, F., & Yeşilyurt, Ö. (2021). Evaluation of health indicators of OECD countries by stochastic frontier analysis. *Journal of Productivity*, 4, 35–49. <https://doi.org/10.51551/verimlilik.734328>
- Şener, M., & Yiğit, V. (2024). Sağlık sistemleri etkinliğinin iki aşamalı dinamik VZA yaklaşımı ile değerlendirilmesi. *Hacettepe Sağlık İdaresi Dergisi*, 27(2), 329-361.
- Taylan, O., Alkabaa, A. S., & Yılmaz, M. T. (2022). Impact of COVID-19 on G20 countries: Analysis of economic recession using data mining approaches. *Financial Innovation*, 8, 81. <https://doi.org/10.1186/s40854-022-00385-y>
- Techi, A. et al. (2025) The impact of seaport cargo on economic development: panel data evidence from Türkiye, *Ekonomika Misao i Praksa*, <https://dx.doi.org/10.17818/EMIP/2025/18>
- Türkoğlu, M. C., & Abiş, T. (2024). Sağlık göstergelerinin teknik etkinlik üzerindeki etkilerinin incelenmesi: seçilmiş G-20 ülkeleri örneği. *Akademik Hassasiyetler*, 12(25), 190-211.
- Welfens, P. J. J. (2020). Macroeconomic and health care aspects of the coronavirus epidemic: EU, US and global perspectives. *International Economics and Economic Policy*, 17, 295–362. <https://doi.org/10.1007/s10368-020-00465-3>
- World Bank. (2020). *Development indicators*. <https://data.worldbank.org>
- Worldometers. (2020). *Coronavirus data*. <https://www.worldometers.info/coronavirus/>

Yesilyurt, O., & Selamzade, F. (2020). Measuring CIS health systems using the stochastic frontier analysis (SFA). *Ekonomika Regiona*, 16(1), 59–68. <https://doi.org/10.17059/2020-1-5>