**REM WORKING PAPER SERIES**

# The impact of bank market competition and stability on bank total factor productivity changes: evidence from a panel of European Union banks

**Cândida Ferreira**

**REM Working Paper 0315-2024**

March 2024

**REM – Research in Economics and Mathematics**
Rua Miguel Lúpi 20,
1249-078 Lisboa,
Portugal

ISSN 2184-108X

**REM – Research in Economics and Mathematics**

Rua Miguel Lupi, 20
1249-078 LISBOA
Portugal

Telephone: +351 - 213 925 912
E-mail: rem@iseg.ulisboa.pt

https://rem.rc.iseg.ulisboa.pt/

REM RESEARCH IN ECONOMICS AND MATHEMATICS

https://twitter.com/ResearchRem

https://www.linkedin.com/company/researchrem/

https://www.facebook.com/researchrem/

**The impact of bank market competition and stability on bank total factor productivity changes: evidence from a panel of European Union banks**

Cândida Ferreira*

ISEG, UL – Lisbon School of Economics and Management of the Universidade de Lisboa
UECE - Research Unit in Complexity and Economics
REM – Research in Economics and Mathematics
LISBOA, PORTUGAL
candidaf@iseg.ulisboa.pt

**Abstract**

This paper contributes to the literature using first a Data Envelopment Analysis (DEA) approach to measure bank efficiency and the results provided by the Malmquist indices to analyse the evolution of the technical, technological, and scale efficiency changes,
in a panel including 784 relevant banks of all the 27 European Union (EU) countries, between 2006 and 2021. In the second stage, the study uses panel dynamic Generalised Method of Moments (GMM) estimations to analyse the impact on the total productivity changes of bank market competition (measured with the estimated Boone indicator) and bank stability (proxied with the estimated Z-score), while controlling for some relevant bank activities, economic growth and the influence of the relevant crises that affected the EU banking sector during the considered period. The main findings reveal that while bank market competition looks like promoting the banks' total factor productivity change, bank loans, bank deposits and short-term funding, as well as bank market stability and economic growth do not contribute to the banks' total factor productivity changes.

Keywords: European Union banking sector; Malmquist indices; bank total factor productivity changes; Z-score; Boone indicator.
JEL Classification: C33; D53 ; F36 ; G21.

* The author acknowledges financial Support from FCT – Fundação para a Ciência e Tecnologia (Portugal), national funding through research grant UIDB/05069/2020

## 1. **Introduction**

Over decades, and particularly after the last global financial crisis and the sovereign debt crisis that affected many European Union (EU) countries, the EU banking sector had to face significant challenges in adaptation to the new economic and financial reality. The EU banks were obliged to adapt to the reshaped bank market regulations and the supervision of the banks, and they have been struggling for their profitability in a very strict environment, including the historically low-interest rate levels.

The profitability and efficiency of the EU banks go on being relevant not only to the banking sector but also to the whole EU economic system, namely because in Europe banks are still the largest providers of credit to producers and households. The good performance of banks is also important to improve the transmission of monetary policy, ensuring the required lending volumes at sustainable lending rates.

There is a large strand of literature analysing the efficiency of the EU banks using frontier methods and estimating efficient production frontiers with parametric and non-parametric approaches. Some of these studies use the Stochastic Frontier Analysis, a parametric approach which is based on a problem of optimisation, that is, the maximisation of the profit or the minimisation of the costs, given the assumption of a stochastic optimal frontier (among others, Lozano-Vivas et al, 2011; Vozková and Kuc, 2017; Kuc, 2018: Huljak et al, 2022).

Data Envelopment Analysis (DEA) is one of the most used non-parametric approaches to estimate efficient production frontiers. It is based on a linear programming methodology that is appropriate to measure the efficiency of different decision-making units (DMUs) using multiple inputs and outputs in a production process. DEA has been used to analyse the efficiency of the European banks in single-country studies (such as Tanna et al, 2011; Novickytė and Droždz, 2018; Ouenniche and Carrales, 2018; Vettas et al, 2022) as well as in multi-country studies (for example; Chortareas et al, 2013; Grigorian and Manole, 2017; San-Jose et al, 2018; Rathore, 2020; Kolia and Papadopoulos, 2022).

This paper uses DEA to measure the efficiency of a relatively large panel of 784 relevant banks of all 27 European Union (EU) countries between 2006 and 2021. More precisely, the paper presents the results of the computed Malmquist index, indicating the evolution of the annual productivity changes as well as the decomposition of these changes into the technological changes and the technical efficiency changes. Moreover, the paper reports the results of the technical efficiency change (with constant returns to scale), the pure technical efficiency change (with variable returns to scale), the scale efficiency change, and the total factor productivity change. To our knowledge, not many papers have computed a Malmquist index for a large number of banks from all EU member states, over a relatively long period, which included three crises that severely affected 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 the 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 contribution of this paper to this strand of literature is the use of panel dynamic Generalised Method of Moments (GMM) estimations to empirically test the relevance of the "quiet life " hypothesis in EU banking. More precisely, the paper tests the impact on the EU bank total factor productivity of two relevant bank market conditions: bank market stability (proxied with the estimated Z-score), of bank market competition (with the estimated Boone indicator), while controlling for the traditional relevant bank activities (in terms of the bank loans, bank deposits and short-term funding), economic growth and the influence of the relevant crises that affected the EU banking sector during the considered period (2006-2021).

The main findings are overall in line with the "quiet life" hypothesis in banking, revealing that bank market competition looks like promoting the EU banks' total factor productivity change while bank market stability does not contribute to these productivity changes. Also, during the years 2006-2021, the increase of the traditional bank activities (the provided bank loans, and the collected bank deposits and short-term funding), as well as the real per capita Gross Domestic Product (GDP) growth do not promote the total factor productivity changes of the considered panel of EU banks. Moreover, the paper confirms that the total factor productivity did not increase during the years of the global financial crisis (2008-2010) nor during the years (2011-2013) of the sovereign debt crisis that affected many EU countries. On the other hand, the results related to the influence of the pandemic crisis (2020-2021), although statistically less robust, point to a positive influence of the dummy representing this crisis on the bank total factor productivity growth, revealing that the EU banking sector was not among the sectors that were deeply affected by the economic stagnation during the pandemic crisis.

The paper proceeds as follows: Section 2 presents some relevant literature; Section 3 introduces the adopted methodology and the used data; Section 4 presents the results obtained; Section 5 concludes.

## 2. **Relevant literature**

The studies on bank efficiency mainly follow the strand of literature that considers the possibility of defining an efficiency frontier as the best combination of the required inputs to get the desired outputs. The firm's efficiency is therefore the deviation of its position from a defined efficiency frontier, which can be obtained with parametric and non-parametric approaches.

Data Envelopment Analysis (DEA) is one of the most used non-parametric approaches that was first introduced by Charnes et al (1978) and developed among others by Ali and Seiford (1993), Lovell (1993), Cooper et al (2006), Cook et al (2014). DEA is based on a linear programming methodology that is appropriate to measure the efficiency of different decision-making units (DMUs) using multiple inputs and outputs in a production process. It has been used often to assess and compare the efficiency performance of banks in different countries or regions.

There is also a large strand of literature analysing the determinants of total factor productivity at the firm level (among others, Isaksson, 2007; Linh, 2021). Several works have analysed the total factor productivity determinants in the banking sector (such as Berger, 2003; Athanasoglou et al, 2008; Fiordelisi and Molyneux, 2010),

The aim of this paper is not to present an exhaustive survey of the published works addressing the measurement of bank efficiency with DEA nor of the analyses of the total factor productivity determinants in the banking sector in the European Union or elsewhere. The paper mainly presents examples of empirical studies measuring the efficiency of European Union banks using the DEA approach, highlighting the heterogeneity of the chosen inputs and outputs, the main findings of the papers and some potential uses of the DEA estimation results.

Casu and Molyneux (2003) considered a sample of 750 from five EU countries (France, Germany, Italy, Spain and the UK) to investigate the existence of improvement and the potential convergence of efficiency across the European banking markets in the aftermath of the creation of the Single Internal Market with efficiency measures obtained with DEA estimations. Following the intermediation approach and using data sourced from the Bankscope database, the DEA estimations included two outputs: total loans and other earning assets, and two inputs: total costs (interest expenses, non-interest expenses, personnel expenses), and total customers and short term funding (total deposits). The main findings suggested that there was a small improvement in the bank efficiency levels but there was no convincing evidence to support the convergence of the EU banks' productive efficiency.

Chortareas et al (2013) used a large sample of commercial banks operating in 27 EU member states over the 2000s and with data sourced from the Bankscope database, they estimated bank-specific efficiency scores with DEA. The variables included as outputs were: total loans, and total other earning assets, and as inputs were: personnel expenses, total fixed assets, and interest expenses. The paper investigated the dynamics between the obtained bank efficiency levels and the financial freedom counterparts of the economic freedom index drawn from the Heritage Foundation database. The main findings suggested that the higher the degree of a country's financial freedom, the higher the benefits for the banks located in the country, in terms of cost advantages and overall efficiency. In addition, the paper suggested that the positive influence of financial freedom on bank efficiency tended to be more relevant when governments formulated and implemented sound policies and higher-quality governance.

Grigorian and Manole (2017) used data from 28 European countries over the period 2006-2011 and DEA estimations. They considered three inputs: personnel and management, leveraged funds, computer hardware and premises (which also captures the extensiveness of a bank's branch network), and three outputs: revenues (defined as the sum of interest and non-interest income), net loans (defined as loans net of loan loss provisions), and liquid assets (defined as the sum of cash, balances with monetary authorities, and holdings of treasury bills). The results of the DEA estimations were used as a proxy for banks' performance and as an explanatory variable of the growth of consumer deposits. The findings of the paper revealed that the growth of consumer deposits was positively affected by the efficiency of banks, as depositors rewarded more efficient banks by increasing their exposure to them. Moreover, the paper concluded that the exposure of the banking sector to sovereign risk negatively affected the growth of consumer deposits much more than the impact of macroeconomic conditions. In addition, during crisis times the perceived risks became more important than financial performance in determining the depositors' choices.

Degl'Innocenti et al (2017) used a two-stage DEA model to analyse the efficiency of 116 banks from nine Central and Eastern European (CEE) countries, members of the EU, covering the period 2004-2015. In the first stage, they included total assets and personnel expenses as two inputs, while deposits were considered as the output of the "value-added activity". Deposits then entered the second stage (the "profitability activity") as inputs, whereas loans and securities were the final outputs. Overall, the findings of the paper indicated a low level of efficiency over the entire period of analysis, especially for Eastern European and Balkan countries. Moreover, the paper concluded that inefficiency in CEE countries was mainly driven by the profitability stage rather than the value-added activity stage.

Asmild and Zhu (2016) analysed the risk and efficiency of the European banks considering a sample of 71 banks from 20 different EU member-states for the years 2006-2009 and data collected directly from each bank's audited financial report. Aiming to analyse the impact of the proposed weight restrictions, they estimated two DEA models: the "Funding mix model", including five inputs (Retail funding expenses, Wholesale funding expenses, Physical capital expenses, Personnel expenses, and Impaired loan) and two outputs (Loans, and Financial assets), and the "Asset mix model", also considering five inputs (Property loan, Non-property loan, Trading financial assets, Non-trading financial assets, and Impaired loan), and two outputs (Income, and Provision for impaired loan loss). The findings reveal that using a more balanced set of weights tended to reduce the estimated efficiency scores more for those banks which were bailed out during the financial crisis, highlighting some potential bias and limitations of the DEA estimations, and showing that the decreases in efficiency scores after weight restrictions were significantly higher for the bailed-out banks than for the non- bailed-out banks.

Kocisova (2017) used DEA estimations to analyse the efficiency of the banking sectors in the European Union countries in 2015 with data compiled from the database of the European Central Bank. Adopting the intermediation approach, the paper considers three inputs: deposits, the number of employees, and fixed assets, 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 with the DEA estimations revealed the large banking sectors appear to be most efficient. Moreover, the paper highlighted the benefits of using DEA as it provides recommendations on how banks should adjust the structure of their inputs and outputs, taking into account output prices, which should result in a shift to the efficiency frontier. On the other hand, the paper also highlighted some potential disadvantages of the DEA method as it is used to calculate relative efficiency, within the selected group of decision-making units (DMUs), and under the selected group of variables (input, output, and prices of the outputs), therefore, a change in the group of DMUs or used variables, can lead to a change in the efficiency frontier as well as in the level of efficiency obtained for each DMU

San-Jose et al (2018) studied the relationship between economic efficiency and sustainability of banking in Europe, applying DEA techniques to a sample of 2752 financial institutions (separately analysing three types of banks: commercial, cooperative, and saving banks) from EU-15 countries in 2014. Using data sourced from the BankScope database, two kinds of efficiency were defined and estimated considering specific inputs and outputs. First, the Social Efficiency for Sustainability was defined as the balance between resources (two inputs: equity, and deposits) and generation of value (four outputs: customer loans, labour, the ratio of social contribution/taxes, and risk) for the society. Second, Economic Efficiency Profitability is defined as the balance between the resources (one input: assets) used to obtain the net profit (the single output). The main findings of the paper highlighted that European banking was not yet harmonized, providing also evidence that there was no trade-off between social efficiency and economic efficiency. Moreover, the paper contributed to the discussion of the strengths and weaknesses of the DEA approach, emphasising that DEA is extremely flexible as there is no pre-established relation between input and outputs, and this permits a quasi-real show of the relationship between variables. However, DEA is also an extreme form and deterministic method that assumes that if a DMU levels output with input, other DMUs should reach the same level; also, the variable selection is of fundamental importance as there are no suitable tests to estimate if the results of the analysis are stable or would vary significantly with other variables.

Rathore (2020) used a sample of 194 banks from 15 EU countries to analyse the impact of the balance sheet data of the banks, macroeconomic conditions, financial development and market structure, as well as the European Banking Authority's capital shock to investigate their impact on the efficiency scores estimated by DEA. In the DEA estimations the paper included five inputs: total deposits, total costs, interest expenses, non-interest expenses, and equity; and three outputs: loans, other earning assets, and non-interest income. The main findings indicated that the European Banking Authority's capital exercise made the banks reconsider their activities in the banking sector and manage their portfolios better. Moreover, after the capital exercise, the efficiency of the banks included in the sample became more stable. In addition, when controlling for all the considered factors, GDP growth, activity in the market and the market had positive impacts on banks' efficiency, while the size of the banks and the bank market concentration had a very negative impact on banks' efficiency.

Kolia and Papadopoulos (2022) investigated the development of bank efficiency and the progress of banking integration between 2013 and 2018, examining whether banking integration among the Euro area countries has developed more than that of the total sum of European countries. They also compare the evolution of efficiency and the progress of banking integration across the Euro area countries with that of the United States. Bank efficiency was measured with DEA estimations, considering three inputs: labour, capital, and deposits, and two outputs: loans and net interest income. The findings showed that the efficiency of the US banking system was considerably higher than that of the Euro area and the EU banks. Moreover, the paper concluded that overall, there was no evidence of convergence across the reported banking groups.

López-Penabad et al (2023) considered a sample of 108 European listed banks over the period 2011-2019 to analyse the impact of corporate social performance on bank efficiency. Using data sourced from Thompson DataStream, and DEA estimations with different combinations of four inputs: personnel expenses, deposits, fixed assets, and average cost of labour, and three outputs: loans, earning assets, and non-interest income, the paper concluded that, in general, the level of bank efficiency in Europe for the considered period is low. In the second stage, the paper tested the significance of the relationship between bank efficiency and corporate social performance as well as its different dimensions, including a set of two categories of control variables: bank-specific and country-level variables. The main findings of the paper suggested the existence of a U-shaped relationship between corporate social performance and bank efficiency, indicating that banks with either high or low corporate social performance levels are the most efficient.

Huljak et al (2022) used an industrial organisation approach to compute the total factor productivity growth in the Euro area banking sector and each of the components of this productivity growth: the technical efficiency, the technological progress, and the equity and scale effects. They considered a sample of banks from 17 Euro area countries over the period from 2006 and 2017. The paper concluded that the overall total factor productivity in the Euro area banking sector decreased during the considered decade. Moreover, the findings indicated that the largest part of bank inefficiency in the Euro area stemmed from persistent inefficiency, suggesting that structural long-term factors such as location, client structure, and macroeconomic environment, played a bigger role in bank inefficiency than time-specific factors. The findings also suggested that more efficient Euro area banks tended to record lower average costs, lower cost-to-income ratios, higher profitability, lower market share, lower credit risk ratios, and tended to be better-capitalised institutions.

## 3. **Methodology and data**

### *3.1. Data Envelopment Analysis and Malmquist index*

In the first stage, the paper uses Data Envelopment Analysis (DEA), a well-tested non-parametric efficiency approach to measure the efficiency of different decision-making units (DMUs), using multiple inputs and outputs in a production process. Despite the recognition that the results obtained with this methodology are very sensitive to the chosen inputs and outputs, as well as that the number of efficient DMUs tends to increase with the inclusion of more input and output variables, DEA is still considered appropriate to measure efficiency, including bank efficiency. In comparison with other tested methodologies, it presents some advantages, such as the possibility of handling multiple inputs and outputs without an explicit definition of a production function, the possibility of being used with any input-output measurement, and the possibility of obtaining efficiency (and inefficiency) measures for every DMU (see, for example, Ali and Lerme, 1997; Johnes, 2006; Berg, 2010).

DEA is based on a linear programming methodology first presented by Charnes et al (1978), considering a model assuming constant returns to scale, and later developed among others by Lovell (1993), Charnes et al (1994), Cooper et al (2006).

The model and the specific application of the DEA methodology were very well specified, for example, in Coelli (1996), with the assumption that each of the considered *N* DMUs uses *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 by solving the following problem:

$$Min_{\theta,\lambda}\ \theta,$$

Subject to: $-y_i + Y\lambda \geq 0;\ \ \theta y_i - X\lambda \geq 0;\ \ \lambda \geq 0$ **(1)**

where $\theta$ is a scalar and $\lambda$ is a $Nx1$ vector of constants.

The solution of this problem provides the efficient score $\theta$ ($\theta \leq 1$) for each of the DMUs. A score $\theta = 1$ reveals that the DMU is in 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 is a comparative measure of how well each DMU uses the inputs to get the outputs, in comparison with the best achieved performance corresponding to the production possibility frontier. The overall measure of the technical efficiency incorporates not only the pure technical efficiency (representing the specific combination of the inputs and outputs) but also the scale efficiency (the scale of the production operation).

As well explained, for example, in Kumar and Gulati (2008) and Fujii et al (2018) the scale efficiency represents the ability of the management to choose the scale of the production and can be obtained as the ratio of the overall technical efficiency (under the assumption of constant returns to scale) and the pure technical efficiency. Pure technical efficiency captures the managerial performance, under the assumption of variable returns to scale.

Following Coelli (1996), the measure of 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:

$Min_{\theta,\lambda}\ \theta,$

Subject to: $-y_i + Y\lambda \geq 0;\ \ \theta y_i - X\lambda \geq 0;\ \ N1'\lambda = 1;\ \ \lambda \geq 0$ **(2)**

where $\theta$ is a scalar, $\lambda$ 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 captures the managerial performance. The scale efficiency represents the ability of the management to choose the scale of the production and can be obtained as the ratio of the overall technical efficiency (under the assumption of constant returns to scale) and the pure technical efficiency (see, among others, Kumar and Gulati, 2008; Fujii et al, 2018).

A DEA linear programme can be used with panel data, to get a Malmquist index that measures the productivity change, decomposing it into the technical change and the technical efficiency change. Following Candemir et al (2011), the Malmquist productivity change index between the period t and the period t+1 can be defined as

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

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) = $\frac{d_0^t(y_{t+1}, x_{t+1})}{d_0^t(y_t, x_t)}$ $\mathbf{(4)}$

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 uses panel estimations to analyse the influence of some bank market conditions, and economic environment on the total factor productivity change, obtained with 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 $t = 1,\ldots,T$:

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

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

The equation is estimated with a dynamic one-step system GMM (Generalized Method of Moments) which deals well with a relevant concern regarding the considered model: the potential existence of endogenous regressors. Dynamic GMM panel estimations not only address the endogeneity problems but also reduce the potential bias of the estimated coefficients. The GMM method proposed, among others by Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998, uses cross-country information and jointly estimates the equations in first difference and in levels, with first differences instrumented by lagged levels of the dependent and independent variables and levels instrumented by first differences of the regressors.

### *3.3.Data*

#### *3.3.1. Data used in DEA estimations*

Banks are considered intermediates between economic agents with a financial surplus and those with a financial deficit (see, among others, Favero and Lapi, 1995; Chen et al, 2008). Therefore, banks attract deposits and other funds and, using labour and other types of inputs such as buildings, equipment and technology, they transform the funds into loans and other assets or securities.

Here banks are assumed to produce three outputs: loans, other earning assets, and non-earning assets using three inputs: interest expenses, non-interest expenses, and equity. The inclusion of equity aims to take into account the relevance of the risk preferences when estimating efficiency (see, for example, Altunbas et al, 2007; Almanza and Rodríguez, 2018).

The variables included as bank outputs and inputs were sourced from Moody's Analytics BankFocus database in December 2022 and the paper considers a relatively large panel of 784 relevant banks of all the 27 European Union (EU) countries between 2006 and 2021. The choice of the banks took into consideration not only the availability of the data but also the size of the banks, as the size of the banks 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, for the EU countries with few banks with a high amount of total assets, the sample includes banks with less than 2 billion Euros of total assets (but not far from 1 billion Euros in 2021). Appendix I indicates the number of the banks for each of the 27 EU countries included in the sample, as well as their representativeness not only in terms of the percentage of the total number of the banks included in the whole sample but also in terms of their percentages of the total deposits and of the total loans provided to costumers.

*3.3.2. Data used in panel dynamic GMM estimations*

In the second stage, the paper applies panel dynamic one-step system GMM estimations to analyse how some specific bank market conditions and economic growth contribute to the evolution of the total factor productivity change that 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 for the years of the relevant crisis that affected the EU countries during the period 2006-2021. Following among others Schaeck and Cihák (2014), IJtsma et al (2017), de-Ramon et al (2018), and Dutta and Saha (2021), the bank sector stability is proxied with the estimated Z-score and the bank market competition is proxied with 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

The Boone indicator looks at competition from an efficient perspective. More precisely, this indicator measures competition between the banks in the bank market by measuring the strength of the relationship between profits and marginal costs for different banks at one moment in time. As the considered sample in this paper includes a different number of banks from each of the 27 EU countries and the banking markets of these countries are not homogeneous, the market share of the profit of bank *i* is related to the sub-sample of the banks of its own country (and not the whole sample of 784 banks), in the year *t*. The Boone indicators for each bank are the values of the coefficients b that are obtained through the estimation of the following linear equation:

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

Where the average variable cost of bank $i$ in year $t$ is proxied by the sum of the interest expense and the non-interest expense to the total bank's profits.

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

The values of the real GDP per capita were sourced in November 2022 from the World Bank database "Global Financial Development", freely available at Global Financial Development Database.

Three dummies were also included for the years of the main crises that affected the EU banking sector during the period 2006-2021: the global subprime financial crisis, $D_1$ (for the years 2008-2010), the sovereign debt crisis, $D_2$ (for 2011-2013), and the pandemic crisis, $D_3$ (for 2020 and 2021).

## 4. Empirical results

### *4.1. Malmquist index*

The values of the computed Malmquist index provide the measures of the annual productivity changes and they allow the decomposition of these changes into the technological changes and the technical efficiency changes. The computed Malmquist index also reports the results of the technical efficiency change (with constant returns to scale), the pure technical efficiency change (with variable returns to scale), the scale efficiency change, and the total factor productivity change.

Values greater than one always indicate positive changes between one year and the next one. For example, values greater than one of the technological changes indicate technological progress, which corresponds to a bank's efficient frontier shifting out as a result of the adoption of new technologies by the most efficient banks. On the other hand, values lower than one of the technological changes reveal 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 provides the values obtained for all the Malmquist indices. Despite some year fluctuations, on average, all the indices had positive changes during the considered period. Comparing the average results of the indices it is possible to conclude that the technological changes (TECHCH) had a higher progress, revealing that new and more productive technologies were adopted by the most efficient banks. On the other hand, lower progress is related to the scale efficiency change (SECH), which represents the ability of the management to choose the scale of the production and is the ratio of the technical efficiency change (EFFCH, with constant returns to scale technology) and the pure technical efficiency change (PECH, with variable returns to scale technology). Appendix II presents graphs with the evolution of each of the five Malmquist indices during the considered period.

### *4.2 Dynamic GMM estimations*

In the second stage, the paper considers potential determinants of the total factor productivity changes that were obtained with the estimation of the Malmquist index. As already mentioned, the explanatory variables included in the panel GMM (Generalised Method of Moments) estimations are: bank sector stability, bank market competition, bank loans, bank deposits, and per capita real GDP growth (GDP). Appendix III presents the descriptive statistics and the pairwise correlations between these variables; as expected, the correlation between bank loans and bank deposits indicates that these two variables should not be included as explanatory variables in the same equation. Three dummy variables are also considered for the years of the relevant crisis that affected the EU countries during the period 2006-2021.

The estimated models are:

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

**Model 2** : $Productivity_{i,t} = \alpha_0 + \alpha_1\ Stability_{i,t} + \alpha_2\ Competition_{i,t}\ + \alpha_3\ Deposits_{i,t} + \alpha_4\ GDP_{j,t}\ + \alpha_5\ D_1 + \alpha_6\ D_2 +\ \alpha_7\ D_3 +\ \varepsilon_{\ i,t}$ (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, …784*)
*t* = year (*t = 2006, …, 2021*)

$j$ = EU country $j (j = 1, ...27)$

$D_1$ = 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.

**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) |
| Sargan test chi2 (Prob > chi2) | 367.97 (0.000) | 372.49 (0.000) | 387.87 (0.000) | 374.17 (0.000) | 377.09 (0.000) | 400.08 (0.000) |

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

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)

Source: Author's calculations.

The results reported in Table 2 overall demonstrate the statistical robustness of all the estimated equations. The Wald test results validate the use of the instruments, and the Sargan tests indicate that the results are not weakened by the inclusion of too many instruments. Moreover, in all situations, the Arellano and Bond (1991) tests reject the null hypothesis of no autocorrelation of the first order and do not reject the hypothesis of no autocorrelation of the second order.

According to the results presented in this table, the stability of the banking market (proxied with the estimated Z-score) does not contribute to the bank's total factor productivity growth. On the other hand, the bank market competition (measured with the computed Boone indicator) promotes the increase of the bank's total factor productivity. These results are overall in line with the well-known “quiet-life” hypothesis, meaning that banks located in dynamic and competitive markets are more likely to increase their total factor productivity.

Moreover, the growth of traditional banking activities (bank loans and bank deposits) does not contribute to the increase of the bank's total factor productivity. In addition, the growth of the real GDP per capita is not in line with the bank total factor productivity growth, revealing that between 2006 and 2021 the dynamic of the EU banking sector productivity (at least of the considered 784 relevant banks from all EU member states) did not follow the increase of the real GDP per capita of their home countries.

Not surprisingly, it looks like the bank total factor productivity did not increase during the years of the global financial crisis (2008-2010) nor during the years (2011-2013) of the sovereign debt crisis that affected many EU countries. However, the results related to the influence of the pandemic crisis (2020-2021), although statistically less robust, point to a positive influence of the dummy representing this crisis on the bank total factor productivity growth, revealing the specific characteristics of this crisis, as well as the fact that the EU banking sector was not among the sectors that were deeply affected by the economic stagnation during the pandemic crisis.

## 5. Concluding remarks

This paper contributes to the literature on the determinants of the total factor productivity of the European Union banking sector, considering a panel with 784 relevant banks of all 27 EU countries, between 2006 and 2021. In the first stage, Data Envelopment Analysis techniques are applied to measure bank efficiency. Banks are assumed to 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 year fluctuations, on average, all the indices had positive changes, revealing an overall increase in the EU bank efficiency during the considered period. The comparison of the average results of the indices shows that the banks' technological changes had higher progress, indicating that new and more productive technologies were adopted by the most efficient EU banks. On the other hand, the results reveal that the lower progress is related to the scale efficiency change, which represents the ability of the management to choose the scale of the production.

In the second stage, the paper uses panel dynamic Generalised Method of Moments (GMM) estimations to analyse the determinants of the total factor productivity changes that were obtained with the estimation of the Malmquist index. Two models are estimated, using as explanatory variables: bank sector stability (proxied with the estimated Z-score), bank market competition (using the estimated Boone indicator), bank loans (in Model I), bank deposits (in Model II), and per capita real GDP growth, and three dummies for the years of the relevant crisis that affected the EU countries during the period 2006-2021 ($D_1$ for the years 2008-2010, corresponding to the global subprime financial crisis; $D_2$ for the years 2011-2013, representing the sovereign debt crisis; and $D_3$ for the years 2020 and 2021, corresponding to the pandemic crisis).

The results obtained demonstrate that the stability of the EU banking market does not contribute to the bank total factor productivity growth, while bank market competition promotes the increase of the bank total factor productivity. These results are overall in line with the well-known "quiet-life" hypothesis, meaning that banks located in dynamic and competitive markets are more likely to increase their total factor productivity. The results also allow the conclusion that the growth of traditional banking activities (bank loans and bank deposits) does not promote the increase of the bank's total factor productivity. Also, the growth of the real GDP per capita is not in line with the bank total factor productivity growth, revealing that between 2006 and 2021 the dynamic of the EU banking sector productivity (at least of the considered 784 relevant banks from all EU member states) did not follow the increase of the real GDP per capita of their home countries.

There is also evidence that, as expected, the bank total factor productivity did not increase during the years of the global financial crisis (2008-2010) nor during the years (2011-2013) of the sovereign debt crisis that affected many EU countries. However, the results related to the influence of the pandemic crisis (2020-2021), although statistically less robust, indicate a positive influence of the dummy representing this crisis on the bank total factor productivity growth, revealing the specific characteristics of this crisis, as well as the fact that the EU banking sector was not amongst the sectors that were deeply affected by the economic stagnation during the pandemic crisis.

The findings of this paper provide room for some recommendations. First, the findings show that in the considered panel of EU banks, between 2006 and 2021 the total bank factor productivity changes did not increase with the traditional bank activities, more precisely with the increase of the bank's deposits and the loans provided to their clients. This result confirms that EU banks were not only intermediaries between savers and investors but also producers of other kinds of services, as a way to overcome the challenges that they had to face, namely due to the historically low interest rates. Despite the relevance of the useful services produced by the banking institutions, their intermediation role is still crucial and banks should go on increasing their efficiency, promoting technological changes, with the adoption of more productive technologies, as well as increasing their management abilities, namely related to their scale of production.

Second, the paper's conclusions that the increase of the bank total factor productivity changes was not fomented by the increase of the real GDP per capita in the EU countries, is overall in line with the findings of the decrease of the importance of the traditional bank activities, but raises questions about the health of the relationship between the evolution of bank productivity and economic growth. This relationship is particularly relevant in Europe, because banks are still the largest providers of credit to producers and households, and it would be desirable to ensure that economic growth goes in line with the good performance of the banking institutions.

Finally, the findings that banks located in dynamic and competitive markets are more likely to increase their total factor productivity, point to the relevance of the bank markets conditions, but also to the importance of the role of the policy makers in providing appropriate regulations to ensure healthy bank market competition. The role of the authorities is also important to prevent economic and financial crises that are detrimental to the increase of the banking total factor productivity.

## References


Ali, A.I. and Seiford, L.M. (1993) "The Mathematical Programming Approach to Efficiency Analysis" in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (Eds), The Measurement of Productive Efficiency, New York, Oxford University Press, pp. 120-159.

Ali, A.I. and Lerme, C.S. (1997) "Comparative advantage and disadvantage in DEA", *Annals of Operations Research*, 73, pp. 215–232.

Almanza, C. and Rodríguez, J. J. M. (2018) "Profit efficiency of banks in Colombia with undesirable output: a directional distance function approach", *Economics: the Open-Access, Open-Assessment e-Journal*, journal article no. 2018-30.

Altunbas, Y., Carbo, S., Gardener, E. P. M. and Molyneux, P. (2007) "Examining the Relationships between Capital, Risk and Efficiency in European Banking", *European Financial Management*, 13, pp. 49–70.

Arellano, M., and Bond, S. (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies*, 58 (2), April, pp. 277-297.

Arellano, M. and Bover, O. (1995) “Another look at the instrumental-variable estimation of error-components model”, *Journal of Econometrics*, 68 (1), July, pp. 29–52.

Asmild, M. and Zhu, M. (2016) “Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis”, *European Journal of Operational Research*, 251, pp. 999-1015.

Athanasoglou. P.P., Georgiou. E. A, and Staikouras, C.C. (2008) *Assessing output and productivity growth in the banking industry*, Bank of Greece, Working Paper No, 92, November, 2003, available at https://www.bankofgreece.gr/Publications/Paper200892.pd

Berg, S. (2010) *Water Utility Benchmarking: Measurement, Methodology, and Performance Incentives*, London and New York, International Water Association. DOI: https://doi.org/10.2166/9781780401690

Berger, A.N., and Mester, L.J. (2003) “Explaining the dramatic changes in the performance of US banks: technological change, deregulation, and dynamic changes in competition” *Journal of Financial Intermediation*, 12, pp. 57–95.

Blundell, R., and Bond, S. (1998) “Initial conditions and moment restrictions in dynamic panel data models”, *Journal of Econometrics*, 87 (1), August, pp. 115–143.

Candemir, M., Ozcan, M., Gunes, M. and Delikas, E. (2011) “Technical Efficiency and Total Factor Productivity in the Hazelnut Agricultural Sales Cooperatives Unions in Turkey”, *Mathematical and Computational Applications*, 16, pp. 66-76.

Castro, C. and Galán, J. G. (2019) “Drivers of productivity in the Spanish banking sector: Recent evidence”, *Journal of Financial Services Research*, 5, pp. 115-141.

Casu, B. and Molyneux, P. (2003) “A comparative study of efficiency in European banking”, *Applied Economics*, 35, pp. 1865-1876.

Charnes A., Cooper W.W. and Rhodes, E. (1978) “Measuring the Efficiency of Decision-Making Units”, *European Journal of Operational Research*, 2, pp. 429 – 444.

Charnes, A., Cooper W.W., Lewin, A.Y. and Seiford, L.M. (1994) *Data Envelopment Analysis: Theory, Methodology and Application, Boston*, Kluwer Academic Publishers.

Chen, T.Y, Chen, C.B. and Peng, S.Y. (2008) “Firm operation performance analysis using data envelopment analysis and balanced scorecard: A case study of a credit cooperative bank”, *International Journal of Productivity and Performance Management*, 57, pp. 523-539.

Choi, I. (2001), “Unit root tests for panel data”, *Journal of International Money and Finance*, 20, 249-272.

Chortareas, G. E., Girardone, C. and Ventouri, A. (2013) "Financial freedom and bank efficiency: Evidence from the European Union," *Journal of Banking & Finance*, 37, pp 1223-1231.

Coelli, T. (1996) *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program*, CEPA Working Paper 96/08.

Cook, W.D., Tone, K., and Zhu, J. (2014) “Data envelopment analysis: Prior to choosing a model”, *Omega*, 44, pp. 1-4.

Cooper, W.W., Seiford, L.M. and Tone, K. (2006) *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, 2nd Ed., New York, Springer.

Degl'Innocenti, M., Kourtzidis, S. A.,Sevic, Z. and Tzeremes, N. G. (2017) "Investigating bank efficiency in transition economies: A window-based weight assurance region approach", *Economic Modelling*, 67, pp 23-33.

de-Ramon, S., Francis, W., and Straughan, M. (2018) *Bank competition and stability in the United Kingdom*, Bank of England working papers 748, Bank of England.

Dutta, K.D. and Saha, M. (2021) “Do competition and efficiency lead to bank stability? Evidence from Bangladesh”, *Future Business Journal*, 7(6), January, available on-line (https://doi.org/10.1186/s43093-020-00047-4).

Favero, C.A. and Papi, L. (1995) “Technical efficiency and scale efficiency in the Italian banking sector: a non-parametric approach”, *Applied Economics*, 27, pp. 385-395.

Fiordelisi, F., and Molyneux, P., (2010) “Total factor productivity and shareholder returns in banking”, *Omega*, 38, pp. 241-253.

Fujii, H., Managi, S., Matousek, R. and Rughoo, A. (2018) “Bank efficiency, productivity, and convergence in EU countries: a weighted Russell directional distance model”, *The European Journal of Finance*, 24, pp. 135-156.

Greene W. H. (2018) *Econometric Analysis*, 8th Edition, Pearson, New York.

Grigorian, D. and Manole, V. (2017) “Sovereign risk and deposit dynamics: evidence from Europe”, *Applied Economics*, 49 (29), pp. 2851-2860.

Huljak, I., Martin, R., and Moccero, D. (2022) “The productivity growth of euro area banks” *Journal of Productivity Analysis*, 58, pp. 15-33.

IJtsma, P. Spierdijk, L., and Shaffer, S. (2017) "The concentration–stability controversy in banking: New evidence from the EU-25," *Journal of Financial Stability*, 33(C), December, pp. 273-284.

Isaksson, A. (2007) *Determinants of Total Factor Productivity: A Literature Review*, Research and Statistics Branch United Nations Industrial Development Organization (UNIDO), July 2007, available at https://rrojasdatabank.info/87573_determinants_of_total_factor_productivity.pdf

Johnes, J. (2006) “Data envelopment analysis and its application to the measurement of efficiency in higher education”, *Economics of Education Review*, 25, pp. 273-288.

Karavias, Y, and Tzavalis, E. (2014), “Testing for unit roots in short panels allowing for a structural break”, *Computational Statistics & Data Analysis*, 76, pp. 391–407.

Kocisova, K. (2017) “Measurement of Revenue Efficiency in European Union Countries: A Comparison of Different Approaches”, *International Journal of Applied Business and Economic Research*, 15, pp. 31-42.

Kolia, D. L. and Papadopoulos, S. (2022) “Integration in banking efficiency: a comparative analysis of the European Union, the Eurozone, and the United States banks”, *Journal of Capital Markets Studies*, 6 (1), pp. 48-70.

Kuc, M. (2018) *Cost Efficiency of European Cooperative Banks*, Institute of Economic Studies (IES) Working paper 21/2018.

Kumar, S. and Gulati, R. (2008) “An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis”, *Eurasian Journal of Business and Economics*, 1, pp. 33-69.

Levin, A., Lin, C. F., and Chu, C. S. (2002), “Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties”, *Journal of Econometrics*, 108, 1-24.

Linh, D.T.T.(2021) “Literature Review on Determinants of Total Factor Productivity (TFP) at the Firm-Level”, *Cross Current International Journal of Economics, Management and Media Studies*, DOI: 10.36344/ccijemms.2021.v03i04.002, Open access, available at https://www.easpublisher.com/media/features_articles/CCIJEMMS_34_47-55_FT.pdf

López-Penabad, M.C., Iglesias-Casal, A., Neto, J.F.S., and Maside-Sanfiz, J.M. (2023) “Does corporate social performance improve bank efficiency? Evidence from European banks” *Review of Managerial Science*, 17, pp. 1399-1437.

Lovell, C.A.K. (1993) “The Mathematical Programming Approach to Efficiency Analysis” in Fried, H.O., Lovell, C.A.K. and Schmidt, S.S, (Eds), *The Measurement of Productive Efficiency*, New York, Oxford University Press, pp. 3-67.

Lozano-Vivas, A., Kumbhakar, S.C., Fethi, M.D. and Shaban, M. (2011) “Consolidation in the European banking industry: How effective is it?”, *Journal of Productivity Analysis*, 36, pp. 247-261.

Maddala, G. S. and Wu, S. (1999), “A comparative study of unit root tests with panel data and a new simple test”, *Oxford Bulletin of Economics and Statistics*, 61, 631-652.

Novickytė. L. and Droždz, J. (2018) "Measuring the Efficiency in the Lithuanian Banking Sector: The DEA Application," *International Journal of Financial Studies*, 6, pp. 1-15.

Ouenniche, J. and Carrales, S. (2018) "Assessing efficiency profiles of UK commercial banks: a DEA analysis with regression-based feedback", *Annals of Operations Research*, 266, pp. 551-587.

Rathore, A. S.  (2020) "EBA's Capital Exercise and the Technical Efficiency of the Banks", *Review of Economic Analysis*, 12, pp. 371-402.

San-Jose,L. Retolaza, J. L., and Lamarque, E. (2018) "The Social Efficiency for Sustainability: European Cooperative Banking Analysis", *Sustainability*, 10, pp. 1-21.

Schaeck, K. and Cihák, M. (2014) "Competition, efficiency, and stability in banking" *Financial Management*,  43 (1), Spring, pp. 215–241.

Tanna, S., Pasiouras, F. and Nnadi, M. (2011) "The effect of board size and composition on the efficiency of UK banks", *International Journal of the Economics of Business*, 18, pp. 441–462.

Vettas, N., Louka, A., Peppas, K. Pountouraki, Y., and Vasileiadis, M. (2022) *Trends in total factor productivity in Greece and its determinants during the period 2005-2019* (December 1, 2022). Bank of Greece Economic Bulletin, Issue 56 DOI: https://doi.org/10.52903/econbull20225601, Available at SSRN: https://ssrn.com/abstract=4382069

Vozková, K. and Kuc, M. (2017) "Cost Efficiency of European Cooperative Banks", *International Journal of Economics and Management Engineering*, 11, pp. 2705-2708.

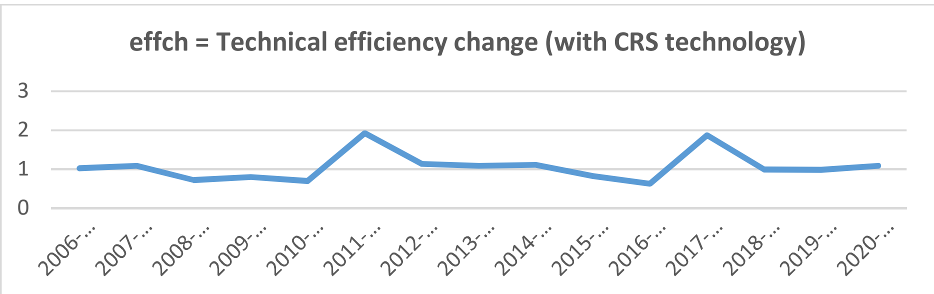
Wooldridge, J. M. (2010) *Econometric Analysis of Cross Section and Panel Data*, the MIT Press, Cambridge, Massachusetts, London, England.

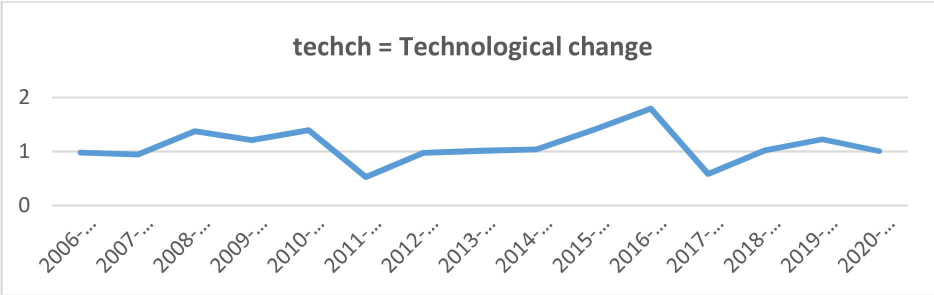
**Appendix I – Number of the considered banks by European Union member-state and their representativeness**

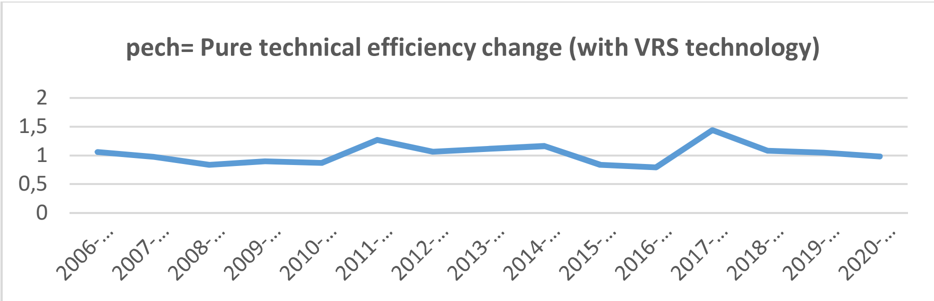
| EU country | Number of banks | % of the total banks | % of the deposits in 2021 | % of the provided loans in 2021 |
|---|---|---|---|---|
| Austria | 27 | 3.44 | 2.62 | 2.44 |
| Belgium | 19 | 2.42 | 3.66 | 3.37 |
| Bulgaria | 9 | 1.15 | 0.20 | 0.14 |
| Croatia | 4 | 0.51 | 0.21 | 0.14 |
| Cyprus | 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 |

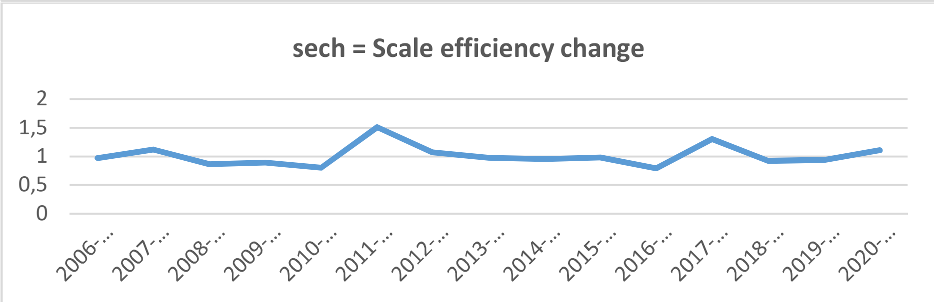
Source: Authors calculations using data sourced from the Moody's Analytics BankFocus database.

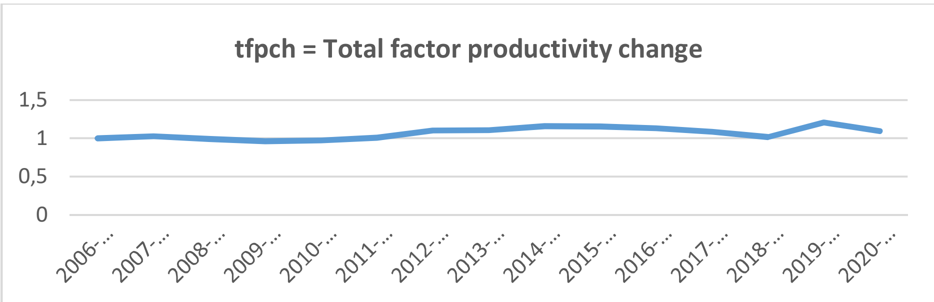
**Appendix II - Annual results of each of the five Malmquist indices**






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

## Appendix III – 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 |

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

Source: Author's calculations

## Appendix IV – 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

Source: Author's calculations