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ORIGINAL ARTICLE

Unveiling endogeneity between competition and efficiency in European banks: a robust econometric-neural network approach

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Abstract
Research on the European banking industry remains inconclusive concerning how its competitive structure and performance are related, especially given the heterogeneity among countries in the region. We develop a Dynamic Network Data Envelopment Analysis (DNDEA) model formed by three consecutive stages—*profit sheet*, *balance sheet*, and *financial health* efficiency—to assess how market structure and competition impact bank efficiency in European countries. Unlike previous research, a Robust Econometric-Neural Network Approach (RENNA) is used to unveil endogeneity among bank competition, market structure, and overall efficiency scores in European banking. Consistent with the competition-efficiency hypothesis, findings reveal that competition positively affects bank efficiency, particularly its *balance sheet* dimension. While macroeconomic factors are robust determinants of efficiency for non-GIIPS banks, Bank Z-score is far more relevant in the GIIPS subsample (Greece, Italy, Ireland, Portugal, and Spain). Furthermore, we find only weak evidence of feedback among the variables across subsamples. Our results have critical policy implications since they highlight the heterogeneous relationship between competition and efficiency for the banking sector.

Keywords European banking competition · Efficiency · Endogeneity · GIIPS and non-GIIPS · Robust approach

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Introduction

There has been an increasing interest among academics and practitioners to identify best practices in the banking industry and how they are affected by market structures and competition levels, which may substantially vary from country to country(Alhassan and Ohene-Asare 2016; Chan et al. 2015; Nguyen et al. 2012; Soedarmono et al. 2011, 2013). Notably, the global financial crisis in 2008 pushed these issues to the top of the research agenda in banking with a particular focus on how potential financial distress situations could be identified early (Kosmidou and Zopounidis 2004; Howland and Rowse 2006; Raunig et al. 2014). In addition, classic profit and balance sheet statements and a set of ancillary financial indicators are crucial elements for monitoring performance (Kellen and Wolf 2003). However, the specific impact of their underlying relationships on bank efficiency and how each country's market and competition structure acts as an intervenient factor is yet to be further explored (Coccorese and Cardone 2020; Wanke et al. 2015).

Since the 2008 world crisis, most bank performance studies have focused on the US and EU, but have paid little attention to the inherent endogeneity that exists among market and competition structures, bank efficiency, and financial distress (Apergis and Polemis 2016; Mokni and Rachdi 2014; Thi et al. 2016). This research fills this gap by focusing on the interplay between bank-specific production structure and competition at the country level. The mapping of the productive structure of each bank is accomplished by a novel Dynamic Network Data Envelopment Analysis (DNDEA) model that accounts for the underlying relationships among major profit sheets, balance sheets, and financial health indicators over time. Besides, we develop a RENNA (Robust Econometric-Neural Network Analysis) capable of cross-checking endogeneity results among market and competition structures and bank efficiency, bridging the gaps between two distinct methodological fields. Both approaches are used in this paper in a complementary analytical fashion.

The primary objective of this paper is to estimate the impact of market structure and competition (Boone Indicator, H-Statistic, Lerner Index, and Asset Concentration) on bank efficiency scores after controlling for bank-specific (e.g., ROA, Leverage, Credit/Deposits, and Non-performing loans) and macroeconomic variables (Gross Gov. Debt (% GDP), Growth GDP, Growth CPI, and Unemployment). To disentangle the multiple effects on bank efficiency, we also use its components (profit sheets, balance sheets, and financial health indicators) as dependent variables. Our sample comprises103 European banks over the period 2004–2016, totaling 1031 bank-year observations.

This paper departs from previous research on banking efficiency in basically two ways. First, the model proposed considers intertemporal dynamic effects measured in the form of carry-overs among the significant accounting and financial indicators used to assess banking efficiency (Wanke et al. 2016, 2018, 2019).

Second, this paper considers a representative sample of EU banks and proposes a novel RENNA to measure and cross-check feedback processes between efficiency scores and market/competition structure variables. The approach used here is entirely different from other efficiency studies and empirical EU banking research (Basten and Sánchez Serrano 2019; Cuestas et al. 2020; Pagano et al. 2014; Wanke et al. 2019). This hybrid DNDEA-RENNA not only contributes to the bank-efficiency literature, but perhaps more importantly, provides more robust results.

Consistent with the competition-efficiency hypothesis, research findings suggest that competition is usually beneficial for efficiency in European banks. According to the baseline fixed effects panel data model, a one S.D. positive shock to Concentration of Assets (one of the proxies to competition) leads to a 3.4% reduction in overall bank efficiency, ceteris paribus. Both statistical and economic perspectives indicate that the partial effects of competition on bank efficiency are more prominent in the non-GIIPS subsample and with the balance sheet dimension of efficiency. Furthermore, we find that efficiency in European banks is generally preceded by bank-level and macroeconomic variables, but not the other way around. Non-performing loans ratio and gross government debt (% of GDP) consistently Granger-cause the overall efficiency index (total sample and both non-GIIPS and GIIPS sub-samples), and there is no evidence of feedback. Finally, macroeconomic factors are more robust determinants of efficiency for non-GIIPS countries, while the Bank Z-score is far more relevant in the GIIPS subsample. These results have important implications for banking supervision and highlight the interplay among bank-level, industry-level, and macroeconomic-level variables on bank efficiency.

The significant contributions of this paper are fourfold. First, this research innovates by examining the efficiency of banks in the European market using the novel robust econometric and neural network approaches. Thus, we bridge the gap between traditional econometric models—particularly panel data estimations—with machine learning approaches to unveil competition and performance in the banking industry. Second, we connect to the recent and growing literature on the interplay among bank efficiency, bank competition, and macroeconomic variables (see, for example, Shamshur and Weill 2019; Fang et al. 2019; Phan et al. 2019; Saif-Alyousfi et al. 2020; Tran et al. 2020; Chen and Lu 2021). Third, we also contribute to the debate on bank efficiency during economic crises (Chen et al. 2018). Finally, the dynamic network DEA model uses the major three indicators (profit, balance sheet, and financial) to derive non-parametric efficiency measurements.

The paper is organized as follows. Section 2 provides the literature review including a brief contextual setting on the EU banking industry. Section 3presents the methodology with an emphasis on the proposed DNDEA-RENNA. Section 4 shows the results and discusses the findings. Finally, we conclude and discuss directions for further research in Sect. 5.

Fig. 1 Common Equity Tier 1 ratio among major European banks. Note: the Tier 1 Capital Ratio is calculated by taking a bank's core capital relative to its risk-weighted assets. Source: EBA Basel III Monitoring Report 2019

Literature review

EU banking sector overview

The EU banking industry is distinct from other economic blocks and regions around the world not only due to the heterogeneous socio-economic and cultural backgrounds of its country-members, but also due to the lax of banking regulatory standards imposed by European authorities to accommodate the specifics of each member (Coccorese and Cardone, 2020; Cuestas et al. 2020). As the Country-Level Index of Financial Stress (CLIFS) from the European Central Bank reveals, the "sovereign debt crisis" of European countries during the 2010s induced a high level of financial stress in the region, particularly to the so-called GIIPS sample: Greece, Ireland, Italy, Portugal, and Spain. Thus, not surprisingly, the EU banking industry presents itself as a challenging research field (Apergis and Polemis 2016; Mokni and Rachdi 2014) since it offers such a notable diversity (Hassan et al. 2009; Rosman et al. 2014).

The economic advancements of the major European countries in the twentieth century significantly inclined the growth of the banking sector development (Pohl 1994). Most distinctively, the 1980s and 1990s were the golden age for European banks because of their growth in terms of both diversification and earnings (Basten and Sánchez Serrano 2019; Pagano et al. 2014). This expansion among the banks was mostly due to the light regional regulation and complex financial innovation (Crotty 2009). For instance, in 1995, only two EU countries had a lower GDP than their respective bank total loan, whereas in 2011 that reached 13 countries (Pagano et al. 2014). However, the global financial crisis in 2008 exposed the flaws these banks had over all those good years. Even after 10 years beyond the crisis, European bank share prices have not recovered from the bottom level of the crisis period (Basten and Sánchez Serrano 2019). Even though falling interest rates in the region have pressured bank margins, European banks have assured high quality in core capital (Tier 1), which means that in the long run these banks will again contribute to

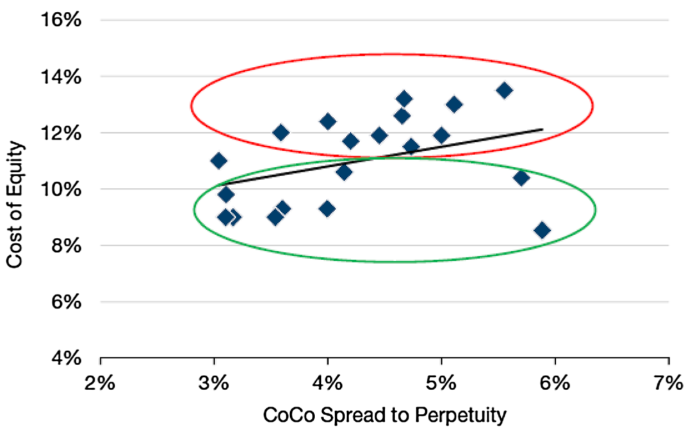

Fig. 2 Cost of equity vs. CoCo yield diagram. Note: CoCo refers to Contingent Convertible instruments, which are hybrid capital securities that absorb losses when the capital of the issuing bank falls below a certain threshold. Source: Bloomberg as of August 28, 2018

economic progress by likely producing less loan loss provisions. Figure 1 shows that European banks have recently had a steady development in Common Equity Tier 1 ratio (core capital vs. risk-weighted assets).

However, the overall banking sector in Europe has a mixed condition: some banks are still facing difficulties in earning adequately for their equity holders. One way to look into it is to examine the cost of equity with contingent convertible (CoCo) bonds, which describe the prospect of the banking sector from the investors' perspective. Figure 2 depicts a scatter diagram of the cost of equity vs. CoCo yield. Banks in the green circle are mostly Scandinavian and Northern European banks. These are listed below the capital structure line meaning that the equity market has priced them rationally. These banks have high return on equity (ROE) compared to their cost of equity. Conversely, banks in the red circle have a low ROE compared to the cost of equity of their investors, seemingly for an indefinite time. Shortly, investors of these banks will tentatively suffer in the equity price unless banks have an opportunity to come down to the capital structure line through M&A, capital restructuring, or macroeconomic impact.

A characteristic of the European banking system that deserves attention is the high financial stress following the sovereign debt crisis during the 2010s. Several countries, in particular GIIPS, faced what Brunnermeier and Reis (2019) called a "diabolic loop". In a nutshell, the mechanics work as follows: liquidity shocks make investors more likely to hold less risky assets such as government bonds, thus reducing their price. Because local banks hold a significant fraction of national bonds, their asset quality deteriorates, decreasing lending, and amplifying the shock. Less lending lowers economic activity, which in turn worsens government finances. The price of government debt falls again, triggering a new turn in the loop (Brunnermeier and Reis 2019). Furthermore, as Miguélez et al. (2019) noted, governments bailed out the banking system to avoid systemic risks, increasing their debt. While this recent European experience reinforced the need for sustainable government finances and sound banking regulations for the financial system to work well, it also strengthened the need for banks to improve their funding and asset risk management (Davies and Ng 2011).

Studies on the efficiency of the EU banking industry

Studies on the EU banking industry are dispersed in terms of scope, but there has been an increase in the number of publications in the last decade, revealing a growing importance in the study of this issue mostly due to the global financial crisis's heterogeneous impact on the Eurozone (Christopoulos et al. 2020; Pagano et al. 2014).

A growing literature on efficiency in the EU banking industry focuses on market integration. Among others, Schure et al. (2004) examined EU banks for the first time using a comprehensive dataset after the implementation of the second banking directive of the EU for financial market integration. They reviewed 1347 savings and 873 commercial banks from 1993 to 1997. Their findings supported the logic behind implementing the second banking directive in the EU: competition among EU banks lowered the cost of banks by 5% annually. Their findings also hinted at future merger and acquisition opportunities among EU banks because their results reveal that EU banks had managerial inefficiency (X-inefficiency) between 17 and 25%. In their words, large banks are on average 20% more efficient than the sample ones. However, their study was limited to a comparative analysis between commercial and saving banks. Later on, Weill (2009) examined EU banks with a larger dataset from1994 to 2005. His findings support the results of Schure et al. 2004. On top of that, their robustness check confirmed that beta and alpha convergence in cross country examination proved that banking integration in the EU increased overall cost efficiency. However, smaller banks with higher loan intensity may also cause a bank to be successful in operations (Barros et al. 2007).

Some studies on EU bank efficiency examined the financial crisis in 2008. Andrieș and Ursu (2016) examined 783 commercial banks from the EU from 2004 to 2010. Their findings revealed that large publicly traded banks were the banks most affected in the EU in terms of both profit and cost-efficiency. The post-crisis efficiency of banks in GIIPS countries was examined by Christopoulos et al. (2020). Their findings revealed that GIIPS banks have been suffering from a high degree of inefficiency. The authors emphasized intense monitoring from both micro (internal bank functions) and macro (GDP, inflation) levels. Pessarossi et al. (2020) examined bank distress in EU countries with high profitability and their findings revealed that high profitability in EU banks predicts possible bank distress within a lag of 3–4 years.

On the other hand, regarding market and competition structures in the EU banking industry, the following papers deserve attention: Shamshur and Weill (2019), using a sample of firms from nine European countries, find that lower bank competition facilitates the transmission of greater bank efficiency to lower cost of credit. More broadly, the authors conclude that improving bank efficiency can foster access to credit at the macroeconomic level. Leroy and Lucotte (2019), estimating both an

Table 1 Variables considered in the profit sheets, balance sheets, and financial health productive stages (in Millions of EUR)

Variable	Mean	SD	p1	p99	CV*	N
Net loans	80,993.31	159,554.00	111.37	703,279.00	1.97	1327
Total earning assets	72,956.26	148,787.40	111.06	711,357.00	2.04	1327
Non-earning assets	2,421.15	7,905.00	– 5.25	32,863.00	3.26	1327
Loan loss provision	695.73	1,719.79	– 46.70	9,557.00	2.47	1327
Non-interest expense	2,759.96	7,356.14	1.80	38,252.51	2.67	1327
Net interest	– 808.78	5,551.54	– 26,334.00	7,225.76	– 6.86	1327
Total equity	8,667.19	17,723.29	20.56	87,611.22	2.04	1327
Total assets	75,635.69	153,146.10	111.28	720,599.00	2.02	1327
Net interest income	2,365.52	5,007.86	6.30	26,298.54	2.12	1327
Total income	479.18	1,841.00	– 3,810.17	7,843.00	3.84	1327

*Coefficient of variation

interacted Vector Autoregressive (VAR) model with macroeconomic data and a single-equation model with bank-level data in Europe, find that a deviation of actual from potential GDP leads to greater credit fluctuations in countries where competition is weak. Such a result suggests that increased market power for banks increases the financial accelerator mechanism. Reinforcing the relationship of the macroeconomic environment on bank-level variables, Saha et al. (2009) find that interest rate volatility significantly affects the net worth of Indian banks. Simultaneously, monopolistic banking may raise macroeconomic volatility by making credit abundant during booms and more expensive during recessions (Leroy and Lucotte 2019).

Though pieces of literature are growing fast, attempts to bridge efficiency in the EU banking system, market, and competition structures and the recent financial crises in the Euro Zone are relatively scarce. This paper attempts to fill this gap by analyzing the impact of market structure and competition variables (BankAsset Concentration, Boone Indicator, H-Statistic, Lerner Index) plus bank-level (liquidity, capital adequacy, asset quality, operational ratios, and risk-taking) and country-level (Gov. Debt as % of GDP, GDP Growth, CPI Growth, and unemployment) variable son efficiency scores. We also investigate a potential non-monotonic relationship between competition and efficiency in EU banks. Finally, to disentangle the multiple facets of bank efficiency, in addition to the overall efficiency index, we also consider (i) profit sheets, (ii) balance sheets, and (iii) financial health efficiency indicators from 2004 to 2016.

Data and methodology

The data

The bank-level data comes from Thomson Reuters Eikon complemented with hand-collected information from the banks' annual reports. Our sample

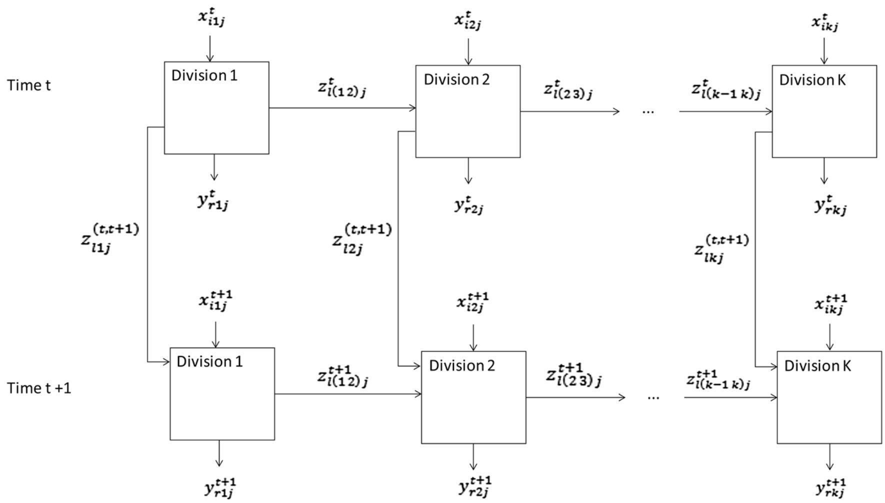

Fig. 3 Generic DNDEA productive structure

comprises all banks operating in the EU with data available from 2004 to 2016. We added macroeconomic and other country-specific variables (competition and market structure) to this dataset downloaded from the World Bank (World Development Indicators and Global Financial Development).

The descriptive inputs, outputs, links, and carryovers included in the DNDEA model are shown in Table 1. The DNDEA is described in terms of its three formative stages, and we selected variables of physical and monetary productive resources using two relevant criteria: data availability and similarity to variables found in previous studies. The monetary inputs and outputs considered in this paper are given in current Euros adjusted by the Eurozone's yearly consumer price index.

After generating the bank-efficiency indices including both overall efficiency and its components of profit sheet, balance sheet, and financial health, which are detailed in the following subsections, we used several variables to investigate the interplay among bank efficiency and bank-level and country-level determinants. While bank-level *asset quality* includes leverage (Total Assets/Shareholders' Equity) and Non-Performing/Gross Loans, *operational ratios* include Net Interest Margin and ROA. We also proxy for *liquidity* (Credit/Deposits) and *risk-taking* (growth of assets and growth of leverage) as in Adrian et al. (2010). Country-level competition variables incorporate Assets concentration, H-Statistic, Lerner Index, and Boone Indicator. Finally, we encompassed macroeconomic country-level variables such as Gov. Gross Debt (% of GDP), Growth of GDP, Growth of CPI, and Unemployment. Our final database comprises 103 European banks over the period 2004–2016, totalizing 1031 bank-year observations. Table A1 (Appendix A) details the definitions of the variables and their respective sources.

DNDEA

Traditional DEA models not only consider DMUs (Decision-Making Units) as productive black-boxes, but also neglect intertemporal carryovers that may impact efficiency scores in subsequent periods. Therefore, this section proposes the novel DNDEA model as generically depicted in Fig. 3.

Let's consider, for example, a banking industry productive process formed by a set of n homogenous DMUs ($j = 1, \dots, n$) with K productive stages ($k = 1, \dots, K$), each one characterized by specific values for m_k, r_k, and L_{kh}, which correspond respectively to the number of inputs and outputs in stage k and to the number of links from stage k to stage h. The following terms characterize the flow of productive resources and deliverables within the ambit of this banking framework: $x_{ikj} \in R^{+}$ denotes the input i in DMU_j to produce the output $y_{rkj} \in R^{+}$,r,DMU_j. Besides, $z_{l(kh)j} \in R^{+}$ denotes a link from stages k to h. Dynamic productive networks should allow consecutive periods to be connected by carryovers all defined in the domain of real numbers such as:

(a) x^{t}_{ikj}, or the input i for DMU_j in stage k in period t.

(b)y^{t}_{rkj}, or the output r for DMU_j in stage k in period t.

(c) $z^{t}_{l(kh)j}$, or the link variable of DMU_j from stages k to h in period t.

(d) $z^{(t,t+1)}_{lkj}$, or the carryover of product l from stage k in period t but subsequently consumed in period $t+1$.

The DNDEA model under the input-oriented and constant returns to scale assumptions is given in model (1).

$$\min \sum_{i=1}^{m_k} \overline{x}^{t}_{iko}$$

$$S.T.$$

$$\sum_{i=1}^{n} \lambda^{t}_{kj} \quad x^{t}_{ikj} \le \overline{x}^{t}_{iko} \quad i = 1, \dots m_k$$

$$\sum_{i=1}^{n} \lambda^{t}_{kj} \quad y^{t}_{rkj} \ge y^{t}_{rko} \quad r = 1, \dots r_k$$

$$\sum_{i=1}^{n} \lambda^{t}_{hj} \quad z^{t}_{l(kh)j} \ge z^{t}_{l(kh)o} \quad l = 1, \dots L_{kh} \tag{1}$$

$$\sum_{i=1}^{n} \lambda^{t}_{kj} \quad z^{t}_{l(hk)j} \le z^{t}_{l(kh)o} \quad l = 1, \dots L_{hk}$$

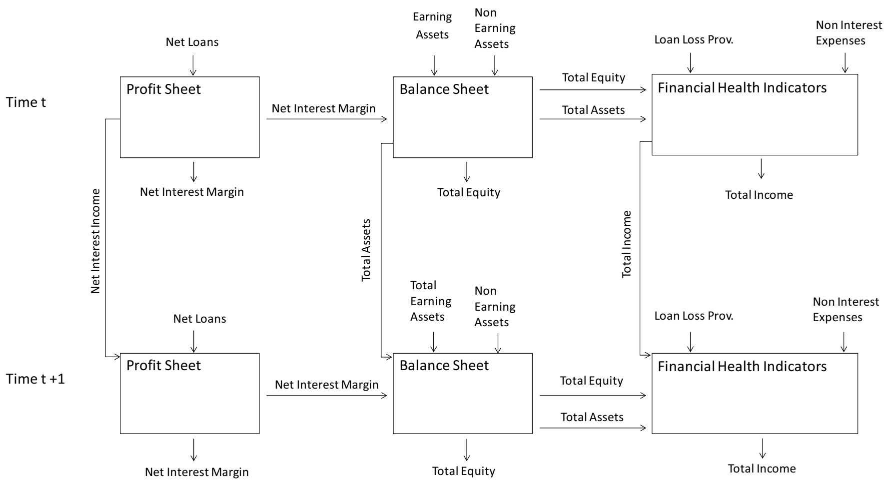

Fig. 4 EU banking industry productive structure

$$\sum_{i=1}^{n} \lambda_{kj}^{t} \quad z_{lkj}^{(t,t+1)} \geq z_{lko}^{(t,t+1)} \qquad l = 1, \dots L_k$$

$$\sum_{i=1}^{n} \lambda_{kj}^{t+1} z_{lkj}^{(t,t+1)} \leq z_{lko}^{(t,t+1)} l = 1, \dots L_k$$

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

To model the variable returns to scale assumption, additional constraints assuring that lambdas sum up to one should be added to the model. While virtual minimal input levels are determined by model (1) for each productive stage, their efficiency scores are computed as observed in Eq. (2). Besides, the overall network efficiency (NE) is defined by observing a weighted sum where each w_{k} represents the respective importance of each stage, as given in Eq. (3):

$$NE_{ko}^{t} = \frac{\sum_{i=1}^{m_k} \overline{x}_{iko}^{t*}}{\sum_{i=1}^{m_k} x_{iko}^{t}} \tag{2}$$

$$NE_{o}^{t} = \sum_{k=1}^{K} w_k NE_{ko}^{t} \tag{3}$$

where $\sum_{k=1}^{K} w_k = 1$.

In this study, there are three efficiency vectors for each network productive stage (profit sheet, balance sheet, and financial health indicators) to which equal weights are assigned. Figure 4 illustrates the inputs (I), outputs (O), carryovers (C), and links

(L) of the intermediate variables within the ambit of the three DNDEA sub-structures for the EU banks. As shown in Fig. 4, the variables of the first stage, called "profit sheet" efficiency, are net loans (I), net interest margin (O and L), and net interest income (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 time to support this activity (Casu et al. 2006). Besides, the performance of this stage impacts the subsequent sub-structure called "balance sheet" efficiency: 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 does the equity generation have a function of asset creation due to banking profitability, but also total assets (L) and equity (L) are the cornerstones of the substructure called "financial health ratio" efficiency. These variables together with non-interest expenses and loan loss provisions (I) are fundamental for producing sound income indicators (O and C), which is the numerator for important financial health ratios in banking such as ROA, ROE, and other risk-taking growth ratios. It is essential to mention that a fair share of 50% was attributed when solving the DNDEA model in the case of a single variable acting simultaneously as an output and a link or carry over in a given productive stage.

Market and competition structures, bank and country-level metrics, and econometric modelling

Once we estimated the overall bank-efficiency measure and its three subcomponents of profit sheet, balance sheet, and financial health indicators, we included these variables in a panel data framework to gauge the partial effect of bank competition/market structure on bank efficiency. In particular, we estimated a panel using bank fixed effects, time fixed effects, and bank-level and country-level lagged controls accordingly to the following equation:

$$y_{ict} = Competition'_{ict-1}\beta + x1'_{it-1}\theta + x2'_{ct-1}\delta + \alpha_i + \delta_t + \varepsilon_{it} \quad (4)$$

where y_{ict} is the efficiency score of the bank located in country c at year t (Overall, Profit Sheet, Balance Sheet, and Financial Health efficiency measures), $Competition_{ict-1}$ is the independent variable of interest (bank market structure and competition measures – Asset concentration, H-statistic, Lerner Index, and Boone Indicator), $x1_{it-1}$ are bank-level controls including proxies for Risk-Taking and Asset Quality, Capital, Operational, and Liquidity ratios, and $x2_{ct-1}$ are country-level controls such as Bank Z-score, Gov. Gross Debt as a % of GDP, GDP Growth, CPI Growth, and Unemployment. α_i and δ_t are bank and year-fixed effects, respectively, and ε_{it} is the idiosyncratic error term. Equation 4 is estimated for the full sample and two subsamples (GIIPS and non-GIIPS countries). Finally, we use Hubber–White's robust standard errors clustered at the bank level to estimate t-Statistics and p-Values.

Complementing the panel data analysis and to potentially identify endogeneity issues arising from simultaneity/feedback effects, we also built on the procedure of Dumitrescu and Hurlin (2012) to estimate Granger causality in panel datasets.

The null hypothesis of the tests is that one independent variable, "x" ("y"), does not Granger-cause the dependent variable "y" ("x"). Failing to reject the null hypothesis is equivalent to rejecting the premise that "x" does not Granger-cause "y". Precisely, we assessed such results based on the following criteria:

- *No Granger causality*: no rejection of H0 for both $x\text{–}>y$ and $y\text{–}>x$ at least at the 5% level.
- *Unidirectional Granger causality (x->y)*: rejection of H0 for $x\text{–}>y$, but not for $y\text{–}>x$ at least at the 5% level.
- *Unidirectional Granger causality (y->x)*: rejection of H0 for $y\text{–}>x$, but not for $x\text{–}>y$ at least at the 5% level.
- *Bidirectional Granger causality (feedback)*: the rejection of H0 for $x\text{–}>y$ and $y\text{–}>x$ at least at the 5% level.

The variables included in Eq. (4) and in the Granger causality tests are winsorized at the 1% level in each tail to mitigate the undesirable impact of outliers. Further, all variables build on previous literature (see, for example, Adrian et al. 2010; Beck et al. 2013), and we analyzed the correlation matrix among all variables to identify and prevent multicol linearity issues. See Table 4 for results.

Finally, because GIIPS and non-GIIPS countries differ in several observable dimensions (see Table 3 for the core descriptive statistics and the t-test for mean differences), we RAN the panel data regressions of Eq. (4) for the full sample (all countries, 2004 to 2016) and for the following subsamples:

- GIIPS subsample: Greece, Ireland, Italy, Portugal, and Spain, as in Acharya and Steffen (2015).
- Non-GIIPS subsample: all other countries in the sample – Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Netherlands, Poland, Sweden, and United Kingdom.

Importantly, GIIPS countries suffered from a meaningful sovereign debt crisis in the 2010s, potentially affecting the bank market structure and its effects on bank efficiency. In Appendix B, we show the time-series of the average efficiency measures for the GIIPS and non-GIIPS groups of countries. As one might note, it seems that the average efficiency decreased for the GIIPS country relative to the non-GIIPS started in the early 2010s, especially for the Overall Index and the Financial Health sub-index. We also provide the dispersion and the average efficiency scores for each country (see Appendix C for details).

Robustness cross-check: RENNA

Artificial neural networks (ANNs) are computational algorithms that are based on the human thinking paradigm. ANNs are formed of processing units (neurons) that are weight connected. These connections motivate the estimation of nonlinear models by using a training data set. Athanassopoulos and Curram (1996) is

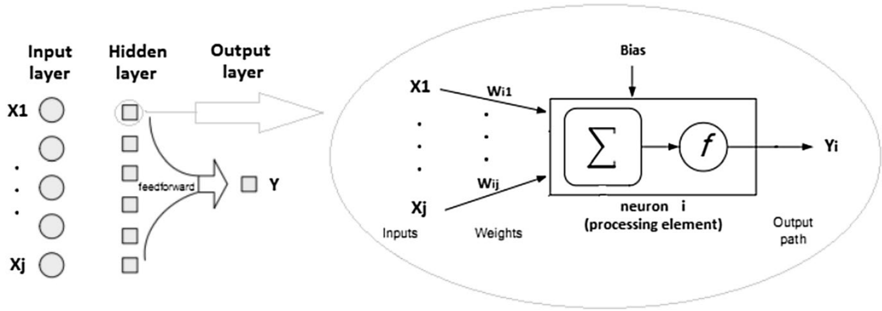

Fig. 5 Multilayer Perceptron (MLP) framework

the first literature insight on combining ANNs and DEA for predicting efficiency scores. Other ANN applications in DEA can be found in the existing literature (Wu et al. 2006) such as Santin et al. (2004), Emrouznejad and Shale (2009), Bashiri et al. (2013), Shokrollahpour et al. (2016), and Misiunas et al. (2016). A specific focus is placed in this research on the multilayer perceptron (MLP) network that has been extensively studied in forecasting applications (Mubiru and Banda, 2008). Within the ambit of an MLP, neurons are pooled in layers and only forward connections are allowed. These features provide a robust architecture capable of learning from any kind of continuous nonlinear mapping. A typical MLP is represented in Fig. 5.

MLP constituents encompass neurons, weights, and transfer functions. An input x_j is transmitted via connections that multiply their respective strength by w_{ij} weights yielding the product $x_j w_{ij}$ used in the transfer function f to compute a specific output y_i given as $y_i = f\left(\sum_{j=1}^{n} x_j w_{ij}\right)$. i is the neuron index in the hidden layer, and j is the input index to the MLP. The modification of the weights of each connection observing some orderly fashion is known as training. During the training, an input is assigned to the network along with the desired output, and the weights are adjusted so that the MLP catches up to the desired output value.

The robustness analysis for RENNA is structured in two steps. In the first step, MLP is employed to evaluate the impact of contextual variables on bank efficiency scores under three distinct models: random effects, fixed effects, and fixed effects with risk-taking variables. Their specification is given as follows:

- Random Effects: Efficiency ~ f(Contextual Variables, Productive Stage, Lag, Winsorized)
- Fixed Effects: Efficiency ~ f(Contextual Variables, Productive Stage, Lag, Winsorized. Country, Trend)
- Fixed Effects with Risk-taking Variables: Efficiency ~ f(Contextual Variables, Productive Stage, Lag, Winsorized. Country, Trend, Risk-taking Variables)

where:

- Contextual Variable set: ROA, ROE, Leverage, Z-Score, Boone Indicator, H-Statistic, Lerner Index, Asset Concentration, Bank Concentration, Credit/Deposits, and Non-Performing/Gross Loans.
- Risk-taking Variable set: ROA Growth, ROE Growth, Leverage Growth, Assets Earning Growth, and Non Assets Earning Growth.

  - Productive Stage is a dummy variable denoting whether efficiency relates to a specific individual productive stage: Profit Sheet, Balance Sheet, and Financial Health or to the Overall productive structure.
  - Lag is a dummy variable denoting whether contextual and risk-taking variables and efficiency are offset by one year lag or not (1 = yes, 0 = no).
  - Winsorized is a dummy variable denoting whether Contextual and Risk-taking Variables have been Winsorized or not (1 = yes, 0 = no).

On the other hand, the RENNA second step focuses on unveiling endogeneity between overall efficiency and competition structure in European banks considering Contextual and Risk-taking Variables as the control ones. Hence, this paper departs from previous research in the banking sector by using an MLP network structure to explore endogeneity between these variables in terms of the following models:

- Model 1: Overall ~ f(Leverage, Z Score, Boone Indicator, H-stat, Lerner, Bank Concentration, Remainder Contextual, and Risk-taking Variables)
- Model 2: Leverage ~ f(Overall, Z Score, Boone Indicator, H-stat, Lerner, Bank Concentration, Growth Leverage, Remainder Contextual, and Risk-taking Variables)
- Model 3: Z score ~ f(Overall, Leverage, Boone Indicator, H-stat, Lerner, Bank Concentration, Growth Leverage, Remainder Contextual, and Risk-taking Variables)
- Model 4: Boone Indicator ~ f(Overall, Leverage, Z Score, H-stat, Lerner, Bank Concentration, Growth Leverage, Remainder Contextual, and Risk-taking Variables)
- Model5: H-Stat ~ f(Overall, Leverage, Z Score, Boone Indicator, Lerner, Bank Concentration, Growth Leverage, Remainder Contextual, and Risk-taking Variables)
- Model 6: Lerner ~ f(Overall, Leverage, Z Score, Boone Indicator, H-stat, Bank Concentration, Growth Leverage, Remainder Contextual, and Risk-taking Variables)
- Model 7: Bank Concentration ~ f(Overall, Leverage, Z Score, Boone Indicator, H-stat, Lerner, Growth Leverage, Remainder Contextual, and Risk-taking Variables)
- Model 8: Growth Leverage ~ f(Overall, Leverage, Z Score, Boone Indicator, H-stat, Lerner, Bank Concentration, Remainder Contextual, and Risk-taking Variables)

The relative importance of Models 1–8 in explaining the feedback process between the competition structure and the overall efficiency scores in the

Table 2 RENNA pseudo code

RENNA Pseudo Code	
Step 1: Variable importance	1) Normalize Contextual and Risk-taking Variables
	2) Run a tenfold cross validation
	2.1) Split dataset into trained dataset (90%) and test dataset (10%)
	2.2) For each trained dataset:
	2.2.1) Run MLP using trained dataset
	2.2.2) MSE using the trained dataset
	3) Run MLP on the complete dataset
	4) Get variable importance using Olden (2002) algorithm
Step 2: Unveiling endogeneity	1) For each one of the 100 bootstrap replications
	1.1) For Models 1—8:
	1.1.1) Run MLP using the complete dataset
	1.1.2) Get the residuals
	1.2) Minimize the covariance matrix of residuals

EU banking industry, besides the endogenous nature of these variables, were explored respectively by the variances of each model and the covariances between the models. The variances and covariances of the residuals (R_i) of these eight models are simultaneously minimized by a nonlinear stochastic optimization problem as presented in Eq. (5).In this equation,w_i stands for the weights, which range from 0 to 1, assigned respectively to the residual vectors of each one of the six models previously described. The values of $w$are optimized so that the variance (*Var*) and covariance (*Covar*) of the pooled residuals are minimal. Model (5) was solved using differential evolution (DE). DE is a research stream of genetic algorithms also emulating the natural selection and evolution. Readers should refer to Ardia et al. (2011) and Mullen et al. (2011) for further details. The results are discussed in the next section.

$$\min\left[Var\left(\sum_{i=1}^{8} w_i * R_i\right) + \left(\sum_{i,j=1}^{8} Covar(w_i * w_j * R_i * R_j), i \neq j, j < i\right)\right]$$

$$\textit{subject to}$$

$$\sum_{i=1}^{8} w_i = 1 \quad 0 \leq w_i \leq 1 \forall i \tag{5}$$

Residuals of the MLP models were bootstrapped 100 times, allowing the collection of a distributional profile of w for the most accurate prediction of the network efficiency scores and competition indexes. Table 2 depicts the pseudo-code for the two-step RENNA.

Results and discussion

In this section, we report and analyze the results of the empirical strategy discussed previously. Before discussing the panel data results and presenting the results from approaches to deal with endogeneity (Granger causality tests and RENNA modelling), we begin by showing the descriptive statistics and correlation coefficients among variables.

Descriptive statistics and correlation coefficients

Table 3 analyzes the descriptive statistics of the variables used in the empirical section. To better understand the differences between the non-GIIPS and GIIPS subsamples, we report Mean, Median, and Standard Deviation for the full sample (Panel A) and each subsample individually (Panels A and B). We also report the results from a t-Test of the difference of means between non-GIIPS and GIIPS countries in the last column of Table 3 ([B-C] *Diff.*).

We infer from Table 3 that the Overall Efficiency Index averages 0.74 for the full sample, and it is similar in magnitude for non-GIIPS (0.75) and GIIPS (0.73) countries. However, this difference (+1.2 points) is statistically significant at the 10% level (see first row, last column). A similar pattern is observed from the overall efficiency sub-indexes (Efficiency-Balance Sheet and Efficiency-Financial Health) except for the Efficiency-Profit Sheet (negative difference, but statistically non-significant). Such a univariate analysis indicates that non-GIIPS banks are systematically more efficient than their GIIPS peers.

Regarding the remaining bank-level and country-level variables, we find significant differences across groups. For example, banks located in non-GIIPS countries show better asset quality ratios (e.g., Non-Performing/Gross Loans, 3.55% vs.11.35%, p-Value < 0.01), better operational ratios (e.g., ROA, 2.76% vs. 0.66%, p-Value < 0.01), and a better macroeconomic outlook (e.g., Growth of GDP [p Value < 0.05], Government Gross Debt [p Value < 0.01], and Unemployment [p Value < 0.01]), on average. Bank competition seems to be lower in non-GIIPS countries (e.g., Asset Concentration, H-Statistic, Lerner Index, and Boone Indicator [p-Value < 0.01 for all these measures]). Furthermore, we find statistically significant differences across groups on bank risk-taking (e.g., Lower Growth of Assets and Growth of Leverage for the Non-GIIPS countries).

Next we analyze the correlation matrix for these variables reported in Table 4. One star reveals a statistical significance at the 1% level (i.e., p-Value < 0.01). As expected, the Overall Efficiency Index is positively and highly correlated with the Profit Sheet sub-index (0.95), but perhaps surprisingly not that much with the Balance Sheet (0.26) and especially with Financial Health (0.05).

The bank-system concentration measures correlate with each other, but not that much. The larger correlation coefficient (either positive or negative) is H-Statistic and Lerner Index = –0.49. In fact, some of these measures are nearly uncorrelated (e.g., Asset Concentration and Lerner Index [0.06] and Asset Concentration and

Table 3 Descriptive statistics for the full sample and subsamples

Variable	(A) Full Sample			(B) Non-GIIPS		
	Mean	*Median*	*SD*	*Mean*	*Median*	*SD*
Eff.—Overall Index	0.74	0.71	0.10	0.75	0.71	0.11
Eff.—Profit Sheet	0.33	0.20	0.32	0.32	0.18	0.33
Eff.—Balance Sheet	0.91	0.92	0.06	0.91	0.92	0.06
Eff.—Fin. Health	0.96	0.99	0.08	0.97	0.99	0.06
Concentration—Assets	78.12	77.18	13.33	79.62	79.08	12.81
H-Statistic	0.70	0.71	0.17	0.68	0.69	0.16
Lerner Index	0.21	0.22	0.10	0.22	0.24	0.09
Boone Indicator	– 0.07	– 0.04	0.26	– 0.04	– 0.04	0.06
Ln(Assets)	23.36	23.37	2.23	22.89	22.90	2.29
Leverage	34.17	8.01	134.31	33.60	7.28	130.74
Credit / Deposits	160.02	123.69	83.78	171.10	123.69	94.58
ROA	2.19	0.86	9.42	2.76	0.97	9.04
Interest Margin	1.54	1.24	0.82	1.46	1.10	0.84
Non Performing / Gross Loans	5.67	3.96	6.96	3.55	3.39	4.87
Z-Score	13.76	14.00	5.63	14.44	14.95	5.55
Growth Assets	0.18	0.03	1.25	0.14	0.04	1.03
Growth Leverage	0.10	– 0.02	1.46	0.07	– 0.03	1.22
Growth Credit/Deposits	0.00	– 0.01	0.07	0.00	– 0.01	0.07
Gov. Gross Debt (% GDP)	75.13	68.43	33.12	62.50	63.66	21.16
Growth GDP	1.16	1.47	2.76	1.54	1.71	2.21

Table 3 (continued)

Variable	(A) Full Sample			(B) Non-GIIPS		
	Mean	*Median*	*SD*	*Mean*	*Median*	*SD*
Growth CPI	0.02	0.02	0.01	0.02	0.02	0.01
Unemployment	8.87	7.85	4.47	7.49	7.49	2.46

Variable	(C) GIIPS			(B-C)
	Mean	*Median*	*SD*	*Diff*
Eff.—Overall Index	0.73	0.71	0.09	0.012*
Eff.—Profit Sheet	0.35	0.25	0.30	– 0.024
Eff.—Balance Sheet	0.90	0.90	0.06	0.011**
Eff.—Fin. Health	0.93	0.97	0.11	0.045***
Concentration—Assets	74.10	73.33	13.88	5.522***
H-Statistic	0.73	0.85	0.21	– 0.048***
Lerner Index	0.18	0.14	0.10	0.048***
Boone Indicator	– 0.13	– 0.04	0.48	0.082***
Ln(Assets)	24.61	24.69	1.46	– 1.721***
Leverage	35.71	10.01	143.64	– 2.114
Credit / Deposits	130.38	125.13	25.90	40.723***
ROA	0.66	0.44	10.24	2.098***
Interest Margin	1.77	1.58	0.74	– 0.313***
Non Performing / Gross Loans	11.35	9.38	8.38	– 7.795***
Z-Score	11.94	13.37	5.42	2.502***
Growth Assets	0.28	0.02	1.69	– 0.138*
Growth Leverage	0.20	– 0.02	1.96	– 0.135
Growth Credit/Deposits	0.00	– 0.01	0.07	– 0.004

Table 3 (continued)

Variable	(C) GIIPS			(B-C)
	Mean	*Median*	*SD*	*Diff*
Gov. Gross Debt (% GDP)	108.91	109.42	35.62	– 46.401***
Growth GDP	0.13	0.60	3.69	1.418***
Growth CPI	0.02	0.02	0.02	0.001
Unemployment	12.57	10.68	6.21	– 5.084***

This Table shows the descriptive statistics of the variables used in this study. Besides reporting core statistics (Mean, Median, and Standard Deviation) for the Full Sample (Panel A), we also collapse our sample into two: non-GIIPS and GIIPS (Greece, Ireland, Italy, Portugal, and Spain) countries. The last column (*Diff.*) reports a t-test of the mean difference for each variable for the Non-GIIPS and GIIPS subsamples. Bank-level characteristics include the estimated measures of efficiency (Overall, Profit Sheet, Balance Sheet, and Financial Health), asset quality (Equity/Total Assets, Nonperforming/Gross Loans), capital ratios (Equity/Total Assets), Operational ratios (Net Interest Margin, ROA), liquidity ratios (Credit/Deposits), size (Ln Assets), solvency risk (Z-Score), and risk-taking (Growth ROA, Growth Equity/Total Assets, and Growth Credit/Deposits). Competition variables at the industry level include Asset Concentration, H-Statistic, Lerner Index, and Boone Indicator. Finally, we include country-level variables such as Gov. Gross Debt (% of GDP), GDP growth, Growth of CPI, and Unemployment. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 4 Correlation matrix of efficiency scores and other bank-level and country-level variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Eff.—Overall Index	1.00										
(2) Eff.—Profit Sheet	0.94*	1.00									
(3) Eff.—Balance Sheet	0.26*	0.09*	1.00								
(4) Eff.—Fin. Health	0.05	– 0.22*	– 0.11*	1.00							
(5) Concentration—Assets	0.01	0.01	– 0.05	0.03	1.00						
(6) H-Statistic	– 0.11*	– 0.13*	– 0.03	0.09*	– 0.19*	1.00					
(7) Lerner Index	0.29*	0.28*	0.04	0.01	0.06	– 0.49*	1.00				
(8) Boone Indicator	– 0.06	– 0.13*	0.01	0.19*	0.06	0.04	– 0.19*	1.00			
(9) Ln(Assets)	– 0.06	0.06	0.12*	– 0.48*	– 0.15*	0.00	– 0.16*	– 0.10*	1.00		
(10) Leverage	– 0.06	– 0.10*	0.05	0.08*	0.00	0.16*	– 0.24*	0.01	0.17*	1.00	
(11) Credit / Deposits	0.17*	0.14*	0.01	0.11*	0.48*	– 0.40*	0.28*	– 0.10*	– 0.46*	– 0.03	1.00
(12) ROA	0.20*	0.16*	0.16*	0.03	– 0.09*	0.08	0.00	– 0.02	– 0.17*	– 0.05	– 0.07
(13) Interest Margin	0.07	0.05	0.04	0.05	– 0.55*	0.22*	0.25*	– 0.07	0.02	– 0.07	– 0.33*
(14) Non Performing / Gross Loans	0.00	0.10*	– 0.29*	– 0.13*	– 0.01	0.21*	– 0.11*	0.07	0.16*	– 0.03	– 0.16*
(15) Z– Score	– 0.11*	– 0.09*	– 0.08	– 0.03	0.08	– 0.04	– 0.06	– 0.24*	– 0.06	0.07	0.24*

Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(16) Growth Assets	0.02	0.03	0.03	– 0.06	– 0.07	0.05	– 0.02	0.01	0.06	– 0.01	– 0.02
(17) Growth Leverage	0.03	0.04	– 0.01	– 0.03	– 0.01	0.04	– 0.02	0.01	0.03	0.01	0.01
(18) Growth Credit/ Deposits	0.03	– 0.02	0.14*	0.08*	– 0.05	0.06	0.02	0.05	– 0.06	– 0.07	0.06
(19) Gov. Gross Debt (% GDP)	– 0.10*	0.00	– 0.20*	– 0.21*	– 0.12*	0.48*	– 0.44*	0.07	0.37*	0.03	– 0.50*
(20) Growth GDP	0.05	0.01	0.00	0.15*	– 0.16*	– 0.16*	0.21*	0.02	– 0.06	– 0.01	– 0.08
(21) Growth CPI	0.08	– 0.02	0.34*	0.09*	– 0.19*	0.06	0.00	– 0.01	– 0.04	0.02	– 0.04
(22) Unemploy-ment	0.02	0.16*	– 0.18*	– 0.33*	– 0.06	– 0.03	0.04	– 0.27*	0.29*	– 0.07	– 0.24*

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) Eff.—Overall Index											
(2) Eff.—Profit Sheet											
(3) Eff.—Balance Sheet											

Table 4 (continued)

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(4) Eff.—Fin. Health											
(5) Concentration—Assets											
(6) H-Statistic											
(7) Lerner Index											
(8) Boone Indicator											
(9) Ln(Assets)											
(10) Leverage											
(11) Credit / Deposits											
(12) ROA	1.00										
(13) Interest Margin	0.02	1.00									
(14) Non Performing / Gross Loans	− 0.15*	0.17*	1.00								
(15) Z–Score	0.01	− 0.31*	− 0.24*	1.00							

Table 4 (continued)

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(16) Growth Assets	– 0.01	0.05	0.03	– 0.03	1.00						
(17) Growth Leverage	– 0.03	0.02	0.05	– 0.04	0.86*	1.00					
(18) Growth Credit/ Deposits	– 0.09*	0.21*	– 0.01	– 0.24*	0.01	0.02	1.00				
(19) Gov. Gross Debt (% GDP)	– 0.10*	0.08	0.67*	– 0.13*	0.04	0.04	– 0.01	1.00			
(20) Growth GDP	0.13*	0.13*	– 0.25*	0.09*	– 0.01	– 0.05	– 0.08*	– 0.36*	1.00		
(21) Growth CPI	0.06	0.21*	– 0.36*	– 0.17*	0.02	0.01	0.35*	– 0.21*	0.15*	1.00	
(22) Unem-ployment	– 0.13*	0.14*	0.65*	– 0.19*	0.02	0.03	– 0.02	0.54*	– 0.22*	– 0.32*	1.00

This Table shows the correlation coefficients among each pair of variables used in this study. * indicates a statistical significance at the 0.01 level

Boone Indicator [0.06]). Country-level variables also correlate to each other, but not that much in magnitude. Such correlation coefficients range from –0.36 (Gov. Gross Debt – % of GDP and Growth GDP) to 0.54 (Gov. Gross Debt – % of GDP and Unemployment).

Critical to our panel estimations, there is no evidence of nearly collinear relationships among the explanatory variables. The most correlated ones are those that are *not* used concomitantly—instead, only one efficiency measure is included in each regression. We switch the proxy for efficiency to understand how different market structures and competition variables (Concentration – Assets, H-Statistic, Lerner Index, and Boone Indicator) affect distinct bank efficiency dimensions.

Panel data regressions: does bank competition matter for bank efficiency?

We now report the panel data fixed-effect regression results as modeled in Eq. (4). We first regress the core bank-efficiency variable (Efficiency-Overall) on each of the bank concentration/competition measures separately (Asset Concentration, H-Statistic, Lerner Index, and Boone Indicator). To gauge the partial effect of bank concentration on efficiency, we include bank-level controls, country-level controls, and bank and year fixed effects. Because the non-GIIPS and GIIPS subsamples differ notably, we also report the results considering the two groups of countries.

Table 5 shows the results of the model using Efficiency-Overall as the dependent variable. Regarding the full sample (cols. 1–4), we infer that the partial effect of competition on bank efficiency is generally negative. The impact of Concentration – Assets on efficiency is not only negative and statistically significant (p-value < 0.05), but also economically meaningful: a 1 SD positive shock leads to (13.33*–0.0019 =)–0.025 points in the overall efficiency. Given the average efficiency score of 0.74, it represents a 3.4% reduction in overall bank efficiency, ceteris paribus. While the other concentration and competition measures are not statistically significant in the model, they suggest the same direction of the impact: the higher the bank concentration, the lower the bank-efficiency, all else being equal.

Furthermore, we find that lagged Loans / Deposits (+), Growth of Assets (+), Growth of Leverage (-), and Growth of Credit/Assets (+) are critical bank-level determinants of overall efficiency in the entire sample (all p-values < 0.05). On the other hand, macroeconomic-level variables do not seem to be trust worthy drivers of bank efficiency with the exception of lagged growth of CPI (–) (p-value < 0.05).

Concerning the non-GIIPS (cols. 5–8) and GIIPS subsamples (cols. 9–12), although the general picture is similar to the entire sample, there are some remarkable differences. First, Concentration of Assets impacts overall efficiency meaningfully only in the non-GIIPS subsample: a one SD positive shock decreases overall efficiency by (12.81*–0.0027 =)–0.035 points.[1]Second, bank stability, as measured by Z-score as in Schaeck and Cihák (2014), is a significant determinant (+) of

[1] It represents a decrease of (–0.035/.75 =)4.61% in overall bank-efficiency, ceteris paribus (calculated over the mean value of "Efficiency – Overall Index" of 0.75 for the non-GIIPS subsample).

Table 5 The role of market structure and competition on bank efficiency – full sample, Non-GIIPS, and GIIPS countries

	A) Full Sample				B) Non-GIIPS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
L.Concentration—Assets	– 0.0019**				– 0.0027**			
	(– 2.29)				(– 2.02)			
L.H-Statistic		0.0502				– 0.0492		
		(0.38)				(– 0.44)		
L.Lerner Index			0.0491				– 0.0039	
			(0.73)				(– 0.05)	
L.Boone Indicator				– 0.0158				0.2647
				(– 1.56)				(1.15)
L.Ln(Assets)	– 0.0106	– 0.0101	– 0.0096	– 0.0100	0.0025	0.0024	0.0026	0.0029
	(– 1.26)	(– 1.17)	(– 1.10)	(– 1.15)	(0.27)	(0.25)	(0.27)	(0.30)
L.Leverage	0.0001*	0.0001*	0.0001*	0.0001*	– 0.0000	– 0.0001	– 0.0001	– 0.0001
	(1.76)	(1.77)	(1.70)	(1.74)	(– 0.82)	(– 0.87)	(– 0.87)	(– 0.95)
L.Loans / Deposits	0.0008***	0.0007***	0.0008***	0.0008***	0.0007***	0.0007***	0.0007***	0.0006**
	(3.12)	(2.82)	(2.90)	(2.92)	(2.98)	(2.70)	(2.88)	(2.05)
L.ROA	– 0.0002	– 0.0001	– 0.0001	– 0.0001	0.0001	0.0001	0.0001	0.0001
	(– 0.94)	(– 0.48)	(– 0.51)	(– 0.49)	(0.27)	(0.38)	(0.39)	(0.38)
L.Net Interest Margin	– 0.0116	0.0026	0.0024	0.0024	– 0.0193	– 0.0132	– 0.0136	– 0.0189
	(– 1.14)	(0.31)	(0.30)	(0.29)	(– 1.23)	(– 0.87)	(– 0.88)	(– 1.50)
L.Non Performing / Gross Loans	0.0011	0.0007	0.0005	0.0006	0.0001	0.0000	0.0002	– 0.0001
	(1.05)	(0.62)	(0.52)	(0.57)	(0.18)	(0.07)	(0.30)	(– 0.07)

Table 5 (continued)

	A) Full Sample				B) Non-GIIPS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
L.Z-Score	0.0002	0.0003	0.0001	0.0003	– 0.0009	– 0.0005	– 0.0006	– 0.0004
	(0.15)	(0.20)	(0.09)	(0.18)	(– 0.36)	(– 0.23)	(– 0.25)	(– 0.19)
L.Growth—Assets	0.0153**	0.0157**	0.0158**	0.0156**	0.0189**	0.0197**	0.0197**	0.0200**
	(2.30)	(2.22)	(2.24)	(2.22)	(2.19)	(2.22)	(2.20)	(2.17)
L.Growth—Leverage	– 0.0089**	– 0.0093**	– 0.0093**	– 0.0092**	– 0.0096*	– 0.0105**	– 0.0105**	– 0.0105*
	(– 2.48)	(– 2.42)	(– 2.43)	(– 2.43)	(– 1.99)	(– 2.07)	(– 2.05)	(– 1.97)
L.Growth—Credit / Assets	0.0987**	0.0711	0.0725	0.0742	0.0794	0.0558	0.0525	0.0468
	(1.99)	(1.31)	(1.34)	(1.33)	(1.39)	(0.87)	(0.79)	(0.74)
L.Gov. Gross Debt	– 0.0005	– 0.0005	– 0.0004	– 0.0005	– 0.0013**	– 0.0012**	– 0.0012**	– 0.0011**
	(– 1.14)	(– 1.31)	(– 0.74)	(– 1.12)	(– 2.45)	(– 2.14)	(– 2.07)	(– 2.15)
L.Growth—GDP	0.0011	– 0.0002	0.0001	– 0.0002	0.0001	– 0.0019	– 0.0017	– 0.0026
	(0.49)	(– 0.11)	(0.05)	(– 0.10)	(0.05)	(– 0.71)	(– 0.62)	(– 0.87)
L.Growth—CPI	– 1.0556**	– 0.8766**	– 0.9321**	– 0.8555**	– 1.3837***	– 1.1186**	– 1.0730**	– 1.1293**
	(– 2.44)	(– 2.05)	(– 2.18)	(– 2.02)	(– 3.09)	(– 2.34)	(– 2.12)	(– 2.22)
L.Unemployment	– 0.0020	– 0.0023	– 0.0025	– 0.0024	0.0032	0.0009	0.0013	0.0015
	(– 0.77)	(– 0.96)	(– 1.00)	(– 0.95)	(1.30)	(0.39)	(0.54)	(0.64)
Obs	1031	1031	1031	1031	751	751	751	751
R-Sq. Within	0.25	0.24	0.24	0.24	0.30	0.30	0.30	0.30

Table 5 (continued)

	A) Full Sample				B) Non-GIIPS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust S.E	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

	C) GIIPS			
	(1)	(2)	(3)	(4)
L.Concentration—Assets	– 0.0008			
	(– 0.46)			
L.H-Statistic		0.1987		
		(0.82)		
L.Lerner Index			– 0.0174	
			(– 0.17)	
L.Boone Indicator				– 0.0175
				(– 0.88)
L.Ln(Assets)	– 0.0196	– 0.0195	– 0.0196	– 0.0193
	(– 1.35)	(– 1.35)	(– 1.35)	(– 1.33)
L.Leverage	0.0002*	0.0002*	0.0002*	0.0002*
	(2.03)	(2.05)	(2.04)	(2.00)
L.Loans / Deposits	0.0019**	0.0021***	0.0019**	0.0020**
	(2.60)	(3.17)	(2.47)	(2.48)
L.ROA	– 0.0007*	– 0.0007*	– 0.0007*	– 0.0007*
	(– 1.98)	(– 1.97)	(– 1.91)	(– 1.95)
L.Net Interest Margin	– 0.0091	– 0.0059	– 0.0033	– 0.0047
	(– 0.39)	(– 0.32)	(– 0.18)	(– 0.24)

Table 5 (continued)

	C) GIIPS			
	(1)	(2)	(3)	(4)
L.Non Performing / Gross Loans	– 0.0006	– 0.0023	– 0.0012	– 0.0017
	(– 0.13)	(– 0.74)	(– 0.32)	(– 0.41)
L.Z-Score	0.0161***	0.0160***	0.0158***	0.0159***
	(2.97)	(3.21)	(3.02)	(2.96)
L.Growth—Assets	0.0199**	0.0200**	0.0201**	0.0198**
	(2.20)	(2.20)	(2.19)	(2.17)
L.Growth—Leverage	– 0.0141***	– 0.0144***	– 0.0143***	– 0.0140***
	(– 3.11)	(– 3.11)	(– 3.14)	(– 3.08)
L.Growth—Credit / Assets	– 0.0808	– 0.0146	– 0.0924	– 0.0503
	(– 0.44)	(– 0.08)	(– 0.52)	(– 0.25)
L.Gov. Gross Debt	0.0002	0.0000	0.0004	0.0003
	(0.31)	(0.08)	(0.54)	(0.37)
L.Growth—GDP	– 0.0041	– 0.0049**	– 0.0040	– 0.0042
	(– 1.47)	(– 2.11)	(– 1.36)	(– 1.34)
L.Growth—CPI	0.6022	0.5536	0.7233	0.8075
	(0.72)	(0.85)	(1.04)	(1.08)
L.Unemployment	– 0.0048	– 0.0031	– 0.0042	– 0.0035
	(– 0.82)	(– 0.68)	(– 0.89)	(– 0.67)
Obs	280	280	280	280
R-Sq. Within	0.29	0.29	0.29	0.29
Year F.E	Yes	Yes	Yes	Yes

Table 5 (continued)

	C) GIIPS			
	(1)	(2)	(3)	(4)
Bank F.E	Yes	Yes	Yes	Yes
Robust S.E	Bank	Bank	Bank	Bank

This Table shows the results from the fixed-effects panel data estimations with the dependent variable Overall Efficiency. Besides the Full Sample (regs. 1–4), we also run the same specification for the Non-GIIPS (regs. 1–4) and the GIIPS subsample (regs. 1–4). GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain. The non-GIIPS subsample includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Netherlands, Poland, Sweden, and the United Kingdom. Each regression includes lagged bank-level, industry-level, and country-level variables besides year and bank fixed effects. Regressions in columns (1), (2), (3), and (4) report the results for the Concentration—Assets, H-Statistic, Lerner Index, and Boone Indicator competition and concentration measures, respectively. T-statistics (in parentheses) are calculated from standard errors clustered at the bank level. ***, **, and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively overall bank efficiency only for the GIIPS subsample. Given the lack of country-level economic stability, it might be plausible that a higher *Z*-score (i.e., a lower chance of insolvency) is more critical for bank efficiency at the GIIPS group. Third, macro-level determinants also differ from GIIPS to non-GIIPS countries. In particular, lagged gross government debt (–) and growth of CPI (–) affects overall efficiency only in the non-GIIPS subsample—a result that contrasts Christopoulos' et al. (2020) evidence that inflation and high levels of Government Debt affect bank efficiency in the GIIPS sample. While a negative effect of inflation on efficiency is consistent with theoretical arguments that high inflation may reduce bank incentives to manage their inputs, the positive association between these variables we find in the GIIPS subsample is compatible with Tan and Anchor's (2017) evidence for the Chinese banking industry.

Some interesting commonalities regarding the bank-level and country-level characteristics for the GIIPS and non-GIIPS subsamples can be drawn from Table 5. Loan / Deposits (+), Growth of Assets (+), and Growth of Leverage (–) are consistent determinants of efficiency on both subsamples. These results reinforce that although generally heterogeneous, some bank-specific determinants are robust across subsamples of countries with vastly different institutional and economic environments. Furthermore, the R-squared consistently ranges from 0.25 to 0.30 in all samples and subsamples, suggesting that nearly 1/3 of the variation of the dependent variable is explained by the independent variable.

Table 6 reports the partial impact of competition on alternative bank-efficiency dependent variables (Panel A – Dependent variable = Profit Sheet Efficiency, Panel B – Dependent variable = Balance Sheet Efficiency, and Panel C – Dependent variable = Financial Health Efficiency). Due to space constraints and for the sake of brevity, we only report coefficients on the core regressors of interest (Concentration – Assets, H-Statistic, Lerner Index, and Boone Indicator). Notably, all the regressions in Table 6 include bank-level (risk-taking and capital, asset quality, liquidity, and operational ratios) and country-level (macroeconomic variables) controls plus bank and year fixed effects.[2] That said, the concentration/competition proxies can still be interpreted as partial, ceteris paribus effects.

Overall, the results reported in Table 6 suggest that lagged competition indicators are particularly relevant to explain bank efficiency for both GIIPS and non-GIIPS countries. To be concrete, the sensitivity of efficiency to competition measures is higher for the Balance Sheet Efficiency (Panel B) – Concentration – Assets (–) is negative and statistically significant at the non-GIIPS subsample. In other words, the higher the concentration of assets in the banking industry (i.e., lower competition), the lower the balance sheet efficiency. Likewise, a higher Lerner-index and a lower Boone Indicator, which implies higher competition in both cases, increases the bank balance sheet efficiency in GIIPS countries. One should recall that the Lerner Index ranges from a high of 1 to a low of 0, and lower numbers imply lower market power, meaning a more competitive market structure. Similarly, the Boone indicator

[2] Besides the practical reasons to include bank fixed effects in the model (i.e., to control the average differences across banks in any observable or unobservable factors), the Hausman Test also suggests using a fixed effects rather than a random effects model.

Table 6 The role of efficiency on bank competition in Europe: other concentration measures

	A) Full Sample				B) Non-GIIPS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Dependent variable = Profit Sheet Efficiency								
L. Concentration—Assets	– 0.0068***				– 0.0065			
	(– 2.91)				(– 1.59)			
L. H-Statistic		0.1695				– 0.0410		
		(0.42)				(– 0.13)		
L. Lerner Index			0.0944				– 0.0493	
			(0.43)				(– 0.20)	
L. Boone Indicator				– 0.0387				0.8480
				(– 1.40)				(1.28)
R-Sq. Within	0.29	0.28	0.28	0.28	0.34	0.34	0.34	0.35
Panel B: Dependent variable = Balance Sheet Efficiency								
L. Concentration—Assets	– 0.0000				– 0.0011*			
	(– 0.03)				(– 1.79)			
L. H-Statistic		– 0.0982***				– 0.0706		
		(– 3.14)				(– 1.44)		
L. Lerner Index			– 0.0397*				– 0.0368	
			(– 1.70)				(– 1.09)	
L. Boone Indicator				0.0196***				– 0.0684
				(4.62)				(– 0.95)
R-Sq. Within	0.68	0.68	0.68	0.68	0.69	0.69	0.69	0.69

Table 6 (continued)

	A) Full Sample				B) Non-GIIPS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel C: Dependent variable = Fin. Health Efficiency								
L. Concentration—Assets	0.0005				– 0.0008			
	(0.54)				(– 1.13)			
L. H-Statistic		0.0894				– 0.0409		
		(1.17)				(– 0.53)		
L. Lerner Index			0.1019				0.0805	
			(1.62)				(1.45)	
L. Boone Indicator				– 0.0248**				0.0335
				(– 2.21)				(0.33)
R-Sq. Within	0.19	0.19	0.19	0.19	0.09	0.09	0.09	0.09
Bank-Level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust S.E	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

	C) GIIPS			
	(1)	(2)	(3)	(4)
Panel A: Dependent variable = Profit Sheet Efficiency				
L. Concentration—Assets	– 0.0054			
	(– 1.10)			

Table 6 (continued)

	C) GIIPS			
	(1)	(2)	(3)	(4)
L. H-Statistic		0.6869		
		(0.88)		
L. Lerner Index			– 0.1465	
			(– 0.43)	
L. Boone Indicator				– 0.0664
				(– 1.06)
R-Sq. Within	0.33	0.33	0.32	0.33
Panel B: Dependent variable = Balance Sheet Efficiency				
L. Concentration—Assets	0.0007			
	(1.59)			
L. H-Statistic		– 0.1648***		
		(– 3.59)		
L. Lerner Index			– 0.1372**	
			(– 2.07)	
L. Boone Indicator				0.0143**
				(2.49)
R-Sq. Within	0.75	0.75	0.75	0.75
Panel C: Dependent variable = Fin. Health Efficiency				
L. Concentration—Assets	0.0012			
	(1.35)			
L. H-Statistic		0.0808		
		(0.33)		

Table 6 (continued)

	C) GIIPS			
	(1)	(2)	(3)	(4)
L. Lerner Index			0.1824*	
			(1.88)	
L. Boone Indicator				0.0063
				(0.42)
R-Sq. Within	0.41	0.41	0.41	0.41
Bank-Level controls	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes
Bank F.E	Yes	Yes	Yes	Yes
Robust S.E	Bank	Bank	Bank	Bank

This Table shows the fixed effects panel data estimations with alternative proxies for bank efficiency. Besides the Full Sample (regs. 1–4), we also run the same specification for the Non-GIIPS (regs. 1–4) and the GIIPS subsample (regs. 1–4). GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain. The non-GIIPS subsample includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Netherlands, Poland, Sweden, and United Kingdom. Each panel (A, B, and C) uses the same independent variables but a different dependent variable to measure bank efficiency: Profit Sheet (Panel A), Balance Sheet (Panel B), and Financial Health (Panel C). For the sake of brevity and due to space constraints, we only report the statistics for the core independent variable of interest – Concentration—Assets (cols. 1), H-Statistic (cols. 2), Lerner Index (cols. 3), and Boone Indicator (cols. 4). Besides year and bank fixed effects, each regression also controls lagged bank-level, industry-level, and country-level variables (the same variables as reported in Table 5). The t-statistics in parentheses are calculated from standard errors clustered at the country level. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively measures the degree of competition (lower elasticity of profits to marginal costs), and lower values indicate a higher degree of competition. Thus, the positive estimated coefficient on the Boone Indicator suggests that competition positively affects the efficiency of European banks.

Although the general picture suggests that competition positively affects bank-efficiency across several dimensions (Overall, Profit Sheet, Balance Sheet, and Financial Health), we find an opposite result concerning the H-Statistic in the GIIPS subsample (see Panel B). The higher this measure (i.e., higher competition), the lower is the estimated bank efficiency at the GIIPS subsample, ceteris paribus. Thus, the evidence available that more competition drives higher efficiency holds for Concentration – Assets, Lerner Index, and Boone Indicator, but not for the H-Statistic. However, this caveat applies only for the Balance Sheet dimension of efficiency.

Are there feedback effects? Granger Causality analysis

Since there is a potential feedback effect between efficiency and the remaining bank-level and country-level variables, meaning efficiency may affect bank concentration, while bank concentration may also impact efficiency scores, we report the results from the Granger causality tests.

Table 7 reports the Granger Causality tests for panel data as proposed by Dumitrescu and Hurlin (2012) for the overall bank-efficiency score (Efficiency-Overall). Each row in the Table reports a bi-variate Granger test between the variable (first column) and Efficiency-Overall (y) for both directions ($x\text{-}>y$ and $y\text{-}>x$). The optimal lag length is selected by minimizing the Bayesian Information Criteria (BIC). Again, we run the analysis for the full sample and the non-GIIPS and GIIPS subsamples.

The overall assessment using a threshold of 95% confidence intervals suggests that in general the efficiency measures are Granger-caused but do *not* Granger-cause the bank and country-level variables. For example, on Panel A (full sample), *Leverage, ROA, Net Interest Margin, Nonperforming/Gross Loans, Growth Assets, Growth Leverage, Gov. Growth of Credit/Assets, Government Gross Debt (% of GDP),* and *Unemployment* Granger-cause the overall efficiency measure, but not the other way around. The test suggests that the only variable that feedback into the overall efficiency measure (Granger bi-causality) in the full sample is *Loans/Deposits*.

Further, except for the variables *Nonperforming/Gross Loans*, and *Gross Gov. Debt*, which consistently Granger-cause the overall efficiency for the full sample and the two subsamples, there seems to be a significant heterogeneity between the GIIPS and non-GIIPS countries. For example, *Growth Assets* and *Net Interest Margin* do not appear to Granger-cause the overall efficiency index in the GIIPS sample, as opposed to the results we find in the entire sample and non-GIIPS subsample. Additionally, bank competition as measured by the *Lerner Index* seems to be Granger-caused by the overall efficiency index, but only in the GIIPS subsample.

The Granger causality tests suggest that overall bank efficiency is generally Granger-caused by bank-level and macroeconomic variables, but not the other way around. Additionally, such a relationship is more reliable in the non-GIIPS than in

Table 7 Granger causality tests with the overall efficiency index (feedback effects and direction of Granger-causality)

Variable (x)	A) Full Sample				B) Non-GIIPS				C) GIIPS			
	p-Value (x->y)	*p-Value (y->x)*	*Opt. Lag*	*Assessment*	*p-Value (x->y)*	*p-Value (y->x)*	*Opt. Lag*	*Assessment*	*p-Value (x->y)*	*p-Value (y->x)*	*Opt. Lag*	*Assessment*
Ln(Assets)	0.721	0.057	2	No Granger Causality	0.665	0.023	2	Unidirectional: y->x	0.983	0.959	2	No Granger Causality
Leverage	0.003	0.781	2	Unidirectional: x->y	0.178	0.676	2	No Granger Causality	0.001	0.227	2	Unidirectional: x->y
Loans/ Deposits	0.000	0.000	2	Bidirectional Granger Caus	0.000	0.000	2	Bidirectional Granger Caus	0.563	0.000	2	Unidirectional: y->x
ROA	0.043	0.743	2	Unidirectional: x->y	0.190	0.850	2	No Granger Causality	0.083	0.751	2	No Granger Causality
Net Interest Margin	0.000	0.276	2	Unidirectional: x->y	0.000	0.428	2	Unidirectional: x->y	0.666	0.430	2	No Granger Causality
Non Performing / Gross Loans	0.001	0.387	2	Unidirectional: x->y	0.008	0.593	2	Unidirectional: x->y	0.043	0.568	2	Unidirectional: x->y
Z-Score	0.795	0.471	2	No Granger Causality	0.889	0.442	2	No Granger Causality	0.789	0.900	2	No Granger Causality
Concentration—Assets	0.376	0.590	2	No Granger Causality	0.198	0.443	2	No Granger Causality	0.688	0.828	2	No Granger Causality

Table 7 (continued)

Variable (x)	A) Full Sample				B) Non-GIIPS				C) GIIPS			
	p-Value (x->y)	*p-Value (y->x)*	*Opt. Lag*	*Assessment*	*p-Value (x->y)*	*p-Value (y->x)*	*Opt. Lag*	*Assessment*	*p-Value (x->y)*	*p-Value (y->x)*	*Opt. Lag*	*Assessment*
H-Statistic	–	–	2	–	–	–	1	–	0.146	0.066	2	No Granger Causality
Lerner Index	0.704	0.577	1	No Granger Causality	0.755	0.577	1	No Granger Causality	0.219	0.049	1	Unidirectional: y–>x
Boone Indicator	0.149	0.580	2	No Granger Causality	0.074	0.831	1	No Granger Causality	0.988	0.478	2	No Granger Causality
Growth—Assets	0.000	0.802	2	Unidirectional: x->y	0.000	0.612	2	Unidirectional: x->y	0.457	0.730	2	No Granger Causality
Growth—Leverage	0.035	0.775	2	Unidirectional: x->y	0.678	0.536	2	No Granger Causality	0.034	0.646	2	Unidirectional: x->y
Growth—Credit / Assets	0.000	0.060	1	Unidirectional: x->y	0.000	0.769	1	Unidirectional: x->y	0.000	0.002	1	Bidirectional Granger Caus
Gov. Gross Debt	0.000	0.115	2	Unidirectional: x->y	0.005	0.181	2	Unidirectional: x->y	0.018	0.407	2	Unidirectional: x->y
Growth—GDP	0.214	0.261	2	No Granger Causality	0.096	0.287	1	No Granger Causality	0.208	0.679	2	No Granger Causality
Growth—CPI	0.550	0.000	1	Unidirectional: y->x	0.423	0.001	1	Unidirectional: y->x	0.654	0.106	2	No Granger Causality

Table 7 (continued)

Variable (x)	A) Full Sample				B) Non-GIIPS				C) GIIPS			
	p-Value (x->y)	*p-Value (y->x)*	*Opt. Lag*	*Assessment*	*p-Value (x->y)*	*p-Value (y->x)*	*Opt. Lag*	*Assessment*	*p-Value (x->y)*	*p-Value (y->x)*	*Opt. Lag*	*Assessment*
Unemployment	0.000	0.307	2	Unidirectional: x->y	0.000	0.002	2	Bidirectional Granger Caus	0.088	0.898	2	No Granger Causality

This Table shows the results of the procedure proposed by Dumitrescu and Hurlin (2012) to detect Granger causality in panel datasets. The null hypothesis of the tests is that one independent variable, "x", does not Granger-cause the dependent variable "y", and vice-versa. The "y" variable is the overall efficiency index. We report the p-Value of all bivariate tests and in both directions (*x->y* and *y->x*). Besides the Full Sample (Panel A), we also run the same specification for the Non-GIIPS (Panel B) and the GIIPS subsample (Panel C). GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain. The non-GIIPS subsample includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Netherlands, Poland, Sweden, and the United Kingdom. For our conclusions, we use the 95% confidence interval as a threshold. Optimal lag is computed using the Bayesian Information Criteria (BIC)

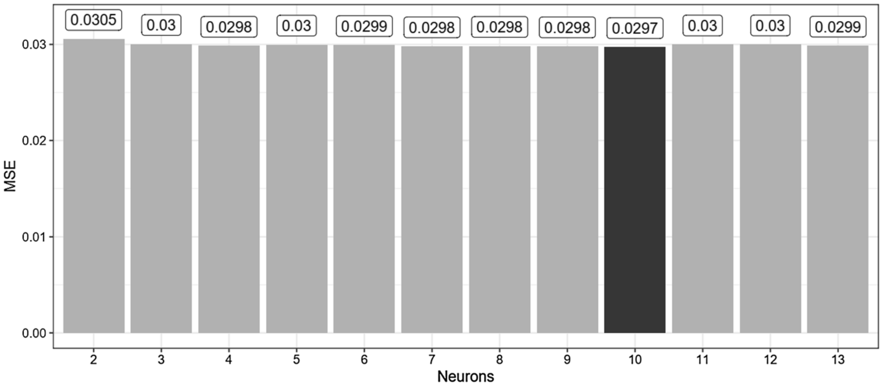

Fig. 6 Tenfold cross-validation result

the GIIPS subsample, where such a nexus is weaker. *Non-performing/Gross Loans* and *Gross Gov. Debt* are the only variables that consistently Granger-causes overall efficiency in all samples. Finally, there is weak evidence of feedback effects from *Efficiency-Overall* and the determinants of efficiency with the exception being *Loans/Deposits* where Granger-causality runs in both directions in the full and non-GIIPS samples.

Robustness check: RENNA modelling

The ten-fold cross-validation (10FCV) technique was applied to determine the best network architecture, mapping the error behavior in different configurations of layers and neurons. The optimum layout search yielded a network architecture formed by 10–10 neurons in a single hidden layer. Figure 6 summarizes the Mean Squared Error (MSE) obtained for each neuron quantity under a single layer when observing the 10FCV technique.

To avoid over fitting, we followed Srivastava et al. (2014) and applied a layer dropout of 20% to regularize the network. Another common problem in evaluating ANN is the sensitivity to backpropagation errors against the outliers present in the dataset. The RENNA procedure performed scale transformation in variables to mitigate the influence of outliers and backpropagated errors using Adam optimization as discussed by Kingma and Ba (2014), which presents features such as little memory requirement, computational efficiency, and robustness against noisy and sparse gradients that can happen in the presence of outliers. The Adam algorithm uses a type of signal-to-noise ratio to influence optimization, forming automatic annealing. The annealing concept is used in robust learning, as pointed by Du and Swamy (2013).

Results presented in Fig. 7 indicate the distributional profile obtained for each one of the 10FCV mean squared errors (MSEs) for the random effects, fixed effects, and fixed effects with risk-taking variable models. The MSEs fluctuated around 0.030 for the three models, thus indicating a good predictability power. Besides, ten neurons were found to be the best configuration for a single-layer structure in each one

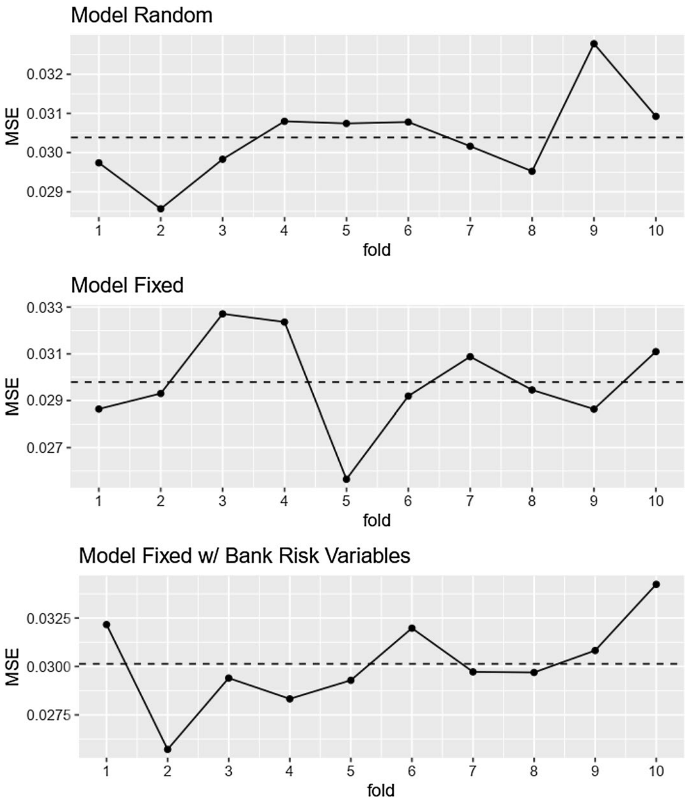

Fig. 7 10FCV results for the single random and the two alternative fixed-effect models

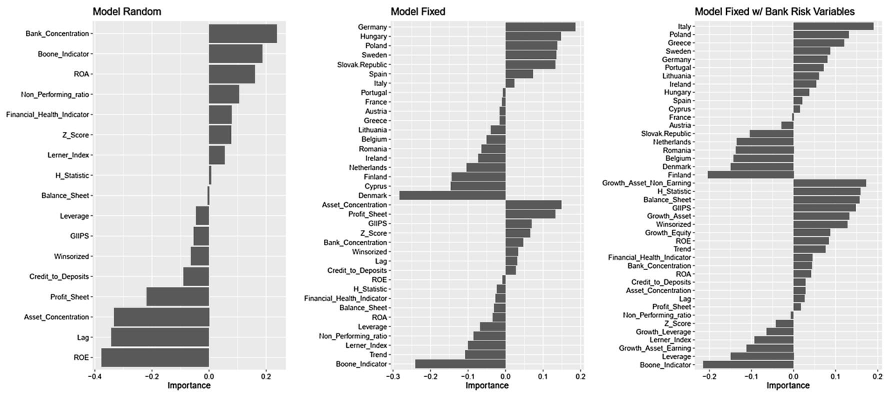

Fig. 8 The relative importance of contextual variables for each model, computed following Olden et al. 2002

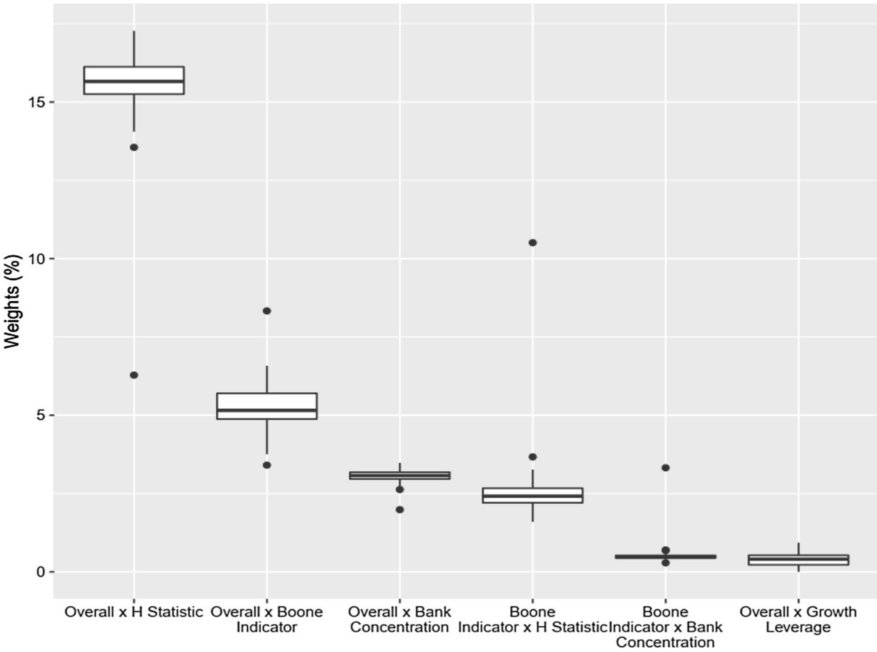

Fig. 9 Endogeneity weights for pairs of models 1–8

of these three models. On the one hand, a single neuron would denote the absence of nonlinear interactions among efficiency and contextual and risk-taking variables. On the other hand, 10 neurons for predicting efficiency scores suggest the presence of strong nonlinear interactions between a competition structure and efficiency scores to accurately predict bank efficiency at profit sheet, balance sheet, and financial performance stages.

Figure 8 reports on the relative importance and signs of the contextual variables impact on efficiency scores in EU banks under three assumptions: random effects, fixed effects, and fixed effects with risk-taking variables. Because our previous econometric analysis focuses on the latter, we anchor our interpretation of results based on the fixed effects with risk-taking variables, giving particular attention to the concentration and competition variables.

Consistent with our previous findings using panel data models, the big picture of the results exposed in Fig. 8 suggests that increasing competition is beneficial for bank efficiency. The contributions of Boone indicator (–), Lerner Index (–), and H-Statistic (+)not only occur in the expected direction, but are also economically meaningful, considering that the Boone Indicator is the single variable that explains efficiency the most. On the other hand, the contribution of Assets Concentration is positive but exceedingly small in magnitude (<0.04). Thus, evidence suggests that increased competition in EU banks improves the efficiency level of best performers, which is consistent with previous findings favoring the competition-efficiency hypothesis.

Notwithstanding these findings, the heterogeneity of the results presented in Fig. 8 is remarkable in terms of the relative importance order and the signs of the contextual variables. These results suggest that the feedback process (endogeneity) between bank efficiency and its competition structure is obfuscated by risk-taking variables given the changes in importance signs when putting all models into perspective. The relative importance of each model and its interaction pairs in explaining overall residual variance are presented in Fig. 9. Putting into perspective the results obtained for 100 bootstrap replications, the overall bank efficiency offers weak feedback with other variables related to bank competition structures apart from Boone Indicator and Bank concentration. The combined feedback effect of all model pairs on overall residual variance is approximately 25%, which is low when compared to the maximal endogeneity effect obtained when all eight models account individually for 12.5% of the total residual variation with a maximal joint effect of 43.75% = 12.5%*12.5%*28, where 28 is the number of combinations taken two by two obtained from models 1–8.

In summary, overall efficiency in EU banks appears to be weakly endogenous to competition due to imperfect, oligopolistic structures where a moderate appetite for risky loans may play a relevant role in short-term performance. Precisely, banks in stagnant economies such as GIIPS may benefit from short-term loan leveraging by losing credit risk controls for bad loans. However, from a longer term perspective, the beneficial effects of bank competition on overall efficiency may counterbalance higher leveraging due to excessive risk-taking. Empirical findings suggest that competition's partial, ceteris paribus effect on efficiency in the European banking sector is generally positive, particularly for the balance sheet dimension of efficiency where impacts are substantial from both statistical and economic standpoints. While non-performing loans and gross government debt (% of GDP) consistently Granger-cause overall efficiency in all samples, we find that macroeconomic variables are more relevant to explain bank efficiency at the non-GIIPS subsample. At the GIIPS subsample, the probability of default of the banking system as measured by the Z-score is an essential determinant of bank efficiency. Furthermore, bank-level and macroeconomic-level variables usually Granger-cause efficiency scores, and we find limited evidence of feedback effects between those variables. As a caution note, although these results indicate interesting precedence relationships, they do not allow us to infer causality from one variable to another.

Conclusions and directions for future research

This paper proposes a novel robust econometric/neural network approach to unveil the relationships between bank efficiency and the market competition structure in the EU banking industry. While a dynamic network DEA model is used as a cornerstone to derive non-parametric efficiency measurements for three relevant productive stages of the banking industry—*profit sheet*, *balance sheet*, and *financial indicators*—this research departs from previous studies by bridging gaps between traditional econometric models and machine learning approaches. By doing that we delimit the feedback boundaries whenever they exist between market structures and bank performance.

Empirical findings suggest that the partial, ceteris paribus effect of competition on efficiency in the European banking sector is generally positive, particularly for the balance sheet dimension of efficiency where impacts are substantial from both statistical and economic standpoints. While non-performing loans and gross government debt (% of GDP) consistently Granger-cause overall efficiency in all samples, we find that macroeconomic variables are more relevant to explain bank efficiency at the non-GIIPS subsample. At the GIIPS subsample, the probability of default of the banking system as measured by the Z-score is an essential determinant of bank efficiency. Furthermore, bank-level and macroeconomic-level variables usually Granger-cause efficiency scores, and we find limited evidence of feedback effects between those variables.

The ruling implications for EU policy makers and regulators are related to an increased fostering of Fintech companies to increase competition, targeting market niches not traditionally addressed by large banks such as micro-finance initiatives that could be adopted by online platforms. On the other hand, novel mechanisms for credit risk scoring should be promoted by authorities such as those based on artificial intelligence and/or fuzzy logic that are capable of capturing borrower nuances that cannot be captured or modeled using traditional econometric models. While bank competition should be encouraged to increase, the joint adoption and full disclosure of novel credit risk assessment should be mandatory, unveiling this classic black-box to the banking industry.

Future research in banking should keep addressing mixed modeling methodologies for capturing the relationships between efficiency and market competition. Notwithstanding the astray nature of econometric and machine learning techniques, a complementary approach is deemed necessary where the advantages of one design can overcome the weaknesses of the other. For example, while econometric methods can capture significant statistical relationships given some certain distributional assumptions, they fall short in simultaneously handling numerous variables with nonlinear interactions among each other.

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Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

Availability of data and materials The data that support the findings of this study are available from Thomson Reuters Eikon, but restrictions apply to the availability of these data since they were used under license for the current study, so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of Thomson Reuters Eikon.

Code availability The codes generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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