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Interfaces with Other Disciplines

Bank branch efficiency under environmental change: A bootstrap DEA on monthly profit and loss accounting statements of Greek retail branches

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ABSTRACT

The objective of this study is to measure efficiency change of bank branches under external environment deterioration. In particular, we utilize a bootstrap input-oriented profit DEA and investigate homogeneous and heterogeneous branches according to branch size and location to measure efficiency change by contrasting expansion, recession and capital control effects that constitute a unique phenomenon in the postwar period in the Eurozone. Our primary research explicitly focuses on the whole retail network of a Greek systemic bank based on unpublished monthly branch Profit and Loss statements and covers the period from January 2006 to July 2016. We find that early and deep recession reduces on average branch network efficiency. The imposition of capital controls (end-month June 2015) initially causes marginal effects with a subsequent efficiency improvement in the first seven months of 2016 when economic conditions are normalized. The paper documents that branch size and location matter. On the whole, we capture efficiency deterioration in the long-run contrary to recent European evidence. Apart from the efficiency measurement over time, we provide directions to bank management for performance improvement in the capital control period. More specifically, a bootstrap DEA-based Decision Tree classification exactly quantifies for the first time a potential upgrading of underperforming branches and a second-stage bootstrap DEA regression locates important efficiency drivers such as the diversification of income and the deposit- oriented activity that could improve efficiency of the total retail network.

1. Introduction

Nowadays a turbulent economic environment stimulates researchers to measure efficiency and performance change in diverse types of businesses. Banks, in particular, are mostly affected by recessions and economic downturns that might cause inefficiency. Fethi and Pasiouras (2010, p. 196) suggest that the estimation of bank branch efficiency over successive time periods is an important area of research deserving special attention. The specific suggestion motivates us to provide an efficiency measurement at bank branch level, taking systematically into account substantial external environmental alteration and diverse stages of recession.[1] More specifically we contrast expansion and recession effects, emphasizing capital control effects that constitute a unique phenomenon in the postwar period in the Eurozone. To the best of our knowledge, this is the first study that provides an in-depth empirical analysis of efficiency change at bottom-level banking across successive stages of recession. But above all the factor that makes our paper original is its focus on the very turbulent period of capital controls since their significance (as that of the Greek crisis as a whole) stretches beyond the borders of Greece, and attracts the interest of academics, bank managers, regulators, and policy makers seeking to explain the nature and the implications of the specific totally unexplored and unpredicted phenomenon that lasts until today (December 2016). Capital controls initially causing the inactivation of important banking function operations given the bank holiday that took place (end-month June 2015), then helped stabilize the liquidity of the banking system through the restraint of deposit outflows and capital transfers abroad. Thus, we offer an attractive case study representing the crisis bank-driven Greek economy that is a member of the Eurozone and its banking institutions are an

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[1] The vast majority of research on bank efficiency and performance concerns the bank as a whole and not its branches (Fethi and Pasiouras, 2010). However, relevant literature (Paradi and Zhu, 2013) claims that from many aspects efficiency analysis at the branch level is more significant and challenging than at the banking institution level. The general assessment of the literature leads to the conclusion that there is no branch efficiency study on exogenous factors such as recession effects, a fact that stimulates our research to thoroughly explore the specific phenomenon.

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integral part of the single European monetary system supervised by the ECB and also characterized by similar banking operations (pure retail banking) with other EU peripheral countries.

In order to do this, our study provides sharper insight into efficiency change within separate periods of recession and capital controls to capture efficiency effects caused by the drastic environmental change of 2008 (Aggelopoulos & Georgopoulos, 2015). More precisely, we start with the last phase of the expansion (Period A: January 2006–August 2008), subsequently moving to early recession (Period B: September 2008–December 2010), afterwards exploring the deep recession (Period C: January 2015–June 2015) and finally ending with the imposition of capital controls (Period D: July 2015–July 2016) to the economy testing the long efficiency persistence of the banking industry under very unfavorable conditions.[2] Due to the considerable research interest, we split the capital control period into two stages, the first stage (Period Da: July 2015–December 2015) where the phenomenon caused a substantial shock to the domestic banks and the second stage (Period Db: January 2016–July 2016), following the successful conclusion of the recapitalization of Greek Banks in December 2015, in the course of which a relative stabilization of the economy is observed as was reflected in the modest pick-up in economic activity and the limited formation of new problem loans (Moody's, 2016).

Utilizing a reliable bank branch efficiency evaluation based on an input-oriented profit bootstrap DEA (Simar & Wilson, 2000, 1998), we are able to fully understand all crucial aspects of the bank's internal operating process (Berger & Humphrey, 1997; Paradi & Zhu, 2013) and measure efficiency across the different selected time periods and diverse branch groups. In this context, we can locate efficiency asymmetries across the retail bank network caused by branch-specific traits such as branch size (small, medium, large branches) and location areas (urban, rural, island) that produce branch heterogeneity and efficiency gaps across different branch types. But we are not interested only in the exploration of efficiency differences over time. We also intend to make suggestions to bank management for efficiency improvement. In this case, the most recent efficiency state of the branches is needed, thus we use their performance assessment for the second stage period of capital controls (that is the latest period of our investigation) as starting point of our analysis and make two contributions. First, we provide an accurate input-oriented direction to bank management determining to what extent the input variables should be reduced in order to upgrade the performance of the inefficient homogeneous branches. In particular, for the first time in banking industry we propose a bootstrap DEA-based Decision Tree (DT) classification[3] to provide the quantitative directions to worse performers on how to upgrade their efficiency in terms of input reduction (Section 5.4).[4] Second, we offer crucial efficiency drivers that reflect branch-specific determinants for the performance improvement of the total retail network utilizing a second-stage regression (for the two-stage bootstrap DEA approach, see Biener, Eling, & Wirfs, 2016) (Section 5.5). The results of the two procedures were incorporated into the operational plans of the executives of the bank under study. Hence, the main contribution of our empirical analysis is that it reveals how capital controls and recession affects branch efficiency and how bank management could take specific measures to upgrade performance within the retail network.

Our internal bank data set is derived from the unpublished monthly Profit and Loss statements of the whole retail network of 362 branches of a large commercial bank. The specific unique dataset at bottom-level banking strengthens our study originality further as bank branches are the primary sources of operational profits and expenses for a banking institution (Berger, Leusner, & Mingo, 1997) and they represent the largest source of them for a bank (Paradi & Zhu, 2013).[5] The oligopolistic nature of the Greek retail banking system consisting of four systemic institutions (i.e., The National Bank of Greece, Piraeus Bank, Alpha Bank and Eurobank) allows a broad generalization of our findings. The specific oligopolistic players exhibit similar strategic behavior, offer very comparable financial services, and show similar structure as regards activities, size and location of their branches as they compete for the same target market. In the case that an oligopolistic player innovates with a new financial product, the other three competitors immediately react and copy the innovating institution thus offering the new product through their retail network as well. Consequently, the branches of the four banks exhibit high comparability.

Our main results indicate an immediate negative efficiency impact of early recession which increases even more when recession deepens concerning all branch groups, with island and small branches presenting a lower efficiency downgrading. In addition, our findings shed light for the first time into the unexplored phenomenon of capital controls, revealing relatively limited efficiency change in the first six months (July 2015–Dec 2015) apart from the tourist branches which were mostly affected by the capital control restrictions during the peak tourist season. Somewhat unexpectedly, we measured a certain efficiency improvement in the first seven months of 2016.

We discussed this finding analytically with the bank managers and concluded that capital controls inactivated vital functions of banks hence limiting some further adverse efficiency effects (i.e., capital transfers abroad). In addition, after the first shock of recession years, banking institutions adjusted to a satisfactory degree to the new environment and were able to manage with greater experience in crisis management the new threats of the external deterioration. Also, as time has gone by under capital controls, the formation of new non-performing loans (NPLs) has been declining, and new opportunities for generating interest and fee income have emerged benefitting from the first signs of improvement in the economic climate of the country as was reflected in the upgrading of credit rating of the Greek Economy from Standard and Poor's (S&P) credit rating agency at the beginning of 2016 (see Table 2, Moody's, 2016). Overall, the above contributions to efficiency change and improvement enable our study to clearly stand apart from several branch efficiency papers (see Berger & Humphrey, 1997; Fethi & Pasiouras, 2010).

The study is structured as follows: Section 2 presents efficiency analysis under branch homogeneity and heterogeneity. Section 3 describes the framework of the employed methodology, while Section 4 presents the data and some descriptive statistics. Section 5 illustrates the empirical results and the last section discusses the main findings.

2. Efficiency analysis and branch heterogeneity

It is important for the efficiency analysis to take into account branch-specific factors that influence branch efficiency such as location and size of branch. We deal with the specific branch

[2] The research ends in July 2016 because the MIS of the specific bank has not updated with the loan loss provisions (input variable) of the last few months.

[3] Until now, this approach has been used for other research tasks and in other industries (Seol et al., 2008; Lee and Park, 2005; Sohn and Moon, 2004).

[4] The resulting classification model can easily be assimilated by managers. Moreover, classification trees construction algorithms do not make any assumptions about the underlying distribution, whereas classification trees can be constructed relatively fast and their accuracy is comparable or superior to other classification methods.

[5] From a managerial point of view, bottom-level managers can substantially control operational cost and credit risk parameters thus notably contributing to the improvement of a bank's overall economic results.

heterogeneity by forming and analyzing groups of branches based on these characteristics.

The location factor refers to the differing business environments and accordingly differentiates branches that operate in urban, rural and island areas (Deville, 2009; Paradi & Zhu, 2013). The diversity of environments might be a crucial efficiency parameter (Camanho & Dyson, 2006; Das, Ray, & Nag, 2009; Fethi & Pasiouras, 2010; Paradi & Schaffnit, 2004; Zenios, Zenios, Agathocleous, & Soteriou, 1999). Depending on the different environment and the structure of the client base, each branch is organized to serve better a different kind of business. For example, branches operating in urban areas, where there is a high rate of population growth and businesses, are organized to deal efficiently with commercial accounts and credit applications. Generally, in an urban environment it is easier for bank branches to loan money but attracting cash savings are more difficult. In turn, branch customers in a rural area, which is characterized by a high rate of operative workers in the agricultural field and a high rate of retirees, tend to save money but are not as likely to be borrowers thus making difficult the granting of loans. Finally, branches in the tourist regions offer more cash based transactions such as currency exchange transactions during the peak tourist season while they deal with credit applications of tourist businesses during the off-peak season. Efficiency evidence on branch location is rather mixed. In particular, Paradi, Rouatt, and Zhu (2011) suggest that the advantage of branches operating in rural and island areas can be attributed to their specific characteristics such as less staff specialization and minimal role differentiation and high levels of cross training between employee types which improve branch productivity. In addition, employees of rural and island branches often remain with the branch for a significant period of time and may know their customers well (high level of Know Your Customer - KYC principle) thus leading to lower bad loans and higher profit efficiency scores. Also, Zenios et al. (1999) show that island branches present better efficiency scores than urban branches during the peak tourist season. Giokas (2008b) and Noulas, Glaveli, and Kiriakopoulos (2008) find that rural and island placed branches in Greece tend on average to be more efficient than urban branches. By contrast, Bos and Kool (2006) point out that urban branches outperform rural ones due to the positive efficiency effect of the population factor.

The second factor, the size of branch, accounts for the effects of scale on efficiency. The branch size is typically indicated by the deposit balances or the number of employees and the branches are split into small, medium and large ones. Each branch group has specific operating characteristics given differences in structures of customer base, branch manager's experience levels and exploitation of economies of scale. In particular, large branches have a broad customer base, various lines of business incomes which serve as a hedge against each other, separate teams for the customer financing and investment services and in most cases high level of branch managers' experience. Also, they are typically located favorably close to significant customer flows. In turn, small branches present increased ability to efficiently generate revenues and control costs. In addition, these branches exploit the high levels of cross training between employee types although in some cases specialized investment and financing advisors have to lend their hand to the daily services which deteriorates their sales performance (Eskelinen, Halme, & Kallio, 2014). Finally, the medium sized branches exploit both the advantages of economies of scale effects and the flexibility that offers them their current level of operations focused solely on boosting their growth rates by increasing the loan (mostly) and deposit balances. Bank efficiency literature demonstrates no agreement on the impact of size on efficiency. More specifically, some studies report that inefficiency increases with bank size (Bauer, Berger, & Humphrey, 1993), since as banks grow larger, it becomes harder to efficiently create revenues compared to small banks, whereas all banks are equally able to control costs. Other studies document an opposite relationship (Berger & Humphrey, 1992; Drake, Maximilian, & Simper, 2006; Galan, Veiga, & Wiper, 2015). As regards studies at the branch level, they document that as branch size (e.g., measured by the size of deposit balances) increases, efficiency rises too (Eken & Kale, 2011; Giokas, 2008b; Noulas et al., 2008).

3. Methodology and efficiency change analysis

3.1. Bootstrap DEA

Due to our investigation of different environmental frameworks, we decide to utilize DEA.[6] DEA's main usefulness lies in its ability to identify inefficient units and the branches to benchmark. This might enable management to develop an understanding of the nature of inefficiencies and re-locate scarce resources to increase productivity and performance. DEA might be an effective performance tool for multidimensional contexts which involve setting multiple inputs against multiple outputs (Camanho & Dyson, 2005; Hartman, Storbeck, & Byrnes, 2001; Paradi & Zhu, 2013). As we explore efficiency change in a dynamic environment, our methodology requires flexibility (Wu, Yang, & Liang, 2006) that can be provided by DEA models in terms of input/output selection, and returns to scale assumptions (Paradi & Zhu, 2013) hence helping us to effectively adjust our methodology to changing real-life circumstances reflected in the dataset. We also view that DEA has the advantage of imposing less structure on the efficient frontier[7] as compared to stochastic frontier approach (SFA) that uses strong assumptions regarding the form of the efficient frontier (Biener et al., 2016). An advantage of DEA is that there is no preconceived structure imposed on the data in determining the efficient braches (Avkiran, 1999).

[6] After a systematic review of the related literature, we were assured that DEA models are well established in the operational research literature (Asmild and Zhu, 2016; Fukuyama and Matousek, 2017; Fethi and Pasiouras, 2010). DEA assigns an efficiency score of each branch with that of each peer and identifies a frontier comprising best performers. Those branches that lie on the frontier are recognized as efficient, and those that do not, as inefficient (Mostafa, 2009). In this way, the specific methodology helps management to identify the operational areas that most need improvement (Paradi and Zhu, 2013). DEA and their extensions dominate bank efficiency literature (Berger and Humphrey, 1997; Fethi and Pasiouras, 2010; Paradi and Zhu, 2013) as compared to classification techniques (e.g., neural networks, support vector machines, multi-criteria decision aid, decision trees) and is expected to play a more important role in bank branch studies in future (Paradi and Zhu, 2013; Ray, 2016). At branch level, Paradi and Zhu (2013) reported recently 80 DEA studies over the period 1985-2011 characterized by a significant diversity in terms of the employed approach (production, profit, and intermediation), the inputs-outputs selection, the returns to scale characterization and the sample sizes. Almost all of them are country-specific in nature (*inter alia* 9 pure Greek studies with traditional DEA) and only 2 studies contain cross-country comparisons. At bank level, there are few studies that attempt to capture efficiency effects of recession analyzing the varying time dimension of its efficiency impact (Tsionas et al. 2015; Fukuyama and Matousek, 2011; Demirgüç-Kunt, Detragiache & Gupta, 2006).

[7] As alternative to traditional bank management tools, frontier efficiency analyses allow management to objectively identify best practices in complex operational environments. Six different approaches, namely, data development analysis (DEA), free disposal hull (FDH), stochastic frontier approach (SFA), econometric frontier approach (EFA), thick frontier approach (TFA), and distribution free approach (DFA), have been reported in the literature as methods to evaluate bank efficiency. These approaches basically differ in how much restriction is imposed on the specification of the best practice frontier and the assumption on random error and inefficiency. Compared to other frontier efficiency methods, DEA is a better way to organize and investigate data because it allows efficiency to change over time and requires no prior assumption on the specification of the best practice frontier (Wu et al., 2006). In addition, DEA methods have been recognized very appropriate for comparative efficiency measurement, especially to capture non-allocative managerial forms of inefficiency, the so-called X-inefficiency (Mostafa, 2009). Thus, DEA is a leading approach for the performance analysis in relevant literature (for example see Wu et al., 2006).

Since conventional DEA has several statistical limitations such as the precision of efficiency estimates (Banker, 1993; Dyson et al., 2001), we use the bootstrap procedure[8] to account for some of these. More precisely, we apply a bootstrap DEA model (Simar & Wilson, 2000, 1998),[9] for the extraction of branch efficiency scores (which we compare with the conventional DEA outcomes) as bootstrap DEA provides confidence intervals for the efficiency estimations and thus allows accurate comparison across diverse branch groups. The use of bootstrap makes it possible to overcome structural deficiencies that are differently biased and bias varies with sample size when standard DEA techniques are used (Staat, 2002). Bootstrap enables to identify the true differences in efficiency and hence to compare branches belonging to different groups through their rescaled individual efficiency scores on one common basis (Staat, 2002). So, Fethi and Pasiouras (2010) conclude that the findings of most DEA studies that do not employ appropriate bootstrapping techniques may be biased.

We ran a bootstrap step proposed by Simar and Wilson (2002) in order to choose between CRS and VRS where the VRS assumption was verified.[10] Thus, having estimated the models with the VRS scale assumption, it is then possible to calculate the bootstrapped efficiency scores of the different bank branches involved in our analysis. Following closely Simar and Wilson's (2000, 1998) methodology, the VRS efficiency measures are estimated in each bootstrap replication (i.e., 2000 bootstrap replications) according to a specific procedure-algorithm that is shown in the Appendix A.[11] We measure efficiency in terms of Shephard's (1970) input distance function, which is the reciprocal of Farrell's measure. Shephard's measure is hence one or larger for the DMU. Consequently, a technically efficient bank branch will have a value of one, whereas a value more than one shows how much the input should be reduced for the bank branch to be considered technically efficient.

It is well known that DEA models are sensitive to extreme outliers in the output, size, and dispersion of the branches. In order to minimize this drawback, we work with branch homogeneity as well. A homogeneous group of branches in DEA is crucial if confounding effects are to be minimized and findings are to be comparable (Avkiran, 1999; Mostafa, 2009). Moreover, DEA can be used more effectively with a smaller sample size than other techniques such as SFA (Banker & Cummins, 2010). This is important for our analysis since in the case of branch homogeneity we inevitably reduce our bank branch sample (however the remaining branches are over 110). Another caveat of DEA, especially in the case of using small homogeneous samples, is that those decision-making units (DMUs) indicated as inefficient are only efficient in relation to others in the sample. In other words, it is possible for a branch outside the sample to achieve a higher performance than the best practice branch in the sample with the result that the latter does not necessarily produce with the minimum input for a given level of output (Avkiran, 1999). Therefore, we also select all the branches in the retail network to create a global efficiency picture.

We define branch management efficiency as the ability to minimize controllable inputs (e.g. controllable operating expenses and loan loss impairments) at a given level of revenue streams (e.g. interest income and fee income) and decide to select the input-oriented[12] DEA approach correspondingly. From this point of view, the most efficient branches will be better at minimizing controllable operating expenses and loan loss impairments and, consequently, will be better at stabilizing profits. This selected approach fully reflects the real conditions in Greece as a significant reduction in the number of bank branches and staff during recession years was observed in the domestic banking industry. In this way, branch management attempted to stabilize branch profitability by reducing operational expenses and managing credit risk.

We adopt in our analysis the profit model[13] because this "…captures the full impact of any adverse environmental factors on revenues as well as costs" (Drake et al., 2006).[14] In addition, the profit model incorporates the service quality dimension and its use might help take into account unmeasured changes in the quality of banking services by including higher revenues paid for the improved quality. We opt for the profit based approach for the additional reason that during a period of recession, management tries to retain the profitability of loan portfolio, instead of increasing the loan balances (intermediation efficiency) and the transaction volumes (production efficiency) that is fully in accordance with the input minimization strategy. More specifically, efficient cost management and branch rationalization can be implemented through reducing controllable operating expenses thus excluding depreciation, bank overhead costs which are allocated to branches, and interest costs (since they are formed according to the bank's cost of funding).[15]

[8] Paradi and Zhu (2013) conclude that although 33 DEA papers at bank branch level have been published during the recent years (2006-2011), none of these applies bootstrap DEA.

[9] Simar and Wilson (1998) developed bootstrap algorithms which can be used to examine the statistical properties (bias, adjusted technical efficiency, confidence intervals etc.) of efficiency scores generated through conventional DEA.

[10] DEA follows a linear programming methodology to construct a non-parametric frontier over the data, and this frontier can then be used as basis to calculate the efficiency measure of the different branches, following either constant returns to scale (CRS - Charnes et al., 1978), or variable returns to scale (VRS – Banker et al., 1984) assumption. CRS implies a proportionate rise in outputs when inputs are increased. By contrast, VRS implies a disproportionate rise or fall in outputs when inputs are increased. Even in a homogeneous sample, branches may be operating at CRS or VRS. In our case, the calculated efficiency scores are based on an assumption of VRS, so that a branch is not penalized for the scale at which operates and over which it has no control (Gaganis et. al., 2009; Giokas, 2008a). Hence, as a branch grows in size, its efficiency would either fall or rise.

[11] Results were produced using the software package Fear 1.15 of Wilson (2008) based on the statistical package R.

[12] A DEA model can be analyzed in two ways, an input orientation and an output orientation. Input orientation examines the extent inputs can be reduced while maintaining output levels for an inefficient branch to become DEA-efficient, whereas output orientation explores the extent outputs can be raised given current input levels for the respective branch to become DEA-efficient (Biener et al., 2016; Mostafa, 2009; Avkiran, 1999). Obviously, during a cost-cutting exercise in the branch network or downsizing, the management could choose input minimization. In turn, during an exercise to expand market share of banking products and services, the strategic management priority could shift to output maximization.

[13] A DEA literature review reveals that branch performance can be measured through three different efficiency approaches: the production, the intermediation and the profit oriented approach. The production model views bank branches as producers of services using labor and other physical resources as inputs and providing services for taking deposits, making loans and others as outputs. The intermediation model recognizes the branches as collectors of deposits and other funds from customers (inputs) and subsequently as lenders of money in various forms of loans. The profit model, proposed by Drake et. al., (2006), in line with the stochastic frontier approach of Berger and Mester (2003), views bank branches as producers of profit components such as interest and fee income (outputs), using cost components as inputs such as operational expenses and the quality of loan portfolio.

[14] Drake et al. (2006) analyzing the impact of the 1997/1998 South East Asian crisis on the efficiency of Hong Kong's banking system found that the intermediation approach showed a marked decline in efficiency levels during 1997/1998 although this decline was not as dramatic as that recorded under the profit approach where in general it produced a much greater diversity in relative efficiency scores both across different size groups and different sectors. This result verified the assertion of Berger and Mester (2003) that in a dynamic external environment, a profit-based approach is better able to capture the diversity of strategic responses by banking institutions which modify costs but also impact on revenue streams.

[15] Credit risk management, in turn, focuses on the reduction of loan loss impairments by concentrating on remedial management via identifying viable customers and businesses, providing restructuring solutions to them, improving the collateral of loan accounts and maximizing recoveries of non-performing loans. In this context, branch managers might exploit the early warning systems to identify problematic situations and ensure proactive handling of potential non-performing loans (NPL).

To sum up, the present study proposes that an input-oriented profit approach is the most effective DEA instrument to measure efficiency change and explore diversity of strategic responses by branch networks, in the face of adverse environmental conditions (Berger & Mester, 2003; Drake et al., 2006) such as recession and capital control effects.

3.2. Input and output specification

Branch retail process is captured by the resources managed (inputs) and the results generated (outputs) by the branch managers. The selection of inputs and outputs is typically different in DEA studies depending on the research objective of each study and the specific nature of the data. A property of bootstrap DEA is that it is valid only asymptotically and its rate of convergence[16] depends on the sample size and the number of inputs and outputs (Kneip, Park, & Simar, 1998).[17]

Given that our study defines branch management efficiency as the ability to minimize controllable inputs (i.e., controllable operating expenses and loan loss impairments) at a given level of revenue streams (i.e., interest income and fee income), we followed the below procedure for the input/output selection: Firstly, we listed all possible inputs and outputs based on the available data set. Secondly, we focused on variables that are affected by branch managers, a task that was the output of a collaborative work with bottom- and top-level managers of the specific bank under study. Thirdly, we determined the level of data aggregation of the selected variables. From this point of view, we primarily decided to use single general input (OPEX, LLP) and output categories (INCOME, FEES). This was in accordance with the study purpose to evaluate consistently the average efficient or inefficient behavior of branch network and different branch groups under recession and capital control effects while at the same time the selected aggregated variables were considered adequate for that purpose by the bank management. Also, this choice was in line with Paradi and Zhu (2013, p. 67) and LaPlante and Paradi (2015, p. 36) who suggest that a certain degree of aggregation is necessary to improve the discriminatory power and reduce the dimensionality of the DEA model.

Therefore, the current study uses two general inputs: direct operating expenses (OPEX) and loan loss provisions (LLP) justifying by the fact that they comprise accounting expenses reported on branch P&L statement. To be more precise, the input OPEX is measured as the sum of three controllable cost components: (a) personnel expenses which include overtime salary costs and incurred losses stemming from operational risk; (b) running expenses of the buildings which include rents, electricity etc. and (c) other operating expenses of the branches, such as those for cash management activities (i.e., charges from cash-in-transit firms), telephone, insurance, advertising expenses, stationary and other supplies. It is worth pointing out, that we excluded depreciation, bank overhead and interest costs which are exogenous parameters for branch management. The input LLP is recorded in the branch P&L statement as an expense (and thus reduces branch net income) and is created on a monthly portfolio basis including consumer loans, small business loans and mortgages loans, using as observable data the day's payments loans are overdue (according to the International Accounting Standard –IAS- 39 and the general rule that a loan is classified as nonperforming when interest or principal has not been paid for more than 90 days). Specific provision coefficients (the criteria for the branch to create a LLP didn't change during the study period) are applied to loan portfolios, taking into account the collateral of each loan.

The incorporation of credit risk into bank efficiency analysis is justified by the relevant literature which indicates a positive relationship between inefficiency and bank risk-taking (Drake & Hall, 2003; Fiordelisi, Marquez-Ibanez, & Molyneux, 2011; Pasiouras, 2008). As regards the handling of bad loans and related factors (such as loan loss impairments) as an input or an output variable to efficiency models, three different approaches have been developed in the literature (Paradi & Zhu, 2013). The first treats bad loans as an output using the inverse value, the second uses bad loans as an undesirable output with an assumption of weak disposability and the last one moves loan losses to the input side where the lower the value is, the better. The intuition of the usage of LLP as an input is that loan loss impairments are actually a cost required to build up loan loss reserves in order to cover estimated loan losses (Laevan & Majnoni, 2003). Given the definition of retail process in Section 3.1 (where branch managers undertake actions to shield branch profitability during recession years through reducing loan loss impairments) and the relevant efficiency literature that verifies empirically the inclusion of LLP as an input variable, both at bank level (Asmild & Zhu, 2016; Drake & Hall, 2003; Drake et al., 2006; Fukuyama & Matousek, 2017; Tsolas & Charles, 2015) and branch level (Gaganis, Liadaki, Doumpos, & Zopounidis, 2009; Paradi et al., 2011), we incorporate LLP as an input in the bootstrap DEA efficiency model.

As regards the outputs side, our model incorporates the two main sources of revenues in retail banking: the non-interest income from fees[18] (FEES output variable) and the net interest income from lending and deposit operations (INCOME output variable). The revenue of non-interest income is recorded directly in the branch P&L statement in the form of fees and commissions which are direct prices for the sale of services linked to the management of customer accounts as well as for the sale of saving products. In turn, the revenue of interest income is recorded indirectly in the branch P&L statement, as a component of interest margins on loans and deposits. The bank prepares the income statement for each branch according to the concept of fund transfer pricing (Kimball, 1998), that allows interest income from lending and deposit transactions to be calculated in isolation for each branch. Consequently, the interest margin on deposits is defined as the difference ("spread") between return on deposits (e.g. a reference rate such as one month Euribor) and interest paid on deposits. Thus, the net interest income on deposits is the interest margin on deposits multiplied by the deposits balance. The same methodology is applied to measure the interest margin on loans which is the difference between interest earned on loans and cost of funding (e.g. a reference rate such as one month Euribor). As a result, the net interest income on loans is the interest margin on loans multiplied by loans balances. Consequently, the model's output variable of net interest income is the sum of net interest income on loans and deposits. During recession years interest income is suppressed and the branch management tries to differentiate sources of revenue by strengthening fee income. On the whole, given the stagnation of revenues in recession years, an input-oriented DEA suggests that the most efficient branches will be those that minimize controllable inputs (OPEX and LLP).

[16] Calculated as O^- (p+q), where p is the number of inputs and q is the number of outputs.

[17] It is well known that DEA is sensitive to variable selection. As the number of variables increases, the ability to discriminate between the branches decreases. Thus, to preserve a discriminatory power of DEA the number of inputs and outputs should be kept at a reasonable level (Mostafa, 2009). At the same time a basic criterion of DEA for selecting an appropriate sample size is to ensure that the sample size is at least three times larger than the sum of number of inputs and outputs (Avkiran, 1999). Our research design satisfies the specific criterion.

[18] Lozano –Vivas and Pasiouras (2010) opt for non-interest income as an additional bank output for a global sample.

3.3. The main methodological steps

In order to conduct an efficiency change analysis that will allow us to evaluate consistently the average efficient or inefficient behavior of branches under recession and capital control effects, the below stepwise methodological procedure is followed: Firstly, for each branch, average monthly input (OPEX, LLP) and output (INCOME, FEES) levels are calculated for each study period (i.e., last phase of expansion period - Period A, early recession period – Period B, deep recession period -Period C and capital control periods – Period Da and Period Db). Secondly, based on these averages and through an input profit-oriented bootstrap DEA model under VRS, independent branch efficiency assessments are conducted for each period and for each branch group (according to size and location) respectively. For detecting outliers, the approach of Wilson (1993) is implemented. Bootstrap estimates were determined for all the observations. Thirdly, given these branch efficiency estimates, average efficiency scores along with its components (DEA distance function estimates, bias corrected distance functions estimates, bootstrap bias, variance estimates, upper 95% confidence interval, lower 95% confidence interval) are calculated for each branch group and for each study period. Then, a bootstrap test proposed by Simar and Wilson (2000) is used to test hypotheses of the statistically significant differences between the means of the efficiency scores of the branch subgroups for the contrasted selected periods (i.e., Period A versus Period B, Period B versus Period C, Period C versus Period Da, and Period Da versus Period Db). Fourthly, based on the above efficiency results, the efficiency scores are summarized, for each branch group given the examined time periods. Then, the analysis concentrates on branch groups that recorded substantial efficiency change between the early and deep recession period in order to reveal the performing characteristics of the branches. Differences in input/output levels of these branches between the two periods are analyzed and these differences are depicted in a radar graph (radar analysis). The last two steps focus on the second stage of the capital control period. The penultimate step contains the application of an integrated bootstrap DEA – based DT approach that is applied to the homogeneous branch group for re-classification and potential current upgrading of the relative inefficient branches. The final step is a second-stage bootstrap DEA regression that is employed for the identification of efficiency drivers for the performance improvement of the total retail network.

4. Data and descriptive statistics

4.1. The economic downturn

As Greece entered the Eurozone (2001), the Greek economy showed remarkable growth rates which boosted the development of the domestic banking sector. In particular, in the growth years till 2008 its four major systemic banks followed an ambitious expansion strategy expanding their networks in Greece and in Southeastern European countries. Instead of investing their assets in toxic products, they strongly participated in public financing acquiring state bonds and short-term securities. At the same time, based on the low interest rates of the ECB, they followed an aggressive credit policy massively lending to households and enterprises. However, state-led demand based on rising public deficit and debt created unfavorable economic conditions. In 2008, the recession led to the collapse of the inter-bank confidence with crucial liquidity and performance implications of domestic banking institutions (Aggelopoulos & Georgopoulos, 2015). Table 1 reveals the deterioration of the whole economic climate for the period 2008–2015 with a return to normalized economic conditions in 2016. Observing the key indicators or the Greek Banking sector, the overall NPL ratio of Greek banks rose to 34.8 % in 2014, from 10.4% in 2010 (with the lower value of 4.5% at 2007), while at the end of June 2015 loans which were 90 days past overdue amounted to 35.6 % of total loans. In addition, the banking system's Cost to Income ratio increased to 69.7% in 2012 compared with 59.6% in 2011, due to a 20% reduction in total operating income (Moody's, 2015) that offset the benefit from the operating cost containment measures taken by Greek banks. The ratio declined to 62.6% in 2014 from 66.8% in 2013 given that banks reduced staff and streamlined their branch networks, although the ratio remained above the 53–58% range recorded during 2006–2010.

For these reasons, the Greek banking industry would seem to be an ideal choice for a case study of the impact of economic alternation on banking efficiency. We split the total recession period into the early recession, the deep recession and the capital control period which starts at the end of June 2015 when a bank holiday took place and capital controls were imposed on the Greek Economy. Due to the considerable research interest for the capital control period, we split it into two stages, the first stage from July 2015 to December 2015 where the phenomenon caused a substantial shock on the domestic banks and the second stage from January 2016 to July 2016 in the course of which a relative stabilization of the economy is observed following the successful conclusion of the recapitalization of Greek Banks in December 2015. Table 2 presents a timeline of the most important economic-political events from the entry of Greece to the Eurozone until the capital control period.

4.2. The data set

The present study is based on a joint project of the researchers (with previous professional banking experience) and the management of the bank under investigation. The specific project carried out due to the necessity of efficiency evaluation of the bank's network since strategic management aimed at its restructuring in order to meet adverse recession effects that caused considerable performance downgrading. In particular, the bank management goals from the conducted efficiency analysis were to derive useful insights related to branch performance asymmetries for the realization of branch merging policies and incentive schemes given diverse branch specific characteristics in terms of size and location.

Our data is derived from the internal Management Information System (MIS) of one of the four largest systemic domestic banks with a retail network of 362 branches across the country with

Table 1
Statistics of the Greek economy and the key indicators for the Greek Banking Sector over the period 2006 to 2016.

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016 (f)
Real GDP growth (%)	4.3%	3.5%	−0.2%	−3.2%	−4.9 %	−9.1%	−7.3%	−3.2%	0.4%	−0.2%	0.0%
Gross Debt (% of GDP)	105%	107%	113%	130%	148 %	172%	159%	177%	180%	177%	182 %
Cost to Income ratio	53.4%	52.5%	55.4%	54.7%	57.9%	59.6%	69.7%	66.8%	62.6%	61.1%	n/a
NPL ratio of banking sector (%)	5.4%	4.5%	5%	7.7%	10.4 %	16%	24.5%	31.7%	34.8%	35.6%	n/a

Notes: This table presents the macroeconomic environment in Greece and the key indicators for the Greek banking Sector during the period 2006 to 2016 (European Parliament's Economic Governance Support Unit, January 2016; Moody's, November 2016).

Table 2
Timeline of the most important political events.

Event	Description
2001 - 2008	Greece adopted the Euro in 2001 and over the next 7 years the country's GDP per capita nearly tripled, from $12,400 in 2001 to $31,700 in 2008.
20 October 2009	A disclosure by the Greek finance minister that the budget deficit is expected to reach 12.5% of GDP. A downgrading of Greece's credit rating follows.
23 April 2010	Greek Prime Minister formally requests an international bailout. European Union, ECB and IMF agree to participate to the first bailout package for 110 billion Euro's.
21 February 2012	A second bailout package is agreed for Greece. It brings the total amount of Eurozone and IMF bailouts to 246 billion Euro's.
29 December 2014	The government falls and parliamentary elections are set to be held on 25 January 2015.
25 January 2015	A new leftist government is formed that promises an end to austerity measures.
20 February 2015	Greece's second bailout extended to June 2015 with the obligation of the Greek government to come up with alternative reform proposals.
15 June 2015	Greece's second bailout expires.
26 June 2015	Greek Prime Minister calls for referendum and halt talks with creditors. Capital controls are imposed on the Greek economy forcing banks to remain closed given the ECB decision to maintain the ELA facility but stopped raising the overall cap.
30 June 2015	The second bailout expires: Greece's misses payments to IMF. From mid December 2014 to end June 2015 more than 25% of total deposits were withdrawn while more than 36% of the total loans were 90 days past due.
5 July 2015	Greeks vote ′′No′′ in referendum.
13 July 2015	Greece's presents new proposal to creditors Eurozone leaders agree to offer Greece a 3rd bailout financial assistance package.
19 August 2015	A Memorandum of Understanding with Greece is signed between the European Commission and Greece for a 3rd bailout of up to 86 billion Euro's for the period 2015-2018.
20 September 2015	General elections. The leftist party wins again and a new coalition government is formed.
4 December 2015	Third recapitalization of the Greek Banking System. Comprehensive assessment by the ECB revealed a total capital shortfall of 4.4 billion at the four systemic Greek banks (funded by the European Stability Mechanism, ESM).
22 January 2016	Standard and Poor's upgraded Greece's credit rating to B- from CCC+.

main clients individuals, micro businesses and small enterprises that exhibit a total retail exposure of less than 1 million Euro and a maximum turnover of 2.5 million Euros (each business unit). It should be mentioned that in the deep recession and afterwards, the data set decreased to 345 branches as some retail branches were closed down between 2011 and 2015 due to cost rationalization measures.

The unique data is divided into two samples. The whole sample consisting of the total branch network (heterogeneous branches) and a homogeneous branch sample. We explore the total sample taking into account the criteria of branch size and location. According to branch size and especially the deposit balances, three branch network groups are formed: small-sized branches with 5-year average total deposit balances between 5 to 20 million Euros (77 branches), medium-sized branches with 5-year average total deposit balances between 20 to 60 million Euros (162 branches) and large-sized branches with 5-year average deposit balances of more than 60 million Euros (123 branches). Moreover, three different sample splits are formed given the branch location: branches operating in urban areas (192 branches), branches operating in rural areas (122 branches) and branches operating on islands which present seasonal variations (48 branches). More specifically, urban branches are scattered mainly among the six major urban cities of the country which are massively populated and they have a high rate of small and medium sized businesses. Rural branches are allocated to rural areas where there is a high rate of workers in the agricultural field and retirees. Island branches, in turn, are established in island areas where there is high rate of tourist businesses with seasonal operation.

Given the homogeneity requirement of DEA (Eskelinen et al., 2014), a homogenous cluster of 117 branches[19] is formed (using 2006 as a reference year) in terms of: (a) branch size reflected in loan volumes between 20 million and 80 million and deposit volumes between 20 million and 60 million; these branches represent medium-sized units with an average Loan to Deposit ratio (L/D ratio) ranging between 1 and 1.2 (b) branch age focusing on branches that have been operating for more than five years and less than fifteen years; branch age might influence the calculation of loan loss impairments and by extension the quality of branch loans portfolio (c) branch location explicitly concentrating on those branches placed in urban areas. The corresponding benchmarks for homogeneity were the output of a collaborative work with bottom- and top-level managers of the specific bank under study. The bank management agreed that the aforementioned criteria characterize its typical bank branch.

In Table 3, the descriptive statistics are presented for all the examined periods and for all different branch groups. More specifically, a significant increase of average monthly LLP is observed for all the samples by moving from the expansion to the early recession period. Its growth rate is somewhat reduced during the deep recession and subsequently exhibits a new acceleration for all branch groups due to the imposition of capital controls and the closure of banks for three weeks (Period Da). It seems that problem loans reached their peak that period since the formation of new 90-days past due loans has slowed down significantly during the second phase of capital control period (Period Db). The INCOME variable decreased slightly in the early recession period for all samples apart from the island placed branches which presented stable interest income levels (214.14 thousand Euro's) and the small branches which almost doubled their income relative to other branches (from 46.10 thousand Euro's to 88.02 thousand Euro's). However, INCOME reduced considerable in the deep recession for all branch groups as a result of the continuously deteriorating economic environment, with a small pick-up during the second phase of capital control given the normalized economic conditions. The OPEX variable increased marginally in the early recession period for all branch groups except a minimal drop in the large branches. Nevertheless, the variable decreased substantially in the deep recession period for all branch groups due to the implementation of cost rationalization measures. In the capital control period OPEX fell even more as the stopping of deposit outflows limited the associated operating costs. Unexpectedly, an increase in the monthly average value of operational expenses is observed for all the branch groups during the second phase of capital control period. Finally, the FEE variable declined shortly in the early recession period (for the vast majority of bank branches), then deteriorated significantly during the deep recession and after the imposition of capital controls it presented an increased trend (for all branch groups) as the specific interventions in the system boosted

[19] In the deep recession and capital control period, the homogenous branch group consisted of 112 branches given the reduced size of the branch network.

Table 3
Descriptive statistics of inputs-outputs used in the efficiency assessment for all the examined periods and for all branch groups (*monthly data, in thousand Euro's*).

Panel A: Expansion and early recession period

		Period A: Expansion period				Period B: Early recession period			
Branch groups	stat.	OPEX	LLP	FEES	INCOME	OPEX	LLP	FEES	INCOME
Total branches	mean	56.42	83.91	20.05	283.93	58.29	194.93	15.61	261.93
	sdev	32.45	65.53	25.69	213.03	30.13	139.23	15.61	165.04
	min	9.75	0.81	1.08	7.39	10.09	14.95	1.37	18.08
	max	264.29	482.14	248.68	1700.51	275.39	1212.31	144.46	1251.53
Homogeneous Branches	mean	61.50	95.62	21.68	333.18	61.76	213.95	16.78	288.13
	sdev	12.13	27.84	15.38	89.02	12.98	78.57	8.00	74.40
	min	38.06	38.70	6.75	158.55	37.29	53.79	5.55	143.54
	max	109.42	157.15	121.47	579.39	104.53	432.32	50.79	458.04
Urban Branches	mean	63.21	87.71	25.17	311.64	63.75	191.36	20.03	271.44
	sdev	34.17	59.61	29.29	218.16	32.43	125.60	18.85	159.88
	min	9.75	1.39	1.33	9.15	20.06	22.82	2.45	28.78
	max	264.29	482.14	248.68	1700.51	275.39	897.46	144.46	1048.51
Rural Branches	mean	54.76	88.18	16.70	282.53	56.77	221.39	11.59	268.89
	sdev	29.69	66.26	22.85	198.11	27.54	131.44	10.02	147.66
	min	14.06	2.99	1.08	12.11	18.41	37.49	1.37	44.25
	max	162,91	373,22	158,53	900,70	163,25	648.79	65.89	718.64
Island Branches	mean	40.13	68.58	11.28	214.68	44.78	155.28	10.35	214.14
	sdev	23.58	80.72	10.61	208.00	21.89	119.75	7.24	146.61
	min	8.47	0.85	0.61	4.63	16.45	16.94	2.24	43.29
	max	132.75	457.73	52.90	988.98	125.00	572.95	32.91	771.02
Small Branches	mean	22.46	14.60	2.85	46.10	31.61	68.74	4.19	88.02
	sdev	8.94	16.13	1.99	41.47	8.32	38.26	1.70	36.93
	min	7.91	0.26	0.61	4.61	16.45	16.94	1.37	28.78
	max	48.37	102.17	14.97	260.67	64.32	214.60	10.15	248.43
Medium Branches	mean	48.55	74.89	13.72	239.49	51.03	191.44	11.68	243.00
	sdev	12.58	37.99	11.32	104.42	14.76	122.77	6.77	120.10
	min	17.76	3.62	1.48	18.30	18.41	22.82	2.82	56.46
	max	90.39	204.48	121.47	549.64	125.00	1212.31	49.17	1251.53
Large Branches	mean	85.62	134.36	38.13	475.11	83.25	270.58	27.45	38,629
	sdev	34.88	70.37	34.51	209.99	34.34	142.69	20.18	159.62
	min	41.71	42.37	8.83	200.23	47.39	53.79	9.16	149.18
	max	264.29	482.14	248.68	1700.51	275.39	897.46	144.46	1048.51

Panel B: Deep recession and capital control periods (1st and 2nd phase)

		Period C: Deep recession period				Period Da: Capital control period, 1st phase			
Branch groups	Stat.	OPEX	LLP	FEES	INCOME	OPEX	LLP	FEES	INCOME
Total branches	mean	42.77	220.63	4.27	77.66	34.68	387.15	5.20	75.48
	sdev	19.99	121.42	3.47	65.12	13,23	261.91	2.77	77.17
	min	15.31	16.52	1.13	1.20	11,92	3.37	1.78	1.10
	max	241.38	731.96	34.12	853.76	108,24	1440,08	26.99	1097.91
Homogeneous branches	mean	45.51	240.31	4.53	82.64	37.75	438.71	5.56	79.51
	sdev	11.02	77.98	2.07	26.41	7.92	171.07	1.62	29.20
	min	27.95	55.36	1.55	20.78	23.72	81.96	2.88	18.33
	max	90.90	470.50	12.59	155.45	65.85	1125.74	11.68	181.91
Urban branches	mean	43.60	223.37	5.24	86.06	36.18	368.70	6.00	85.93
	sdev	16.16	116.22	4.39	84.67	13.22	226.41	3.30	102.57
	min	19.69	39.69	1.44	3.23	1650	27.42	2.34	3.10
	max	123.12	731.96	34.12	853.76	108.24	1250.68	26.99	1097.91
Rural branches	mean	44.93	231.96	3.49	71.36	34.95	45,274	4.55	65.92
	sdev	25.70	118.40	1.95	3962	13.74	285.10	1.88	39.70
	min	16.91	35.30	1.13	5.30	15.02	36.26	1.78	3.15
	max	241.38	554.06	10.46	179.98	78.63	1440.08	12.41	197.75
Island branches	mean	36.40	206.40	2.94	66.29	30.13	344.31	4.20	64.04
	sdev	15.50	130.13	1.35	39.02	11.14	283.94	1.69	41.84
	min	15.31	16.88	1.35	5.41	11.92	16.65	1.80	1.20
	max	80.07	642.40	8.01	184.65	55.51	1017.84	8.99	187.32
Small branches	mean	27.96	104.61	2.09	31.90	22.94	144.76	3.06	29.54
	sdev	9.41	52.35	0.71	12.29	5.55	117.51	0.79	13.30
	min	15.31	16.88	1.13	5.30	11.92	16.65	1.78	3.15
	max	78.82	257.80	4.48	84.80	38.45	561.61	5.06	8.,66
Medium branches	mean	38.64	211.11	3.36	64.09	31.93	374.71	4.54	59.68
	sdev	10.71	80.54	1.53	25.15	8.29	206.44	1.41	26.86
	min	20.22	50.80	1.40	1.06	15.51	27.42	2.13	1.00
	max	82.47	420.19	10.75	147.45	62.43	1212.28	11.68	144.14
Large branches	mean	56.68	306.11	6.73	121.90	45.27	557.31	7.35	122.50
	sdev	24.16	122.89	4.67	91.66	13.88	257.85	3.38	113.78
	min	30.23	55.36	2.21	1.20	24.46	81.96	3.20	1.00
	max	241.38	731.96	34.12	853.76	108.24	1440.08	26.99	1097.91

(*continued on next page.*)

Table 3
(continued)

Branch groups	Period Db: Capital control, 2nd phase stat.	OPEX	LLP	FEES	INCOME
Total branches	mean	42.45	342.25	4.36	84.27
	sdev	16.37	264.26	2.76	59.91
	min	13.59	0	0.55	1.20
	max	128.48	1881.16	26.28	658.27
Homogeneous branches	mean	47.16	387.62	4.84	93.78
	sdev	12.97	209.93	1.66	29.47
	min	30.14	0	1.72	29.67
	max	90.79	993.36	10.87	192.37
Urban branches	mean	42.72	406.40	5.12	92.41
	sdev	15.44	280.45	3.20	71.23
	min	18.62	0	1.29	1.20
	max	128.48	1881.16	26.28	658.27
Rural branches	mean	44.87	286.72	3.79	79.98
	sdev	18,53	227.92	2.07	45.56
	min	18.22	0	0.67	9.07
	max	93.47	1091.26	10.32	192.37
Island branches	mean	36.69	270.46	3.17	70.27
	sdev	12.89	223.61	1.72	42.59
	min	13.59	0.24	0.55	19.92
	max	59.39	1192.87	7.88	180.22
Small branches	mean	27.15	150.54	2.02	33.08
	sdev	6.87	126.47	0.84	12.39
	min	13.59	0.24	0.55	9.07
	max	47.44	507.55	3.81	87.53
Medium branches	mean	39.94	321.37	3.69	72.18
	sdev	12.51	198.93	1.53	30.40
	min	20.32	0	1.08	17.29
	max	90.79	1520.35	10.19	192.37
Large branches	mean	54.01	479.73	6.49	128.09
	sdev	16.25	308.91	3.20	73.18
	min	28.12	0	2.19	1.20
	max	128.48	1881.16	26.28	658.27

the use of bank electronic payments. However, the recorded decline in the average value of fee income during the second phase of the capital control period reflects the reduced non-interest income earned from the electronic transactions since the competition among banks (mainly for market share in debit and credit cards, Point of Sales – P.O.S – transactions between customers and enterprises) forced them to reduce charges on these services or repricing downwards existing customer relationships.

5. Empirical findings

This section describes the efficiency results. In particular, Table 4 presents the DEA findings for all the samples during the expansion and the early recession period, Table 5 presents the efficiency estimates for the deep recession and the first phase of the capital control period correspondingly while Table 6 compares the efficiency results between the first and the second phase of capital control period. The last two columns at each table depict the differences between the DEA efficiency scores and the bias corrected efficiency scores respectively for each branch group given the contrasted time periods. In addition, a pairwise - test comparison of the group estimates is performed (a bootstrap test proposed by Simar & Wilson, 2000) assuming under the null hypothesis that the estimates related to the two groups are equal. In all cases, the null hypothesis is rejected which means that a difference exists between the average performance behavior of the two groups under comparison.

In Appendix B, the efficiency scores of the branch network are plotted in a scatter diagram separately for each examined period, while a box-and-whisker diagram summarizes the average efficiency scores of the branch network for all the examined periods. Generally, the results show high levels of technical inefficiency for many branches and considerable variations in efficiency levels across them which potentially indicates that branch efficiency is determined by the branch management and branch characteristics.[20]

5.1. *Efficiency scores in the expansion and early recession period*

Looking at the total branch network (Table 4), traditional DEA model results for profit efficiency in the expansion period give an average uncorrected technical efficiency score of 1.394, while the bootstrap model generates an average bias-corrected score of 1.478 (mean bootstrap bias of −0.084 for the traditional DEA scores which was expected). This bias-corrected distance function estimate suggests that the same outputs in terms of interest and fee income could have been produced for the branch network while scaling inputs back by more than 47%. The estimated 95% confidence interval indicates that inputs could have been reduced by between 40% and 56%. In the early recession period, the average uncorrected technical efficiency under traditional DEA model is 1.524 while the bootstrap model gives an average corrected score of 1.632 (bootstrap bias −0.108). This bias-corrected estimate in the early recession period shows that the same outputs could have been produced for the branch network while scaling inputs back by more than 63% on average. Consequently, during the early recession period the profit efficiency of the branch network decreases substantially by 15.4 points (1.478–1.632).

[20] For robustness reasons, we broke down the aggregated variable OPEX into three individual cost categories (i.e. personnel expenses, running expenses and other operating expenses), as we described analytically in Section 3.2, and run our models again for the branch network (see Table C1). The specific disaggregated analysis (column A of Table C1) didn't differentiate our findings as regards the efficiency change over the successive periods since it provides similar values with the employed aggregated model (column B of Table C1). The full set of results regarding diverse branch characteristics are available upon request.

Table 4
Technical efficiency scores (under VRS) for the branch network and branch groups based on the traditional DEA and bootstrap DEA (expansion period and early recession period).

Samples	#	Expansion period (January 2006–August 2008)						Early recession period (September 2008–December 2010)						Differences	
		DEA distance function estimates	bias-corrected distance function estimates	bootstrap bias	variance estimates	Upper 95% C.I	Lower 95% C.I	DEA distance function estimates	bias-corrected distance function estimates	bootstrap bias	variance estimates	Upper 95% C.I	Lower 95% C.I	DEA estimates	bias-corrected
Network	362	1.394	1.478	−0.084	0.0032	1.408	1.560	1.524	1.632	−0.108	0.003	1.547	1.729	−**0.129**	−**0.154**
location															
urban	192	1.412	1.508	−0.096	0.002	1.427	1.601	1.387	1.479	−0.092	0.002	1.402	1.570	**0.025**	**0.029**
rural	122	1.211	1.259	−0.049	0.001	1.217	1.317	1.298	1.389	−0.091	0002	1.309	1.479	−**0.087**	−**0.130**
island	48	1.129	1.185	−0.057	0.000	1.133	1.269	1.270	1.384	−0.114	0002	1.281	1.512	−**0.142**	−**0.199**
size															
small	77	1.257	1.355	−0.098	0.001	1.266	1.460	1.259	1.354	−0.095	0.002	1.268	1.457	−**0.002**	**0.001**
medium	162	1.206	1.252	−0.046	0.001	1.213	1.304	1.480	1.607	−0.127	0.004	1502	1.726	−**0.274**	−**0.355**
large	123	1.212	1.272	−0.060	0.000	1.220	1.333	1.223	1.277	−0.055	0.003	1.229	1.341	−**0.010**	−**0.005**
Homogenous branches	117	1.184	1.233	−0.049	0.001	1.189	1.286	1.305	1.388	−0.083	0.003	1.315	1.475	−**0.120**	−**0.155**

*Note***:** This table reports the average monthly efficiency results (DEA distance function estimates, the bias-corrected distance function estimates, the bootstrap bias, the variance estimates and the estimated 95% confidence bounds) for each branch group, before (expansion period) and during the recession (early recession period). The employed methodology is an input-oriented bootstrap DEA profit approach under the assumption of variable returns to scale. Results are produced using 2000 bootstrap replications.

Table 5
Technical efficiency scores (under VRS) for the branch network and branch groups based on the traditional DEA and bootstrap DEA (deep recession and capital control period, 1st phase).

Samples	#	Deep recession period (January 2015–June 2015)						Capital control period, 1st phase (July 2015–December 2015)						Differences	
		DEA distance function estimates	Bias-corrected distance function estimates	Bootstrap bias	Variance estimates	Upper 95% C.I	Lower 95% C.I	DEA distance function estimates	Bias-corrected distance function estimates	Bootstrap bias	Variance estimates	Upper 95% C.I	Lower 95% C.I	DEA estimates	Bias-corrected
Network	345	1.832	1.963	−0.131	0.009	1.868	2.099	1.766	1.926	−0.159	0.012	1.808	2.063	+0.065	+0.036
Location															
Urban	179	1.571	1.695	−0.123	0.009	1.593	1.815	1.552	1.671	−0.118	0.019	1.573	1.786	+0.019	+0.024
Rural	118	1.492	1.636	−0.144	0.011	1.510	1.778	1.345	1.443	−0.098	0.013	1.356	1.545	+0.147	+0.193
Island	48	1.375	1.534	−0.159	0.015	1.391	1.700	1.390	1.559	−0.169	0.015	1.403	1.749	−0.015	−0.025
Size															
Small	67	1.452	1.597	−0.145	0.094	1.468	1.750	1.347	1.466	−0.119	0.010	1.361	1.591	+0.105	+0.131
Medium	159	1.533	1.672	−0.140	0.004	1.555	1.797	1.505	1.635	−0.129	0.009	1.527	1.751	+0.028	+0.037
Large	119	1.561	1.691	−0.130	0.006	1.582	1.811	1.552	1.676	−0.125	0.012	1.573	1.797	+0.009	+0.015
Homogenous *branches*	112	1.428	1.530	−0.100	0.023	1.443	1.631	1.443	1.538	−0.096	0.017	1.459	1.643	−0.015	−0.012

*Note***:** This table reports the average monthly efficiency results (DEA distance function estimates, the bias-corrected distance function estimates, the bootstrap bias, the variance estimates and the estimated 95% confidence bounds) for each branch group, before (deep recession period) and during the impositions of capital controls (1st phase of the capital control period). The employed methodology is an input-oriented bootstrap DEA profit approach under the assumption of variable returns to scale. Results are produced using 2000 bootstrap replications.

Table 6
Technical efficiency scores (under VRS) for the branch network and branch groups based on the traditional DEA and bootstrap DEA in the capital control period (1st phase and 2nd phase).

Samples	#	Capital control period, 1st phase (July 2015–December 2015)						Capital control period, 2nd phase (January 2016–July 2016)						Differences	
		DEA distance function estimates	Bias-corrected distance function estimates	Bootstrap bias	Variance estimates	Upper 95% C.I	Lower 95% C.I	DEA distance function estimates	Bias-corrected distance function estimates	Bootstrap bias	Variance estimates	Upper 95% C.I	Lower 95% C.I	DEA estimates	Bias-corrected
Network	345	1.766	1.926	−0.159	0.012	1.808	2.063	1.631	1.750	−0.119	0.010	1.653	1.864	+0.135	+0.176
Location															
Urban	179	1.552	1.671	−0.118	0.019	1.573	1.786	1.454	1.554	−0.101	0.006	1.468	1.656	+0.098	+0.117
Rural	118	1.345	1.443	−0.098	0.013	1.356	1.545	1.416	1.538	−0.122	0.009	1.428	1.669	− 0.071	− 0.095
Island	48	1.390	1.559	−0.169	0.015	1.403	1.749	1.334	1.467	−0.1334	0.011	1.348	1.604	+0.056	+0.092
Size															
Small	67	1.347	1.466	−0.119	0.010	1.361	1.591	1.465	1.624	−0.159	0.012	1.479	1.799	− 0.118	−0.158
Medium	159	1.505	1.635	−0.129	0.009	1.527	1.751	1.365	1.450	−0.085	0.002	1.375	1.539	+0.140	+0.185
Large	119	1.552	1.676	−0.125	0.012	1.573	1.797	1.388	1.482	−0.094	0.006	1.404	1.572	+0.164	+0.194
Homogenous branches	112	1.443	1.538	−0.096	0.017	1.459	1.643	1.296	1.377	−0.081	0.005	1.468	1.655	+0.147	+0.161

Note: This table reports the average monthly efficiency results (DEA distance function estimates, the bias-corrected distance function estimates, the bootstrap bias, the variance estimates and the estimated 95% confidence bounds) for each branch group, in the 1st and the 2nd phase of capital control period respectively. The employed methodology is an input-oriented bootstrap DEA profit approach under the assumption of variable returns to scale. Results are produced using 2000 bootstrap replications.

Efficiency is measured for two branch groups based on branch size and branch location. As regards branch size, the medium-sized branches present higher efficiency in the expansion period with a bias corrected efficiency score of 1.252 (confidence interval: 1.213 and 1.304). The large-sized branches exhibit an average bias corrected efficiency score of 1.272 (confidence interval: 1.220 and 1.333) while the small-sized branches show the highest inefficiency with a score of 1.355 (confidence interval: 1.266 and 1.460). During the early recession, the profit efficiency of medium sized branches decreases substantially by 35.5 points (1.252–1.607) indicating that inputs on these branches could have been reduced on average by more than 60%. This efficiency reversal - from a best efficiency branch group in the expansion to the worst one in the recession - is analyzed in the next section (see below 5.3) through employing a radar graph analysis. On the contrary, both the small-sized branches and the large-sized branches (instead of their high loan balances) present similar efficiency levels as during the expansion period. As regards branch location, branches operating in island areas present better average bias-corrected efficiency than the other samples, with a value of 1.185 in the expansion period (the estimated 95% confidence interval ranges between 1.133 and 1.269). The average bias-corrected efficiency score of rural branches is 1.259 while high inefficiency presents the branches operating in urban areas with a value of 1.508. During the early recession, the profit efficiency of island placed branches decreases substantially by 19.9 points (1.185–1.384), while a significant efficiency decrease by 13.00 points reports the branches operating in rural areas (1.259–1.389). Thus, while both the bias-corrected efficiency scores of the island and rural branches are almost equal (1.38), looking at the confidence intervals shows that the efficiency level is higher for rural branches due to the narrower confidence interval. In turn, the urban branches present a slightly efficiency improvement with a bias corrected efficiency score of 1.479 (1.508 in the expansion period) showing a more efficient response to the adverse recession effects in comparison to the rural and island branches.

Taking into account the strict homogeneity criterion (sample of 117 homogenous branches), traditional DEA model results in the expansion period give an average uncorrected technical efficiency score of 1.184 (versus an efficiency score of 1.394 of the branch network) while the bootstrap model generates an average bias-corrected score of 1.233 (versus an efficiency score of 1.478 of the branch network). The traditional DEA scores present a mean bias −0.049 with the estimated 95% confidence interval ranging between 1.189 and 1.286. So the homogeneous branches seem to present better efficiency than the network branches in the expansion period, indicating that the homogeneity factor affects substantially efficiency. In the early recession, the bias-corrected efficiency score increases to 1.388 (versus 1.233 in the expansion period) indicating that the same outputs could have been produced for the branch network while scaling inputs back by more than 38% on average. Thus, during the early recession the profit efficiency of the branch network decreases substantially by 15.5 points (1.233–1.388) that is similar to the recorded efficiency destruction of the total branch network. Thus, early recession affects substantially the efficiency of bank retail branches in the short run.

5.2. Efficiency scores in the deep recession and capital control period (1st and 2nd phase)

Focusing on the deep recession (period C) and the first phase of capital control period (period Da) and looking at the branch network (see Table 5), the bootstrapped DEA efficiency results in the deep recession give an average bias-corrected score of 1.963. During the capital control period, the average bias-corrected efficiency is 1.926 which means that the profit efficiency performance of branch network is slightly improved in comparison to the deep

Table 7
Summary of efficiency results for all time periods (branch network and branch groups).

Time periods	All branches	Homogeneous branches	*Size criterion*			*Location criterion*		
			Small	Medium	Large	Urban	Rural	Island
Expansion	1.478	1.233	1.355	1.252	1.272	1.508	1.259	1.185
Early recession	1.632	1.388	1.354	1.607	1.277	1.479	1.389	1.389
Deep recession	1.963	1.530	1.597	1.672	1.691	1.695	1.636	1.534
Capital control, 1st phase	1.926	1.538	1.466	1.635	1.676	1.671	1.443	1.569
Capital control, 2nd phase	1.750	1.377	1.624	1.450	1.482	1.554	1.538	1.467

recession. Generally, comparing the efficiency level of the branch network in the deep recession period to the recorded efficiency level of the branch network during the early recession period (i.e., efficiency score of 1.632 at Table 4), a significant profit efficiency downgrading is observed in the long run (almost 30%), as a consequence of the deteriorated economic environment and quality of loans in the Greek Banking Sector during the period 2010–2015. As regards branch size, small branches in the deep recession present the highest average bias-corrected efficiency score (1.597) while they exhibit substantial efficiency improvement during the capital control period (1.466). As regards branch location, branches operating in island areas present better average efficiency than the others during the deep recession period (1.534), with the rural branches recording substantial efficiency gains by 19.3 points (1.636 – 1.443) when capital controls imposed to economy. Focusing on the homogeneous sample (112 branches), their efficiency performance in the deep recession (bias corrected score 1.530) outperforms the efficiency of the branch network branches (1.963), confirming that the homogeneity factor increases efficiency. In the capital control period, the average bias-corrected efficiency score of the homogeneous branches didn't change significant.

Comparing the efficiency level of the branch network (see Table 6) in the first phase of capital control period (i.e., bias-corrected efficiency score of 1.926) to the recorded efficiency level of the branch network during the second phase of capital control (i.e., bias-corrected efficiency score of 1.750), a significant profit efficiency improvement is observed (17.6 points), owing to normalizing economic conditions, declining funding costs and reduced provisions during the period January 2016 – July 2016. Similar efficiency enhancement (16.1 points) presents the homogenous sample with an average efficiency score of 1.377. Again, is confirmed that homogeneity affects efficiency positively.

As regards branch size, medium and large sized branches in the second phase of capital control present a substantial efficiency improvement in comparison to the first phase (by 18.5 and 19.4 points respectively), while branches operating in island areas represent the most efficient branch group (i.e., bias-corrected efficiency score of 1.467) in comparison to rural and urban branch groups.

5.3. *Efficiency change analysis*

Table 7 summarizes the efficiency results for each branch group throughout the examined time periods.

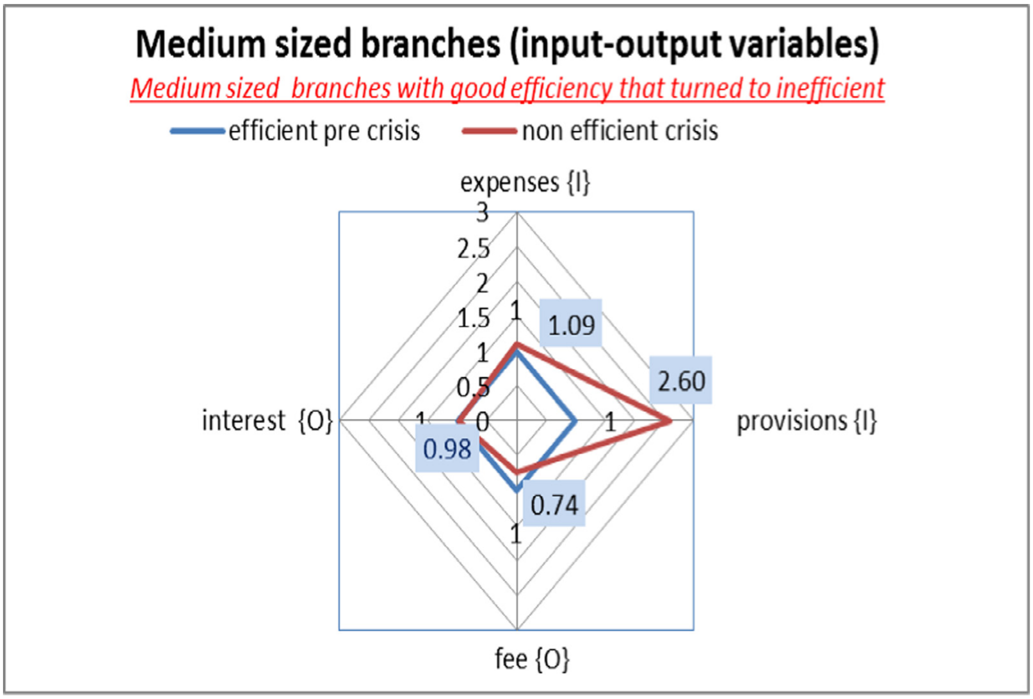
Generally, the results show that recession reduces on average branch network efficiency in the short (i.e., early recession period) and long run (i.e., deep recession period) while the imposition of capital controls initially causes a marginal efficiency improvement (i.e., 1st phase of capital control period) that increases even more when economic conditions are normalizing (i.e., second phase of capital control period). Specifying the unequally distributed inefficiency given the size criterion, we conclude that in the expansion period the small sized branches are less efficient in comparison to others, especially to the medium sized branches that are presenting the best efficiency behavior. However, adverse effects of the early recession substantially reduce their efficiency without having any significant efficiency impact on small and large branches. In the long run, the deep recession conditions increase substantially the inefficiency levels of all groups with small branches exhibiting the highest score. The imposition of capital controls along with the return to gradual recovery – as that is depicted on the derived efficiency scores in the second phase of capital control – improves substantially the efficiency of medium and large sized branches. As regards location, the island placed branches are more efficient throughout the expansion period than the urban and rural branches with the urban units getting the lowest efficiency score in the retail network. Nevertheless, the coming of recession reverses the efficiency picture again by negatively affecting the island branches; at the same time, the rural branches lose efficiency, whereas the urban units retain a similar efficiency level as before the recession. Taking into account the adverse recession effects over the long run, the analysis shows an inefficiency increase for all branch groups with tourist branches being on average more efficient than urban and rural ones. The imposition of capital controls during the peak tourist season reduces the efficiency of island branches marginally, with a subsequent significant efficiency improvement during the second phase of the capital control period when economic conditions are normalized.

Next, we make some specifications as regards the considerable structural efficiency change in the medium sized branches mentioned above taking into account the methodological problem of the choice of the efficiency threshold that can be arbitrary (Portela & Thanassoulis, 2007). The chosen thresholds in the efficiency analysis are the result of deliberation with the bank management. Firstly, taking as a threshold of the efficiency change the average efficiency score of medium sized branches in the expansion period (an efficiency score of 1.252), we conclude that 76 branches out of 162 of the specific branches transformed from good performers in the expansion period to bad performing units in the early recession. The radar graph in Fig. 1 exhibits the aforementioned structural effect. Values for each variable are normalized by the values observed for the branches with good efficiency in the expansion period. As regards the input variables, the radar graph shows that these branches increased both their operating expenses (1.09 times the average expenses) and LLP (2.60 times the average LLP) during the early recession period. Thus, the main reason for their efficiency downgrading was the bad quality loan portfolio that granted at the expansion period which caused important loan losses on their P&L statements when the economy entered into the early recession stage.

5.4. *A DEA – based DT approach for the capital control period for potential upgrading of inefficient branches*

The bootstrap DEA- based Decision Tree approach consists of two steps: First, bootstrap DEA is conducted to measure efficiency with the selected inputs and outputs. Second, a decision tree is formed[21] based on efficiency scores obtained from bootstrap DEA

[21] For the implementation of decision rules, we employ the CART modeling decision tree algorithm via rpart routines of statistical package R (Rokach and Maimon, 2014).



	expenses {I}	provisions {I}	fee {O}	interest {O}
expansion	1	1	1	1
early recession	1.09	2.60	0.74	0.98

Fig. 1. The average profit efficiency variables of medium sized branches in the expansion period compared to those in the early recession period.

in order to investigate the impact of input variables on efficiency. Thus, the efficiency score is used as a target variable and input variables are used as predictor variables. The scope of this approach is to find meaningful relationships between input variables, by systemically breaking down the data information, affecting the classification of bank branches into efficient and inefficient groups. For the implementation of decision trees rules, it is necessary to divide the branches into classes. Given the main finding of the present study that inefficiency is distributed unequally among bank branches with different characteristics and the strategic plan of the specific bank to rationalize its branch network, the bank management required specific recommendations for the efficiency improvement of its homogeneous[22] branches. More specifically, after consultation and agreement with the bank executives, and in accordance with banking efficiency literature (Wu et al., 2006), we classify the homogeneous branch network in four categories based on the efficiency scores: The efficiency score interval A (scores between 1–1.10) is referred as strong relative efficient interval, the efficiency score interval B (scores between 1.10–1.30) is referred as relative efficient interval, the efficiency score interval C (scores between 1.30–1.90) is referred as relative inefficient interval and the last interval D (scores more than 1.90) is referred as very inefficient interval.

Fig. 2 shows the decision tree formed by the integrated bootstrap DEA-based DT approach. The current classification of 112 homogeneous branches, based on their bias-corrected efficiency scores during the second phase of capital control period, is: 7% at the strong efficient interval A (8 branches), 39% at the relative efficient interval B (43 branches), 47% at the relative inefficient interval C (53 branches) and 7% at the very inefficient interval D (8 branches). Thus, the majority of branches are located at efficient interval C. Decision tree algorithms have an embedded feature selection process to find the most important factor that is very useful in our case (Manolopoulou, Kotsiantis, & Tzelepis, 2015). As shown at the top of the DT in Fig. 2, operational expenses play the most influential role in classifying the efficiency level of homogenous branches. Each node in a decision tree represents a feature in an example to be classified (i.e., homogeneous branches are classified in four categories) and each branch represents a value that the node could have. Based on the DT and the rules in Table 8, bank management can set priorities to improve the efficiency classification of homogeneous branches. In general, three recommendations can be made to bank management: Firstly, a basic condition for the improvement of efficiency classification of homogeneous branches is the reduction of monthly average expenses below 39,000 Euros (21% of branches are classified to the strong efficient interval A and 79% to the relative efficient interval B) while an even greater reduction of expenses (less than 34,000 Euro's) moves the 62% of branches to interval A and the 38% to interval B. Secondly, in the case that bank management cannot reduce expenses to less than 39,000 Euros, a priority should be made on the reduction of provisions of less than 235,000 Euro's. In that case the majority of branches are located at efficient interval B (64%) while 36% of branches remain relatively inefficient (interval C). Lastly, if provisions cannot be reduced to less than 235,000 Euro's, the next move in order to maintain the current efficiency level is to keep expenses below 66,000 Euro's, otherwise the majority of branches (62%) will be positioned at the very inefficient interval D.

[22] We use the homogeneous sample due to comparability considerations.

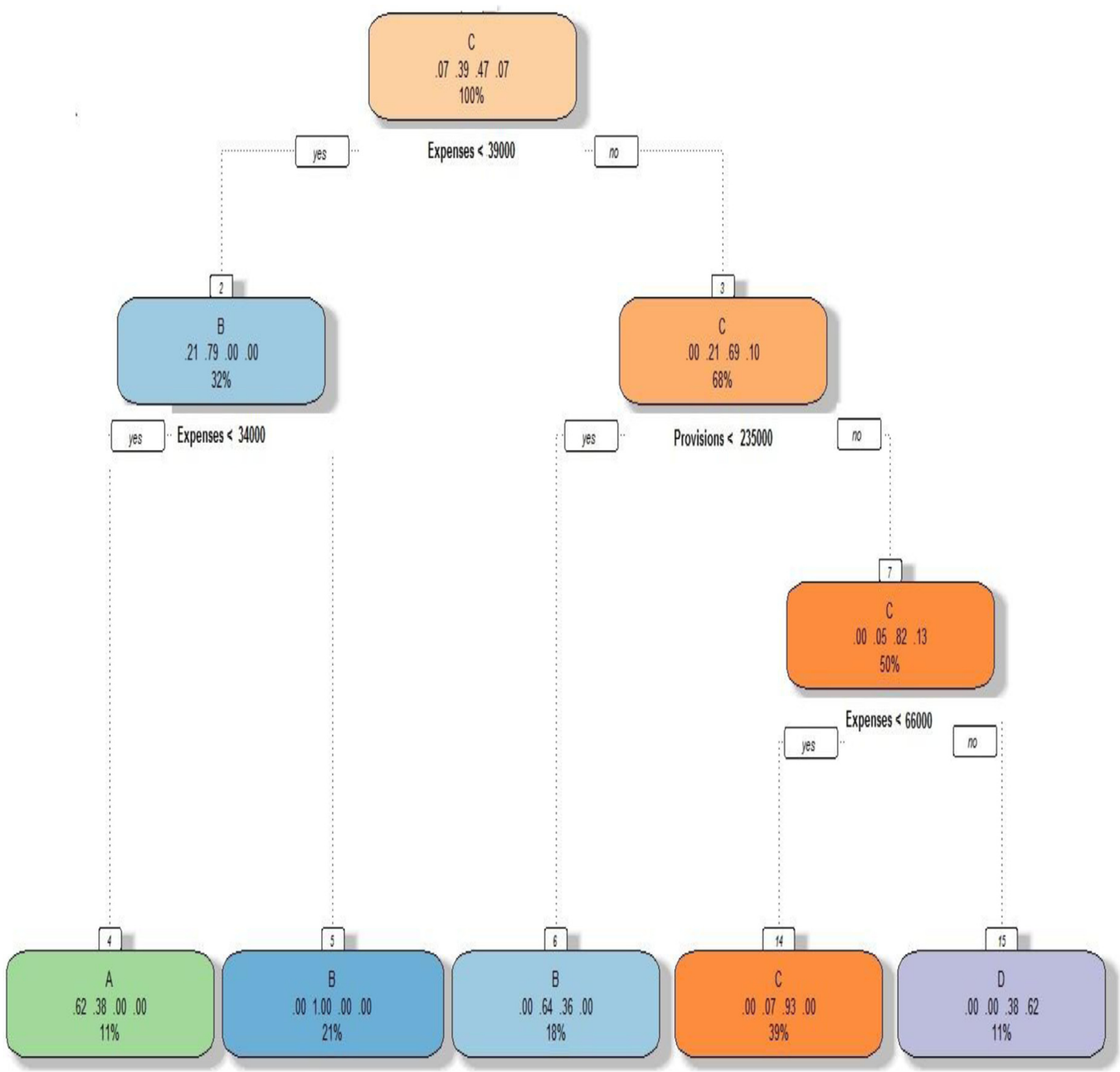


Fig. 2. The results of DT.
Notes: For the construction of DT, we employ the CART modeling decision tree algorithm via rpat routines of statistical package R (Rokach & Maimon, 2014). In each node, the dominant efficient interval is depicted (A, B, C, D), along with the classification of branches to each interval (percentage representation).
Definition of efficient intervals: ***Interval A****: strong efficient interval,* ***Interval B****: relative efficient interval,* ***Interval C****: relative inefficient interval,* ***Interval D****: very inefficient interval.*

5.5. Second-stage regression for the capital control period for identification of efficiency drivers

In order to identify crucial efficiency drivers and thus propose significant Key Performance Indicators (KPIs) to bank management, we explore the impact of branch-specific determinants on efficiency within a second-stage regression.[23] In particular, we apply Simar and Wilson's (2007) method in a two-stage double bootstrap procedure (following Biener et al., 2016) to regress the bootstrapped DEA scores with branch specific attributes.[24] Taking into account relevant literature on the Greek banking system (see Gaganis et al., 2009), and the important peculiarities of the system during the capital control period, we primarily focus on two crucial branch-specific characteristics that could be considerable efficiency drivers: first, diversification of income as a proxy for branch's diversification strategy into non-interest activities (DIV, i.e., ratio of fee income to pre-provision income), and second loan to deposits ratio which indicates whether branches are directed towards providing more loans or deposit services to their customers (LD, i.e., ratio of Loans to Deposits). We also use four control variables, that is: (a) return on capital employed as a proxy for the returns generated from the capital employed by the branch (ROC, i.e., ratio of profit or loss to capital employed by each branch where the latter is obtained by applying the capital requirements for retail exposures against credit and operational risks according to Basel II rules); (b) a size indicator variable based on branch total budgeted funds (SIZE, i.e., sum of total deposit balances and total investment funds namely bonds, mutual funds etc., bancassurance balances); (c) a LOC1 indicator variable that expresses the location for urban branches (dummy variable of 1 for urban branches, otherwise 0)

[23] We utilize the total retail network of the bank under study in order to locate important asymmetries in branch-specific characteristics that could work as efficiency drivers.

[24] According to Eling and Schaper (2017), two-stage bootstrapping procedures (Barros, Nektarios, & Assaf, 2010) belong to innovative DEA applications. The two-stage double bootstrap truncated regression outperforms the second-stage OLS estimation that is consistent only with very strict conditions (Biener et al., 2016). However, as Biener et al. (2016), we also run a second stage ordinary least squares (OLS) regression as a robustness test and the results verify those drawn from the truncated regression procedure.

Table 8
Rules generated from DT.

Rule number	Description
1	If expenses below 34,000 Euro's, the majority of branches are located at efficient interval A. *(prob =0.00).*
2	If expenses between 39,000 Euro's and 34,000 Euro's, the majority of branches are located at efficient interval B. *(prob =0.00).*
3	If expenses over 39,000 Euro's and provisions below 235,000 Euro's, the majority of branches are located at efficient interval B. *(prob =0.00).*
4	If expenses between 66,000 and 39,000 Euro's and provisions over 235,000 Euro's, the majority of branches are located at efficient interval C. *(prob =0.00).*
5	If expenses over 66,000 Euro's and provisions over 235,000 Euro's, the majority of branches are located at efficient interval D. *(prob =5.00).*

Notes: Branches are classified in four categories based on their efficiency scores: The efficiency score **interval A** (scores between 1–1.10) is referred as **strong efficient interval**, the efficiency score **interval B** (scores between 1.10–1.30) is referred as **relative efficient interval**, the efficiency score **interval C** (scores between 1.30–1.90) is referred as **relative inefficient interval** and the last **interval D** (scores more than 1.90) is referred as **very inefficient interval**.

Table 9
Truncated regression results.

Variable	Definition	Coefficient
LD	***Loan to Deposit balances***	***0.050*****
DIV	***Diversification of income****: Fee income to pre-provision income*	***−1.584******
ROC	***Return on capital employed****: Profit/loss to capital employed*	***−0.880******
SIZE	***Branch size****: Total Budgeted Funds*	***4.187******
LOC1	***Location 1 indicator*** *(urban/non-urban)*	***−0.1399*****
LOC2	***Location 2 indicator*** *(rural/non-rural)*	***0.1241****
Sigma		***0.3285******
Number of observations		*345*

Notes: The model that is estimated has a left truncation point at 1. The dependent variable is the efficiency score (i.e., the value of 1 defines an efficient branch) of each branch.
p-values in parentheses are estimated for each coefficient based on 2000 bootstrap replications (see Biener et al., 2016). **Statistical Significance Index: *** at 1%, **at 5%, * at 10%.**

and finally (d) a LOC2 indicator variable that reflects the location for rural branches (dummy variable of 1 for rural branches, otherwise 0). Given that a technically efficient branch has a value of one, that means that as the efficiency score increases the branch network inefficiency increases too. So, there is an inverse relationship between the branch-specific determinants and the efficiency (dependent variable) which means that a positive regression coefficient of a determinant increases inefficiency (i.e., decreases efficiency).

The second-stage regression model that is estimated has a left truncation point at 1 and takes the below form:

$$ES_i = \beta_0 + \beta_1 DIV_i + \beta_2 LD_i + \beta_3 ROC_i + \beta_4 SIZE_i + \beta_5 LOC1_i + \beta_6 LOC2_i + u_i \quad (1)$$

where the dependent variable is the bias – corrected efficiency score (ES) of each branch (stage 1), β is the estimated coefficient for each independent variable, i denotes the number of retail branches (1 to 345).

In Table 9, we present the second stage regression results as regards interactions of efficiency estimates and a set of six employed covariates. We calculate p-values for each coefficient based on 2000 bootstrap replications. Regarding the impact of diversification of income on inefficiency it is observed that the specific diversification decreases inefficiency, as shown by the negative and statistically significant coefficient (−1.584) at the 1% level. This result implies that branches tend to become more managerially efficient as they increase their income stemming from non-interest sources. This finding reflects the increased fee and commission income that the Greek Banking System recorded after the imposition of capital controls (which restrict the use of cash), stemming from the wide use of on-line cashless transactional banking services from bank clients. Moreover, we examine the impact of loan oriented activity on efficiency where it is observed that branches with a high share of loans relative to deposits increase inefficiency as shown by the positive and statistically significant coefficient (+0.050) at the 5% level. This result indicates that branches tend to become more profit efficient as they increase their deposit volumes relative to loans balances, thus indicating the importance in attracting more deposits during the capital control period. This is justified by the large deposit outflows that took place before the imposition of capital control restrictions along with scarce lending opportunities in the capital control period.

As regards the control variables, looking at the impact of ROC on efficiency, it is observed that higher returns on equity employed decrease inefficiency (i.e., increase efficiency) as shown by the negative and statistically significant coefficient (−0.880) at the 1% level. Regarding the impact of branch size on efficiency, it is observed that as branch size increases, inefficiency increases too, as shown by the positive and statistically significant coefficient (4.187) at the 1% level. This finding indicates that small and medium sized branches present better profit efficiency characteristics compared to larger branches may due to their superior capabilities of creating revenues, reducing loan loss impairments, and controlling costs thus restoring profitability. Branch location in urban areas positively influences branch efficiency (−0.1399, at 5% level), whereas branch location in rural places increases inefficiency (0.1241, at 10% level).

Next section summarizes the main findings of the paper and presents some policy implications for management.

6. Conclusion and discussion

This paper explores efficiency change in retail banking taking into account external environmental transformation such as recession and capital control effects which followed the expansion years hence shedding new light on the unique phenomenon of capital controls and the successive recession stages. We utilize a bootstrap input-oriented profit DEA to measure efficiency change by moving from one economic stage to another. Furthermore, a bootstrap DEA-based decision tree model qualifies in terms of input minimization the relative inefficient branches, whereas a second-stage regression reveals important efficiency drivers within the whole retail network. The analysis at bank branch level allows the measurement of efficiency creation and destruction directly at the primary sources of operational profits and expenses, whereas the primary monthly information ensured the immediate capture of any efficiency change. To deal with heterogeneity we investigated a homogeneous sample of branches according to branch size and location defined by bottom- and top-level management.

The study reveals substantial efficiency deterioration during the early and the deep recession period. The efficiency destruction seems to fade out in the first stage of capital controls, whereas in the first seven months of 2016 an efficiency improvement is observed. The analysis shows that branch size and location matter. Furthermore, we propose an input orientation strategy that suggests the way of transformation of the most inefficient homogeneous branches into the most efficient ones. In particular, an input-oriented bootstrap DEA-based DT classification is applied to the homogenous branch group during the second stage of the capital control period. Our specific methodology offers bank management clear efficiency guidelines for branch network consolidation and restructuring. Especially, the approach outcome defines the boundaries for the efficient management of operational expenses and provisions and prioritizes the strategic steps for the efficiency improvement of the most inefficient branches. Based on the derived DT results, the executives of the bank under study focused initially on the reduction of operational expenses primarily through branch mergers given the high concentration of the homogeneous branches in urban areas with a relative low dispersion rate. Subsequently, they attempted to reduce loan loss impairments by concentrating on remedial management. Generally, this combined approach offers bank managers accurate information to what extent they should reduce inputs (i.e., expenses, provisions) in order to increase branch efficiency hence moving poorly performing homogenous branches from the last two to the first two efficiency categories. This integrated procedure can be used by management for classification, prediction, and potential upgrading of the relative inefficient bank branches hence our study offers an additional, simple tool to bank management. We adjust the specific approach to our input orientation bootstrap DEA concept clearly distinguishing our paper from other studies that used the specific methodology for other research purposes and in other industries.[25] Our approach provides some considerable advantages in efficiency analysis in banking. In particular, it makes the relationships between individual inputs and branch performance easy to understand. Secondly, it enables managers to set priorities to input choices which are vital for branch efficiency improvement especially in turbulent years. Thirdly, it is important for determining the desired level of controllable operating expenses of new branches created by merger policies which constitute a common consolidation tool during difficult times. To the best of our knowledge there is no operational research application in banking that effectively combines bootstrap DEA and DT to provide accurate input-oriented directions to bank management determining to what extent the input variables should be reduced in order to upgrade the efficiency classification within the branch network.

Our empirical analysis on the identification of efficiency drivers offers some interesting results as well. This reveals that bank branches should diversify their income and increase it from non-interest sources given the substantial increase of bad performing loans in the recession years and the scarce lending opportunities. Also, they should focus on a more deposit-oriented activity as large deposit outflows recently substantially limited the funding sources of banks and hampered the financing of new projects. These two efficiency drivers seem also to be consistent with expansionary perspectives given the first signs of economic recovery.

The study's findings justified our methodological choice of comparing diverse external environments indicating that efficiency measurement and valuation has very distinctive time- and context-specific characteristics otherwise sticking to a single period normally leads management to incorrect general performance assessment. In the same vein, this mitigates the general importance of the results of many other single period studies reported in this article mostly focusing on expansion years.

The conclusion of increasing inefficiency by moving from the early to deep recession period might differentiate our results from existing studies at bank level (Fukuyama & Matousek, 2011; Tsionas, Assaf, & Matousek, 2015; Demirgüç et al., 2006) whose report for the European banking, Greece as well (Tsionas et al., 2015), concludes an immediate improvement in performance after the emergence of recession and thus a high ability of banks to almost immediately absorb shock effects. This may be attributed to differences in the methodology (parametric method and intermediation approach) and the data set (broader data set including Greek commercial banks at corporate level) employed by the authors. However, their finding might need further documentation since all basic economic and banking indices of the Greek economy deteriorated substantially during the 2011–2015 period as shown in the present study.

Undoubtedly a relative stabilization in the adverse developments and a specific efficiency improvement that we located in the first half of 2016 was the result of the unique capital controls which inhibited core functions of the domestic banking market which consequently almost totally inactivated a part of the European banking system. By contrast efficiency substantially deteriorated in the early recession years (as compared to the capital control period) because banking institutions were not well prepared to face the crisis. Indeed, during the preceding expansion period, they tried to acquire greater market shares in an oligopolistic environment lending more and more unreliable customers. Such low-quality loans were converted immediately into Non-Performing Loans (NPLs) with the sudden advent of recession causing a considerable inefficiency at branch level. So, early and deep recession had already caused great efficiency destruction, before the enforcement of capital controls. In addition, after the first shock of recession years banking institutions took various adjustment measures and accumulated greater experience in crisis management. So, there was no longer enough room for further efficiency destruction in the capital control period. Consequently, capital control measures that hamper capital flight abroad in connection with a certain economic recovery seem to play a positive role in performance improvement.

On the whole, the proposed methodology sheds light on the issue of bank branch efficiency during turbulent economic periods exhibiting the specific challenge for the bank management in diverse external environments and locating inefficiency areas that provide important implications for both bank management and policy makers. As efficiency is unequally distributed among different branch types and evolves dynamically with variations, the study provides important implications related to branch merging policies and effective branch performance measurement (i.e., different region handling) which can improve retail banking performance in difficult times. In conjunction with this, the specific methodology can be easily understood and implemented by effective bank managers who have direct access to primary information knowing very well the internal operational environment of their institution thus helping them to substantially improve the efficiency dynamic of crucial value drivers. Our methodological approach is generally applicable after obtaining specific information for the input and output variables of the model and can be utilized in diverse changing environments of a different nature and form that cause efficiency change and are not mandatory in recession situations in the crisis countries of the Eurozone. The banking industry (but not only) facilitates the application of our methodology as the industry is subject to both multiple and unpredictable transformations offering an attractive context to measure efficiency change and identify critical sources of inefficiencies across a differentiated retail network.

As mentioned above, a basic condition for the successful bank branch application of such a methodology is the access to the internal operational environment of a bank network. The acquisition of reliable internal information enables researchers to compare efficiency of different groups of branches within the same banking institution. In this case, familiarity with the internal environment of retail network (e.g., knowledge of internal information system, reliable analysis of profit and loss statements) and effective cooperation with bottom-level managers are needed. Obviously, researchers who are interested in a comparative study have greater

[25] Their analysis refers to the impact of external factors on organizational efficiency in public services (Seol et al. 2008), the identification of segments of potentially profitable customers (Lee and Park, 2005) and the forecasting of the degree of new technology commercialization in the information technology industry (Sohn and Moon, 2004).

difficulty to get access to more than one bank because of the secretive nature of the oligopolistic environment. Nevertheless, this limitation does not necessarily prevent generalization of findings from a certain case study (as ours) since strategic players within retail banking industry are basically similar thus their branches are very comparable. We hope our study will provoke further debate on the topic and will motivate future research to address new aspects of the impact of external environmental change on the efficiency and performance of bank branches. In this context, issues such as institutional change, integration of an economy in a single economic area or even withdrawal from that might be interesting research topics. Moreover, future research is needed to highlight the efficiency effect of recessions, external shocks, etc. in emerging economies or in other European Mediterranean crisis economies which suffer from great instability.

Appendix A

The bootstrapped DEA approach introduced by Simar and Wilson (1998) is used to examine the statistical properties (bias, adjusted technical efficiency, confidence intervals etc.) of efficiency scores generated through conventional DEA. The key assumption is that the known bootstrap distribution will mimic the original unknown distribution, if the known data generating process (DGP) is a consistent estimator of the unknown DGP. The bootstrap process will therefore generate values that mimic the distributions which would be generated from the unobserved and unknown DGP. Specifically, the bootstrap approach is based on the DEA estimators themselves by drawing with replacement from the original estimates of theta, and then applies the reflection method proposed by Silverman (1986). Assuming n branch observations $\{(x_i,\ y_i\ ), i = 1, \ldots, n)\}$ that use multiple inputs x to produce multiple outputs y, a summary of the Simar and Wilson's (1998, 2000) methodology to estimate the VRS pure technical efficiency of the sample observations is described in the following steps:

1. For each branch observation $\{(x_k,\ y_k\ ), k = 1, \ldots, n)\}$, we compute $\hat{\theta}_k$ (i.e., the DEA-estimated efficiency) as solution to the linear program formula:

$$\hat{\theta}_k = \min\left\{\theta \ subject\ to\ \theta x_k \geq \sum_{i=1}^{n} z_i x_i;\ y_k \leq \sum_{i=1}^{n} z_i y_i;\ \sum_{i=1}^{n} z_i = 1;\ z_i \geq 0\right\} \tag{A1}$$

2. We use bootstrap via smooth sampling from $\hat{\theta}_1, \ldots, \hat{\theta}_n$ to obtain a bootstrap replica $\theta_1^*, \ldots, \theta_n^*$. This is implemented as follows:
   a. We draw with replacement (bootstrap) from $\hat{\theta}_1, \ldots, \hat{\theta}_n$ to generate $\beta_1^*, \ldots, \beta_n^*$
   b. We smooth the sampled estimates using the following formula:

$$\tilde{\theta}_i^* = \begin{cases} \beta_i^* + h\varepsilon_i^* & if \quad \beta_i^* + h\varepsilon_i^* \leq 1 \\ 2 - \beta_i^* - h\varepsilon_i^*, & otherwise \end{cases} \tag{A2}$$

   where h is the bandwidth of a standard normal kernel density and ε_i^* is a random error drawn randomly from the standard normal distribution. The cross-validation method (Silverman, 1986) can be used to determine the bandwidth parameter as detailed by Simar and Wilson (1999).
   c. We correct the variance of the bootstrap estimates by computing:

$$\theta_i^* = \bar{\beta}^* + \frac{\tilde{\theta}_i^* - \bar{\beta}^*}{\sqrt{1 + h^2/\hat{\sigma}_{\hat{\theta}}^2}} \tag{A3}$$

   where $\bar{\beta}^*$ is the average of $\beta_1^*, \ldots, \beta_n^*$ and $\hat{\sigma}_{\hat{\theta}}^2$ is the sample variance of $\hat{\theta}_1, \ldots, \hat{\theta}_n$
3. We generate a pseudo-data set $\eta_b^* = \{(x_{ib}^*, y_i),\ i = 1, \ldots, n\}$ given $x_{ib}^* = \frac{\hat{\theta}_i}{\theta_{ib}^*} x_i$ (i.e., the calculated bootstrapped input based on bootstrap efficiency).
4. We solve the DEA program to estimate $\hat{\theta}_{k,b}^*$ (i.e., the bootstrap replica b estimate based on the replica technology T^b)

$$\hat{\theta}_{k,b}^* = \min\left\{\theta \ subject\ to\ \theta x_k \geq \sum_{i=1}^{n} z_i x_{ib}^*;\ y_k \leq \sum_{i=1}^{n} z_i y_i;\ \sum_{i=1}^{n} z_i = 1;\ z_i \geq 0\right\} \tag{A4}$$

5. We repeat the steps 2–4: 2000 times (B =2000 times) to obtain a set of bootstrap estimates $\hat{\theta}_{k,b}^*$ (b =1,...,B, k =1,...,n)

More details regarding the bootstrap DEA such as the establishment of confidence intervals and bias correction, are provided in Simar and Wilson (2000).

Appendix B

In the below scatter diagrams Figs. B1–B5, the estimated branch efficiency scores for the branch network are depicted, separately

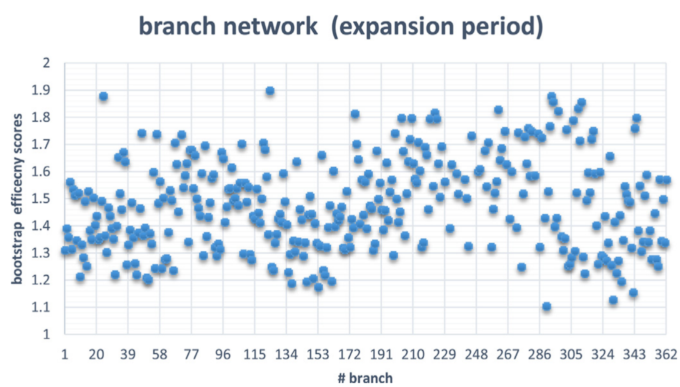


Fig. B1. Depiction of estimated branch efficiency scores in the expansion period.
Notes: This figure depicts the branch efficiency scores of the total branch network (362 branches) for the expansion period.

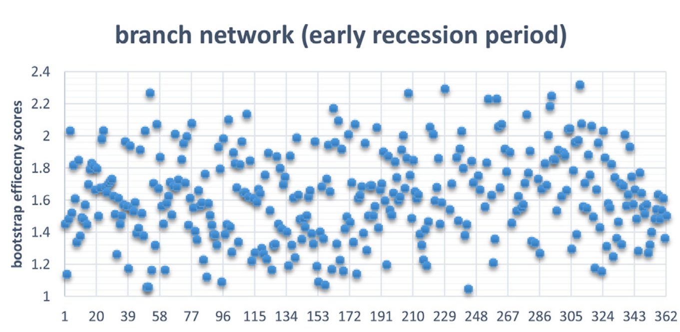


Fig. B2. Depiction of estimated branch efficiency scores in the early recession period.
Notes: This figure depicts the branch efficiency scores of the total branch network (362 branches) for the expansion period.

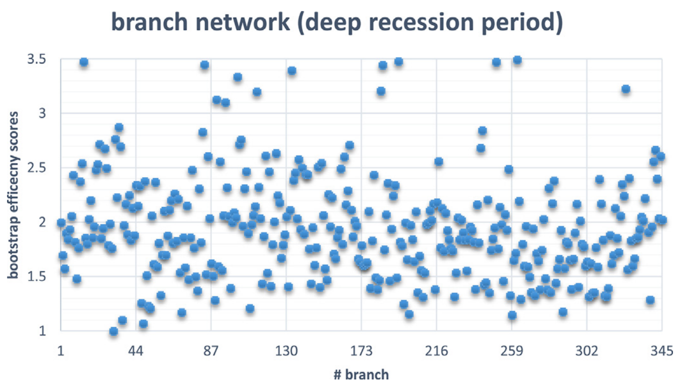


Fig. B3. Depiction of estimated branch efficiency scores in the deep recession period.
Notes: This figure depicts the branch efficiency scores of the total branch network (345 branches) for the deep recession period.

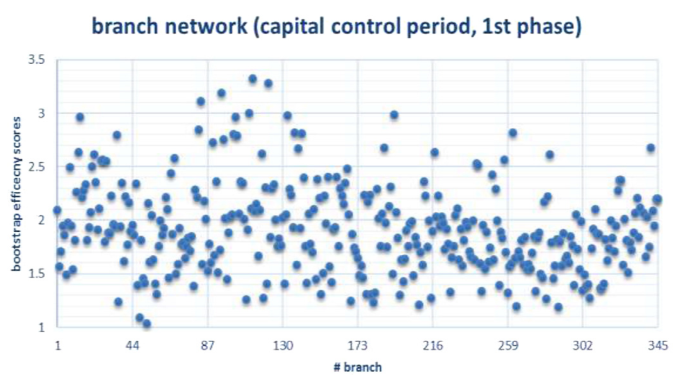


Fig. B4. Depiction of estimated branch efficiency scores in the first phase of the capital control period.
Notes: This figure depicts the branch efficiency scores of the total branch network (345 branches) for the first phase of the capital control period.

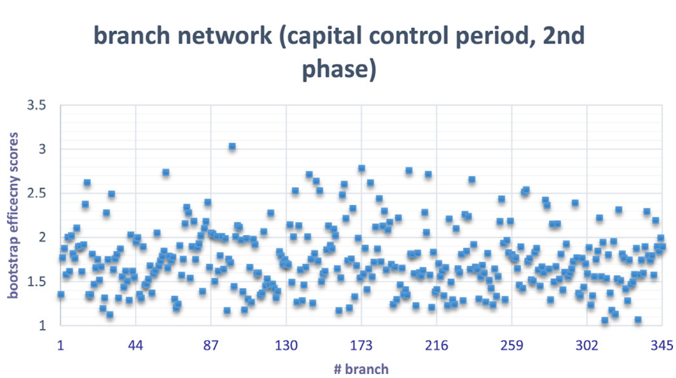


Fig. B5. Depiction of estimated branch efficiency scores in the second phase of the capital control period.
Notes: This figure depicts the branch efficiency scores of the total branch network (345 branches) for the second phase of the capital control period.

for each examined period (expansion period, early recession period, deep recession period, first and second phase of the capital control period respectively). Also, the average efficiency scores of the branch network – for all the time periods – are summarized, with the use of a box-and-whisker diagram Fig. B6.

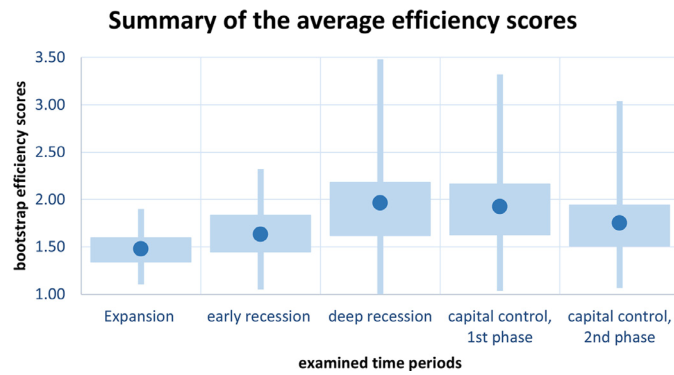


Fig. B6. Depiction of average branch efficiency scores throughout the examined period.
Notes: A box-and-whisker diagram for the average efficiency scores for each period.

Appendix C

Table C1.

Table C1
Average efficiency results for the branch network for both specifications (aggregated and disaggregated).

Time periods	Efficiency results for the disaggregated specification (A)	Efficiency results for the aggregated specification (B)
Expansion	1.465	1.478
Early recession	1.614	1.632
Deep recession	1.948	1.963
Capital control period 1st phase	1.905	1.926
Capital control period 2nd phase	1.729	1.750

Notes: This table presents the average efficiency results over the successive periods for the disaggregated specification (column A) and aggregated specification (column B), respectively.

References

Aggelopoulos, E., & Georgopoulos, A. (2015). The determinants of shareholder value in retail banking during crisis years: the case of Greece. *Multinational Finance Journal, 19*(2), 109–147.
Asmild, M., & Zhu, M. (2016). Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis. *European Journal of Operational Research, 251*, 999–1015.
Avkiran, N. (1999). An application reference for data envelopment analysis in branch banking: Helping the novice researcher. *International Journal of Bank Marketing, 17*, 206–220.
Banker, R., & Cummins, J. (2010). Performance measurement in the financial services sector: Frontier efficiency methodologies and other innovative techniques. *Journal of Banking and Finance, 34*, 1413–1416.
Banker, R. (1993). Maximum likelihood, consistency and data envelopment analysis: A statistical foundation. *Management Science, 39*, 1265–1273.
Banker, R., Charnes, A., & Cooper, W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*, 1078–1092.
Barros, C., Nektarios, M., & Assaf, A. (2010). Efficiency in the Greek insurance industry. *European Journal of Operational Research, 205*, 431–436.
Bauer, P., Berger, A., & Humphrey, D. (1993). Efficiency and productivity growth in the US banking. . In H. Fried, C. Lovell, & S. Schmidt (Eds.), *The measurement of productive efficiency: Techniques and applications* (pp. 386–413). Oxford: Oxford University Press.
Berger, A., & Humphrey, D. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research, 98*, 175–212.
Berger, A., & Humphrey, D. (1992). Measurement and efficiency issues in commercial banking. In Z. Griliches (Ed.), *Measurement issues in the service sector* (pp. 245–279). Chicago: National Bureau of Economic Research, University of Chicago Press.
Berger, A., Leusner, J., & Mingo, J. (1997). The efficiency of bank branches. *Journal of Monetary Economics, 40*, 141–162.
Berger, A., & Mester, J. (2003). Explaining the dramatic changes in performance of US Banks: Tecjnological change, Deregulation, and dynamic changes in competition. *Journal of Financial Intermediation, 12*, 57–95.

Biener, C., Eling, M., & Wirfs, J. (2016). The determinants of efficiency and productivity in the Swiss insurance industry. *European Journal of Operational Research, 248*, 703–714.
Bos, J., & Kool, C. (2006). Bank efficiency: The role of bank strategy and local market conditions. *Journal of Banking and Finance, 30*, 1953–1974.
Camanho, A., & Dyson, R. (2006). Cost efficiency, production and value-added models in the analysis of bank branch performance. *Journal of the Operational Research Society, 56*, 483–494.
Camanho, A., & Dyson, R. (2005). Cost efficiency measurements with price uncertainty: A DEA application to bank branch assessments. *European Journal of Operational Research, 161*, 432–446.
Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*, 95–112.
Das, A., Ray, S., & Nag, A. (2009). Labor-use efficiency in Indian banking: A branch-level analysis. *Omega, 37*, 411–425.
Demirgüç-Kunt, A., Detragiache, E., & Gupta, P. (2006). Inside the crises: An empirical analysis of banking systems in distress. *Journal of International Money and Finance, 25*, 702–718.
Deville, A. (2009). Branch banking network assessment using DEA: A benchmarking analysis – A note. *Management Accounting Research, 20*, 252–261.
Drake, L., & Hall, M. (2003). Efficiency in Japanese banking: An empirical analysis. *Journal of Banking and Finance, 27*, 891–917.
Drake, L., Maximilian, J., & Simper, R. (2006). The impact of macroeconomic and regulatory factors on bank efficiency: A non-parametric analysis of Hong Kong's banking system. *Journal of Banking and Finance, 30*, 1443–1466.
Dyson, R., Allen, R., Camanho, A., Podinovski, V., Sarrico, C., & Shale, E. (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research, 132*, 245–259.
Eken, M., & Kale, S. (2011). Measuring bank branch performance using data envelopment analysis (DEA): The case of Turkish bank branches. *African Journal of Business Management, 5*, 889–901.
Eling, M., & Schaper, P. (2017). Under pressure: How the business environment affects productivity and efficiency of European life insurance companies. *European Journal of Operational Research, 258*, 1082–1094.
Eskelinen, J., Halme, M., & Kallio, M. (2014). Bank branch sales evaluation using extended value efficiency analysis. *European Journal of Operational Research, 232*, 654–663.
European Parliament's Economic Governance Support Unit (2016, January). Greece's financial assistance programme. Available at: http://www.europarl.europa.eu/RegData/etudes/IDAN/2016/574389/IPOL_IDA(2016)574389_EN.pdf.
Fethi, M., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research, 204*, 189–198.
Fiordelisi, F., Marquez-Ibanez, D., & Molyneux, P. (2011). Efficiency and risk taking in European banking. *Journal of Banking and Finance, 35*, 1189–1200.
Fukuyama, H., & Matousek, R. (2017). Modelling bank performance: A network DEA approach. *European Journal of Operational Research, 259*, 721–732.
Fukuyama, H., & Matousek, R. (2011). Efficiency of Turkish banking: Two- stage network system. Variable returns to scale. *Journal of International Financial Markets, Institutions and Money, 21*, 75–91.
Galan, J., Veiga, H., & Wiper, M. (2015). Dynamic effect in inefficiency: Evidence from the Colombian Banking sector. *European Journal of Operational Research, 240*, 562–571.
Gaganis, C., Liadaki, A., Doumpos, M., & Zopounidis, C. (2009). Estimating and analyzing the efficiency and productivity of bank branches: Evidence from Greece. *Managerial Finance, 35*, 202–218.
Giokas, D. (2008a). Assessing the efficiency in operations of a large Greek bank branch network adopting different economic behaviors. *Economic Modeling, 25*, 559–574.
Giokas, D. (2008b). Cost efficiency impact of bank branch characteristics and location: An illustrative application to Greek bank branches. *Managerial Finance, 34*, 172–185.
Hartman, T., Storbeck, J., & Byrnes, P. (2001). Allocative efficiency in branch banking. *European Journal of Operational Research, 134*, 232–242.
Kimball, R. (1998). *Economic profit and performance measurement in banking*. New England Economic Review, Federal Reserve of Boston.
Kneip, A., Park, B., & Simar, L. (1998). A note on the convergence of nonparametric DEA estimators for production efficiency scores. *Econometric theory, 14*, 783–793.
LaPlante, A., & Paradi, J. (2015). Evaluation of bank branch growth potential using data envelopment analysis. *Omega, 52*, 33–41.
Leaven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: Too much, too late? *Journal of Financial Intermediation, 12*, 178–197.
Lee, J., & Park, S. (2005). Intelligent profitable customers segmentation system based on business intelligence tools. *Expert systems with applications, 29*, 145–152.
Lozano-Vivas, A., & Pasiouras, F. (2010). The impact of non-traditional activities on the estimation of bank efficiency: International evidence. *Journal of Banking and Finance, 34*, 1436–1449.
Manolopoulou, E., Kotsiantis, S., & Tzelepis, D. (2015). Application of association and decision rules on intellectual capital. *Knowledge Management Research & Practice, 13*, 225–234.
Moody's (2016, November 22). Banking system outlook - Greece: stable outlook reflects improved funding and profitability prospects balanced against still sizeable problem loans. Moody's.
Moody's (2015, May 19). Banking system outlook of Greece. Moody's . Available at: http://alfaalliance.info/wp-content/uploads/2015/05/Moodys-Greek-Banking-Sector-Outlook-May-19-2015.pdf.
Mostafa, M. (2009). Modeling the efficiency of top Arab banks: A DEA–neural network approach. *Expert Systems with Applications, 36*, 309–320.
Noulas, A., Glaveli, N., & Kiriakopoulos, I. (2008). Investigating cost efficiency in the branch network of a Greek bank: An empirical study. *Managerial Finance, 34*, 160–171.
Paradi, J., & Zhu, H. (2013). A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega, 41*, 61–79.
Paradi, J., Rouatt, S., & Zhu, H. (2011). Two-stage evaluation of bank branch efficiency using data envelopment analysis. *Omega, 39*, 99–109.
Paradi, J., & Schaffnit, C. (2004). Commercial branch performance evaluation and results communications in a Canadian Bank – a DEA application. *European Journal of Operational Research, 156*, 719–735.
Pasiouras, F. (2008). Estimating the technical and scale efficiency of Greek Commercial Banks: The impact of credit risk, off balance sheet activities and international operations. *Research in International Business and Finance, 2*, 247–440.
Portela, M., & Thanassoulis, E. (2007). Comparative efficiency analysis of Portuguese bank branches. *European Journal of Operational Research, 177*, 1275–1288.
Ray, S. (2016). Cost efficiency in an Indian bank branch network: A centralized resource allocation model. *Omega, 65*, 68–81.
Rokach, L., & Maimon, O. (2014). *Data mining with decision trees: Theory and applications* (2nd edition). World scientific.
Seol, H., Lee, H., Kim, S., & Park, Y. (2008). The impact of information technology on organizational efficiency in public services: A DEA-based DT approach. *Journal of the Operational Research Society, 59*, 231–238.
Shephard, R. (1970). *Theory of cost and production functions*. Princeton: Princeton University Press.
Silverman, B. (1986). *Density estimation of statistics and data analysis*. London: Chapman and Hall.
Simar, L., & Wilson, P. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparapametric frontier models. *Management Science, 44*, 49–61.
Simar, L., & Wilson, P. (1999). Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research, 115*, 459–471.
Simar, L., & Wilson, P. (2000). A general methodology for bootstrapping nonparametric frontier models. *Journal of Applied Statistics, 27*, 779–802.
Simar, L., & Wilson, P. (2002). Nonparametric tests of returns to scale. *European Journal of Operational Research, 139*, 115–132.
Simar, L., & Wilson, P. (2007). Estimation and inference in two-stage, semiparametric models of production processes. *Journal of Econometrics, 136*, 31–64.
Sohn, S., & Moon, T. (2004). Decision tree based on data envelopment analysis for effective technology commercialization. *Expert Systems with Applications, 26*, 279–284.
Staat, M. (2002). Bootstrapped efficiency estimates for a model for groups and hierarchies in DEA. *European Journal of Operational Research, 138*, 1–8.
Tsionas, E., Assaf, G., & Matousek (2015). Dynamic technical and allocative efficiencies in European banking. *Journal of Banking and Finance, 52*, 130–139.
Tsolas, I., & Charles, V. (2015). Incorporating risk into bank efficiency: A satisficing DEA approach to assess the Greek banking crisis. *Expert Systems with Application, 41*, 3491–3500.
Zenios, C., Zenios, S., Agathocleous, K., & Soteriou, A. (1999). Benchmarks of the efficiency of bank branches. *Interfaces, 29*, 37–51.
Wilson, P. W. (1993). Detecting outliers in deterministic nonparametric frontier models with multiple outputs. *Journal of Business and Economic Statistics, 11*, 319–323.
Wilson, P. W. (2008). Fear: A software package for frontier efficiency analysis with R. *Socio-Economic Planning Sciences, 42*, 247–254.
Wu, D., Yang, Z., & Liang, L. (2006). Using DEA-neural network approach to evaluate branch efficiency of a large Canadian bank. *Expert Systems with Applications, 31*, 108–115.