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How Market Competition and Stability in the Banking Sector Affect Total Factor Productivity Changes: Evidence from a Panel of European Union Banks

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Abstract

This paper contributes to the literature by first employing a Data Envelopment Analysis (DEA) approach to measure bank efficiency. The results, presented through Malmquist indices, analyse changes in technical, technological, and scale efficiency across a panel of 784 relevant banks from all 27 European Union (EU) countries between 2006 and 2021. In the second stage, the study utilises panel dynamic Generalized Method of Moments (GMM) estimations to assess the impact of bank market competition (measured using the estimated Boone indicator) and bank stability (represented by the estimated Z-score) on total productivity changes. This analysis controls for various relevant bank activities, economic growth, and the influence of significant crises that affected the EU banking sector during the study period. The principal findings suggest that while bank market competition appears to foster enhancements in total factor productivity, variables such as bank loans, bank deposits and short-term funding, bank market stability, and economic growth do not demonstrate a clear contribution to changes in total factor productivity for the considered banks.

Keywords: Bank total factor productivity changes, Boone indicator, European union banking sector, Malmquist indices, Z-score.

1. Introduction

Over the decades, particularly after the last global financial crisis and the subsequent sovereign debt crisis that impacted many European Union (EU) countries, the EU banking sector faced significant challenges in adapting to the new economic and financial reality. EU banks were required to adjust to reformed market regulations supervision, while striving for profitability in an exceptionally strict environment characterised by historically low interest rates.

The profitability and efficiency of EU banks remain crucial not only for the banking sector but also for the entire European economic system. This is primarily because banks in Europe continue to be the largest providers of credit to both producers and households. Additionally, the strong performance of banks plays a vital role in improving the transmission of monetary policy, ensuring that the required lending volumes are met at sustainable rates.

There is a substantial body of literature analyzing the efficiency of EU banks using frontier methods. These studies estimate efficient production frontiers through both parametric and non-parametric approaches. Among these methods is Stochastic Frontier Analysis, a parametric approach focused on optimization. This involves maximizing profits or minimizing costs while assuming the existence of a stochastic optimal frontier. Notable contributions to this field include works by Lozano-Vivas et al. (2011), Vozková and Kuc (2017), Kuc (2018), and Huljak et al. (2022).

Data Envelopment Analysis (DEA) is a widely used non-parametric method for estimating efficient production frontiers. It employs linear programming techniques to measure the efficiency of various decision-making units (DMUs) that utilize multiple inputs and outputs in their production processes. DEA has been utilised to analyse the efficiency of European banks in both single-country studies, such as those by Tanna et al. (2011), Novickytė and Droždz (2018), Ouenniche and Carrales (2018), and Vettas et al. (2022), as well as in multi-country studies, including works by Chortareas et al. (2013), Grigorian and Manole (2017), San-Jose et al. (2018), Rathore (2020), and Kolia and Papadopoulos (2022).

This paper employs DEA to assess the efficiency of a substantial panel of 784 banks across all 27 European Union (EU) countries from 2006 to 2021. Specifically, it presents the results of the computed Malmquist index, which indicates the annual changes in productivity and breaks down these changes into technological changes and technical efficiency changes. Additionally, the paper reports findings on technical efficiency changes (assuming constant returns to scale), pure technical efficiency changes (with variable returns to scale), scale efficiency changes, and total factor productivity changes. To our knowledge, few studies have computed a Malmquist index for such a

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large number of banks from all EU member states over an extended period, especially one that includes three crises that significantly impacted the EU banking sector.

The research in this paper is also related to another strand of literature discussing the determinants of total factor productivity at firm level (among others, Isaksson, 2007; Linh, 2021) and particularly those works that have analysed the total factor productivity determinants in the banking sector (such as Athanasoglou et al, 2008; Fiordelisi and Molyneux, 2010; Castro and Galán, 2019; Huljak et al, 2022; López-Penabad et al, 2023).

The paper contributes to the existing literature by employing panel dynamic Generalised Method of Moments (GMM) estimations to empirically assess the relevance of the "quiet life" hypothesis in the context of EU banking. Specifically, the study analyses the impact of two key market conditions on the total factor productivity of banks in the EU: bank market stability (measured by the estimated Z-score) and bank market competition (assessed using the estimated Boone indicator). The analysis controls for traditional factors related to bank activities, including bank loans, bank deposits and short-term funding, as well as economic growth and the influence of significant crises that impacted the EU banking sector during the period from 2006 to 2021.

The main findings of this study align with the "quiet life" hypothesis in banking. They reveal that competition in the banking market appears to enhance the total factor productivity of EU banks, while market stability does not seem to have a clear impact on these productivity changes. From 2006 to 2021, the growth of traditional banking activities - such as loans provided, and deposits collected - along with the increase in real per capita Gross Domestic Product (GDP) did not significantly drive changes in total factor productivity for the EU banks analysed.

Furthermore, the paper confirms that banks' total factor productivity did not increase during the global financial crisis from 2008 to 2010, nor during the sovereign debt crisis affecting many EU countries from 2011 to 2013. In contrast, the findings related to the impact of the pandemic crisis (2020-2021), although statistically less robust, suggest a positive influence of this crisis on bank total factor productivity growth. This indicates that the EU banking sector was not one of the sectors significantly affected by the economic stagnation during the pandemic.

The paper is structured as follows: Section 2 reviews relevant literature; Section 3 describes the methodology and data used; Section 4 presents the obtained results; and Section 5 concludes the study.

2. Relevant Literature

The research on bank efficiency primarily follows a body of literature that explores the concept of an efficiency frontier, which represents the optimal combination of inputs needed to achieve desired outputs. A firm's efficiency is assessed based on how far it deviates from this established efficiency frontier, which can be determined using both parametric and non-parametric methods.

Data Envelopment Analysis (DEA) is a widely used non-parametric approach that was first introduced by Charnes et al. in 1978 and further developed by researchers such as Ali and Seiford (1993), Lovell (1993), Cooper et al. (2006), and Cook et al. (2014). DEA employs a linear programming methodology to measure the efficiency of different decision-making units (DMUs) using multiple inputs and outputs in a production process. It has frequently been used to evaluate and compare the efficiency performance of banks in various countries or regions.

Additionally, there is a substantial body of literature examining the determinants of total factor productivity at the firm level (see Isaksson, 2007; Linh, 2021). Several studies have specifically investigated the factors influencing total factor productivity in the banking sector, including works by Berger (2003), Athanasoglou et al. (2008), and Fiordelisi and Molyneux (2010).

The goal of this paper is not to provide a comprehensive overview of the existing research on measuring bank efficiency using DEA or to analyse the determinants of total factor productivity in the banking sector within the European Union (EU) or beyond. Instead, this paper focuses on presenting examples of empirical studies that assess the efficiency of banks in the EU through the DEA approach. It emphasises the diversity of inputs and outputs used, summarises some of the key findings of these studies, and discusses some potential applications of the DEA results.

Casu and Molyneux (2003) examined a sample of 750 banks from five EU countries - France, Germany, Italy, Spain, and the UK - to investigate improvements and the possible convergence of efficiency across European banking markets following the establishment of the Single Internal Market. Their efficiency measures were derived from DEA estimations, which employed the intermediation approach and utilized data from the *Bankscope* database. The analysis included two outputs: total loans and other earning assets, and two inputs: total costs (which encompassed interest expenses, non-interest expenses, and personnel expenses) along with total customers and short-term funding (total deposits). The main findings indicated a slight improvement in bank efficiency levels; however, there was no strong evidence to suggest a convergence in the productive efficiency of EU banks.

Chortareas et al. (2013) conducted a study using a large sample of commercial banks operating in 27 EU member states during the 2000s. They sourced their data from the *Bankscope* database and estimated bank-specific efficiency scores using Data Envelopment Analysis (DEA). The outputs included total loans and total other earning assets, while the inputs comprised personnel expenses, total fixed assets, and interest expenses. The paper examined the relationship between the bank efficiency levels and the financial freedom components of the economic freedom index, which was drawn from the Heritage Foundation database. The main findings indicated that a higher degree of financial freedom in a country correlates with increased benefits for banks in that country, particularly in terms of cost advantages and overall efficiency. Furthermore, the research suggested that the positive impact of financial freedom on bank efficiency was more pronounced when governments implemented sound policies and maintained high-quality governance.

Grigorian and Manole (2017) analysed data from 28 European countries covering the period from 2006 to 2011, using DEA estimations. They considered three inputs: personnel and management, leveraged funds, and computer hardware and premises (the latter also reflects the extent of a bank's branch network). They measured three outputs: revenues (defined as the sum of interest and non-interest income), net loans (loans net of loan loss provisions), and liquid assets (the sum of cash, balances with monetary authorities, and holdings of treasury bills). The results of the DEA estimations served as a proxy for banks' performance and as an explanatory variable for the

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growth of consumer deposits. The findings revealed that the efficiency of banks positively influenced the growth of consumer deposits, with depositors favouring more efficient banks by increasing their deposits with them. Furthermore, the study concluded that the banking sector's exposure to sovereign risk had a more negative impact on the growth of consumer deposits than macroeconomic conditions. Additionally, during times of crisis, perceived risks became more significant than financial performance in influencing depositors' choices.

Degl'Innocenti et al. (2017) utilised a two-stage DEA model to examine the efficiency of 116 banks across nine Central and Eastern European (CEE) countries that are members of the European Union, covering the period from 2004 to 2015. In the first stage, the analysis focused on total assets and personnel expenses as inputs, while deposits were considered the output of the "value-added activity." In the second stage, deposits served as inputs for the "profitability activity," with loans and securities as the final outputs. The findings of the study revealed a generally low level of efficiency throughout the entire analysis period, particularly among Eastern European and Balkan countries. Additionally, the authors concluded that the inefficiency observed in CEE countries was primarily driven by the profitability stage, rather than the value-added activity stage.

Asmild and Zhu (2016) analysed the risks and efficiencies of European banks considering a sample of 71 banks from 20 different EU member states during the years 2006 to 2009. The data was collected directly from each bank's audited financial reports. To assess the impact of the proposed weight restrictions, they estimated two DEA models: the "Funding Mix Model" and the "Asset Mix Model. "The Funding Mix Model included five inputs: retail funding expenses, wholesale funding expenses, physical capital expenses, personnel expenses, and impaired loans. The outputs for this model were loans and financial assets. Meanwhile, the Asset Mix Model considered five different inputs: property loans, non-property loans, trading financial assets, non-trading financial assets, and impaired loans, with its outputs being income and provisions for impaired loan losses. The findings revealed that adopting a more balanced set of weights generally reduced the estimated efficiency scores more significantly for banks that had been bailed out during the financial crisis. This highlights potential biases and limitations in DEA estimations. Specifically, the decreases in efficiency scores following the weight restrictions were notably more pronounced for bailed-out banks compared to those that did not receive bailouts.

Kocisova (2017) conducted a study using DEA to examine the efficiency of the banking sectors in European Union countries in 2015, utilizing data from the European Central Bank's database. The study adopted an intermediation approach, considering three inputs: deposits, number of employees, and fixed assets, alongside two outputs: loans and other earning assets, as well as the prices of each output: the ratio of interest income to loans (a proxy for the price of the loans), and the ratio of total non-interest income to other earning assets (representing the price of the other earning assets). The results obtained from the DEA estimations indicated that larger banking sectors tend to be more efficient. The paper also emphasised the advantages of using DEA, as it provides insights into how banks can adjust their input and output structures, considering output prices, to move toward the efficiency frontier. Conversely, the study pointed out potential disadvantages of the DEA method, noting that it calculates relative efficiency within a specific group of Decision-Making Units (DMUs) and selected variables (inputs, outputs, and output prices). Therefore, changes in the group of DMUs or the variables used can affect both the efficiency frontier and the level of efficiency assigned to each DMU.

San-Jose et al. (2018) examined the relationship between economic efficiency and sustainability in European banking by applying DEA techniques to a sample of 2,752 financial institutions. They analysed three types of banks - commercial, cooperative, and savings banks - across EU-15 countries in 2014, using data sourced from the *Bankscope* database. The researchers defined two types of efficiency. The first, Social Efficiency for Sustainability, refers to the balance between resources (two inputs: equity and deposits) and the generation of value (four outputs: customer loans, labour, the ratio of social contributions to taxes, and risk) for society. The second, Economic Efficiency Profitability, is defined as the balance between the resources (one input: assets) used to obtain net profit (the single output). The main findings of the study indicated that European banking was not yet harmonized and demonstrated that there was no trade-off between social efficiency and economic efficiency. Additionally, the paper contributed to the ongoing discussion regarding the strengths and weaknesses of the DEA approach. It emphasized that DEA is highly flexible, as there is no pre-established relationship between inputs and outputs, allowing for a quasi-real demonstration of the relationships between variables. However, DEA is also a simplistic and deterministic method that assumes if one Decision-Making Unit (DMU) achieves a certain level of output with its inputs, other DMUs should achieve the same level. Furthermore, the selection of variables is crucial since there are no reliable tests to determine whether the results of the analysis are stable or would change significantly with different variables.

Rathore (2020) conducted a study using a sample of 194 banks from 15 EU countries to analyse the impact of various factors, including balance sheet data, macroeconomic conditions, financial development, and market structure, on the efficiency scores estimated applying DEA. The study incorporated five inputs: total deposits, total costs, interest expenses, non-interest expenses, and equity; as well as three outputs: loans, other earning assets, and non-interest income. The main findings revealed that the European Banking Authority's capital exercise prompted banks to reassess their activities within the banking sector and manage their portfolios more effectively. Following the capital exercise, the efficiency of the banks in the sample became more stable. Additionally, when controlling for the factors considered, GDP growth, market activity, and market conditions positively influenced the banks' efficiency. In contrast, the size of the banks and market concentration had a significantly negative impact on their efficiency.

Kolia and Papadopoulos (2022) examined the development of bank efficiency and the progress of banking integration between 2013 and 2018. They aimed to determine whether banking integration among Euro area countries had progressed more than that of the total number of European countries. Additionally, they compared the evolution of efficiency and banking integration in the Euro area with that of the United States. Bank efficiency was measured using DEA, which considered three inputs: labour, capital, and deposits, and two outputs: loans and net interest income. The findings revealed that the efficiency of the US banking system was significantly higher than that of banks in the Euro area and the European Union. Furthermore, the study concluded that there was no evidence of convergence among the banking groups studied.

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López-Penabad et al. (2023) analysed a sample of 108 European listed banks from 2011 to 2019 to study the impact of corporate social performance on bank efficiency. They sourced data from Thompson DataStream and employed DEA with various combinations of four inputs: personnel expenses, deposits, fixed assets, and average labour costs. For outputs, they considered loans, earning assets, and non-interest income. The study concluded that, overall, the level of bank efficiency in Europe during this period was low. In the second stage of their analysis, the authors assessed the significance of the relationship between bank efficiency and corporate social performance, including various dimensions of corporate social performance, while controlling for bank-specific and country-level variables. The main findings indicated a U-shaped relationship between corporate social performance and bank efficiency, suggesting that banks with either high or low levels of corporate social performance tend to be the most efficient.

Huljak et al. (2022) employed an industrial organisation approach to analyse total factor productivity growth in the Euro area banking sector, along with its components: technical efficiency, technological progress, and equity and scale effects. They examined a sample of banks from 17 Euro area countries over the period from 2006 to 2017. Overall, the study concluded that total factor productivity in the Euro area banking sector decreased during this decade. Furthermore, the findings indicated that the majority of bank inefficiency in the Euro area was attributed to persistent inefficiency. This suggests that structural long-term factors - such as location, client structure, and the macroeconomic environment - had a more significant impact on bank inefficiency than temporary factors. The results also indicated that more efficient banks in the Euro area tended to have lower average costs, lower cost-to-income ratios, higher profitability, a smaller market share, lower credit risk ratios, and were generally better capitalised.

3. Methodology and Data

3.1. Data Envelopment Analysis and Malmquist Index

In the first stage, this paper employs Data Envelopment Analysis (DEA), a well-established non-parametric method for measuring the efficiency of various decision-making units (DMUs) based on multiple inputs and outputs in a production process. Although it is widely acknowledged that the results obtained from this methodology are highly sensitive to the selection of inputs and outputs—and that the number of efficient DMUs tends to increase as more input and output variables are included—DEA remains a suitable approach for assessing efficiency, including in the banking sector. Compared to other methodologies, DEA offers several advantages: it can handle multiple inputs and outputs without the need for an explicit production function, can be used with any form of input-output measurement, and provides efficiency (and inefficiency) measures for each DMU. Notable references in this field include works by Ali and Lerme (1997), Johnes (2006), and Berg (2010). DEA is based on a linear programming methodology initially introduced by Charnes et al. (1978), which assumes constant returns to scale. This approach has since been further developed by researchers such as Lovell (1993) and Charnes et al. (1994), and Cooper et al. (2006).

The model and the specific application of the DEA methodology was very well specified, for example, in Coelli (1996), with the assumption that each of the considered N DMUs use K inputs to produce M outputs. If X is the KxN the input matrix and Y is the MxN output matrix it is possible to measure the efficiency of each DMU solving the following problem:

$$Min_{\theta\lambda}\ \theta,$$
$$\text{Subject to:} \quad -y_i + Y\lambda \geq 0; \quad \theta y_i - X\lambda \geq 0; \quad \lambda \geq 0 \qquad (1)$$

where θ is a scalar and λ is a $Nx1$ vector of constants.

The solution of this problem provides an efficiency score θ ($\theta \leq 1$) for each of the DMUs. A score $\theta = 1$ reveals that the DMU is on the efficient frontier, while a score $\theta < 1$ indicates that the DMU is below the frontier and the measure of the technical inefficiency of this DMU is the distance to the frontier ($1- \theta$). The score of the technical efficiency obtained with the DEA approach serves as a comparative measure of how effectively each DMU utilises its inputs to produce outputs, in relation to the best performance represented by the production possibility frontier. Furthermore, the overall measure of technical efficiency includes not only pure technical efficiency - which reflects the specific combination of inputs and outputs - but also scale efficiency, which pertains to the scale of the production operation.

As explained, for example, by Kumar and Gulati (2008) and Fujii et al. (2018), scale efficiency refers to a management's ability to select the appropriate production scale. It can be calculated as the ratio of overall technical efficiency - assuming constant returns to scale - to pure technical efficiency. Pure technical efficiency, in turn, measures managerial performance under the assumption of variable returns to scale.

Following Coelli (1996), the measure of the pure technical efficiency can be obtained with the introduction of the assumption of variable returns to scale, and the inclusion of the convexity constrain $N1'\lambda = 1$ in model (1), to solve the following linear programming problem:

$$Min_{\theta\lambda}\ \theta,$$
$$\text{Subject to:} \quad -y_i + Y\lambda \geq 0; \quad \theta y_i - X\lambda \geq 0; \quad N1'\lambda = 1; \quad \lambda \geq 0 \qquad (2)$$

where θ is a scalar, λ is a $Nx1$ vector of constants, and $N1$ is a $Nx1$ vector of ones.

Under the assumption of variable returns to scale, the measure of pure technical efficiency essentially reflects managerial performance. Scale efficiency, on the other hand, represents management's ability to select the appropriate scale of production. It can be calculated as the ratio of overall technical efficiency (assuming constant returns to scale) to pure technical efficiency (see, among others, Kumar and Gulati, 2008; Fujii et al, 2018).

A DEA linear programme can be utilised with panel data to derive a Malmquist index, which measures changes in productivity. This index decomposes productivity change into technical change and changes in technical efficiency. Following Candemir et al. (2011), the Malmquist productivity change index between period t and period t+1 can be defined as:

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$$m_0(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d_0^t(y_{t+1}, x_{t+1})}{d_0^t(y_t, x_t)} \times \frac{d_1^{t+1}(y_{t+1}, x_{t+1})}{d_1^{t+1}(y_t, x_t)}\right]^{1/2} \quad (3)$$

Where $d_1^{t+1}(y_t, x_t)$ is the distance from the period t observation to the period t+1 technology.

This index can be decomposed into the Efficiency Change (EC) = $\frac{d_0^t(y_{t+1},x_{t+1})}{d_0^t(y_t,x_t)}$ (4)

and the Technical Change (TC) = $\left[\frac{d_0^t(y_{t+1},x_{t+1})}{d_1^{t+1}(y_{t+1},x_{t+1})} \times \frac{d_0^t(y_t,x_t)}{d_1^{t+1}(y_t,x_t)}\right]^{1/2}$ (5)

Or $m_0(y_{t+1}, x_{t+1}, y_t, x_t)$ = Efficiency Change x Technical Change

3.2. Dinamic panel Generalized Method of Moments Estimations

In the second stage, the paper analyses the impact of various bank market conditions and the economic environment on changes in total factor productivity, measured using the computed Malmquist index.

Following, among others, Wooldridge (2010) and Greene (2018), the paper considers a general panel regression model for the cross units (the DMUs) $i = 1,\ldots,N$, which are observed for several time periods $t = 1,\ldots,T$:

$$y_{i,t} = \alpha + x'_{i,t}\beta + c_i + \varepsilon_{i,t} \qquad \textbf{(6)}$$

where: $y_{i,t}$ is the dependent variable; □ is the intercept; $x_{i,t}$ is a K-dimensional row vector of the considered explanatory variables excluding the constant; □ is a K-dimensional column vector of parameters and □$_{□,t}$ is an idiosyncratic error term.

The equation is estimated using dynamic one-step system Generalized Method of Moments (GMM), which effectively addresses a key concern regarding the model: the potential presence of endogenous regressors. Dynamic GMM panel estimations not only tackle endogeneity issues but also help reduce potential bias in the estimated coefficients. The GMM method, proposed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), utilizes cross-country information and jointly estimates the equations in first differences and levels. In this method, first differences are instrumented using lagged levels of both the dependent and independent variables, while levels are instrumented with first differences of the regressors.

3.3.Data

3.3.1. Data Used in DEA Estimations

Banks are considered as intermediaries between economic agents who have financial surplus and those who face financial deficits (see, among others, Favero and Lapi, 1995; Chen et al, 2008). Banks attract deposits and other funds and utilize labour and various inputs, such as buildings, equipment, and technology, to transform these funds into loans and other financial assets or securities.

In this context, banks are assumed to produce three types of outputs: loans, other earning assets, and non-earning assets. They achieve this using three inputs: interest expenses, non-interest expenses, and equity. The inclusion of equity is important as it accounts for the significance of risk preferences when estimating efficiency (see, for example, Altunbas et al., 2007; Almanza and Rodríguez, 2018).

The data for bank inputs and outputs were sourced from the Moody's Analytics BankFocus database in December 2022. This analysis focuses on a substantial sample of 784 banks across all 27 European Union (EU) countries, covering the period from 2006 to 2021. The selection of banks was based not only on data availability but also on their size, as banks' size is likely to affect their behaviour. Overall, banks with less than 2 billion Euros of total assets in 2021 were excluded from the sample. However, in EU countries where few banks had high total assets, banks with total assets slightly below 2 billion Euros (but near 1 billion Euros) were included. Appendix 1 provides details on the number of banks from each of the 27 EU countries included in the sample. It also highlights their representativeness in terms of the proportion of the total number of banks in the entire sample, as well as their percentages of total deposits and total loans provided to customers.

3.3.2. Data used in panel dynamic GMM estimations

The paper employs panel dynamic one-step system GMM estimations to analyse how specific bank market conditions and economic growth contribute to the evolution of the total factor productivity change, which was obtained with the Malmquist index computation.

The explanatory variables included in the panel dynamic GMM estimations are: bank sector stability, bank market competition, bank loans, bank deposits, per capita real GDP growth, and three dummy variables representing the years affected by significant crises in EU countries from 2006 to 2021. Following among others Schaeck and Cihák (2014), IJtsma et al. (2017), de Ramon et al. (2018), and Dutta and Saha (2021), bank sector stability is proxied by the estimated Z-score, while bank market competition is proxied by the estimated Boone indicator.

Considering the usual procedure, the Z-score of bank i in the year t $(Z_{i,t})$ is computed with the expression:

$$Z_{i,t} = \frac{ROA_{i,t} + \left(\frac{E}{TA}\right)_{i,t}}{\sigma ROA_{i,t}} \qquad \textbf{(7)}$$

Where:

$ROA_{i,t}$ = return on average assets (%)

$\left(\frac{E}{TA}\right)_{i,t}$ = equity / total assets (%) = capital ratio

$\sigma ROA_{i,t}$ = standard deviation of the return on average assets

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The Boone indicator evaluates competition from an efficiency standpoint. Specifically, it measures the competition among banks within the banking market by analysing the relationship between profits and marginal costs for various banks at a single point in time. In this study, the sample includes a varying number of banks from each of the 27 EU countries, and because the banking markets in these countries are not homogeneous, the market share of the profit of bank *i*, is assessed in relation to the sub-sample of the banks of its own country (and not the entire sample of 784 banks), for the year *t*. The Boone indicators for each bank are calculated using the coefficients (□) obtained from estimating the following linear equation:

$$Boone\text{: } ln(Market\ share\ of\ the\ profits)_{i,t} = \alpha + \beta\ ln(Average\ variable\ cost)_{i,t} \quad (8)$$

Average variable cost of bank i in year t is proxied by the sum of interest expense and non-interest expense divided by total bank profits.

The data used to estimate both the Z-score and the Boone indicator were sourced from Moody's Analytics BankFocus database in December 2022. This also applies to the two additional explanatory variables included in the dynamic GMM estimations: bank loans, and bank deposits and short-term funding.

The values for real GDP per capita were obtained from the World Bank's "Global Financial Development" database in November 2022, which is freely accessible.

Additionally, three dummy variables were included to represent the years of the major crises that affected the EU banking sector from 2006 to 2021: D1 for the global subprime financial crisis (2008-2010), D2 for the sovereign debt crisis (2011-2013), and D3 for the pandemic crisis (2020-2021).

4. Empirical Results

4.1. Malmquist Index

The Malmquist index values measure annual productivity changes and allow for the decomposition of these changes into technological changes and changes in technical efficiency. The computed Malmquist index also provides results for technical efficiency change (under constant returns to scale), pure technical efficiency change (under variable returns to scale), scale efficiency change, and total factor productivity change.

Values greater than one indicate positive changes from one year to the next. For instance, when technological change values exceed one, it signifies technological progress. This progress corresponds to an outward shift in a bank's efficient frontier due to the adoption of new technologies by the most efficient banks. Conversely, values less than one in technological change indicate technological regress.

Table 1. Results obtained for the Malmquist indices.

	EFFCH	TECHCH	PECH	SECH	TFPCH
2006-2007	1.026	0.975	1.057	0.97	1
2007-2008	1.092	0.945	0.977	1.118	1.032
2008-2009	0.723	1.376	0.838	0.863	0.995
2009-2010	0.798	1.208	0.897	0.89	0.964
2010-2011	0.698	1.395	0.871	0.802	0.974
2011-2012	1.92	0.526	1.272	1.51	1.009
2012-2013	1.138	0.969	1.062	1.071	1.102
2013-2014	1.091	1.014	1.114	0.98	1.106
2014-2015	1.113	1.043	1.162	0.958	1.161
2015-2016	0.822	1.404	0.838	0.981	1.154
2016-2017	0.63	1.796	0.794	0.793	1.131
2017-2018	1.872	0.581	1.439	1.301	1.088
2018-2019	0.995	1.024	1.081	0.921	1.019
2019-2020	0.985	1.228	1.047	0.94	1.209
2020-2021	1.088	1.004	0.984	1.106	1.093
Average	1.066	1.099	1.029	1.014	1.069

Where:
EFFCH = Technical efficiency change, with CRS technology.
TECHCH = Technological change.
PECH = Pure technical efficiency change, with VRS technology.
SECH = Scale efficiency change.
TFPCH = Total factor productivity change.

Table 1 presents the obtained values of all the Malmquist indices. Despite some fluctuations from year to year, all indices showed an overall positive trend during the studied period. By comparing the average results of these indices, it is possible to conclude that technological change (TECHCH) experienced the most significant improvement, indicating that the most efficient banks adopted newer and more productive technologies. In contrast, the scale efficiency change (SECH) showed less progress. This measure represents management's ability to determine the optimal production scale and is the ratio of technical efficiency change (EFFCH, assuming constant returns to scale technology) to pure technical efficiency change (PECH, assuming variable returns to scale technology). Additionally, Appendix 2 includes graphs illustrating the evolution of each of the five Malmquist indices over the considered period.

4.2. Dynamic GMM Estimations

In the second stage, this paper analyses the potential determinants of changes in total factor productivity, as derived from the estimation of the Malmquist index. As previously mentioned, the explanatory variables included in the panel GMM estimations are: bank sector stability, bank market competition, bank loans, bank deposits, and

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per capita real GDP growth. Appendix 3 presents the descriptive statistics and pairwise correlations between these variables. As expected, the correlation between bank loans and bank deposits suggests that these two variables should not be included as explanatory variables in the same equation. Additionally, three dummy variables are considered to account for the relevant crises that affected EU countries during the period from 2006 to 2021.
The estimated models are:

$$\text{Model 1}: Productivity_{i,t} = \alpha_0 + \alpha_1\ Stability_{i,t} + \alpha_2\ Competition_{i,t} + \alpha_3\ Loans_{i,t} + \alpha_4\ GDP_{j,t} + \alpha_5\ D_1 + \alpha_6\ D_2 + \alpha_7\ D_3 + \varepsilon_{\ i,t} \qquad (9)$$

$$\text{Model 2}: Productivity_{i,t} = \alpha_0 + \alpha_1\ Stability_{i,t} + \alpha_2\ Competition_{i,t} + \alpha_3\ Deposits_{i,t} + \alpha_4\ GDP_{j,t} + \alpha_5\ D_1 + \alpha_6\ D_2 + \alpha_7\ D_3 + \varepsilon_{\ i,t} \qquad (10)$$

Where:
Productivity = natural logarithm of the computed Malmquist index total factor productivity change
Stability = computed Z-score measure
Competition = computed Boone indicator
Loans = natural logarithm of the bank loans
Deposits = natural logarithm of the bank deposits & short term funding
GDP = natural logarithm of the real per capita Gross Domestic Product
i = EU bank ($i = 1, \ldots 784$)
t = year ($t = 2006, \ldots, 2021$)
j = EU country j($j = 1, \ldots 27$)
D_1 = crisis dummy for the years 2008-2010 (corresponding to the global subprime financial crisis)
D_2 = crisis dummy for the years 2011-2013 (representing the sovereign debt crisis)
D_3 = crisis dummy for the years 2020 and 2021 (the pandemic crisis)
$\varepsilon_{i,t}$ = error term

Before proceeding with the panel GMM estimations, the stationarity of the considered series is analysed using three widely recommended panel unit root tests: the Levin-Lin-Chu test (Levin et al., 2002), the Fisher-type test (ADF) (Choi, 2001; Maddala and Wu, 1999), and the panel unit root tests suggested by Karavias and Tzavalis (2014), which allows for breaks both in the intercepts of the individual series and in linear trends. The results from these three panel unit root tests are reported in Appendix 4, and overall, they demonstrate the stationarity of the series.

The results obtained from the dynamic panel-data estimation, one-step system GMM estimations are presented in Table 2. The difference between Model 1 and Model 2 lies in the inclusion of either bank loans or bank deposits. In both models, three equations are estimated: the first includes all three crisis dummies (D_1, D_2, D_3); the second excludes the dummy related to the pandemic crisis (D_3); and the third includes only the dummy for the global financial crisis years (D_1).

Overall, the results presented in Table 2 demonstrate the statistical robustness of the estimated equations. The Wald test results confirm the validity of the instruments used. In every case, the Arellano and Bond (1991) tests reject the null hypothesis of no first-order autocorrelation while failing to reject the hypothesis of no second-order autocorrelation.

The results presented in this table indicate that the stability of the banking market, as measured by the estimated Z-score, does not contribute to the growth of total factor productivity in banks. In contrast, bank market competition, assessed using the computed Boone indicator, significantly enhances the growth of total factor productivity. These findings support the well-known "quiet-life" hypothesis, which suggests that banks operating in dynamic and competitive markets are more likely to improve their total factor productivity.

Table 2. Results obtained with dynamic one-step system GMM estimations.

Variables	Model 1			Model 2		
Stability	-.0140*** (-4.03)	-.0161*** (-4.83)	-.0122*** (-3.97)	-.0212*** (-6.26)	-.0219*** (-6.54)	-.0165*** (-5.52)
Competition	.0455*** (3.50)	.0415*** (3.23)	.0383*** (3.00)	.0497*** (3.79)	.0463*** (3.58)	.0463*** (3.58)
Loans	-.0331*** (-6.87)	-.0280*** (-6.64)	-.0249*** (-6.11)			
Deposits				-.0351*** (-5.63)	-.0300*** (-5.52)	-.0219*** (-4.45)
GDP	-.0860*** (-4.06)	-.0903*** (-4.28)	-.0717*** (-3.56)	-.0800*** (-3.63)	-.0850*** (-3.90)	-.0700*** (-3.31)
D_1	-.0245*** (-5.71)	-.0259*** (-6.09)	-.0198*** (-5.26)	-.0275*** (-5.93)	-.0279*** (-6.02)	-.0188*** (-4.83)
D_2	-.0085*** (-2.69)	-.0098*** (-3.16)		-.0120*** (-3.59)	-.0124*** (-3.73)	
D_3	.0081** (2.19)			.0062* (1.66)		
Const	1.373*** (6.22)	1.348*** (6.11)	1.085*** (5.35)	1.389*** (6.20)	1.364*** (6.11)	1.053*** (5.14)
Wald chi2(7) test (Prob > chi2)	17818.95 (0.000)	17800.05 (0.000)	18041.30 (0.000)	17401.54 (0.000)	17407.11 (0.000)	17798.24 (0.000)
AB AR(1) z (Pr > z)	-39.25 (0.000)	-37.35 (0.000)	-37.49 (0.000)	-31.92 (0.000)	-31.12 (0.000)	-33.95 (0.000)
AB AR(2) z (Pr > z)	-0.86 (0.392)	-0.77 (0.443)	-0.68 (0.500)	-0.73 (0.463)	-0.66 (0.507)	-0.55 (0.580)

Note: ***significant at 1% level; ** significant at 5% level; * significant at 10% level.

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Dependent variable: Productivity (natural logarithm of the computed Malmquist index total factor productivity change).

Explanatory variables: Stability (computed Z-score measure), Competition (computed Boone indicator), Loans (natural logarithm of the bank loans), Deposits (natural logarithm of the bank deposits & short term funding), GDP (natural logarithm of the real per capita Gross Domestic Product), D_1 (crisis dummy for the years 2008-2010, corresponding to the global subprime financial crisis), D_2 (crisis dummy for the years 2011-2013, representing the sovereign debt crisis), D_3 (crisis dummy for the years 2020 and 2021, years of the pandemic crisis)

The results indicate that the growth of traditional banking activities, such as bank loans and deposits, does not significantly contribute to the increase in total factor productivity of banks. Additionally, the growth in real GDP per capita does not align with the growth of bank total factor productivity. This suggests that between 2006 and 2021, the productivity dynamics of the EU banking sector - at least among the 784 relevant banks from all EU member states - did not follow the increase in real GDP per capita in their respective countries.

It is not surprising that the total factor productivity of banks did not increase during the global financial crisis from 2008 to 2010, nor during the sovereign debt crisis that affected many EU countries from 2011 to 2013. However, the results regarding the impact of the pandemic crisis (2020-2021), although statistically less robust, suggest a positive influence of this crisis on the growth of bank total factor productivity. This indicates the unique characteristics of the pandemic crisis and highlights that the EU banking sector was not one of the sectors severely impacted by the economic stagnation during this time.

5. Concluding Remarks

This paper contributes to the literature on the factors affecting total factor productivity in the European Union banking sector. It analyses a panel of 784 relevant banks across all 27 EU countries from 2006 to 2021. In the first stage, Data Envelopment Analysis techniques are applied to measure bank efficiency. The analysis assumes that banks produce three outputs: loans, other earning assets, and non-earning assets, using three inputs: interest expenses, non-interest expenses, and equity. The computed five Malmquist indices indicate that, despite some fluctuations year to year, there has been an overall positive change in efficiency within the EU banking sector during the assessed period. A comparison of the average results of the indices reveals that technological advancements have made significant progress, suggesting that the most efficient EU banks have adopted new and more productive technologies. Conversely, the findings indicate that progress related to scale efficiency change - an aspect that reflects management's ability to determine the optimal scale of production - has been relatively lower.

In the second stage, the paper employs panel dynamic Generalised Method of Moments (GMM) estimations to analyse the determinants of changes in total factor productivity, as determined by the Malmquist index. Two models are estimated, utilizing the following explanatory variables: bank sector stability (measured using the estimated Z-score), bank market competition (assessed with the Boone indicator), bank loans (in Model I), bank deposits (in Model II), per capita real GDP growth, and three dummy variables representing the years of relevant crises that impacted EU countries between 2006 and 2021. The dummy variables are as follows: D_1 for the years 2008-2010, which corresponds to the global subprime financial crisis; D_2 for 2011-2013, reflecting the sovereign debt crisis; and D_3 for the years 2020 and 2021, associated with the pandemic crisis.

The results obtained indicate that the stability of the EU banking market does not contribute to the growth of total factor productivity in banks. In contrast, competition in the banking market clearly promotes an increase in total factor productivity. These findings are consistent with the well-known "quiet-life" hypothesis, which suggests that banks operating in dynamic and competitive environments are more likely to enhance their total factor productivity. Furthermore, the growth of traditional banking activities, such as bank loans and deposits, does not appear to significantly promote increases in total factor productivity. Additionally, the growth of real GDP per capita is not aligned with the growth of bank total factor productivity. This reveals that between 2006 and 2021, the productivity dynamics of the EU banking sector - specifically for the 784 relevant banks from all EU member states - did not correspond with the increase in real GDP per capita of their home countries.

There is evidence indicating that, as expected, the total factor productivity of banks did not increase during the global financial crisis from 2008 to 2010, nor during the sovereign debt crisis that affected many EU countries from 2011 to 2013. However, the findings regarding the impact of the pandemic crisis (2020-2021), while statistically less robust, suggest a positive influence of this crisis on the growth of bank total factor productivity. This highlights the unique characteristics of the pandemic crisis and suggests that the EU banking sector was not among the sectors most adversely impacted by the economic stagnation during this period.

The findings of this paper offer several recommendations. The results indicate that, in the analysed panel of EU banks from 2006 to 2021, overall bank factor productivity did not increase alongside traditional banking activities, specifically the growth of bank deposits and loans provided to clients. This suggests that EU banks were not only intermediaries between savers and investors but also producers of various other services in response to the challenges posed by historically low interest rates. While the additional services provided by banking institutions are significant, their role as intermediaries remains essential. Therefore, banks should continue to enhance their efficiency by promoting technological advancements through the adoption of more productive technologies and by improving their management capabilities, particularly in relation to their production scale.

The paper concludes that the increase in total factor productivity of banks is not driven by the rise in real GDP per capita in EU countries. This finding aligns with the observed decline in the significance of traditional banking activities, but it raises concerns about the relationship between bank productivity and economic growth. This relationship is particularly important in Europe, where banks remain the largest providers of credit to both businesses and households. It is crucial to ensure that economic growth is aligned with the strong performance of banking institutions.

Additionally, the findings indicate that banks operating in dynamic and competitive markets are more likely to enhance their total factor productivity. This underscores the importance of market conditions for banks, as well as the role of policymakers in establishing appropriate regulations to foster healthy competition in the banking sector.

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Authorities also play a vital role in preventing economic and financial crises, which can negatively impact the total factor productivity of banks.

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Appendix 1. Number of the considered banks by European Union member-state and their representativeness.

EU country	Number of banks	% of the total banks	% of the deposits in 2021	% of the provided loans in 2021
Austria	27	3.44	2.62	2.44
Belgium	19	2.42	3.66	3.37
Bulgaria	9	1.15	0.20	0.14
Croatia	4	0.51	0.21	0.14
Cyprus	5	0.64	0.42	0.30
Czech Rep.	12	1.53	0.96	0.70
Denmark	15	1.91	1.17	1.85
Estonia	4	0.51	0.09	0.08
Finland	7	0.89	1.39	1.81
France	129	16.45	31.05	32.97
Germany	322	41.07	26.82	26.30
Greece	6	0.77	0.76	0.50
Hungary	6	0.77	0.44	0.29
Ireland	6	0.77	1.23	0.82
Italy	63	8.04	9.66	9.68
Latvia	5	0.64	0.08	0.05
Lithuania	4	0.51	0.13	0.07
Luxembourg	34	4.34	1.33	0.94
Malta	7	0.89	0.12	0.07
Netherlands	16	2.04	6.68	7.28
Poland	18	2.30	1.47	1.16
Portugal	12	1.53	1.27	0.94
Romania	6	0.77	0.30	0.19
Slovakia	5	0.64	0.19	0.20
Slovenia	7	0.89	0.17	0.11
Spain	28	3.57	5.55	4.74
Sweden	8	1.02	2.05	2.84

Source: Authors calculations using data sourced from the Moody's Analytics BankFocus database.

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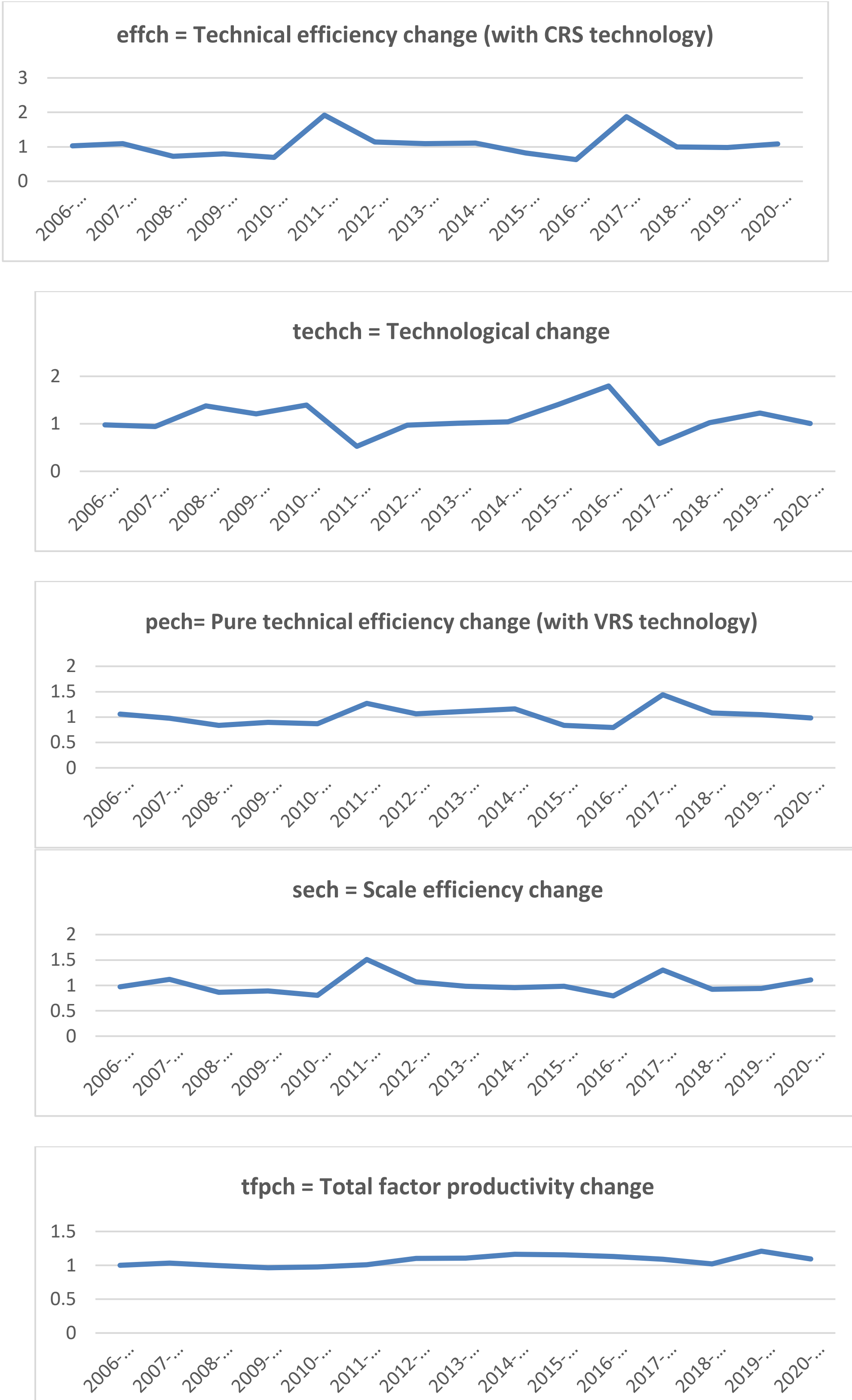

Appendix 2. Annual results of each of the five Malmquist indices.
Source: Authors calculations using data sourced from the Moody's Analytics BankFocus database.

Appendix 3. Descriptive statistics and correlation matrix.

Descriptive statistics

Variables(*)	Mean	Std. Dev.	Min.	Max.
Productivity	-.1212218	.1062056	-3.244194	9.20251
Stability	3.963375	2.511147	-14.35	90.96
Competition	-.7505235	.5469668	-4.47	1.55
Loans	15.08022	1.763441	.8501509	21.05635
Deposits	15.492	1.506488	3.526361	21.37306
GDP	10.47276	.4480094	8.64	11.63

Correlation Matrix

	Productivity	Stability	Competition	Loans	Deposits	GDP
Productivity	1.0000					
Stability	-0.1382	1.0000				
Competition	-0.0092	-0.0334	1.0000			
Loans	-0.1037	-0.1975	0.1005	1.0000		
Deposits	-0.0555	-0.2650	0.1124	0.8940	1.0000	
GDP	0.0213	-0.0862	0.4118	-0.0051	0.0476	1.0000

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Productivity = natural logarithm of the computed Malmquist index productivity change
Stability = computed Z-score measure
Competition = computed Boone indicator
Loans = natural logarithm of the bank loans
Deposits = natural logarithm of the bank deposits & short term funding
GDP = natural logarithm of the real per capita Gross Domestic Product

Appendix 4. Results obtained with panel unit root tests (p-values).

	Productivity	Stability	Competition	Loans	Deposits	GDP
Levin Li						
Levels	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Levels trend	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Fisher (P statistic)						
Levels	0.0000	0.0000	0.0000	0.0001	0.8855	0.8112
Levels trend	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Karavias and Tzavalis (2014)						
One unknown break	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Productivity = natural logarithm of the computed Malmquist index productivity change
Stability = computed Z-score measure
Competition = computed Boone indicator
Loans = natural logarithm of the bank loans
Deposits = natural logarithm of the bank deposits & short term funding
GDP = natural logarithm of the real per capita Gross Domestic Product.

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