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Dynamic network DEA and SFA models for accounting and financial indicators with an analysis of super-efficiency in stochastic frontiers: An efficiency comparison in OECD banking

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ABSTRACT

This paper presents an assessment of 124 OECD banks during 2004–2013 in light of relevant accounting and financial indicators that reflect banking production process and performance. Novel DEA and SFA Dynamic Network Super-efficiency models are developed to handle the underlying relationships among major accounting and financial indicators. Additionally, we develop a novel super-efficiency concept for SFA to compare DEA and SFA on common grounds to the extent possible. Firstly, a relational model encompassing major profit sheet indicators, balance sheet indicators, and net income is presented under a dynamic network structure for both models under the non-parametric and parametric specifications. Subsequently, the dynamic effect of carry-over indicators is incorporated into them, so that efficiency scores can be properly computed for these three sub-structures. Differences in scores and ranks are explored by bootstrapped regressions. It reveals that results generated from the proposed models interact differently with the socio-economic and business-related variables.

1. Introduction

Since the adoption of efficiency measurement in the banking industry, many studies have neglected the impact of alternative parametric and non-parametric approaches or methods on performance levels. Rather, they have focused on analyzing, given a specific type of model, how banking productive resources (or inputs) were converted into banking products (or outputs), observing one out of two possible approaches: intermediation and production. In fact, the use of accounting and financial indicators to assess banking performance has found a more fertile ground under the application of multi-criteria decision-making models (MCDM) instead of the alternative techniques for measuring efficiency: non-parametric and parametric ones (e.g. Wanke, Azad, & Barros, 2016; 2016, 2018). This happens because commonly used financial and accounting indicators fail to properly consider the effects of multiple outputs and inputs, which can be properly handled by dynamic network structures in place of the traditional black box approach.

Precisely, previous banking efficiency studies mostly rely on the use of the aforementioned techniques (Athanassopoulos, 1998; Berger & Humphrey, 1997; Brandouy, Briec, Kerstens, & van de Woestyne, 2010; Briec & Liang, 2011; Brissimis, Delis, & Tsionas, 2010;

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Cummins & Rubio-Misas, 2006; De Borger, Ferrier, & Kerstens, 1998; Kerstens, Mounir, & van de Woestyne, 2011; Lampe & Hilgers, 2014). As regards the parametric research strand, Stochastic Frontier Analysis (SFA) is the most popular; while as regards DEA, acronym that stands for Data Envelopment Analysis, it stands as the most popular technique in the non-parametric research strand (Chen, 2002; Deliktaş & Balcilar, 2005; Doan, Lin, & Doong, 2018; Gunay, 2012; Li, Liu, Liu, & Whitmore, 2001; Tözüm, 2002; Yang, 2009). It is worth mentioning, however, that non-parametric techniques present a widespread use in banking industries of different countries (Paradi, Rouatt, & Zhu, 2011; Matousek, Rughoo, Sarantis, & Assaf, 2014; Wanke, Azad, Barros, & Hadi-Vencheh, 2015; Chen et al., 2018, 2018). As far as we are concerned, none of these previous researches had addressed the issue of score comparison computed within the ambit of parametric and non-parametric dynamic network models. Besides, none of these studies had used business related and socio-economic contextual variables to better apprehend the underlying differences in score ranking, dispersion, and discriminatory power.

Yet, most banking performance studies focused, however, on the US and other developed countries with little attention paid to emerging markets and economic blocks (Apergis & Polemis, 2016; Mokni & Rachdi, 2014; Thi, Daly, & Akhter, 2016). Therefore, this research fills a literature gap by focusing on the banking industry of OECD countries. Novel versions of the Dynamic Network DEA and SFA models that allows accounting for the underlying relationships between major profit sheet indicators, balance sheet indicators, and net income over the course of time are proposed here. Specifically, for the SFA model, extensions were derived so that super-efficiency scores could be computed and compared against those ones from DEA. The underlying rationale for deriving super-efficiency scores in SFA is based on the leave-one-out approach, where the removal of a DMU at each time is measured relatively in terms of variations on efficiency scores considering the full set of observations as the base case.

Putting it more specifically, the major purpose of this research is to address the impact of business-related and socio-economic variables on different accounting and financial indicators, in light of the underlying cultural and regulatory barriers of the OECD countries. Parametric and non-parametric efficiency scores for (i) profit sheet indicators, (ii) balance sheet indicators and (iii) net income over the course of the time frame analyzed (2004–2013) are computed by means of Dynamic Network DEA and SFA models that arranges these three types of indicators within the ambit of a three-stage process structure. The impacts of such variables on these three efficiency sub-structures are further computed by a bootstrapped regression approach.

In this research, a comprehensive set of socio-economic variables at the country level is tested. Annual Inflation Rate (AIR, in % per annum), Gini index for wealth concentration, Human Development Index (HDI), GDP growth per annum (%), GDP per capita in Power Purchase Parity (PPP), Foreign Direct Investment (FDI), Energy Use (EU, in kg equivalent of oil per capita), Infant Mortality Rate (IMR, per 1000 births), Average Life Expectancy (ALV, in years), Global Innovation Index (GII), and Logistics Performance Index (LPI). Besides, information regarding bank ownership (whether public or private), past information on merger and acquisitions (M&A), and whether or not the country is affiliated to one specific economic block (NAFTA, UE etc) are also tested. These are business-related variables at the bank level.

This research builds upon previous studies, and contributes to the banking efficiency literature, by developing ways for comparing discrepancies and divergences in Dynamic Network DEA and SFA models based on financial and accounting indicators. As a direct consequence, results presented here shed light on how socio-economic variables, bank ownership, and M&A may impact on the discriminatory power of the efficiency scores in light of the model approach adopted.

The rest of the manuscript is structured as described next. Section 2 gives a conceptual background on profit sheet indicators, balance sheet indicators and net profit, besides a discussion on country level and bank related variables that may affect efficiency. Section 3 is focused on the novel Dynamic Network DEA model. Section 4 is dedicated to the novel Dynamic Network SA model. Data analysis and discussion of results follow in Section 5. Conclusions follow in Section 6.

2. Background

2.1. Relationships between profit sheet, balance sheet indicators and net income

The interrelations between profit sheet indicators and balance sheet indicators with net income are significant. These relationships are often ignored in previous research (Casu, Girardone, & Molyneux, 2006). For instance, the profit and the balance sheets, as well as the cash flow statement, are the three financial statements issued every quarter or year by all listed companies. The profit sheet, however, similarly to the cash flow statement, indicates modifications in accounts that occur over a given timeframe. The balance sheet, differently, is an instantaneous image of a very different nature, showing what is owned and owed at a single moment (Varian, 2014).

Profit sheets should be compared from distinct accounting periods, so that the changes in operating costs, revenues and net income could be properly compared, revealing the dynamics of the company. For instance, although the income of a company might be growing, its expenses could be increasing at a faster pace, signaling financial distress in the future. Putting into to other words, a profit sheet is an accounting statement that synthesizes the revenues, income, and costs verified over a given timeframe. It gives information about a company's dynamic capability of generating profit by either increasing revenues or reducing costs.

Profit sheet items are mostly linked with the bank performance over a period. In fact, the long-term influence of profit seen items can be seen in balance sheet. Besides this relationship between profit sheet and balance sheet, the net income of a bank is the resultant relative movement of a bank's performance (profit items) in relation to its balance sheet items (assets, equities, and liabilities). A way in which to calculate the overall financial health of a financial institution that includes the assets amount it owns and how much income it must generate to cover regular costs and other expenses. Thus, this research, for the first time, examines comparative bank efficiency of OECD countries based on these three source of data to define the best alternative variables in describing the relative bank performance (efficiency).

2.2. Impacts of socio-economic and business-related variables on banking efficiency

Contextual or business related variables that impact on banking efficiency can be either considered as exogenous or endogenous. Broadly speaking, exogenous variables present a unidirectional impact on banking efficiency levels, while endogenous variables present a bidirectional and, sometimes, simultaneous impact on these levels. The fact that exogenous contextual variables are not impacted by efficiency levels in a reverse causation increases their appeal in terms of policy formulation.

M&As and bank ownership are examples of two exogenous variables frequently explored in previous researches on banking efficiency in different countries (e.g. Assaf, Barros, & Matousek, 2011, 2011, 2012). There is substantive evidence in favor of a positive impact of merging on cost and profit efficiency in banking (Andrade, Mitchell, & Stafford, 2001; Garette & Dussauge, 2000), as a result of a better resource allocation and increased market share. On the other hand, with respect to foreign ownership, there is also evidence that the origin of the bank affects significantly efficiency levels (Lee & Kim, 2013; Minh, Long, & Hung, 2013; Pancurova & Lyocsa, 2013; Sufian & Kamarudin, 2015), mostly due to cultural differences and regulatory barriers that may exist between the country of origin and the country of operation. As regards public vs. private ownership, there is an ongoing debate (Dinc, 2005) on whether private banks are more efficient than public ones (Kumar & Gulati, 2010; Mohan & Ray, 2004), although no definite conclusion have been found yet.

Endogenous business-related variables differ from the exogenous ones as regards the “country effect” and their socio-economic and demographic underlying variables (Athanasoglou, Brissimis, & Delis, 2008). A large body of literature suggests that financial institutions exert a powerful influence on economic development, poverty alleviation, and economic stability (Levine, 1997 and 2005). However, the reverse impact of socio-economic variables on banking efficiency is much less studied than the impacts caused by business related variables. Recently, as regards the impact of endogenous variables - or the “country effect” - on banking efficiency, Wanke, Azad, and Emrouznejad (2018) analyzed the banking efficiency of BRICS countries using fuzzy logic. Results indicate that the country gross savings and the Gini index ratio positively impact banking efficiency. On the other hand, banking efficiency is negatively associated with relatively high inflation ratios, thus suggesting an interesting trade-off between banking efficiency and social-welfare, while there is a trade-in between banking efficiency and macro-economic variables.

3. Dynamic network DEA model

DEA is a non-parametric method for assessing efficiency levels of DMUs, based on linear programming, as originally proposed by Charnes, Cooper, and Rhodes (1978). In DEA, multiple inputs and outputs are allowed and, unlike the parametric methods, some specific functional form does not determine the efficient frontier. Instead, the efficiency frontier is convexly built based on the input/output set of the DMUs that form the sample. Very often, DEA studies in banking have focused solely on the “black-box” structure of the productive process. Only very few studies have attempted to study the impact of banking internal activities on efficiency measurement. In fact, a DMU may consist of several sub-structures that may affect overall efficiency levels differently. Network DEA models were proposed to overcome this limitation. Modeling such network structures has been critically debated over the course of time in different industries (Kao, 2009, 2009, 2014; Cook, Zhu, Bi, & Yang, 2010; Färe & Grosskopf, 1996; Golany, Hackman, & Passy, 2006; Lewis & Sexton, 2004; Paradi et al., 2011; Sexton & Lewis, 2003; Tone & Tsutsui, 2010).

The above literature on network DEA - and on structures that are connected in parallel - also sheds some light on the very nature of dynamic systems, where the operation of a DMU continuously occurs over different periods and where two consecutive periods are connected by carry-overs, a concept originally proposed by Färe and Grosskopf (1996). Such systems have received considerable attention due to its resemblance to real life systems (Nemoto & Goto, 1999, 2003; Tone & Tsutsui, 2009, 2014). For instance, in real world business, each bank at each term t has its respective inputs and outputs along with the carry-over to the consecutive term t+1. Failure to capturing this dynamic nature in bank performance assessment in prior studies can end up with biased efficiency estimates and which in turn can badly effect on banks’ long term strategic decisions. This issue is addressed by the dynamic DEA model developed

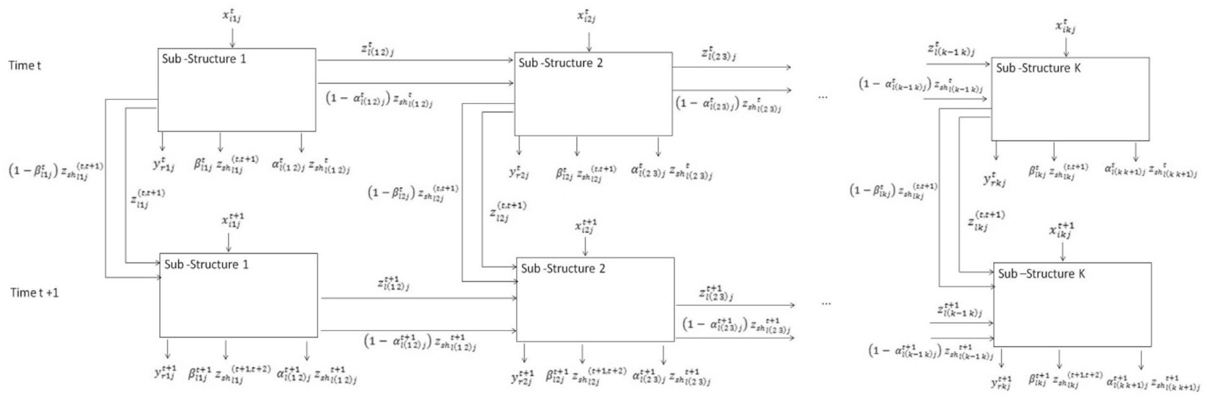

Fig. 1. General Dynamic Network DEA model.

by several studies (Bogetoft, Färe, Grosskopf, Hayes, & Taylor, 2008; Kao, 2008; Park & Park, 2009) based on the network DEA models of Färe and Grosskopf (1997). The rationale is that current inputs or outputs may potentially influence future the input or output levels and consider the connecting production functions between two consecutive time-periods. Applications of Dynamic Network DEA in the banking industry can be found in different studies (see, for instance, Avkiran, 2015; Fukuyama & Weber, 2013,2015; Wanke et al., 2016). Since banks are engaged in complex business structure and outcome in banking can be achieved over a period, dynamic studies are most meaningful (Wanke et al., 2016, 2019). The relational DEA model used in this research to compute efficiency scores in dynamic network structures is generically depicted in Fig. 1.

Let's consider n DMUs $(j = 1, \ldots, n)$ consisting of K sub-structures $(k = 1, \ldots, K)$. Let m_k, r_k, L_{kh}, L_{shkh} be, respectively, the number of inputs and outputs in sub-structure k, the set of links leading from sub-structure k to sub-structure h and the number of shared links between outputs and links from k to sub-structure h. The term $x_{ikj} \in R^+(i = 1, \ldots, m_k; k = 1, \ldots, K; j = 1, \ldots, n)$ is used for denoting the input i in DMU_j to produce the output $y_{rkj} \in R^+(r = 1, \ldots, r_k; k = 1, \ldots, K; j = 1, \ldots, n)$, that is, to produce the output r from DMU_j. Further, the term $z_{l(kh)j} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_{kh})$ is used as an intermediate link from sub-structure k to sub-structure h, and $z_{shl(kh)j} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_{shkh})$ is used as a shared output-intermediate link from sub-structure k to sub-structure h.

In a dynamic network, two consecutive periods are connected by carry-overs and shared variables between outputs and carry-overs. For each DMU_j, the following terms should be additionally defined:

(a) $x^t_{ikj} \in R^+(i = 1, \ldots, m_k; k = 1, \ldots, K; j = 1, \ldots, n; t = 1, \ldots, T)$ is the input i into DMU_j for sub-structure k in period t.
(b) $y^t_{rkj} \in R^+(r = 1, \ldots, r_k; k = 1, \ldots, K; j = 1, \ldots, n; t = 1, \ldots, T)$ is the output r from DMU_j for sub-structure k in period t.
(c) $z^t_{l(kh)j} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_{kh}; t = 1, \ldots, T)$ is the linking intermediate input/output of DMU_j from sub-structure k to sub-structure h in period t.
(d) $z^{(t,t+1)}_{lkj} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_k; k = 1, \ldots, K;\ t = 1, \ldots, T-1)$ is the carry-over product l produced by sub-structure k in period t and consumed in period $t+1$.
(e) $z_{sh}{}^t_{l(kh)j} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_{shkh}; t = 1, \ldots, T)$ is the shared linking intermediate input/output of DMU_j from sub-structure k to sub-structure h in period t, shared as output of DMU_j in sub-structure k and period t.
(f) $z_{sh}{}^{(t,t+1)}_{lkj} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_{shk}; k = 1, \ldots, K;\ t = 1, \ldots, T-1)$ is the shared carry-over product l produced by sub-structure k in period t and consumed in period $t+1$, shared as output of DMU_j in sub-structure k and period t

The input-oriented dynamic network DEA model is estimated by solving the following linear programming problem given as shown in model (1).

$$\max \sum_{i=1}^{m_k} W_{ko}\ \theta_{ko}$$

$$S.T.$$

$$\sum_{i=1}^{n} \lambda^t_{kj} x^t_{ikj} \le \theta_{ko} x^t_{iko} \qquad i = 1, \ldots m_k$$

$$\sum_{i=1}^{n} \lambda^t_{kj} y^t_{rkj} \ge y^t_{rko} \qquad r = 1, \ldots r_k$$

$$\sum_{i=1}^{n} \lambda^t_{kj} \alpha^t_{l(kh)j}\ z_{sh}{}^t_{l(kh)j} \ge \alpha^t_{l(kh)o}\ z_{sh}{}^t_{l(kh)o} \qquad l = 1, \ldots L_{shkh} \quad \sum_{i=1}^{n} \lambda^t_{kj}\ \beta^t_{lkj}\ z_{sh}{}^{(t,t+1)}_{lkj} \ge \beta^t_{lko}\ z_{sh}{}^{(t,t+1)}_{lko} \qquad l = 1, \ldots L_{shk}$$

$$\sum_{i=1}^{n} \lambda^t_{hj} z^t_{l(kh)j} \ge z^t_{l(kh)o} \qquad l = 1, \ldots L_{kh} \tag{1}$$

$$\sum_{i=1}^{n} \lambda^t_{kj} z^t_{l(hk)j} \le z^t_{l(hk)o} \qquad l = 1, \ldots L_{hk}$$

$$\sum_{i=1}^{n} \lambda^t_{kj} z^{(t,t+1)}_{lkj} \ge z^{(t,t+1)}_{lko} \qquad l = 1, \ldots L_k$$

$$\sum_{i=1}^{n} \lambda^{t+1}_{kj}\ z^{(t,t+1)}_{lkj} \le z^{(t,t+1)}_{lko} \qquad l = 1, \ldots L_k$$

$$\sum_{i=1}^{n} \lambda_{hj}^{t}\left(1-\alpha_{l(kh)j}^{t}\right) z_{sh}{}_{l(kh)j}^{t} \geq \left(1-\alpha_{l(kh)o}^{t}\right) z_{sh}{}_{l(kh)o}^{t} \qquad l=1,\ldots L_{shkh}$$

$$\sum_{i=1}^{n} \lambda_{kj}^{t}\left(1-\alpha_{l(hk)j}^{t}\right) z_{sh}{}_{l(hk)j}^{t} \leq \left(1-\alpha_{l(hk)o}^{t}\right) z_{sh}{}_{l(hk)o}^{t} \qquad l=1,\ldots L_{shhk} \quad \sum_{i=1}^{n} \lambda_{kj}^{t}\left(1-\beta_{lkj}^{t}\right) z_{sh}{}_{lkj}^{(t,t+1)} \geq \left(1-\beta_{lko}^{t}\right) z_{sh}{}_{lko}^{(t,t+1)} \qquad l=1,\ldots L_{shk}$$

$$\sum_{i=1}^{n} \lambda_{kj}^{t+1}\left(1-\beta_{lkj}^{t}\right) z_{sh}{}_{lkj}^{(t,t+1)} \leq \left(1-\beta_{lko}^{t}\right) z_{sh}{}_{lko}^{(t,t+1)} \qquad l=1,\ldots L_{shk}$$

$$W_{kj} \geq 0.2, \qquad \forall k,\, j$$

$$\sum_{k=1}^{K} W_{kj} = 1, \qquad \forall j$$

$$0 \leq \alpha_{l(kh)j}^{t} \leq 0, \quad \forall l, k,\, j$$

$$0 \leq \beta_{lkj}^{t} \leq 0, \qquad \forall l, k,\, j$$

$$\lambda_{kj}^{t+1}, \lambda_{kj}^{t}, \overline{x}_{iko}^{t} \geq 0$$

Where $\alpha_{l(kh)j}^{t}$ is the weight for shared output in shared output/linking intermediate input/output and β_{lkj}^{t} is the weight for shared output in shared output/carry-over variable. Model (1) yields a CRS specification. If one wants to assess efficiency scores under a VRS technology assumption, additional constraints assuring that lambdas $(\lambda_{kj}^{t+1}, \lambda_{kj}^{t})$ sum up to one should be implemented.

The super-efficiency approach is an alternative to make a better discrimination for each DMU. For instance, Andersen and Petersen (1993) used super-efficiency for ranking efficient DMUs and Boyd et al. (2016) measured a super-efficiency DEA to remove outliers. Model (1) can be extended to a Super-efficiency Dynamic Network DEA removing DMU $j^{'}$ under evaluation from the reference set: $j = (1, \ldots, J),\ j \neq j^{'}$ as expressed in Seiford and Zhu (1999).

First, the linear programming presented in model (1) is solved for $t = 1, \ldots, T$, where a minimal virtual input vector is found for each period. Then, each sub-structure super-efficiency is calculated as it follows in eq. (2) and the overall structure super-efficiency (network efficiency – NE) is defined observing a weighted mean where each $W_{ko,}$ the sub-structure weight for DMU_o calculated in Model (1), is applied in overall efficiency computation as presented in eq. (3):

$$NE_{ko}^{t} = \theta_{ko} \tag{2}$$

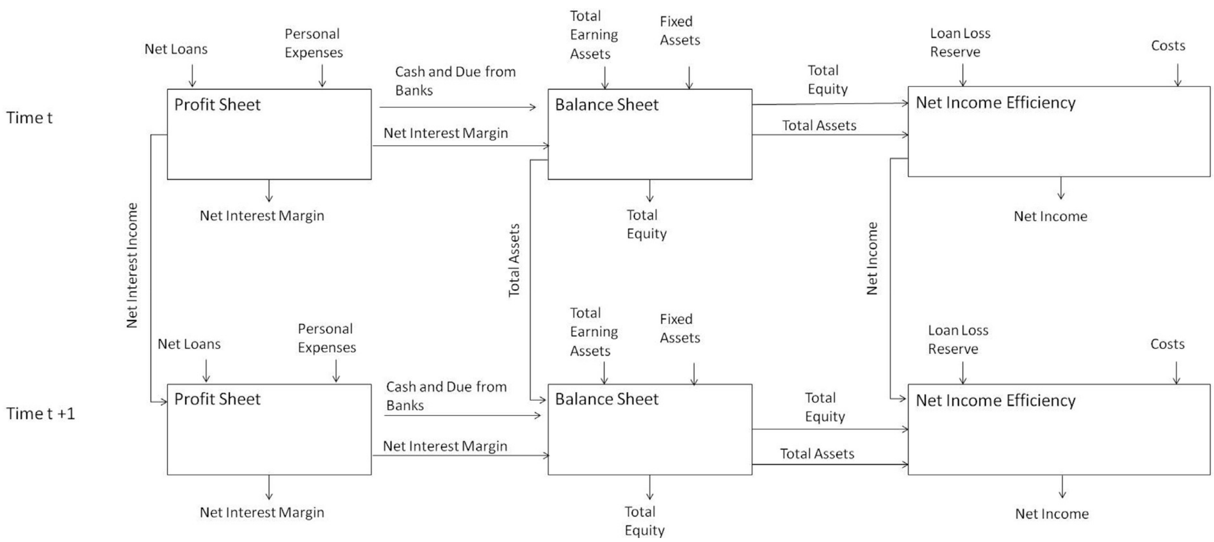

Fig. 2. Dynamic Network DEA model for OECD banks.

$$NE_o^t = \sum_{k=1}^{K} W_{ko} NE_{ko}^t \tag{3}$$

Fig. 2 illustrates the inputs (I), outputs (O), carry-overs (C), and linking (L) intermediate variables within the ambit of the three sub-structures of the dynamic network designed for the OECD banks, based on data availability from BankScope for different countries under the same timeframe. The specific statistical details of the data are further discussed in Section 5. As shown in Fig. 2, the variables of the first stage, called "profit sheet" efficiency, are: net loans (I), net interest margin (O and L), and gross loans (C). This stage represents the profitability of the banking industry due to the loan activity. It is necessary for banks to attain a certain level of gross loans over the course of time to support this activity (Casu et al., 2006). Besides, the performance of this stage impacts the subsequent sub-structure, called "balance sheet" efficiency, where earning and non-earning assets (I) are converted - altogether with the profitability of the loan activity - into equity (O and L) and total assets (C and L). Not only the equity generation depends over the course of the time on the asset creation due to banking profitability derived from the loan activity and their inherent liabilities (Casu et al., 2006), but both variables, total assets (L) and equity (L), are the cornerstones of the substructure called "net profit" efficiency. These variables, altogether with cost and loan loss provisions (I), are fundamental not only for producing sound indicators of income (O and C), which is the numerator for important financial health ratios in banking, such as ROA (income/asset ratio), ROE (income/equity ratio), income to cost ratio, loan exposure (income to loan loss provision) etc (Casu et al., 2006). It is important to mention that common variables, that is, acting simultaneously as outputs and as links or carry-overs in a given sub-structured, had their respective weights optimized during the computations of the Dynamic Network DEA model.

4. Dynamic network SFA model

In this section, we present a novel simultaneous equation model to account for network structure in a stochastic frontier model (SFM) context. The model is given by the following equations, where: Π = Profit Sheet, BS=Balance Sheet, NI=Net Income, NIM = net interest margin, LLR = Loan Loss Reserves, TA = Total Assets, TEA = Total Earning Assets, FA=Fixed Assets, NL=Net Loans, L = Personnel Expenses, TE = Total Equity.

$$\Pi = f_1(\Pi_{t-1},\ NL, L, NetInterest\ Income_{t-1}) - u_1$$

$$BS = f_2(BS_{t-1},\ TEA, FA, NIM, CashAndDue,\ TA_{t-1}) - u_2$$

$$NI = f_3(\ LLR, Costs, TE, TA,\ NI_{t-1}) - u_3$$

$$NIM = f_4(\Pi)$$

$$TE = f_5(BS)$$

In this model, u_1, u_2 and u_3 are nonnegative random variables representing technical inefficiency in the three different stages of the network. Suppose all equations are linear and denote by β_1 the coefficient of Π in the NIM equation and by β_2 the coefficient of BS in the TE equation. Then the Jacobian of transformation in the simultaneous equation model is $J = |\beta_1 \beta_2|$. We omit the calculation as it is tedious. Assuming we have panel data $(i = 1, \ldots, n, t = 1, \ldots, T)$ the model can be written as follows:

$$f(x_{it}, y_{it}; \beta) = v_{it} - u_{it}, i = 1, ..., n, t = 1, \ldots, T, \tag{4}$$

Where y_{it} is the 5x1 vector of endogenous variables (Π, BS, NI, NIM and TE), x_{it} is the vector of predetermined variables, β is the vector of coefficients, v_{it} is a 5x1 vector of two-sided error terms and u_{it} is the 3x1 vector of technical inefficiency error terms. We use the following stochastic assumption:

$$v_{it} \tilde{} N_5(0, \Sigma), \tag{5}$$

where Σ is a 5x5 covariance matrix. Our assumptions on technical inefficiency follow Cornwell, Schmidt, and Sickles (1990, CSS):

$$\begin{aligned} u_{1,it} &= \beta_{1,it}^{(1)} + \beta_{2,it}^{(1)} t + \beta_{3,it}^{(1)}\ t^2, \\ u_{2,it} &= \beta_{1,it}^{(2)} + \beta_{2,it}^{(2)} t + \beta_{3,it}^{(2)}\ t^2, \\ u_{3,it} &= \beta_{1,it}^{(3)} + \beta_{2,it}^{(3)} t + \beta_{3,it}^{(3)}\ t^2. \end{aligned} \tag{6}$$

To convert the error terms to nonnegative we use the transformation:

$$u_{j,it} := \max_{i,t} : u_{j,it} - u_{j,it}.$$

After substituting (6) in (4) we can write the system as follows:

$$F(x_{it}, y_{it}; \beta) = v_{it}, \tag{7}$$

where β is enlarged to include the parameters $\beta_{k,it}^{(j)}$, $k,j = 1, 2, 3$. These parameters are linear functions of bank-specific and time-specific dummy variables. The likelihood function of the simultaneous equation model is as follows:

$$L(\beta; Y) = (2\pi)^{-\frac{nT}{2}} |\Sigma|^{-\frac{nT}{2}} |\beta_1 \beta_2|^{\frac{nT}{2}} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \sum_{t=1}^{T} F(x_{it}, y_{it}; \beta)' \Sigma^{-1} F(x_{it}, y_{it}; \beta) \right\} \Bigg\},$$

where $Y = \{y_{it}, x_{it}; i = 1, \ldots, n, t = 1, \ldots, T\}$ denotes the data. After concentrating with respect to the different elements of Σ, the likelihood function becomes:

$$L(\beta; Y) \propto |\beta_1 \beta_2|^{\frac{nT}{2}} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \sum_{t=1}^{T} F(x_{it}, y_{it}; \beta) F(x_{it}, y_{it}; \beta) \right\}' \Bigg\}. \tag{9}$$

The likelihood can be maximized using standard iterative techniques.

4.1. Explaining the difference between DEA and SFA super-efficiency scores

Super-efficiency concept is traditionally used in DEA to break the ties between fully efficient units. In SFA, the problem does not arise as full efficiency arises with probability zero. However, it is possible to introduce a super-efficiency concept in SFA. Suppose in the original sample efficiency estimates are $\{\tilde{r}_{it}\}$, where $\tilde{r}_{it} = \exp(-\tilde{u}_{it})$ after omitting all observations for bank i the efficiency estimates become $\{\tilde{r}_{(-i),t}\}$. *The frontiers are re-estimated to account properly for the omission of bank i.* In turn, we can use the ratio of average estimated efficiencies as a super-efficiency concept:

$$SE_{it} = \frac{((n-1)T)^{-1} \sum_{j \neq i,t} \tilde{r}_{j,t}}{(nT)^{-1} \sum_{i,t} \tilde{r}_{it}}, i = 1, .., n, t = 1, \ldots, T. \tag{10}$$

The SFA super-efficiency measure shows by how much efficiency changes if bank i is omitted and the frontier changes to account for omitting bank i. If $SE_{it} > 1$ then average efficiency increases after omitting bank i, thus suggesting that more observations moved towards to the newly computed efficiency frontier at each time a given bank is omitted.

To explain the differences of super-efficiency measures in DEA and SFA we take the DEA measure as given but we bootstrap the SFA measure and therefore the difference between SFA and DEA measures. In the bootstrap we omit each block of time observations for a given bank and we regress the difference between SFA and DEA measures on the contextual variables. We use 500 replications of the block bootstrap. For comparison purposes we also compute the difference between SFA and DEA efficiency measures and we regress them on the contextual variables using the bootstrap. The bootstrap is particularly demanding here as SFA super-efficiency measures are computed by omitting all time observations for any given bank at a time.

5. Analysis and discussion of results

Dynamic Network DEA and SFA models were applied on the dataset of inputs, outputs, links, and carry-overs for the OCDE banks, obtained from the BankScope database. Bank sample was selected on the basis of forming a balanced panel dataset for the period under analysis, which is a requirement of the dynamic network DEA and SFA super efficiency models presented in this research, due to the

Table 1
Descriptive statistics for the inputs, outputs, links and carry-overs.

Variables		Max	Mean	SD	CV
Inputs	Net Loans (NL)	6252275.00	173743.91	508429.33	2.93
	Personnel Expenses (L)	266565.00	1443.09	10573.92	7.33
	Total Earning Assets (TEA)	204499500.00	1298147.56	11641527.46	8.97
	Fixed Assets (FA)	1999633.00	6534.08	65390.60	10.01
	Loan Loss Reserve (LLR)	941905.23	9986.71	49713.85	4.98
	Costs	3704749.37	23052.64	204797.21	8.88
Outputs	Net Interest Margin (NIM) - Shared	71.33	3.90	8.82	2.26
	Total Equity (TE)	25894626.00	158274.80	1539320.42	9.73
	Net Income (NI)	3606859.00	31805.67	255852.91	8.04
Intermediate	Cash and Due From Banks	23409741.00	110077.15	1088526.61	9.89
	Net Interest Margin (NIM) - Shared	71.33	3.90	8.82	2.26
	Total Equity (TE) - Shared	25894626.00	158274.80	1539320.42	9.73
	Total Assets (TA) - Shared	241619140.00	1453461.38	13281972.72	9.14
Carry-Over	Net Interest Income (NIM)	6842265.00	60399.51	456110.90	7.55
	Total Assets (TA) - Shared	241619140.00	1453461.38	13281972.72	9.14
	Net Income (NI) - Shared	3606859.00	31805.67	255852.91	8.04

presence of links and carry-overs that require a unique relationship with the DMUs under study over the course of time. Table 1 presents the descriptive statistics for the inputs, outputs, links, and carry-overs considered in the analysis. All monetary values are expressed in current USD and have been corrected for each country annual inflation rate. The production approach in banking is adopted here so that, for instance, net loans and other labor and capital inputs are minimized to the detriment of net interest margins and other profit and equity outputs, which are maximized. The banking production assumption of considering relatively large margins is due to bringing a higher degree of stability for the banking systems of the different countries analyzed (Saunders & Schumacher, 2000), as long as banks are compared across different countries and size.

Additionally, a set of contextual variables related to the socio economic and demographic characteristics of each one of the OECD countries presented in the sample were also collected. Besides, information on bank ownership and a previous past of M&A events were also collected; Their descriptives are given in Table 2, while their respective sources are presented in Appendix 1. Readers should recall from previous sections that this set of contextual variables encompass both exogenous (business-related variables at the bank level) and endogenous ones (socio-economic variables at the country level) with respect to efficiency levels in OECD banking.

Comparative descriptive statistics for the super-efficiency scores obtained using the DEA and SFA dynamic network models previously presented are given in Table 3, for each one of the three productive sub-structures. Results indicate that DEA scores are more dispersed than SFA ones and that median scores are ranked differently among the different sub-structures considering the modelling approach. While in DEA the rank order is NI-BS-PS, in SFA it is BS-PS-NI. This may suggest that contextual variables, besides differences in models assumptions, may be causing differences in rank order.

As regards isotonicity between network DEA and SFA super-efficiency scores for the three productive substructures, results for the Spearman's rank correlation coefficient are given in Table 4. One can easily see that there are substantial differences between rank orders between DEA and SFA models (correlations are low), although correlations appear to be moderately high between each sub-stage considering under the same modelling approach.

Isotonicity within the ambit of dynamic network SFA super-efficiency scores as regards inputs, outputs, links, and carry-over scan also be checked in Table 5, where RESET is a modification of the Regression Specification Error Test. In RESET, squares, third and fourth powers of the fitted values are included in the equations. We report the p-value of the null hypothesis that the coefficients of these additional regressors are zero, which should be the case if the model is "correctly specified". As we can see, the null cannot be rejected. This being the case, it is worth mentioning that there are significant positive carry-overs (lagged efficiency coefficients) and links, with the exception of cash and due, with a significant negative impact, for each one of the three productive sub-structures in OECD banks. It is also interesting to note that, although not every input variable present a negative significant contribution to each productive sub-structure efficiency, as in the case of loan loss reserves and costs for net income efficiency, their magnitude is considerably smaller when compared to their respective outputs and, therefore, their contributions to super-efficiency scores is less than proportional.

Bootstrapped regression results for the differences between network dynamic SFA and DEA scores for the three different productive substructures are presented in Table 6. If DEA and SFA scores do not present significant differences in light of business-related (bank level) and/or socio-economic contextual variables (country level), these methods can be regarded simply as alternative approaches for measuring the same phenomenon, i.e., technical efficiency of productive processes and its sub-structures. For instance, Gini Index, GDP per capita (PPP), Energy use, Infant mortality, NAFTA, Pacific Alliance, and OPEC did not show significant impact on differences computed between dynamic network DEA and SFA super-efficiency and efficiency scores. Therefore, it is possible to affirm that bank efficiency levels in OECD countries - as captured by alternative parametric and non-parametric techniques - do not interact with some specific socio-economic variables at the country level. Precisely, as presented in Table 6, these variables are related to measurements with respect to wealth concentration and economic development (Gini Index and GDP per capita - PPP), social welfare (Infant mortality), industrial development and economic sophistication (Energy use), and to most of the locational business-related variables. These variables AIRdescribe the economic block to which a given bank belongs to (NAFTA, Pacific Alliance, and OPEC). It is also interesting to

Table 2
Descriptive statistics for the contextual variables.

Variables		Min	Max	Mean	SD	CV
Contextual variables	Annual Inflation Rate (AIR) (%)	−4.48	10.58	2.39	1.48	0.62
	Humand Development Index (HDI)	0.68	0.95	0.89	0.04	0.05
	GDP Growth (%)	−10.75	11.11	1.16	2.92	2.52
	GDP Per Capita ($)	10868.23	103304.16	40507.80	12417.15	0.31
	Foreign Direct Investment (FDI) ($)	−29679425810.05	734010312477.36	96806141413.46	118434120821.80	1.22
	Infant Mortality (per 1000 births)	1.60	24.80	5.33	2.68	0.50
	Life Expectancy	72.03	83.08	79.06	1.84	0.02
	Energy Use (kg equivalent oil per capita)	1204.72	9428.81	5102.68	1955.47	0.38
	Gini Index	22.79	51.11	34.35	5.23	0.15
	Global Innovation Index (GII)	28.26	67.76	54.43	8.13	0.15
	Logistics Performance Index (LII)	2.79	4.18	3.73	0.26	0.07
	Trend	1.00	10.00	5.50	2.87	0.52
	Trend^2	1.00	100.00	38.50	32.43	0.84
	Private bank	Yes:	33.80%		No:	66.20%
	Merger and acquisition (1 = Yes)	Yes:	99.19%		No:	0.81%
	Economic Block	NAFTA:	26.61%		EU:	58.06%
		Pacific Alliance:	3.23%		APEC:	30.65%

Table 3
Descriptive statistics for dynamic network DEA and SFA models.

	Profit Sheet Efficency		Balance Sheet Efficiency		Net Income Efficiency		Overall Efficiency	
	DEA	SFA	DEA	SFA	DEA	SFA	DEA	SFA
Min	0.058	0.779	0.436	0.832	0.454	0.762	0.339	0.782
Median	0.448	0.871	0.837	0.899	0.902	0.844	0.723	0.855
Max	1.331	0.987	2.038	0.992	1.328	0.989	1.328	0.992
SD	0.278	0.032	0.133	0.025	0.120	0.044	0.120	0.032

Table 4
Spearman's rank correlation results.

		Profit Sheet Efficency		Balance Sheet Efficiency		Net Income Efficiency		Overall Efficiency	
		DEA	SFA	DEA	SFA	DEA	SFA	DEA	SFA
Profit Sheet Efficiency	DEA	1.000	0.225	0.617	0.116	0.701	0.191	0.718	0.145
	SFA		1.000	0.120	0.713	0.212	0.818	0.103	0.745
Balance Sheet Efficiency	DEA			1.000	0.223	0.700	0.177	0.655	0.812
	SFA				1.000	0.212	0.782	0.111	0.799
Net Income Efficiency	DEA					1.000	0.216	0.355	0.103
	SFA						1.000	0.110	0.788
Overall Efficiency	DEA							1.000	0.166
	SFA								1.000

Table 5
Parameter estimates for the dynamic network SFA model.

Profit Sheet Efficiency (Π equation)		Balance Sheet Efficiency (BS equation)		Net Income Efficiency (NI equation)	
Π_{t-1}	0.5432 (0.013)	BS_{t-1}	0.317 (0.024)	LLR	−0.144 (0.025)
NL	0.433 (0.021)	TEA	0.440 (0.018)	Costs	−0.366 (0.007)
L	0.255 (0.017)	FA	0.212 (0.015)	TE	0.044 (0.004)
$NetInterestIncome_{t-1}$	0.315 (0.037)	NIM	0.133 (0.006)	TA	0.133 (0.004)
		CashAndDue	−0.0014 (0.0002)	NI_{t-1}	0.210 (0.015)
		TA_{t-1}	0.144 (0.032)		
R^2	0.778	0.814		0.515	
RESET	0.118	0.203		0.414	
NIM equation		**TE equation**			
Π	0.335 (0.020)	BS	0.113 (0.014)		
$\overline{R}^2$	0.443		0.507		
RESET	0.216		0.551		

Note: Standard errors are reported in parentheses.

note that, although the sample of OECD banks used in this research covers the period of the Global Financial Crisis (GFC), the comparison between super efficiency DEA and SFA network methods was incapable of capturing the impact of abnormal variations of efficiency scores on wealth concentration, economic development, and social welfare on a worldwide basis. Previous recent studies on the impact of GFC on banking productivity followed a different research path, using novel variations of network Malmquist indexes and bank convergence measures while solely focusing on the impact of GFC over the banking industry (Degl'Innocenti, Kourtzidis, Sevic, & Tzeremes, 2017; Kourtzidis, Matousek, & Tzeremes, 2019). Although the research locus and focus maybe different, the comparison of our findings with other recent studies makes evident a subtle aspect of banking efficiency studies. It appears that the measured impact of GFC on banking productivity maybe diluted, depending not only upon the method used – which is expected - but also in terms of how it is reflected on other economic indicators – which is not so obvious. This reinforces the importance of alternative method comparison such as what is proposed in this research: depending on the economic variable set and on the banking research delimitation, one efficient frontier method may be favored to the detriment of the other so that certain relationships with other macro/micro economic variables may be adequately captured.

Otherwise, if their scores significantly differ, there is evidence in favor of the fact that these approaches capture distinctive aspects of a given productive process and its interactions with the socio-economic variables at the country-level, apart from differences in their basic underlying assumptions. A positive sign indicates that dynamic network SFA scores are higher than those computed under the non-parametric DEA approach. Putting it in other words, a negative sign indicates that the dynamic network SFA model yielded higher

Table 6
Bootstrapped regression parameter estimates.

Contextual variable	Efficiency	Super-efficiency
AIR	0.014 (0.0015)	0.012 (0.0027)
Gini	−0.0012 (0.0023)	−0.0015 (0.0021)
HDI	0.014 (0.0035)	0.011 (0.0023)
GDP growth	0.012 (0.0032)	0.010 (0.0027)
GDP per capita (PPP)	−0.0032 (0.045)	−0.0017 (0.032)
FDI	−0.0075 (0.0015)	−0.0068 (0.0026)
Energy use	0.0032 (0.0044)	0.0028 (0.0033)
Infant mortality	−0.0031 (0.0045)	−0.0044 (0.0070)
Life expectancy	0.0081 (0.0014)	0.0077 (0.0013)
GII	0.017 (0.0014)	0.014 (0.0020)
LPI	−0.0074 (0.0020)	−0.0083 (0.0017)
NAFTA	0.0032 (0.0015)	0.0028 (0.0019)
EU	0.027 (0.0014)	0.021 (0.0040)
Pacific Alliance	−0.0017 (0.0020)	−0.0023 (0.0025)
APEC	0.0015 (0.0017)	−0.0022 (0.0034)
Public Bank	−0.015 (0.0033)	−0.010 (0.0028)
Merger & Acquisition	−0.028 (0.0027)	−0.019 (0.0030)
trend	0.0032 (0.0044)	0.0027 (0.0019)
trend^2	−0.0017 (0.0035)	−0.0018 (0.0028)
$\overline{R}^2$	0.430	0.443

Note: The dependent variable is $log\frac{r_{SFA}}{r\_DEA}$ where r_{SFA} is the SFA efficiency score and r_{DEA} is the DEA efficiency score. Efficiency and super-efficiency scores are estimated by omitting all time observations of a given bank and the bootstrap is applied to estimate the regression (we use 500 replications). Bootstrap standard errors are reported in parentheses. R2 is computed as an average across bootstrap replications.

discrimination between OECD banks. Conversely, a positive sign suggests that a higher discrimination in efficiency scores was obtained under the dynamic network DEA model.

On the other hand, and differently from previous studies, it is also noteworthy that the productive process of the banking industry interacts with the socio-economics at the country level by several ways that goes beyond the productive convergence metrics of financial institutions, since its productive structure is embedded within the overall socio-economic picture of the country. For instance, HDI and life expectancy may impact mostly on labor productivity at the micro-business level, while GII and LPI, altogether with FDI and inflation, may impact mostly on the overall productivity of the industry – including banks - a company lies within, being responsible for changes or stagnation in the two major effects in productivity change: frontier-shift and catch-up.

Yet, results from Table 6 also illustrate that the two business related variables (at the country level) – M&A and public/private bank – also interact differently with respect to the modelling approach adopted. However, no possible claim can be made about whether all of these measured interactions with socio-economic and business-related variables are either increasing or decreasing over the course of time, as long as the two trend components were found to be insignificant, possibly due to an effect of the GFC during the period of the analyzed sample. The next paragraphs explore, for each one of the significant socio-economic (country level) and business-related (bank level) variables, what are their rationales behind higher/lower efficiency levels and how do they may interact with different modelling approaches. Before proceeding, it is worth noting that, both dynamic network DEA and SFA models yielded higher discriminatory power for both types of contextual variables – socio-economic and business-related – thus suggesting that it is not possible to affirm that one type of modelling is preferable to the other given the nature of the contextual variable used.

5.1. Significant variables with positive impact on score difference

This is the set of variables where the Dynamic Network DEA model showed higher discriminatory power when compared to SFA scores. Interesting to note that most of these variables are either traceable to the individual level in terms of average wealth, skills, and social/political capabilities or may impact on his/her financial behavior in the short and long terms. This suggests a bottom-up perspective on the banking productive processes where inputs and outputs seem to be accumulated from a number of several individual decisions over the course of time, and which are likely to be mostly impacted by the GFC. This finding is also in line with the seminal views of Cullinane and Song (2003, 2006) with respect to the adequacy of basic DEA and SFA models. These authors point out that SFA is more oriented towards macro-economic decision and policy making, taking different alternatives of industrial organization as basis of comparison. In its turn, DEA is more oriented towards managerial decision-making at the micro-economic level, where slacks and efficiency scores comparison may reveal the improvement paths to increase efficiency.

Annual Inflation Rate. It is expected that efficiency in the banking industry will react negatively in countries with high inflation rates. Banking efficiency may be affected through two distinct channels when inflation is high: GDP growth slows down and unemployment raises up. Not only credit market friction increases, bringing negative impacts on banking efficiency but also the credit default risks increase, and banks are more parsimonious in lending money.

GDP Growth. Presents an inverse effect on efficiency levels when compared to annual inflation rates. Banks are less parsimonious and credit default risks are smaller when economy is growing, provided that inflation ratios are kept under control. People are also more avid to contract loans, mortgages etc.

Human Development Index (HDI). The Human Development Index (HDI) is the geometric mean of normalized indices for each of three dimensions: Life Expectancy, Gini Index, and Education Index. It is expected that healthier, wealthier, and better-educated people will positively contribute to banking efficiency in several dimensions, ranging from labor productivity (which tends to be higher when workforce is not illiterate) to a wealthier and better educated consumer base in terms of financial education (which tends to mitigate default risks).

Life Expectancy. Similarly to HDI, life expectancy denotes a healthier population, possibly leading to smaller absenteeism rates at work and yielding higher labor productivity.

Global Innovation Index (GII). GII is focused on the innovation performance of different countries. This index is composed by several metrics that take into account several different dimensions such as political environment, education, infrastructure and business sophistication. That is, GII indicators constitute different proxies for human and physical capital altogether with an assessment of institutional solidity, corruption levels, and political stability. It is expected banking efficiency to be higher when there is a positive business environment and a solid institutional framework in a democratic country with educated population and good level of infrastructure intensity.

European Union (EU). EU rules on prudential requirements mainly concern the amount of capital and liquidity that banks hold. These rules are necessary to increase the resilience of the EU banking sector in terms of absorbing economic shocks, while ensuring the sustainability of the banking sector in terms of promoting economic growth. Tighter regulatory marks often imply lower banking efficiency, as long as parsimony in loans and in credit risk assessment is high.

5.2. Significant variables with negative impact on score difference

This is the set of variables where the Dynamic Network SFA model showed higher discriminatory power when compared to DEA scores. Interesting to note that most of these variables are related to the country level but not direct traceable to the individual level as an average competence, skill, profile. These results suggest a "top-down" perspective on banking efficiency, where inputs and outputs are rather geared by socio-economic and business related variables that can be tracked mostly to the bank business. With the exception of FDI, the remainder variables are less likely to be impacted by abnormal fluctuations of efficiency scores due to the GFC.

Foreign Direct Investment (FDI). Foreign direct investment not only denotes the attractiveness of a country to foreign investors, but also its openness to new managerial practices and technologies. Banking efficiency tend to increase when there is knowledge transfer and sharing of best practices between banks of different origins, yielding to what is called "cross-breeding" in efficiency markets theory.

Logistics Performance Index (LPI). The LPI is an indicator created by the World Bank to help countries in identifying improvement opportunities on trade logistic. The underlying idea is that supply chains are only as good as their weakest link, and sustainable business and country development depends on improvements in areas such as infrastructure, trade facilitation and services. It is expected that banking efficiency will be pushed higher by the increased needs of trading agents for financial intermediation and speedy financial flows.

Public bank. As indicated in previous studies, efficiency in public banks tend to be low when compared to its private counterparts on a given country.

M&A. Although increasingly studied, but with no define conclusion on it is impacts on banking industry, it is expected that M&A will increase banking efficiency, due to the exploration of the synergistic effects that may emerge from business amalgamation.

6. Conclusions

This paper contributed to the banking efficiency literature by presenting two novel DEA and SFA dynamic network models that served as cornerstones for efficiency scores comparison between these two most common non-parametric and parametric approaches. The computation of super-efficiency scores in SFA models is an additional distinctive feature of this paper, so that a comparison between DEA and SFA scores is possible. Super-efficiency scores in SFA were computed by emulating the DEA case, where the leave-one-out analysis is the cornerstone for assessing the impact on efficiency scores. Under SFA, however, this analysis was conducted in a stochastic fashion.

A comprehensive sample of OECD banks was considered as the base case for analysis. Three productive substructures – profit sheet efficiency, balance sheet efficiency, and net income efficiency – were considered in light of different socio-economic and business related variables, used as their predictors in bootstrapped regressions. Research findings suggest not only a number of practical implications for decision-makers but also future research venues as regards comparability between DEA and SFA approaches. While this research unveiled the specifics of the banking productive process that are differently captured by parametric and non-parametric approaches, showing how banking inputs and outputs interact with the contextual variables, it opens rooms for replication in different countries, industries and modelling approaches (black-box models, network models etc).

Precisely, results corroborate the seminal understandings as regards the dichotomy between DEA/SFA adequacy. While DEA would be more adequate for managerial decision-making in the banking industry, as long as inputs and outputs seem to be built upon a bottom-up approach by a number of individual transactions, SFA seems to be more country or business-oriented, observing a top-down perspective where inputs and outputs are set at the industry level.

In fact, it was very interesting to observe that most of the socio-economic variables that yielded higher discriminatory power on DEA scores could be traceable at the individual level, in terms of average behaviors, skills, health, or wealth. Conversely, most of the socio-economic variables related to higher discriminatory power on SFA scores are limited to the country or business attractiveness, with not so straightforward links to the individuals.

The practical implications for future research on banking efficiency is the choice of the proper lens, that is, the methodological approach, for investigating this phenomenon. Future research using DEA or SFA models should avoid stating generic objectives, such as simply measuring banking efficiency in "country X″ or "region Y". Future research should rather address an in-depth discussion on whether banking inputs and outputs observe a bottom-up or top-down building approach, where socio-economic variables used to discriminate banks are either linked, respectively, to individuals or to the business/country attractiveness.

Appendix 1. Sources of the Contextual Variables

Variable	Source
Inflation Rate (%)	https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG
HDI	hdr.undp.org/en/data
GDP Growth (%)	https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG
GDP Per Capita ($)	https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD
FDI ($)	https://data.worldbank.org/indicator/BX.KLT.DINV.CD.WD
Infant Mortality (per 1000 births)	https://data.worldbank.org/indicator/SP.DYN.IMRT.IN
Life Expectancy	https://data.worldbank.org/indicator/SP.DYN.LE00.IN
Energy Use (kg equivalent oil per capita)	https://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE
Gini Index	https://data.worldbank.org/indicator/SI.POV.GINI
Global Innovation Index	https://www.globalinnovationindex.org/analysis-indicator
Logistics Performance Index	https://data.worldbank.org/indicator/LP.LPI.OVRL.XQ

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