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Evaluating the Efficiency of Turkish Banking Sector Using Data Envelopment Analysis and Malmquist Productivity Index: Covid-19 Pandemic and After

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Abstract

The Covid-19 pandemic has created a deep crisis with social, cultural, economic, and political consequences all over the world. In this study, we used the Malmquist Total Factor Productivity Change Index (TFPCH) and Data Envelopment Analysis (DEA) methods to assess the efficiency and performance of banks during the Covid-19 pandemic and the post-pandemic era. We performed the application for 17 banks in Türkiye of which data structure is suitable for analysis. For the analysis, data from 2019, the beginning of the Covid-19 epidemic, to 2022, when the epidemic had almost ended, were used. The highest value of the general efficiency average of banks was 0.943 in 2020. 2020 was also the year with the highest number of effective banks, with a total of 9 effective banks. The highest value of the TFPCH general average is 1.543 in the 2021-2022 period. It was determined that state banks had the highest average efficiency percentage and the highest TFPCH average for the entire period of 2019-2022.

Key Words: Banking Sector, Covid-19 Pandemic, Data Envelopment Analysis, Malmquist Index of Total Factor Productivity Change.

Mathematical Subject Classification: 62P05,62P20,62P25

1. Introduction

Covid-19 was initially identified in Wuhan, China, in December 2019. On 11 March 2020, the World Health Organization officially described Covid-19 as a global pandemic and declared it a worldwide public health emergency. (Altındağ, 2020; Elnahass et al., 2021). Due to the virus's transmission, governments were compelled to implement a range of containment strategies, which encompassed social distancing, lockdowns, and business closures. These strategies have led to adverse economic consequences for businesses and households. Thus, the global economy was hit hard and fast, and its losses surpassed the 2008 global financial crisis (Duan et al. 2021, Feyen et al. 2021). Financial institutions, such as banks, have suffered from Covid-19, a sudden external shock that required them to be prepared for the extremely difficult and varied challenges ahead (Sembiring et al., 2020; Altındağ, 2021; Elnahass et al., 2021). Considering these unparalleled circumstances, central banks and governments have implemented a wide range of policy measures and interventions. While certain actions aimed to significantly enhance short-term financial constraints, others supported the accessibility of credit to businesses. This was achieved through either direct involvement in credit markets or by relaxing constraints on banks' utilization of capital reserves (Demirgüç-Kunt et al., 2021). The management strategies adopted by banks will affect the post-pandemic recovery of the economy. Banks hold a pivotal position in the global economy by enabling and fostering both domestic and international trade. Major disruptions to this system will have a profound impact on society. Trust plays a critical role in this context, serving as a fundamental element for the proper functioning of the banking system and the economy (Marcu, 2021; Luo, 2022). Even minor shocks to the financial sector may magnify and worsen the crisis, resulting in negative effects on the real economy (Tabak et al., 2022).

Crises, although brutal, often create opportunities for research. The Covid-19 crisis is one of them. Crisis situations frequently give rise to numerous research opportunities for three primary reasons. Initially, the most effective approach to gaining insights in economics, finance, or any research domain is to examine the outcomes that emerge when breakdowns occur. Secondly, crises typically trigger the implementation of novel government policies, generating a wealth of research papers dedicated to their evaluation. Thirdly, crises serve as exogenous shocks that can be leveraged as quasi-natural experiments to explore and tackle both existing and emerging research inquiries. Such shocks provide the best possible econometric description when they exhibit a degree of exogeneity, meaning that they impact the real economy or financial system without being driven by economic or financial factors. Especially within the realm of banking research, occurrences like natural disasters, weather-related events, the discovery of natural resources, and government policy innovations frequently offer quasi-natural experiments for investigating the impacts of banks on the real economy (Berger & Demirgüç-Kunt, 2021).

The efficiency of a bank for a particular year can be quantified using the DEA (Data Envelopment Analysis) technique. Nonetheless, if we seek to assess changes in a bank’s efficiency over two distinct periods or investigate technical progress across these intervals, the most suitable approach is to employ a combination of DEA and the Malmquist Total Factor Efficiency Index methods (Jiang & He, 2018). DEA is a productivity evaluation model rooted in mathematical programming theory. DEA presents a distinct approach to gleaning insights from sample data when compared to traditional statistical methods. Unlike parametric techniques like regression analysis, which aim to find a single regression plane to fit the data, DEA seeks to optimize each data point with the objective of determining a discrete, piecewise boundary defined by a set of Pareto-efficient Decision Management Units (DMUs).. In other words, DEA focuses on individual data points, in contrast to conventional statistical optimization approaches that focus on parameter averages (Tongzon, 2001). Productivity growth plays a major role in shaping the progress of financial institutions. The Malmquist productivity index (MPI) demonstrates alterations in production efficiency concerning both cross-sectional and time-series dynamics compared with a benchmark of best practices (Cho and Chen, 2021).

This paper aims to measure changes in the technical efficiency and total factor efficiency of banks, the basis of the financial system, during and after the Covid-19 pandemic. For this purpose, the data of state, private and foreign-owned banks in Turkey for period (2019-2022) were analyzed using DEA and Malmquist Total Factor Productivity Index methods.

2. Methodology

2.1. Data envelopment analysis (DEA) and the CCR model

Charnes et al. first introduced the DEA model in 1978. This method is referred to as the CCR model. DEA method, which is a linear programming formulation, defines the nonparametric relationship between multiple inputs and multiple outputs (Charnes et al., 1978). Within DEA, entities tasked with converting inputs into outputs are referred to as Decision-Making Units (DMUs). This usage is generic and covers the activities of many different organizations and their subdivisions (Banker et al., 1989). In 1984, Banker et al. introduced a novel DEA method called as the BCC model, which allows variable returns to scale within the model (Jiang & He, 2018). In DEA, the solution probabilities obtained from the observed input and output values for all DMUs are examined with mathematical programming methods. The solutions obtained are used to evaluate the performance of DMU. Solutions must satisfy constraints that do not allow any of the observed input values of the DMU to increase or any of the observed output values to decrease. Mathematically, for each input and output of the DMU, a properly directed inequality constraint is applied to ensure that the solutions satisfy this condition. Inequalities rather than equations are used to allow solutions that can enhance certain inputs or outputs (while not deteriorating other inputs or outputs). To avoid the exhaustive trial and error or simulation search for such improvement possibilities, the optimization mechanism of mathematical programming is used to find the "best" solution. When interpreted geometrically, this best solution will exist at a limit where the DMU’s behavior comparison can be affected. Due to constraints, no input or output is worsened. If this best solution does not improve any input or output, the DMU is rated 100% efficient; otherwise, it is rated as inefficient, and a simple reading of the solution identifies the sources and amounts of inefficiency in each input and output (Banker et al., 1989).

Sherman and Gold (1985) pioneered the application of DEA on financial institutions, focusing on the evaluation of 14 bank branches. This study confirmed the limitations of traditional performance measurement techniques like profitability and transaction costs, which fail to account for the intricate nature of branch operations and the multiple outputs generated from various inputs, as pointed out by Henriques et al. (2018). DEA has been widely used in recent years for the purpose of efficiency assessment in various fields, primarily in the banking sector. Furthermore, DEA is recognized as an effective means to explore banking efficiency (Jiang & He, 2018). The literature contains numerous different DEA models, which have been applied in studies related to both banking and bank branches. The most commonly encountered applications are the three primary methods: Production Model, Profitability Model, and Intermediation Model. Classically, the production approach evaluates the efficiency of a branch in generating transaction services (outputs) by considering its utilization of capital and labour (inputs). The intermediation approach assesses the performance of a branch functioning as an institution that offers loans and investments (outputs) in relation to the monetary assets (inputs) it has gathered. The profitability approach is employed to measure the branch's profit potential, taking expenses as input and revenues as output. It is interesting that similar models were occasionally used in both bank studies (DMU is a complete bank) and bank branch studies (Paradi et al., 2011).

The CCR model, which is proposed to assess the efficiency of any Decision Making Unit (DMU), is derived as the highest value attained by the ratio of weighted outputs to weighted inputs, provided that similar ratios are less than or equal to one for each DMU (Charnes vd., 1978).

CCR model is as below:

$$\max h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1; \qquad j = 1, \dots, n,$$

$$u_r, v_i \ge 0; \qquad r = 1, \dots, s; \qquad i = 1, \dots, m.$$

Where

n	Number of DMUs being evaluated;
s	Number of outputs;
m	Number of inputs;
u_r	Weight in the r-th output of *DMUo(o = 1,…,n);*
v_i	Weight in the i-th input of *DMUo;*
y_{rj}	Value of the r-th output of *DMUj;*
x_{ij}	Value of the i-th input of *DMUj;*
y_{ro}	Value of the r-th output for the measured efficiency of *DMUo;*
x_{io}	Value of the i-th input for the measured efficiency of *DMUo.*

2.2. Malmquist Productivity Index

Malmquist introduced the standard of living index in 1953. Then, in 1982, Caves, Christensen, and Diewert introduced a groundbreaking concept, the ratios of input/output distance functions, which is called the Malmquist Productivity Index (MPI), that form a productivity index. Based on this approach, Färe, Grosskopf, Lindgren, and Roos (1994) played a pioneering role in the development of an empirical productivity measurement index. Their study assumed constant returns to scale (CRS) for benchmarking technology, leading them to divide this index into two distinct productivity measurement components. These indexes are known as measures of technical efficiency change and technical change (Kevork et al., 2017).

MPI method, introduced by Färe et al. in 1989, is associated with the use of distance functions that characterize multi-input/multi-output production technology. What sets it apart is that it does not require the inclusion of explicit price data or the specification of behavioral assumptions like profit maximization or cost minimization. These distance functions are categorized into output and input distance functions. An output (input) distance function is defined as the reciprocal of the maximum (minimum) proportional expansion (contraction) of the output (input) vector given an input (output) vector (Fare et al., 1994; Rezitis, 2006). The Malmquist Total Factor Productivity Change Index (TFPCH) quantifies productivity disparities between two companies or two time periods within a company. It can be computed from both input and output orientations to elucidate the factors behind changes in productivity. This index is grounded in alterations in technical efficiency and technology (Fare et al., 1994).

Let St, a multi-input and multi-output production technology, be defined at time t as follows (Fare et al., 1994).

$$S^t = \left\{ \left(x^t, y^t \right) : x^t \; can \;\; produce \;\; y^t \right\}, \quad t = 1, \ldots, T \,, \tag{1}$$

where x^t is an $\left(N \times 1 \right)$ input vector and y^t is an $\left(M \times 1 \right)$ output vector. After this definition, the distance function at time t is defined as follows:

$$D_0^t \left(x^t, y^t \right) = \inf \left\{ \theta : \left(y^t / \theta \right) \in S^t \right\}, \quad t = 1, \ldots, T. \tag{2}$$

The distance function is defined as the inverse of the maximum proportional expansion of the output vector y^t relative to the input vector x^t. (Rezitis, 2006; Fare, 1994).

TFPCH (output axis) calculated by Färe et al. (1994) based on these distance functions is as follows. In this index (*t*) denotes the base year and (*t+1*) denotes the next year (Fare et al., 1994);

$$M_0 \left(x^{t+1}, y^{t+1}, x^t, y^t \right) = \left[\left(\frac{D_0^t \left(x^{t+1}, y^{t+1} \right)}{D_0^t \left(x^t, y^t \right)} \right) \left(\frac{D_0^{t+1} \left(x^{t+1}, y^{t+1} \right)}{D_0^{t+1} \left(x^t, y^t \right)} \right) \right]^{1/2} \tag{3}$$

Equation (3) is the geometric mean of the (*t*) and (*t+1)* period indices. The first represents th*e (t)* period technology, and the second represents the (*t+1)* period technology. In this equation $D_0^t \left(x^t, y^t \right)$, refers to the distance between the (*t+1)* period observation from the *(t)* period technology.

Equation (3) can also be written as

$$M_0 \left(x^{t+1}, y^{t+1}, x^t, y^t \right) = \frac{D_0^{t+1} \left(x^{t+1}, y^{t+1} \right)}{D_0^t \left(x^t, y^t \right)} \times \left[\left(\frac{D_0^t \left(x^{t+1}, y^{t+1} \right)}{D_0^t \left(x^t, y^t \right)} \right) \left(\frac{D_0^t \left(x^{t+1}, y^{t+1} \right)}{D_0^t \left(x^t, y^t \right)} \right) \right]^{1/2} \tag{4}$$

Decomposition of TFPCH into technical efficiency change and technological change components, it becomes possible to determine the specific influence of each factor on total factor productivity. Thus, equation (4) can measure change in efficiency and change in technology separately when divided into two parts as follows:

$$\text{Efficiency Change} = \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^{t}\left(x^{t}, y^{t}\right)} \tag{5}$$

$$\text{Technological Change} = \left[\left(\frac{D_0^{t}\left(x^{t+1}, y^{t+1}\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right) \times \frac{D_0^{t}\left(x^{t}, y^{t}\right)}{D_0^{t+1}\left(x^{t}, y^{t}\right)}\right]^{1/2} \tag{6}$$

In these equations, the efficiency change (EC) expresses an evaluation of the decision units approaching the efficient frontier, while the technological change (TC) shows changes in the efficient frontier over time (Akyüz et al., 2013). The product of EC and TC gives the change in total factor productivity. That is:

$$TFPCH = M_0\left(x^{t+1}, y^{t+1}, x^{t}, y^{t}\right) = EC(\text{Catching up Effect}) \times TC(\text{Frontier Effect}) \tag{7}$$

A TFPCH value exceeding 1 indicates an increase in total factor productivity from period (*t*) to period (*t+1*). Conversely, a value below 1 implies a reduction in total factor productivity between periods (*t*) and period (*t+1*) (Deliktaş, 2002).

In 1994, Färe et al. demonstrated that the EC index can be described by multiplying two distinct components. These are the pure efficiency change (*PECH*) component and the scale efficiency change component (*SECH*) (Rezitis, 2006).

$$PECH = \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1} \setminus VRS\right)}{D_0^{t+1}\left(x^{t}, y^{t} \setminus VRS\right)} \tag{8}$$

$$SECH = \left[\frac{D_0^{t}\left(x^{t}, y^{t} \setminus VRS\right)}{D_0^{t}\left(x^{t}, y^{t}\right)} \times \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^{t+1}\left(x^{t+1}, y^{t+1} \setminus VRS\right)}\right]^{1/2} \tag{9}$$

where VRS represents variable returns to scale and $D_0\left(\bullet \setminus VRS\right)$ represents distance functions calculated assuming variable returns to scale. A *SECH* value greater than one indicates that the operating unit is more scale efficient (Rezitis, 2006).

3. Results

The study used data from 17 banks covering the period from 2019 to 2022. The output data of the study are interest income, net operating profit, and net period profit. The input data of the study are the number of bank branches, personnel expenses, and total interest expense. Bank information was obtained from the Banks Association of Türkiye website. The efficiency scores, technological change, efficiency change scores and total factor productivity change indexes of 17 banks were calculated through the application DEA and TFPCH methods. The obtained findings were commented on using tables and graphics. The R-studio program was used to calculate these indexes.

Table 1 presents the DEA efficiency scores of 17 banks from 2019 to 2022 using the input-oriented CCR model. When analyzing Table 1, it is seen that almost all Turkish banks have high CCR productivity scores during the study period.

Table 1: Efficiency Scores of Selected Banks during 2019–2022

Capital Structure	Banks	2019	2020	2021	2022	Mean
State	Ziraatbank	1	1	1	1	1
	Halkbank	0.945	1	0.967	0.966	0.970
	Vakifbank	0.897	1	1	1	0.974
Efficiency means for State Banks		0.947	1	0.989	0.989	0.981
Number of effective State Banks		1	3	2	2	
Private	Akbank	1	1	1	1	1
	Anadolubank	0.872	0.876	0.676	0.679	0.776
	Fidabanka	0.789	0.814	0.9	0.785	0.822
	TEB	0.875	0.847	0.789	0.757	0.817
	Isbank	0.916	0.846	0.868	0.883	0.878
	Yapıkredibank	0.934	0.86	0.899	0.917	0.903
Efficiency means for Private Banks		0,898	0.874	0.855	0.837	0.866
Number of effective Private Banks		1	1	1	1	
Foreign Owned	Arapturkbank	1	1	1	1	1
	Burganbank	1	1	1	1	1
	Denizbank	0.902	0.901	0.91	0.821	0.884
	HSBCbank	0.811	0.986	0.888	0.668	0.838
	ICBCTurkey	0.743	1	0.705	1	0.862
	INGbank	1	1	0.781	0.706	0.872
	QNBFinansbank	0.911	0.901	0.978	0.869	0.915
	Garantibank	1	1	1	1	1
Efficiency means for Foreign Owned Banks		0.921	0.973	0.908	0.883	0.921
Number of effective Foreign Owned Banks		4	5	3	4	
Total Efficiency Mean		0.917	0.943	0.904	0.885	0.912
Total Effective Number of Banks		6	9	6	7	

Ziraatbank, Akbank, Arapturkbank, Burganbank, and Garantibank became the most efficient banks during the Covid-19 period and after. Anadolubank, Fidabanka and TEB were among the last three banks in the efficient ranking for these periods. According to Table 1: in 2019, 6 banks are efficient, and the general efficiency average of banks is 0.917; in 2020 9 banks are efficient, and the general efficiency average of banks is 0.943; in 2021, 6 banks are efficient, and the general efficiency average of banks is 0.904; in 2022 7 banks are efficient, and the general efficiency average of banks is 0.885. Table 2 presents the efficiency statistics based on the capital structures of banks.

Table 2: Efficiency Statistics According to the Capital Structure of Banks

Banks		2019	2020	2021	2022	General
State	Efficiency percentage	% 94.7	% 100	% 98.9	% 98.9	% 98.1
	Number of effective banks	1	3	2	2	
Private	Efficiency percentage	% 89.8	%87.4	% 85.5	% 83.7	% 86.6
	Number of effective banks	1	1	1	1	
Foreign Owned	Efficiency percentage	% 92.1	% 97.3	% 90.8	% 88.3	% 92.1
	Number of effective banks	4	5	3	4	

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Table 2 shows that public, private, and foreign capital banks had the highest efficiency averages in 2020, the most intense period of the Covid-19 epidemic. In addition, it is noticeable that all public banks were effective in 2020. After 2020, there is a decreasing trend in the efficiency percentage of all bank groups.

The number of efficient/ineffective banks, distribution of ineffective banks, and reference set statistics for ineffective banks for 2019-2022 years are given in Figure 1(a-b).

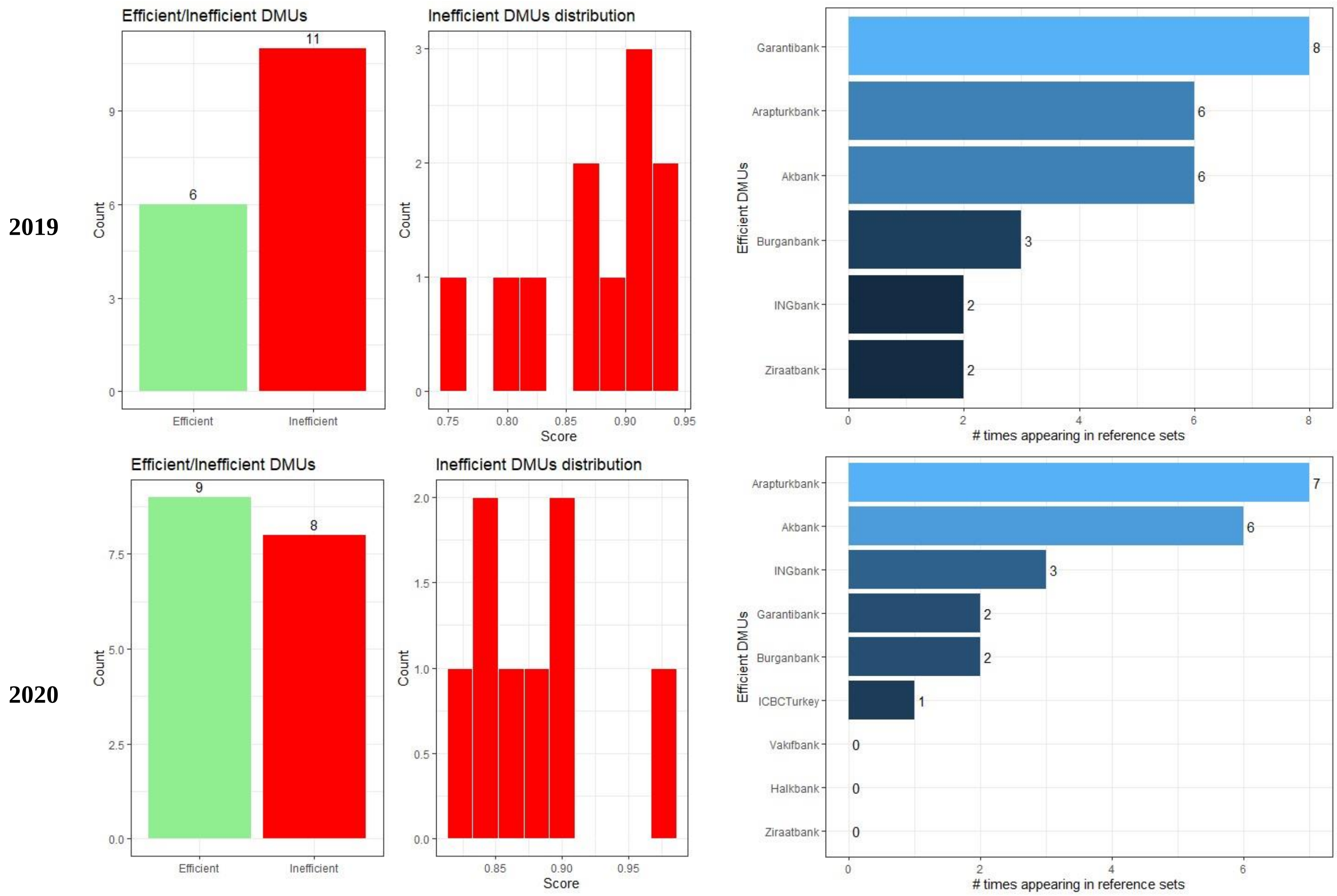

Figure 1-a: DEA analysis summary statistics for banks (2019-2020)

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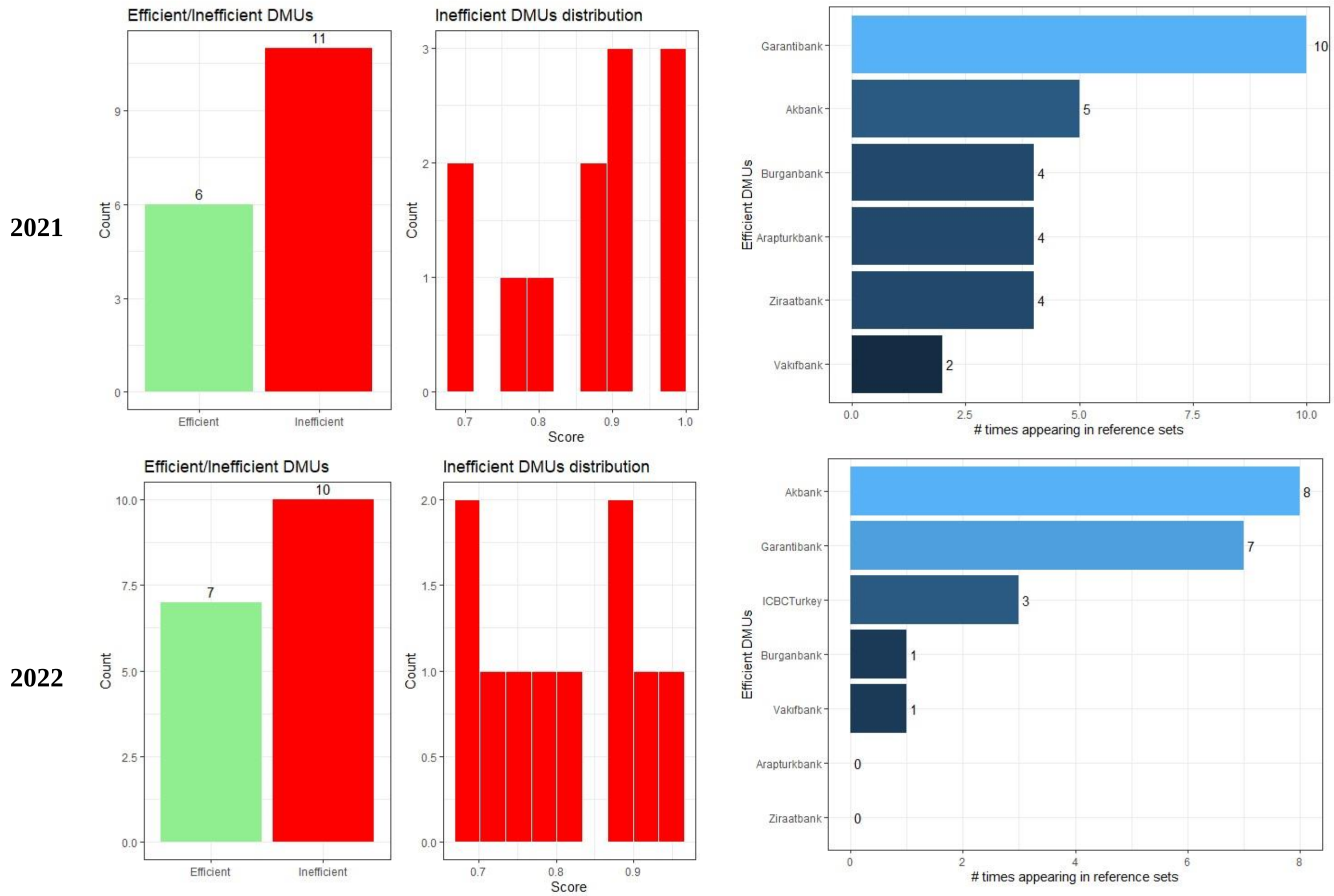

Figure 1-b: DEA analysis summary statistics for banks (2021-2022)

In the 2019-2022 period, the most referenced efficient banks are Garantibank (8), Arapturkbank (7), Garantibank (10) and Akbank (8), in order of years.

TFPCH, TC, PECH, SECH, and EC scores of Turkish banks during 2019–2022 are presented in Table 3.

Table 3: Average Productivity Changes of Turkish Banks during 2019–2022.

Capital Structure	Banks	TFPCH	TC	PECH	SECH	EC
State	Ziraatbank	1.109	1.109	1	1	1
	Halkbank	1.179	1.171	1	1.007	1.007
	Vakifbank	1.151	1.11	1.024	1.012	1.037
	Mean	1.146	1.130	1.008	1.006	1.015
Private	Akbank	1.276	1.276	1	1	1
	Anadolubank	0.916	0.995	0.963	0.956	0.92
	Fidabanka	1.22	1.222	0.987	1.011	0.998
	TEB	1.028	1.079	0.95	1.004	0.953
	Isbank	1.158	1.172	1.005	0.983	0.988
	Yapıkredibank	1.212	1.22	0.992	1.002	0.994
	Mean	1.135	1.161	0.983	0.993	0.976

Foreign Owned	Arapturkbank	0.84	0.84	1	1	1
	Burganbank	1.267	1.267	1	1	1
	Denizbank	1.063	1.097	0.97	0.999	0.969
	HSBCbank	1.02	1.088	0.879	1.067	0.938
	ICBCTurkey	1.252	1.134	1.091	1.012	1.104
	INGbank	0.861	0.967	0.901	0.988	0.89
	QNBFinansbank	1.087	1.104	0.986	0.999	0.985
	Garantibank	1.185	1.185	1	1	1
	Mean	1.072	1.085	0.978	1.008	0.986
	General Mean	1.107	1.12	0.985	1.002	0.987

Based on efficiency change scores, 17.6% of the banks demonstrated an improvement in their annual average efficiency, while 52.9% experienced a decline. Additionally, five banks exhibited no change in their efficiency (Ziraatbank, Akbank, Arapturkbank, Burganbank, and Garantibank). The banks that made progress in technical efficiency were Halkbank (100.7%), Vakifbank (103.7%), and ICBCTurkey (110.4%). INGbank (89%), Anadolubank (92%) and HSBCbank (93.8%) are among the top three banks that showed a decline in technical efficiency. We can say that the decrease in technical efficiency for HSBC Bank is only the decrease in Pure Efficiency Change. However, for Anadolubank and ING Bank, decrease in technical efficiency is related to the decrease in both Pure Efficiency Change and Scale Efficiency Change. These results are suitable with the convergence theory, which predicts that INGbank, Anadolubank, and HSBCbank will grow faster by using their resources more effectively than other banks.

According to the technological change index, an annual average of 12% progress was measured in the field of technology. Technological progress is observed in 82.35% of banks throughout the period. The three banks that showed technological decline are Arapturkbank (16%), INGbank (3.3%), and Anadolubank (0.5%).

In accordance with the Malmquist Index of total factor productivity change, the annual average progress is 10.7%. The reason for this is the 12% improvement in the technological change index. Among the banks that achieved the highest progress in total factor productivity, the top three are Akbank (27.6%), Burganbank (26.7%), and ICBC Turkey (25.2%). The progress of the Akbank and Burganbank banks is only due to Technological change, while there has been progress in both Technological change and Efficiency change in ICBCTurkey. Only three banks' Malmquist Index of total factor productivity decreased. These banks are Arapturkbank (16%), INGbank (13.9%), and Anadolubank (8.4%). The decrease in Arapturkbank is due to technological change, while there has been a decrease in both technological change and efficiency change in Anadolubank and INGbank. According to Malmquist Index of total factor productivity, we can conclude that Akbank, Burganbank, and ICBCTurkey banks display higher efficiency than others.

The changes in TFPCH, TC, and EC during 2019–2022 are presented in Table 4.

Table 4: Changes in TFPCH, TC and EC Overtime.

Capital Structure	Banks	2019-2020			2020-2021			2021-2022		
		TFPCH	TC	EC	TFPCH	TC	EC	TFPCH	TC	EC
State	Ziraatbank	1.083	1.083	1	0.893	0.893	1	1.409	1.409	1
	Halkbank	1.057	0.999	1.058	1.068	1.104	0.967	1.453	1.456	0.998
	Vakifbank	1.126	1.010	1.115	0.924	0.924	1.000	1.466	1.466	1
	Mean	1.089	1.031	1.058	0.961	0.974	0.989	1.443	1.444	0.999
Private	Akbank	1.092	1.092	1.000	0.927	0.927	1.000	2.054	2.054	1.000
	Anadolubank	0.967	0.963	1.004	0.544	0.705	0.772	1.461	1.453	1.005
	Fidabanka	1.065	1.033	1.031	1.053	0.952	1.106	1.618	1.856	0.872
	TEB	1.175	1.213	0.969	0.685	0.736	0.931	1.350	1.407	0.960
	Isbank	1.049	1.135	0.924	0.901	0.878	1.026	1.643	1.615	1.017
	Yapıkredibank	0.991	1.075	0.921	0.916	0.876	1.045	1.964	1.926	1.020

	Mean	1.056	1.085	0.975	0.837	0.845	0.980	1.682	1.719	0.979
Foreign Owned	Arapturkbank	0.580	0.580	1.000	1.059	1.059	1	0.965	0.965	1
	Burganbank	0.834	0.834	1.000	1.225	1.225	1	1.991	1.991	1
	Denizbank	1.219	1.220	0.999	0.801	0.793	1.010	1.231	1.365	0.901
	HSBCbank	0.962	0.792	1.216	0.831	0.923	0.901	1.327	1.762	0.753
	ICBCTurkey	1.162	0.864	1.345	0.676	0.960	0.705	2.497	1.761	1.418
	INGbank	0.925	0.925	1	0.561	0.718	0.781	1.230	1.360	0.904
	QNBFinansbank	1.135	1.148	0.989	0.843	0.776	1.086	1.344	1.512	0.889
	Garantibank	1.074	1.074	1	0.899	0.899	1.000	1.721	1.721	1
	Mean	0.986	0.930	1.069	0.862	0.919	0.935	1.538	1.555	0.983
	General Mean	1.029	1.002	1.034	0.871	0.903	0.961	1.572	1.593	0.985

The Malmquist Index of total factor productivity change graphs by banks for the period 2019-2022 is given Figure 2.

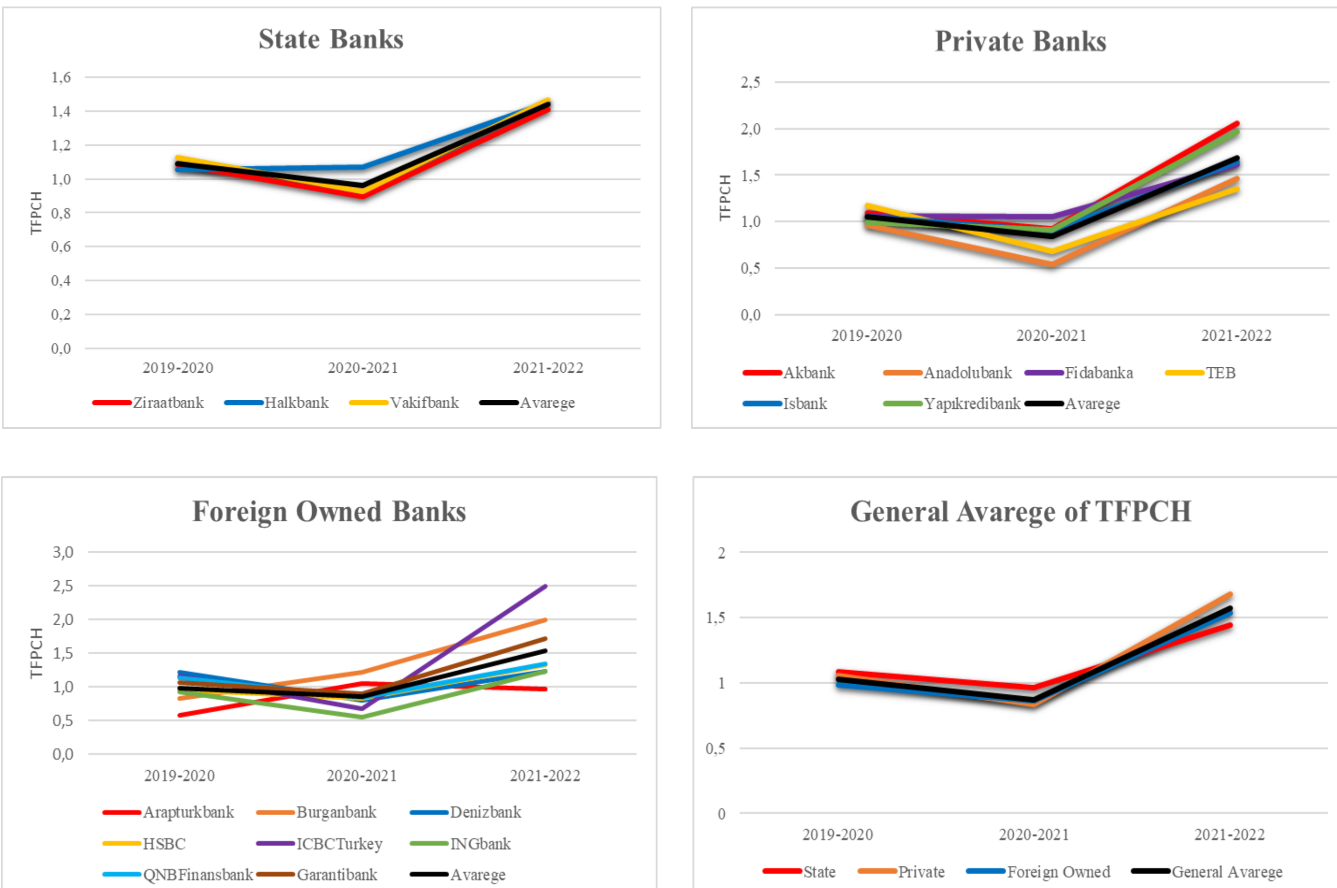

Figure 2: Distribution of TFPCH Scores by Year

Fluctuations in the average Total Factor Productivity Change (TFPCH) scores are observed over the years. In the 2020-2021 period, when the Covid-19 pandemic affected the whole world intensely, TFPCH scores decreased by 0.158 points compared to the previous period, which was the beginning of the pandemic. In the 2021-2022 period, when the Covid-19 pandemic effect is almost over, the TFPCH score increased by 0.701 points and reached a level of 1.572, which is higher than the 2019-2020 period. According to the capital structure of banks, it has been determined that there is a similar situation to the general average TFPCH scores of public and private banks, that is, TFPCH scores are at the lowest level in the 2020-2021 period and reach the highest level in the 2021-2022 period. However, there are two foreign-owned banks with different results from this situation. These banks are Arapturkbank and Burganbank. Burganbank increased its TFPCH score in both periods and completed its highest value in the 2021-2022 period. In contrast to the general situation in Arapturkbank, it achieved the highest TFPCH score (1.059) in the period of 2020-2021, the most intense period of the Covid-19 pandemic. Arapturkbank's TFPCH scores decreased by 0.094 points in the 2021-2022 period.

4. Discussion and Conclusion

Banks are an active and important factor in shaping the financial and economic progress of a country. The effectiveness of a banking system profoundly influences a country's economic growth in various sectors. For this reason, efficiency scores with DEA and TFPCH were calculated for the period from the beginning of the pandemic to 2022 for 17 banks operating in Turkey. We determined efficiency of banks by considering their capital structures. While total interest income, net operating profit, and net period profit are used as outputs, the number of bank branches, personnel expenses, and total interest expenses are used as inputs.

It was determined that there were five effective banks from the onset of the Covid-19 pandemic in 2019 until 2022. These effective banks include Ziraatbank from the state bank group, Akbank from the private bank group, and Arapturkbank, Burganbank, and Garantibank from the foreign bank group. According to these results, when the number of effective bank rates is calculated, it can be said that the best bank rank is foreign capital bank with 37.5%, the second rank is state bank with 33.33%, and private bank at the last rank with 16.66%. Based on this result, it can be concluded that necessary improvements should be implemented to increase the efficiency of foreign banks in particular.

In the period of 2020-2021, the average EC of banks was 0.961, which is less than one. There is a decrease relative to the previous period. The decrease in EC indicates that resources are not efficiently used, and the maximum possible output cannot be obtained using the production factors used. In other words, it indicates that the use of resources in production has deteriorated during the period of 2020-2021, when the number of Covid-19 cases is maximum. The average EC increased by 0.024 points to 0.985 in the 2021-2022 period. According to the capital structures of banks, the EC average of state and foreign owned banks is similar to the general average. That is, the EC average dropped to its lowest level in the 2020-2021 period and rises in the next period. In private banks, unlike the general situation, the highest EC value is in the 2020-2021 period.

It was determined that, in general and according to banks' capital structures, the TC averages show a similar course. In the period 2020-2021, when the number of Covid-19 cases was at its maximum, the TC averages were the lowest. In the 2021-2021 period, when the effect of the Covid-19 pandemic decreased, TC increased by a general average of 0.69 points and reached its highest value.

The TFPCH scores, obtained by multiplying EC and TC scores, have the highest overall average score (1.572) in the 2021-2022 period, when most of the Covid-19 pandemic restrictions are over. In the 2019-2020 period, which is considered the onset of the Covid-19 pandemic, the general average of TFPCH scores is greater than 1 (1.029). The lowest general average of TFPCH scores (0.871) was in the 2020-2021 period. The course of average TFPCH scores according to capital structure of banks was similar to general average TFPCH scores in this study. The highest and lowest TFPCH scores are in foreign owned banks. The highest TFPCH score was for the ICBCTurkey bank in the 2021-2022 period, and the lowest TFPCH score was for the Arapturkbank in the 2019-2020 period.

The literature contains numerous input/output variables used to measure bank efficiency. The input/output variables used significantly affect the results obtained using DEA and the Malmquist productivity index New studies can be carried out by considering different inputs and outputs and using different analysis models for new research to be carried out after the Covid-19 pandemic. Statistical comparisons can be made between the results obtained and those of new studies. Consequently, sectoral analyses and evaluations may be conducted.

One of the limitations of this study is that the DEA method used can only be applied with positive inputs and outputs. Therefore, the analysis was conducted on 17 banks that provided a dataset compatible with positive values. Rather than covering all banks in Türkiye, only those suitable for the analysis were included, which constricted the scope of the research. Despite this, the findings provide important information about the overall performance of the banking sector. Notably, performance disparities among foreign-owned banks were observed, with some banks achieving high levels of efficiency, while others experienced declines. These findings suggest that foreign banks may need to reconsider their resource utilization strategies. Another key result, which can be generalized to similar banking systems in developing countries, is that state-owned banks tend to be more resilient during crises.

In conclusion, although this study is limited to data from the Turkish banking sector, the findings offer valuable results with implications for the global banking sector. The study provides generalizable conclusions on how banks can operate more effectively during crises, the advantages of state-owned banks in crisis management, and areas for improvement in private and foreign-owned banks. In this context, our findings have the potential to guide the banking sector not only in Turkey but also in other countries.

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