Branch manager characteristics and efficiency during capital controls

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Abstract: This paper investigates the impact of manager characteristics on bank branch efficiency during the extreme economic event of capital controls. A unique branch-level data set comprising of accounting and personal managerial information of a representative Greek systemic bank is utilised. A profit-oriented bootstrapped DEA model is run for both the total branch network of the bank under investigation and a homogeneous group of its branches, covering the period from January 2016 to February 2017. It is found that university graduate managers outperform on average their colleagues with a secondary education level regardless of the sample used. In the case of the homogeneous sample, more experienced managers can tackle adverse crisis effects on branch performance more effectively than inexperienced managers; this is even more applicable to the large branches. In this homogeneous branch framework, management experience can satisfactorily compensate for educational limitations caused by a manager not having higher education qualifications.

Keywords: banking; bank branch efficiency; manager characteristics; experience level; educational background; accounting information; profit and loss statements; bootstrap DEA; capital controls; Greece.

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Biographical notes: Eleftherios Aggelopoulos is an Adjunct Lecturer in Financial Accounting at the Department of Business Administration, University of Patras, Greece. His working experience is associated with retail and corporate banking while his research interests are focused on banking performance and management accounting. His work has been presented in international conferences such as the Annual European Accounting Association Congress, Annual Conference of Centre for Money, Banking and Institutions of University of Surrey and Annual Conference of Multinational Finance Society, etc. His recent publications include European Journal of Operational Research, Advances in Management Accounting, Multinational Finance Journal, Journal of Accounting and Taxation and Journal of Accounting and Management Information Systems, etc.
1 Introduction

How do branch manager characteristics affect bank branch performance during difficult times for the banking sector? More precisely, do branches with more educated or experienced managers address the adverse crisis effects more effectively than others? Our starting position is that personnel related factors such as educational background and experience differ among individuals. Thus, it is proposed that managerial variations in these fields can have a significant impact on branch efficiency. Therefore, the branch efficiency is related to the characteristics of the branch manager and the significance of this relationship during the capital control period is explored.

The empirical analysis is applied to the bank-driven Greek economy suffering from adverse recession and capital control effects and characterised by similar banking operations (pure retail banking, granting loans to micro and small enterprises) with other EU peripheral countries. The unique detailed data set is derived both from the curriculum vitae of branch managers that were collected manually and the unpublished monthly profit and loss (P&L) statements from the bank’s management information system (MIS) during the period January 2016 to February 2017. The examined samples include both the total branch network of a large systemic commercial bank and a homogeneous subsample of it with 145 retail branches that are located in the capital of Greece (Athens). Few data sets of this kind are available and this provides originality in the present study. The data set is representative as the Greek banking industry is very oligopolistic (i.e., there are four systemic Greek commercial banks: The National Bank of Greece, Piraeus Bank, Eurobank and Alpha Bank) and quite homogeneous in the way in which they operate in commercial retail banking.

To measure branch performance, firstly the branch activity should be defined and afterwards the appropriate methodological tool for tracking the branch retail process should be selected. More specifically, branch activity is captured via the resources managed (inputs) and the results generated (outputs) by the branch managers. Moreover, given that no approach (e.g., the production, the intermediation and the profit oriented approach) is able to fully capture the multi-role nature of bank branches, and that bank branch management during recession periods seeks for the stabilisation of branch profitability, this paper considers branch management effectiveness as the ability to minimise 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). Therefore, the present study applies a profit approach which can track the profit stabilisation goal by including all critical aspects of the branch’s internal operating processes such as revenues and costs, service quality and diversity of strategic management responses to dynamic environmental conditions caused by capital control effects. Relevant literature suggests that benchmarking models such as the non-parametric technique of data envelopment analysis (DEA)² (Paradi and Zhu, 2013, Fethi and Pasiouras, 2010) are very appropriate to conduct a branch performance analysis since they take simultaneous account of all resources and outputs in assessing performance. Consequently, an input-oriented profit bootstrap DEA (Simar and Wilson, 2000, 1998) is selected as the suitable model for measuring branch efficiency under input
minimisation considerations, given that conventional DEA has several statistical limitations such as the non-precision of efficiency estimates (Dyson et al., 2001; Banker, 1993). Afterwards, the Simar and Wilson’s (2007) method in a two-stage double bootstrap procedure is applied to investigate if the manager characteristics are important efficiency drivers. For reasons of robustness, a model tree (MT) with linear regression functions (see Kotsiantis et al., 2005) is also produced.

Overall, the results indicate that education and experience affect profit efficiency. Managers with higher education seem to outperform, on average, their colleagues with a secondary level education for both the total branch network and the homogeneous branches. When the efficiency analysis controls for environmental factors and the homogenous group of retail branches is examined, there is evidence that more experienced managers can address crisis effects more effectively than inexperienced managers and this finding is more evidenced in the large branches. In this homogeneous branch network, the experience factor appears to offset the negative efficiency effects of not having a university degree.

The main contributions of this study are as follows: initially, this is the first study which investigates the impact of manager’s characteristics on efficiency at the branch level since to the best of my knowledge the only existing study on this topic (Kauko, 2009) provides evidence at bank level and for the pre-crisis period. Generally, branch level studies are much less frequent than bank level ones, although bank branches are the essential income generators (with specific cost and risk characteristics) that can help bank management to improve bank’s overall performance (Berger et al., 1997). Secondly, the paper examines this issue during the extreme economic event of capital controls in Greece which is a unique phenomenon in the postwar period in the Eurozone. This provides the originality of this study. Thirdly, the study offers useful directions to banking institutions for profit efficiency improvement during difficult times through an effective human capital management.

The study is structured as follows: the following section reviews previous literature. Section 3 describes the data while the method and the specification are presented in Section 4. Empirical results are presented on Section 5 and the conclusion section summarises the findings.

2 Literature and the institutional setting

2.1 Managers characteristics and bank efficiency related literature

As regards the effects of education on efficiency, the theoretical justification comes from Becker (1962) which supports that education creates valuable human capital (human capital theory). Also, Spence (1973) introduced the signalling theory where the skilled managers acquire education to signal their type. Hence, it is expected the manager’s education level positively correlates with bank efficiency.

Concerning the effects of experience on efficiency, Holmström (1982) provides evidence that less experienced managers, due to career concerns, outperform the more experienced managers. On the other hand, the ‘learning by doing process’ argument provides an efficiency advantage to experienced and mature branch managers. The most recent econometric research that investigates the impact of manager characteristics on bank performance is the study of Kauko (2009). The author linked cost efficiency
behaviour of a sample of Finnish savings and cooperative banks in 1999–2004 to specific
bank managers features and found inter alia that mature managers mostly outperform
their young colleagues, while the educational background seems to be less important for
young managers than for mature ones. Also, he reported that a university degree is useful,
mainly in the largest banks of the sample.

A general review of the existing literature reveals that there is no branch-level study
in this research sector.

2.2 Branch efficiency literature

For measuring efficiency, alternative models are found in the banking literature (Fethi
and Pasiouras, 2010). In particular, six different approaches, namely, 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 organise 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). Moreover, DEA methods have been
recognised very appropriate for comparative efficiency measurement, especially to
capture non-allocative managerial forms of inefficiency, the so-called X-inefficiency
(Mostafa, 2009).

After a systematic review of the related literature, it is found that DEA and their
extensions dominate bank and branch banking efficiency literature (Berger and
Humphrey, 1997; Fethi and Pasiouras, 2010; Paradi and Zhu, 2013). The DEA model
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 recognised 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. In a recent review of the branch performance literature, Paradi and Zhu
(2013) reported recently 80 DEA studies over the period 1985–2011 characterised by a
significant diversity in terms of the employed approach (production, profit, and
intermediation), the inputs-outputs selection, the returns to scale characterisation and the
sample sizes. Almost all of them are country-specific in nature (inter alia nine pure
Greek studies with traditional DEA) and only two studies contain cross-country
comparisons.

As mentioned in the introduction, branch performance can be defined through three
different DEA approaches: the production, the intermediation and the profit oriented
approach. The production model views bank branches as producers of services using
labour and other physical resources as inputs and providing services for taking deposits,
making loans and others as outputs. The intermediation model recognises 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), 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. Berger and Mester (2003) support that in a dynamic external
environment a profit-based approach is better able to capture the diversity of strategic responses by banking institutions. In addition, the profit model might take into account unmeasured changes in the quality of banking services by including higher revenues paid for the improved quality (Portela and Thanassoulis, 2007).

2.3 The institutional setting

The data set contains retail branches of a large Greek commercial bank which is representative of the Greek banking industry and its evolution from 1990’s until the imposition of capital controls in the Greek economy.

It should be emphasised that after a drastic deregulation and liberalisation of banking operations during the 1990’s, a new dynamic banking industry was created. Moreover, as Greece entered the Eurozone in 2001, the local economy showed remarkable growth rates which boosted the development of the domestic banking sector. Many banking institutions were established within this specific period and new employees were recruited in the banking industry with diverse personal characteristics. Thus, in the growth years till 2008 its four major systemic banks (i.e., The National Bank of Greece, Piraeus Bank, Eurobank and Alpha Bank) 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 unfavourable economic conditions the following years with crucial liquidity and performance implications of domestic banking institutions (Aggelopoulos and Georgopoulos, 2015). However, the economic and financial situation in July 2015 became worse since capital control was imposed to Greek Economy by ECB in order to limit a massive export of deposits abroad which started already in the beginning of the crisis. Several banking activities were limited temporarily and serious capital crunch effects threatened the stability of the economic-political system. Finally, in August 2015 a new memorandum of understanding (MoU) was signed between the European Commission and Greece for a 3rd bailout of up to 86 billion Euro’s for the period 2015–2018 and subsequently the banks operations were restored. Following the successful conclusion of the recapitalisation of Greek banks in December 2015, a relative stabilisation 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). Capital controls were relaxed somewhat, whereas banks started to provide the first new loans to the economy at the beginning of 2016.

3 The dataset

The available data set contains complete information on 325 retail branches spread across Greece (the total branch network) which provide products to individuals and micro and small enterprises. Also, the study controls for environmental factors (Aggelopoulos and Georgopoulos, 2017; Paradi et al., 2011; Gaganis et al., 2009; Das et al., 2009; Deville, 2009) and a subsample of 145 branches located in Athens is also examined. Accounting data are from the monthly P&L statements of each branch, derived from the internal MIS
of the specific bank of the study for the period January 2016 to February 2017. Data on branch manager’s characteristics is collected manually from their curriculum vitae. Manager specific data is referred to the person who was in charge as of 1st of January and hold his/her position until February 2017. This data contains complete information on managers’ education, experience and internal training programmes that each manager attended. Since almost all the branch managers attended the same internal programmes, this variable was not included in the analysis. Also, for confidentiality reasons the age of the branch managers could not be disclosed but this is not an issue since the experience variable reveals the same information. Table 1 presents the descriptive statistics on manager characteristics for both the total branch network and the homogenous sample branches. In particular, the managers’ experience is defined with three length categories (more than 25 years, less than 15 years, and finally between 15 and 25 years), while two categories describe the managers’ education (university degree and non-university education). As it can be observed on Table 1, there is substantial variation in the personal data related factors of branch managers for both samples.

Table 1 Descriptive statistics on managers

<table>
<thead>
<tr>
<th>Samples</th>
<th>Number of managers</th>
<th>Education level</th>
<th>Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>With a master degree</td>
<td>With a university degree</td>
</tr>
<tr>
<td>Branch network</td>
<td>325</td>
<td>68 (21%)</td>
<td>145 (45%)</td>
</tr>
<tr>
<td>Homogenous branches</td>
<td>145</td>
<td>33 (23%)</td>
<td>53 (36%)</td>
</tr>
</tbody>
</table>

Notes: This table presents the distribution of each sample according to the manager characteristics. In parentheses, the proportion of each category of manager characteristics on the corresponding sample. Manager specific data is referred to the person who was in charge as of 1st of January and hold his/her position until February 2017.

As regards the accounting data, the various cost and revenue generating elements that define the input and output variables respectively of the profit efficiency approach (see below the methodology section), are specified from the branch P&L statement. Specifically, two input variables – direct operating expenses (OPEX) and loan loss provisions (LLP) are used. The input OPEX is measured as the sum of all controllable operational expenses (aggregated variable), excluding depreciation and bank overhead costs which are not the outcome of branch management. Specifically, three cost categories from the bank’s classification of expenses are incorporated into the analysis: personnel expenses which include also overtime salary costs and incurred losses stemming from operational risk; running expenses of the buildings which include rents, electricity, etc. and other operating expenses of the branches namely telephone, insurance, advertising, stationary and other supplies expenses. The input LLP is recorded in the branch P&L statement as an expense (thus reduces branch net income) and is created on a monthly portfolio basis (consumer loans, small business loans and mortgages loans) according to the international accounting standard 39 (IAS 39) and the general rule that a loan is classified as non-performing when interest or principal has not
been paid for more than 90 days. As regards output side, the present study considers two outputs of retail branches linked to their main sources of income: non-interest income from fees (FEES output variable) and 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. Table 2 presents the descriptive statistics of the input and output variables that are used for the derivation of the profit efficiency estimates.

### Table 2

Descriptive statistics of inputs-outputs used in the efficiency assessment for the branch groups (monthly data, in Euro’s)

<table>
<thead>
<tr>
<th>Branch groups</th>
<th>Stat.</th>
<th>OPEX</th>
<th>LLP</th>
<th>FEES</th>
<th>INCOME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch network</td>
<td>mean</td>
<td>42,716</td>
<td>276,591</td>
<td>12,528</td>
<td>146,473</td>
</tr>
<tr>
<td></td>
<td>sdev</td>
<td>15,461</td>
<td>164,198</td>
<td>7,507</td>
<td>81,460</td>
</tr>
<tr>
<td></td>
<td>min</td>
<td>15,504</td>
<td>18,800</td>
<td>922</td>
<td>6,600</td>
</tr>
<tr>
<td></td>
<td>max</td>
<td>134,710</td>
<td>1,022,012</td>
<td>47,884</td>
<td>413,643</td>
</tr>
<tr>
<td>Homogeneous Branches</td>
<td>mean</td>
<td>42,657</td>
<td>302,812</td>
<td>15,076</td>
<td>139,723</td>
</tr>
<tr>
<td></td>
<td>sdev</td>
<td>15,138</td>
<td>167,737</td>
<td>7,554</td>
<td>71,297</td>
</tr>
<tr>
<td></td>
<td>min</td>
<td>21,445</td>
<td>18,800</td>
<td>3,551</td>
<td>28,711</td>
</tr>
<tr>
<td></td>
<td>max</td>
<td>134,710</td>
<td>1,022,012</td>
<td>44,235</td>
<td>402,217</td>
</tr>
</tbody>
</table>

Note: This table presents the monthly average value (in Euro’s) for each variable used for the derivation of efficiency estimates for both samples.

### 4 Methodology

#### 4.1 Bootstrap DEA (two stage)

As it is mentioned in the literature section, the DEA model is considered an effective performance tool for multidimensional contexts such as banks and branches which involve setting multiple inputs against multiple outputs (Paradi and Zhu, 2013; Camanho and Dyson, 2005; Hartman et al., 2001). Taking also into account that DEA has the advantage of imposing less structure on the efficient frontier as compared to SFA that uses strong assumptions regarding the form of the efficient frontier (Biener et al., 2016), the present study utilises DEA for the derivation of efficiency scores. More precisely, a bootstrap DEA model (Simar and Wilson, 2000, 1998)\(^5\), is applied for the extraction of branch efficiency scores as this method provides also and confidence intervals for the efficiency estimations.\(^6\) For the definition of branch activity, the profit input oriented model is adopted. In particular, the profit based approach is selected compared to other approaches since 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 minimisation strategy. Consequently, the branch management efficiency is defined as the
ability to minimise 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).

Below are summarised the methodological steps for the derivation of significant efficiency drivers related to managers’ branch characteristics: firstly, for each branch, average monthly input (OPEX, LLP) and output (INCOME, FEES) levels are calculated for the period January 2016 to February 2017. Secondly, a bootstrap step proposed by Simar and Wilson (2002) is run in order to choose between CRS and VRS where the VRS assumption is verified. Thirdly, based on the average values of input and output variables and following closely Simar and Wilson’s (2000, 1998) methodology, the VRS efficiency measures are estimated in each bootstrap replication (i.e., 2,000 bootstrap replications) according to a specific procedure-algorithm that is shown in the Appendix A.7 Thus, bootstrap estimates along with its component (DEA distance function estimates, bias corrected distance functions estimates, bootstrap bias, variance estimates, upper 95% confidence interval, lower 95% confidence interval) are calculated for all the branches of each examined sample. Efficiency scores are measured 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. The final step is to link the derived efficiency scores with the managers’ characteristics through a second-stage bootstrap DEA regression model (Simar and Wilson, 2007). This model has a left truncation point at 1 and takes the below form:

\[ ES_i = \beta_0 + \beta_1 \text{UNIV}_i + \beta_2 \text{OVER25Y}_i + \beta_3 \text{OVER25Y}_i \ast \text{SEC}_i + \beta_4 \text{DEPOSITS}_i + \beta_5 \text{LOC\_URBAN}_i + u_i \]

where the dependent variable is the bias – corrected efficiency score (ES) of each branch, \( \beta \) is the estimated coefficient for each independent variable, \( i \) denotes the number of retail branches (1 to 325). Taking into account the relevant banking literature on the link between manager characteristics and efficiency (see Kauko, 2009), the study focuses on two crucial branch manager characteristics that could be considerable efficiency drivers: first, the education level of the branch manager (dummy variable \( \text{UNIV} \): university education takes the value one, otherwise zero), and second the professional experience of the manager (dummy variable \( \text{OVER25Y} \): a manager with more than 25 years’ experience takes the value one, otherwise zero). In addition, an interaction variable that indicates the experienced managers with a non-university education is introduced (dummy variable \( \text{OVER25Y} \ast \text{SEC} \): a manager with more than 25 years’ experience and a secondary level education background takes the value one, otherwise zero). Also, the study controls for:

- a The size of each branch with a size indicator variable based on branch deposit balances (\( \text{DEPOSITS} \): logarithmic value of deposits for each branch).
- b The branch location with an indicator variable that expresses the location for urban branches (dummy variable \( \text{LOC\_URBAN} \): takes the value of one for urban branches, otherwise zero).

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 manager characteristics and the efficiency (dependent
variable) which means that a positive regression coefficient of a determinant increases inefficiency (i.e., decreases efficiency).

4.2 Robustness check (MT with linear regression functions)

In order to examine the robustness of the second-stage bootstrap DEA regression model results, a MT with linear regression functions is applied to the branch network sample. MTs that originate from machine learning are binary decision trees with linear regression functions at the leaf nodes. A MT is generated in two stages: the first builds an ordinary decision tree using as splitting criterion the maximisation of the intra-subset variation of the target value (the efficiency score in our case). The second limits this tree back by replacing sub-trees with linear regression functions. The construction of the MT in the present study is implemented through the M5’ algorithm scheme (see Kotsiantis et al., 2005). The learning procedure of the M5’ MT algorithm effectively divides the instance space into regions using a decision tree and strives to minimise the expected mean squared error between the MT’s output and the target values. The training instances that lie in a particular region can be viewed as samples from an underlying probability distribution that assigns class values. After the tree has been expanded, a linear multiple regression models is built for every inner node, using the data associated with that node and all the features that participate in tests in the sub-tree rooted at that node. The next section presents the rules that the MT generates along with the derived linear regression functions which reveal the association between efficiency and branch manager characteristics.

5 Results

5.1 Truncated regression results for the branch network and robustness check (MT)

This section describes the derived efficiency scores and their association with the specific branch manager characteristics and control variables. In particular, Table 3 presents 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 both the total branch network and the homogeneous branch network respectively. Looking at the total branch network, the bootstrap model generates an average bias-corrected score of 1.503 (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 50%. The estimated 95% confidence interval indicates that inputs could have been reduced by between 43% and 58%. Taking into account the strict homogeneity criterion (sample of 145 homogenous branches), the bootstrap model generates an average bias-corrected score of 1.346 (versus an efficiency score of 1.503 of the branch network). So, the homogeneous branches seem to present better efficiency than the network branches, indicating that the homogeneity factor affects substantially efficiency.
Table 3  Technical efficiency scores (under VRS) for the branch network and the homogeneous branch group based on the bootstrap DEA

<table>
<thead>
<tr>
<th></th>
<th>#</th>
<th>DEA distance function estimates</th>
<th>Bias-corrected distance function estimates</th>
<th>Bootstrap bias</th>
<th>Variance estimates</th>
<th>Upper 95% C.I.</th>
<th>Lower 95% C.I</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch network</td>
<td>325</td>
<td>1.419</td>
<td>1.503</td>
<td>0.084</td>
<td>0.0031</td>
<td>1.433</td>
<td>1.584</td>
</tr>
<tr>
<td>Homogenous branches</td>
<td>145</td>
<td>1.273</td>
<td>1.346</td>
<td>0.073</td>
<td>0.0014</td>
<td>1.282</td>
<td>1.426</td>
</tr>
</tbody>
</table>

Notes: 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, for the capital control period January 2016–February 2017. The employed methodology is an input-oriented bootstrap DEA profit approach under the assumption of variable returns to scale. Results are produced using 2,000 bootstrap replications.

Table 4  Truncated regression results (total branch network)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNIV_EDUC</td>
<td>Education indicator (university education/non-university)</td>
<td>–0.3383***</td>
</tr>
<tr>
<td>OVER25Y</td>
<td>Experience indicator (over 25 years’ experience/other)</td>
<td>–0.0717</td>
</tr>
<tr>
<td>OVER25Y*SEC</td>
<td>Interaction variable (experience over 25 years and a secondary educational background/other)</td>
<td>–0.1552</td>
</tr>
<tr>
<td>DEPOSITS</td>
<td>Branch size indicator: (log. value of Deposit balances)</td>
<td>0.3447***</td>
</tr>
<tr>
<td>LOC_URBAN</td>
<td>Location indicator (urban/non-urban)</td>
<td>–0.1354**</td>
</tr>
<tr>
<td>Sigma</td>
<td></td>
<td>0.2808***</td>
</tr>
<tr>
<td>Branches</td>
<td></td>
<td>325</td>
</tr>
</tbody>
</table>

Notes: The model that is estimated has a left truncation point at one. The dependent variable is the efficiency score (i.e., the value of one defines an efficient branch) of each branch. p-values in parentheses are estimated for each coefficient based on 2,000 bootstrap replications. Statistical significance index: *** at 1%, ** at 5%, * at 10%.

Source: see Biener et al. (2016)

In Table 4, the second-stage regression results for the branch network are presented. The p-values for each coefficient are calculated based on 2,000 bootstrap replications. Regarding the impact of the education level on inefficiency, it is observed that branches that are managed by a branch manager with a higher education level (university degree) decrease inefficiency, as shown by the negative and statistically significant coefficient (–0.3383) at the 1% level. This result reveals that university graduate branch managers have a comparative efficiency advantage in managing retail branches thus confirming the
human capital hypothesis. Moreover, the impact of experience on efficiency is examined where it is observed that branches with more experienced branch managers increase inefficiency as shown by the negative coefficient (−0.0717), but without this effect being statistically significant. In this direction, branches that are managed by managers that combine, a high level of experience along with a non-university educational background, are associated with a lower profit inefficiency (−0.1552), but again this effect is not statistically significant. As regards the control variables, looking at 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 (0.3447) at the 1% level. Also, the branch location in urban areas positively influences branch efficiency (−0.1354, at 5% level). Consequently, size and environmental effects seem to be related with changes in efficiency thus a more homogenous sample should be also examined in order to confirm the above relationships.

Table 5  Rules generated from a MT and the derived linear regression functions

<table>
<thead>
<tr>
<th>Rule number</th>
<th>Description</th>
</tr>
</thead>
</table>
| 1           | If monthly deposits (logarithmic value) below 4.363, then the linear regression function is:  
\[ ES = -0.0032 \times UNIV + 0.0387 \times DEPOSITS -0.1106 \times LOC_{URBAN} + 1.1958 \]  
\( (prob = 0.00) \) |
| 2           | If monthly deposits (logarithmic value) between 4.363 and 4.692, then the linear regression function is:  
\[ ES = -0.0032 \times UNIV + 0.0329 \times DEPOSITS -0.0077 \times LOC_{URBAN} + 1.3725 \]  
\( (prob = 0.00) \) |
| 3           | If monthly deposits (logarithmic value) above 4.692 and \( UNIV = 0.5 \) then the linear regression function is:  
\[ ES = -0.1665 \times UNIV - 0.03866 \times OVER25Y + 0.5971 \times DEPOSITS -0.1643 \times LOC_{URBAN} - 0.8072 \]  
\( (prob = 0.00) \) |
| 4           | If monthly deposits (logarithmic value) above 4.692 and \( UNIV = 1 \) then the linear regression function is:  
\[ ES = -0.0837 \times UNIV - 0.0317 \times OVER25Y + 0.3074 \times DEPOSITS -0.0089 \times LOC_{URBAN} - 0.1539 \]  
\( (prob = 0.00) \) |

Note: The construction of the MT and the derivation of the linear regression functions for each rule is implemented through the M5’ algorithm scheme.

Source: see Kotsiantis et al. (2005)

For robustness reasons, Table 5 presents the rules generated by the MT and the corresponding derived regression linear functions. As it is observed, in all generated rules the education variable (UNIV) is included with a negative value thus confirming the above econometric results. Also, the control variables (DEPOSITS and LOC_URBAN) seem to affect the efficiency score. Finally, the experience variable (OVER25Y) is included in the linear regression function of the last two rules, with a negative sign. Thus, the learning procedure of the MT reveals that the experience variable may affect the profit efficiency which can be verified through the homogeneous sample.
5.2 Truncated regression results for the homogenous branches

Table 6 presents the regression results for the homogeneous sample of 145 branches located in Athens. In order to further confirm the results, the homogenous sample is divided into two sub-samples based on the size of the branches, as this is indicated by the average managed deposit funds of each branch during the examined period. Thus, two sub-samples of branches located in Athens are formed: a branch group with large branches (deposit funds more than 55 million Euro’s) and a branch group with small branches located (deposit funds less than 30 million Euro’s). In this direction, table 6 contains also the regression results for the large (55 branches) and small urban branches (45 branches) respectively.

Table 6  Truncated regression results (homogeneous branch group)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Column 1 coefficient</th>
<th>Column 2 coefficient</th>
<th>Column 3 coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNIV_EDUC</td>
<td>–0.4999***</td>
<td>–1.123***</td>
<td>–0.1019</td>
</tr>
<tr>
<td>OVER25Y</td>
<td>–0.3713***</td>
<td>–0.9818***</td>
<td>0.1617</td>
</tr>
<tr>
<td>OVER25Y*SEC</td>
<td>–0.4389*</td>
<td>–0.9155**</td>
<td>0.1778</td>
</tr>
<tr>
<td>DEPOSITS</td>
<td>0.3467***</td>
<td>0.6382***</td>
<td>0.2303***</td>
</tr>
<tr>
<td>Sigma</td>
<td>0.2514***</td>
<td>0.3289***</td>
<td>0.2172***</td>
</tr>
<tr>
<td>Branches</td>
<td>145</td>
<td>55</td>
<td>45</td>
</tr>
</tbody>
</table>

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

Source: see Biener et al. (2016)

The results for the homogenous branch group (column1) confirm the positive efficiency effect of the education variable given the negative (–0.49999) and statistically significant coefficient at the 1% level. This result is also found for the large branches (column 2: –1.123 and statistically significant at 1% level), thus confirming the result of Kauko (2009) who found that university graduates have a competitive advantage in managing large banks. On contrary, there is no evidence that the education level affects the efficiency for the small branches (column 3). Interestingly, homogeneous branches managed by experienced bank managers seem to present better efficiency behaviour during the crisis period than their peers as shown by the negative (–0.3713) and statistically significant coefficient at 1% level. This finding is also applicable to the large branches sample (–0.9818 and statistically significant coefficient at 1% level). Moreover, the homogenous sample provides some evidence for the interaction variable $OVER25Y*SEC$. The results show that branch managers with great experience but without having a university level education can tackle adverse crisis effect and improve efficiency as shown by the negative (–0.4389) and statistically significant coefficient at 10% level. This relationship is more evidenced for the large branches given the negative (–0.9155) and statistically significant coefficient at the 5% level. The main implication of
this finding is that management experience can satisfactorily compensate for educational gaps caused by secondary educational level background.

6 Conclusions

This paper has presented evidence on the impact of branch manager characteristics on profit efficiency during difficult periods for the banking sector such as the capital control period. A unique branch-level data set is formed including both internal accounting data and information on the education and experience of the branch managers of a branch network of a representative Greek systemic commercial bank. The examined samples included both the total branch network and a homogeneous sample of branches located in the capital of Greece, for the period January 2016–February 2017. Branch activity is defined according to the profit approach and efficiency scores are calculated with a bootstrap input-oriented profit DEA model (Simar and Wilson, 2000). The association between efficiency and branch manager characteristics is examined through a second-stage bootstrap DEA regression model (Simar and Wilson, 2007) and verified through a MT with linear regression functions (M5’ algorithm, Kotsiantis et al., 2005).

The results on the positive efficiency effect of the deviation of the educational level on branch efficiency suggest that the theoretical arguments (human capital hypothesis) behind the positive forces of education are the dominant ones in all the examined samples. In particular, university graduate branch managers seem to storm the crisis more efficiently than their colleagues with a secondary level education, regardless of the sample used. When the study controls for environmental factors and a homogeneous branch group is examined, the findings reveal that more experienced managers can address crisis effects more effectively than inexperienced managers and this finding is more evidenced in the large branches. In the homogeneous branch framework, the efficiency analysis provides some evidence that the experience factor may offset the negative efficiency effects of not having the manager a university degree.

The findings of the study have important implications for an effective human capital management policy during difficult times for the banking sector where profitability is suppressed and the bank management tries to improve efficiency. The study findings open up future paths of research in identifying other branch manager characteristics that may influence branch efficiency. Given the availability of data and the condition that the values differ among individuals, the examination of the impact of internal educational training programmes that each bank or central bank organises or the effect of branch manager’s previous experience in another bank, might have predictive power as efficiency drivers.

References


Notes

1 Branch managers undertake specific cost and credit risk management actions. The efficient cost management by branch managers is implemented through reducing controllable operating expenses thus excluding depreciation, bank overhead costs and interest costs. Credit risk management by branch managers, 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 maximising recoveries of non-performing loans (NPL). Also, branch managers might exploit the early warning systems to identify problematic situations and ensure proactive handling of potential NPL.

2 According to DEA method, the best branches are identified from the data set and thus they form the empirically efficient frontier. Thereafter, an evaluation is conducted on how well a branch performs in relation to the best of their peers.

3 For the input/output selection the below procedure is followed: firstly, all possible inputs and outputs based on the available data set were listed. Secondly, a choice of variables that are affected by branch managers took place. Thirdly, the level of data aggregation of the selected variables was determined. Since the purpose of the study was to evaluate consistently the average efficient or inefficient behaviour of branches during the period 2016–2017, single general input (OPEX, LLP) and output categories (INCOME, FEES) were used. Also, this choice was in line with Paradi and Zhu (2013, p.67) who suggest that a certain degree of aggregation is necessary to improve the discriminatory power and reduce the dimensionality of the DEA model.

4 For robustness reasons, the aggregated variable OPEX was broken down into three individual cost categories (i.e., personnel expenses, running expenses and other operating expenses). The specific disaggregated analysis didn’t differentiate the findings of the analysis that are presented below.

5 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.

6 Fethi and Pasiouras (2010) support that the findings of most DEA studies that do not employ appropriate bootstrapping techniques may be biased.

7 Results were produced using the software package Fear 1.15 of Wilson (2008) based on the statistical package R.
Appendix A

The bootstrapped DEA 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:

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

(A1)

2. We use bootstrap via smooth sampling from \(\hat{\theta}_1, \ldots, \hat{\theta}_n\) to obtain a bootstrap replica \(\hat{\theta}_1^*, \ldots, \hat{\theta}_n^*\). 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:

\[
\hat{\theta}_i^* = \frac{\beta_i^* + h \epsilon_i^*}{\sqrt{1 + h^2 / \hat{\sigma}_i^2}} \quad \text{if } \beta_i^* + h \epsilon_i^* \leq 1
\]

\[
2 - \beta_i^* - h \epsilon_i^* \quad \text{otherwise}
\]

(A2)

where \(h\) is the bandwidth of a standard normal kernel density and \(\epsilon_i^*\) 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:

\[
\hat{\theta}_i^* = \bar{\beta}^* + \frac{\hat{\theta}_i^* - \bar{\beta}^*}{\sqrt{1 + h^2 / \hat{\sigma}_i^2}}
\]

(A3)

3. We generate a pseudo-data set \(\eta_i^* = \{(x_i^*, y_i), i = 1, \ldots, n\}\) given \(x_i^* = \frac{\hat{\theta}_i^*}{\hat{\theta}_{0i}^*} x_i\) (i.e., the calculated bootstrapped input based on bootstrap efficiency).

4. We solve the DEA program to estimate \(\hat{\theta}_{i,b}^*\) (i.e., the bootstrap replica based on the replica technology \(T^*\)).

\[
\hat{\theta}_{i,b}^* = \min \left\{ \theta \text{ subject to } \theta x_k \geq \sum_{i=1}^{n} z_i x_i^*; y_k \leq \sum_{i=1}^{n} z_i y_i; \sum_{i=1}^{n} z_i = 1; z_i \geq 0 \right\}
\]

(A4)
We repeat the steps 2–4: 2,000 times ($B = 2,000$ times) to obtain a set of bootstrap estimates $\hat{\theta}_{k,b} (b = 1, \ldots B, k = 1 \ldots n)$. More details regarding the bootstrap DEA such as the establishment of confidence intervals and bias correction are provided in Simar and Wilson (2000).