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Two-stage evaluation of bank branch efficiency using data envelopment analysis

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ABSTRACT

There are two key motivations for this paper: (1) the need to respond to the often observed rejections of efficiency studies' results by management as they claim that a single-perspective evaluation cannot fully reflect the operating units' multi-function nature; and (2) a detailed bank branch performance assessment that is acceptable to both line managers and senior executives is still needed. In this context, a two-stage Data Envelopment Analysis approach is developed for simultaneously benchmarking the performance of operating units along different dimensions (for line managers) and a modified Slacks-Based Measure model is applied for the first time to aggregate the obtained efficiency scores from stage one and generate a composite performance index for each unit. This approach is illustrated by using the data from a major Canadian bank with 816 branches operating across the nation. Three important branch performance dimensions are evaluated: Production, Profitability, and Intermediation. This approach improves the reality of the performance assessment method and enables branch managers to clearly identify the strengths and weaknesses in their operations. Branch scale efficiency and the impacts of geographic location and market size on branch performance are also investigated. This multi-dimensional performance evaluation approach may improve management acceptance of the practical applications of DEA in real businesses.

1. Introduction

Banking is one of the most complex industries in the world—and a major contributor to a country's wealth (in the UK 25% of the GDP is produced by its financial services sector). Today's banks offer a wide range of products and services ranging from simple checking accounts to retirement plans, mutual funds, home mortgages, consumer loans, and many others. The conduit through which banks handle these transactions is the branch network that serves as the main contact with and existing as well as potential clients. Notwithstanding the rapid rise in the use of the Internet in banking and numerous other available transaction channels, it is through a branch that customers do a large percentage of their more value added banking activities, including mortgages, loans, investment accounts, securities brokerage, to name just a few. A recent Canadian study found that 61% of bank customers still visited their bank branches in person and on average made four trips per month [1]. However, branches are one of the largest operational expenses for a bank. With increasing foreign and alternative channel entrants in the Canadian banking industry, there is a significant need for improving branch performance in order to remain competitive.

Bank branch performance measurement is a very difficult task. Branches come in a variety of sizes, offering different services to different customers while operating in different economic regions. Such performance evaluation, both within a country and globally, remains an important area for research and is a subject of continual investigations. There are numerous techniques used to measure bank branch operational efficiency, such as ratios [2], indices [3,4], and regression analyses [5–7]. While effective in many circumstances (used to measure just about every aspect or to compare similar branches), traditional techniques have a number of inherent limitations making them unsuitable for fully reflecting the increasingly complex nature of branch banking. For example, traditional financial ratio analysis does not allow for objectively combining independent evaluations into a single performance score and it is difficult to use for comparative purposes. A branch might have strong results for some ratios but show poorly in others making it difficult to judge whether the branch is, on average or on some other basis, efficient or not. Simply aggregating these results together can give a misleading indicator of performance or worse, hide under-performing business components within the overall

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numbers. Although, some more complex ratios can take the form of index numbers, determining the weights to be used (as they are often not known) and discovering under-performing activities due to aggregated numbers are just two of the difficulties using indices. Another way to measure efficiency is regression analysis (RA), a parametric method that requires a general production model to be specified. Moreover, RA is a central tendency method and is only suitable to model single input-multiple outputs or multiple inputs-single output systems.

In recent years, academic research on the performance of financial institutions has increasingly focused on the efficient production frontier based models which estimate how well a firm performs relative to the best firms if they are doing business under the same operating conditions. The main advantage of such a method over other approaches is that it removes the effects of differences in prices and other exogenous market factors and produces an objectively determined quantitative measure [8]. Berger and Humphrey [9] concluded that the frontier approach could offer an objective numerical efficiency score and a ranking of firms together with the economic optimization mechanism in complex operational environments. Two competing frontier efficiency approaches are: the Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA). The primary differences between these are the assumptions imposed on the specifications of the efficient frontier, the existence of random error, and the distribution of the inefficiencies and random error [9]. SFA is a regression-based approach and basically, assumes a particular functional form (e.g. Cobb–Douglas) for the production or cost function [10]. A review of the SFA applications in the banking industry can be found in Kumbhakar and Lovell (2000) [11]. SFA can deal with the presence of noise in the data and allow statistical inference but with the risks of imposing improper functional forms or distribution assumptions [12–16]. Ruggiero in 2007 [17] showed that the SFA model did not produce better results than DEA. Another drawback of SFA is that until recently it only allowed a single output, or multiple outputs with using a cost function if price data are available [18].

As one of non-parametric frontier approaches, DEA is recognized as an excellent and robust efficiency analysis tool with a broad range of applications. DEA was introduced by Charnes et al., [19] based on the work of Farrell [20]. This watershed paper [19] described a mathematical programming approach assuming constant returns to scale (named after the authors as CCR) for the construction of a practically efficient frontier, which was formed as the piecewise linear combination that connects the set of the best practice observations. A DEA efficient frontier is not determined by some specific functional form, but by the actual data from the evaluated production units referred to as Decision Making Units (DMUs)—a rather fortuitous choice of a name as DEA is about measuring performance that is based on human decisions. Therefore, the DEA efficiency score for a specific DMU is not defined by an absolute standard, but is measured with respect to the empirically constructed efficient frontier defined by the best performing DMUs.

The capability of dealing with multi-input/multi-output settings without requiring explicit specifications of the relationships between the inputs and outputs provides DEA an edge over other analytical tools. Since 1978, DEA has been applied to problems in many areas, both for profit and not-for-profit industries, and numerous theoretical additions have been made. The most notable one is the BCC model proposed by Banker et al., 1984 [21], which permits variable returns to scale (VRS) and measures an operating unit's pure technical efficiency. Other theoretical and applied extensions include the additive model and Slacks-Based Measure model to consider both input- and output- orientations simultaneously; models with weight restrictions; models that incorporate exogenous factors which are treated as categorical or non-discretionary variables; window analyses and Malmquist indices to examine the efficiency changes over time and many others. Färe and Grosskopf [22] and Tone and Tsutsui [23] proposed the concept of the dynamic DEA model to incorporate carry-over activities between consecutive time periods into the model. For a comprehensive treatment of DEA refer to the textbook by Cooper et al. [24].

Aside from any theoretical developments in the DEA literature, this research is designed to address the serious problem of management's rejection of suggested improvements from DEA studies because they find the process not only difficult to understand, but more importantly, psychologically unacceptable as they see the process as unfair and inequitable because, as they see it, it does not consider their "unique" environment. To make matters worse, many studies actually rank the branches from 1 to whatever the size of the branch network according to a single-aspect measure [25,26]. This paper is aimed to establish a new DEA approach to explore bank branch performance in different dimensions and identify the best-practice branches in all aspects simultaneously.

The remainder of this paper is organized as follows: Section 2 briefly reviews the literature on DEA used in bank efficiency analysis; Section 3 discusses the motivation for applying multi-dimensional DMU performance evaluation; Section 4 focuses on the methodology and data used for this study; Section 5 reports on the main results of the empirical tests; and the main conclusions are revealed in Section 6.

2. DEA in bank branch efficiency analysis

DEA has been demonstrated to be effective for benchmarking in many service industries involving complex input–output relationships (Cooper et al. [24]; Zhu [27]). In the last two decades, there have been numerous published applications of DEA to measure the efficiency of banks and branch systems, which have further motivated the development and improvement of DEA techniques (such as, [28–33]). However, due to the much easier availability of corporate data (typically from the regulator), the majority of the studies focusing on bank efficiency measurements are at the institutional level, rather than at the branch level. To the authors' knowledge, since 1997 there are 65 published papers on bank branches using DEA for efficiency measurements compared to 163 papers on bank efficiency analysis. The first published paper on a DEA application in a bank branch setting was by Sherman and Gold [34] examining a small sample of fourteen branches of a US bank. Since then many other DEA studies have been completed around the world, for instance, Vassiloglou and Giokas [35] on bank branches in Greece; Oral and Yolalan [36] in Turkey; Giokas [37] in Greece; Al-Faraj et al. [38] in Saudi Arabia; Tulkens [39] in Belgium; Drake and Howcroft [40,41] in the UK; Lovell and Pastor [42] in Spain; Golany and Storbeck [43] in the US; Kantor and Maital [44] in Israel; Porembski [45] in Germany; Camanho and Dyson [46] and Portela and Thanassoulis [47] in Portugal; Das et al. [48] in India, Avkiran [49] in United Arab Emirates, and there are others.

There are some published papers about DEA applications on Canadian bank branches. Parkan [50] evaluated a small sampling (35 branches) of a large Canadian bank in Calgary for operational efficiency using a CCR model. In particular, he included space quality and marketing activity ranking as inputs, and number of error corrections as outputs. In 1997, Schaffnit et al. [51] examined 291 branches from a major Canadian bank operating in the province of Ontario. They developed a variable returns to scale production efficiency model using five types of personnel as inputs and different transaction types and number of accounts as outputs. Using assurance regions, multiplier constraints based on standard transaction times were included to sharpen the efficiency estimates. In 2000, Cook et al. [52], with a database of 1300 Canadian branches, derived a multi-component model that allowed sales and service functions to be split apart and then rolled up into an aggregated DEA model. Cook and Hababou [25] extended a DEA additive model using goal programming concepts to capture both sales and service functions within 20 Canadian bank branches. Bala and Cook [53] in 2003 presented a modified additive DEA model to incorporate expert knowledge and applied it to 200 Canadian bank branches. Cook et al. [54] examined whether the e-branches exhibited productivity gain for bank branches (1200 branches). Wu et al. [55] analyzed 808 cross-region bank branches by introducing a fuzzy logic formulation into the DEA model. Wade [56] and Cook and Zhu [57] separately developed a process to generate standard production units and incorporate them into DEA efficiency analyses for bank branches. Alirezaee and Afsharian [26] fully ranked the efficient and inefficient branches (79 branches) based on branch's DEA efficiency score and balance index. Paradi and Schaffnit [58] evaluated the performance of 90 commercial branches of a large Canadian bank with considering the environmental effects on branch operations. Yang and Paradi [59] introduced a "Handicapped" DEA model to adjust corporate culture's effects on bank branch's performance when conducting cross firm branch benchmarking. McEachern and Paradi [60] assessed bank branch profitability and productivity in seven national branch networks owned and operated by a multi-national financial services corporation.

Many different DEA models can be found in the literature and these have been applied to both banking and bank branch studies, however, three main approaches (Production Model, Profitability Model, and Intermediation Model) appear most often. Of course, these models are often different as to their inputs and outputs (mostly depending on what data are available) and therefore the reader must not assume that the models are the same, even if their names are. For example, the intermediation models established by Athanassopoulos in 1997 [61] and Giokas in 2008 [62] are similar to a profit efficiency assessment using the weighted sum of expenses as inputs and the weighted sum of revenues as outputs. Typically, the production approach measures how a branch produces transaction services (outputs) based on the use of capital and labour (inputs). The intermediation approach involves measuring how a branch operates as an entity making loans and investments (outputs) based on the monetary assets it gathers (inputs). The profitability approach has been used to measure a branch's profitability based on expenses as inputs and revenues as outputs. Interestingly, similar models were used from time-to-time for both bank studies (the DMU is a complete bank) and bank branch studies.

3. Bank branch multiple dimensional analyses in the literature

Many studies have been done to explore accurate ways of measuring bank branch efficiency. As discussed by Kinsella [63], one of the reasons why bank performance is difficult to measure is that they offer multiple products, have complex services (many of which are interdependent), provide some services that are not directly paid for, and have complex government regulations that may affect the way in which services are offered or priced. Given these circumstances, it is obvious that there is no one way of accurately capturing branch performance and that a combined set of metrics is clearly required.

However, most of the previous studies were limited to measuring one or two performance dimensions, which cannot fully reflect the overall branch functions. Only few researchers have tried to assess bank branch performance from different perspectives at the same time [47,61,62,64]. Portela and Thanassoulis [47] assessed branch performance in fostering the use of new transaction channels, increasing sales and customer base, and generating profits. Athanassopoulos [61] evaluated branch efficiency in managing accounts and processing transactions, and converting branch operating costs into financial products. Manandhar and Tang [64] evaluated branch production and profitability efficiency based on a 'service-profit chain' concept. Giokas [62] assessed branch performance using three approaches: contrasting the branch operating costs with the volume of financial products and the number of transactions, and comparing the volume of overall cost (interest and non-interest) with the volume of generated profits. It is clear that, although these previous studies explored branch performance from different perspectives, however, none of them have covered all of the key bank branch roles as mentioned in Section 1. Furthermore, except for Manandhar and Tang [64], no other study has tried to investigate branch performance from both the individual and the overall perspectives.

In this paper, a two-stage approach is employed to overcome this problem and provide a more sound methodology for assessing a branch's overall performance. In the first stage, we construct three DEA models for evaluating three important dimensions of bank branch performance: production, profitability, and intermediation. To the authors' knowledge, there is no published study which has ever measured bank branch performance from all the three perspectives simultaneously. This provides a comprehensive picture of branch performance, but perhaps more importantly, the branch manager will find that his/her performance will be a mixture of successes and opportunities for improvements. Psychologically, when someone sees that he/she excels in his/her efforts in some way, they are much more likely to accept suggestions on how to improve in other areas—especially when suggestions on learning from their peers are included. In other words, being perceived as fair and equitable, any measuring tool or system has a much better chance to be accepted and acted upon than when the opposite is true. This approach finds significant support from those being measured because everyone is interested in improving their performance, but want to do it within a reasonable framework. In the second stage the three efficiency scores are aggregated into a single scalar value for the purpose of overall ranking, mainly to satisfy senior management's needs for this information. In the general case, this stage offers a defendable ranking process for whatever study is being undertaken.

4. Data source

The collaborating bank in this study is one of the 'Big Five' Canadian banks with assets of over $600 Billion CAD and is ranked in the top 75 banks world wide in terms of asset size. The Bank offers a full range of financial products and services to customers across the world, including personal, commercial and corporate banking; mortgages, lines of credit and loans; brokerage, mutual fund and investment services; corporate and investment banking; credit card, foreign exchange, wired funds, bank drafts and many more banking products. The data provided by the Bank are based upon their entire Canadian branch network in 2001. Due to missing information, inconsistencies, and irregularities, the total number of testable branches is reduced to 816.

Branch information is further subdivided into five regions—Atlantic (the four Provinces bordering the Atlantic Ocean), Quebec, Ontario, the Prairie Provinces (three), and British

Columbia (B.C.). The branches are also sorted by market size—Major Urban, Small Urban, and Rural. Market size classification is based on Canada Post's market definitions: Rural markets are those areas with rural postal codes, Small Urban represent cities with a population under 100,000 and Major Urban are cities with populations greater than 100,000. Due to the information confidentiality, exact regional and market splits of the branches are unavailable. Ontario is the largest region and Major Urban comprises the largest percentage of the branches.

5. DEA models

5.1. DEA models

In this study, both CCR and BCC models are used to evaluate branch performance from three different dimensions: production, profitability, and intermediation. The branches' scale efficiency is calculated using the ratio of CCR efficiency to BCC efficiency. In this study, input-oriented models are selected because the amount of business available to a branch depends largely on customer demand for services and is beyond the branch managers' control. Moreover, the Canadian banks are governed by the Bank Act of Canada that sets rigid requirements for the banking industry, so the differences in product offerings and their pricing between the competing banks are often minimal. For example, on interest rates charged, they act in essentially the same manner for a particular firm or individual regardless of which bank such entity is dealing with. Therefore, the need for minimizing the consumption of resources for a given level of products and services produced has always been one of the main concerns of Canadian bank managements.

5.2. BCC model

$$\text{Minimize}: \ z_0 = \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{1}$$

$$\text{Subject to}: \ 0 = \theta x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_i^- \tag{2}$$

$$y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \tag{3}$$

$$1 = \sum \lambda_j \tag{4}$$

$$\lambda_j \geq 0, \text{ for } j = 1,2,\ldots,n \tag{5}$$

$$s_i^- \geq 0, \text{ for } i = 1,2,\ldots,m \tag{6}$$

$$s_r^+ \geq 0, \text{ for } r = 1,2,\ldots,s \tag{7}$$

where θ is the radial efficiency score—a value between 0 and 1; λ_j the optimal weights of referenced units for unit j; x_{ij} the value of the ith input to unit j; y_{rj} the value of the rth output from unit j; $s_r{}^+$ the output slack/shortfall for the rth output; $s_i{}^-$ the input slack/excess for the ith input; and ε the non-Archimedean infinitesimal. The formula of CCR model is similar with BCC model, the only difference is that in CCR model the convexity constraint, $1 = \sum \lambda_j$, is relaxed.

5.3. The production model

This approach views bank branches as producers of services and products using labour and other resources as inputs and providing deposits, loans, and others as outputs. The input–output variables used in the Production models are shown in Table 1.

Staffing is the most important branch operating expense, often accounting for up to 75% of the total. Combining all different types of staff together may lead to a confusing result due to their different responsibilities (and salary costs). The Bank has three main business lines: Personal, Commercial, and Personal and Commercial. Under each business line the staff are further classified according to different services performed. In total, 9 staff types are identified on the input side. Personal and Commercial Specialists handle mortgages, loans and the like; Personal Specialists handle investment planning, private wealth management, and retirement planning; customer service representatives (CSRs) handle face to face customer service transactions; Relationship personnel handle a broader range of CSR duties including lending; Managers are branch supervisors and managers; and Other personnel handle a variety of transactions including accounting and back office. Although other factors, such as the layout of the branch and the computer systems used, can also affect the production process, they are not included in this study due to our inability to measure their impact and lacking a reliable and quantifiable measurement. Furthermore, a bank usually has a consistent IT system facility installed across its branch system, therefore including these factors in an analysis is unnecessary, as it adds no value. Interest costs are also excluded, as only physical inputs are required for the transactions to be performed.

On the output side, the transactions are separated according to customer types and the difficulty required to complete the transaction. The Bank suggests three main customer types: corporate, commercial, and retail. Individuals are considered Retail customers, SME businesses are considered Commercial, and large businesses (i.e.: Wal-Mart, Microsoft, and Air Canada) are considered Corporate. The transactions under each customer type are further split based on the transaction difficulty. The relationship transaction includes mortgage and loan applications and approvals, as well as retirement plan transactions. Service transactions include deposits, withdrawals, money orders, and account inquiries. Internal is back office transactions with little or no customer contact including error corrections, accounting entries, chargebacks, ABM servicing, and others. Totally, there are 9 different types of transactions on the output side.

5.4. Intermediary model

The branch's intermediary role is mainly used to examine how organizationally efficient the branch is in collecting deposits and other funds from customers (inputs) and then lending the money in various forms of loans, mortgages, and other assets (i.e.: investments, etc.). A branch's intermediation efficiency is a strong indicator of the strength of its lending ability, which is, in turn,

Table 1
A general production model.

Inputs (# of full time equivalent personnel)	Outputs (# of transactions)
Personal	Retail
• Relationship	• Relationship
• Specialist	• Service
• Other	• Internal
Commercial	Commercial
• Relationship	• Relationship
• Other	• Service
Personal and Commercial	• Internal
• Customer service representative	Corporate
• Manager	• Relationship
• Relationship	• Service
• Specialist	• Internal

directly tied to a bank's ability to operate as a going concern. The majority of researchers focusing on the causes of bank failures find that there is a strong relationship between the proportions of non-performing loans and bank failures [65].

There has been much debate on whether to include deposits as an input or as an output. In order to maximize income, the branches should attempt to lend or invest as much money as possible. However, characterizing deposits as an input unfairly penalizes branches for taking in customers and their funds. This is especially unfair as banks generate a significant amount of revenue from the deposits. And for deposits as a whole, experience with the data shows that they are consistently modeled as outputs under the user cost approach [66]. Colwell et al. [67] also found that using just earning assets (loans plus investments) and excluding other assets inflated the unit costs of larger banks. Notwithstanding these arguments, for this study, deposits are considered as outputs. The intermediary model is summarized in Table 2.

In this model, Cash Balances comprise cash on hand at the branches, Fixed Assets/Accruals are assets held by the branch, and other liabilities are other obligations held by the branch. Net Non-Performing Loans are loans that are considered in default by the branch (90 days unpaid interest due). Loan Loss Experience is the amounts booked as expenses to cover bad loans and is again included to compensate or penalize branches with "risky" lending behaviour. Outputs are comprised of the six main business lines of the Bank (in dollars and represent total volume of business). There is no strong correlation (>0.50) between any of the inputs.

5.5. Profitability analyses

Profitability analysis is used to assess the ability of a branch to convert its expenses into revenues. Expenses included are those that branch management are able to directly influence. Table 3 presents the Profitability model used in this study.

The expenses include employee expenses, occupancy expenses, branch cross charges, and other operational expenses. Other Expenses include personnel recruiting and general expenses include travel, training expenses, stationery, and other miscellaneous expenses. Some expenses not included are depreciation and capital expenditures on projects as they are not controllable by branch management. The inclusion of loan losses as an input (while this is a legitimate output, is to show that less is better) accounts for the risk in a branch's choice of investments. This penalizes those branches with higher losses for making poor lending decisions or taking on "riskier" clients.

On the output side, Revenues are based on all of the Bank's lines of business (in dollars and represent actual revenues): non-interest revenues (i.e. bank fees); net interest earnings from the Bank's six main lines of business (wealth management, home mortgages, consumer lending, consumer deposits, commercial lending, and commercial deposits); and commission revenues earned by the branch from Wealth Management; and other referrals (i.e. credit card, insurance, etc.). Sundry is undesired revenue charges incurred by the branch; therefore it is treated as input in the Profitability model.

Table 2
The intermediary model.

Inputs (fund resources in $ values)	Outputs (earning assets in $ values)
Cash balances	Wealth management
Fixed assets/accruals	Homeowner mortgages
Other liabilities	Consumer lending
Net non-performing loans	Commercial loans
Loan loss experience	Commercial deposits
	Consumer deposits

Table 3
Profitability model.

Inputs (expenses in $ values)	Outputs (revenues in $ values)
Employee expense	Commissions
Occupancy/computer expense	Consumer deposits
Loan losses	Consumer lending
Cross charges	Wealth management
Other expenses	Home mortgages
Sundry	Commercial deposits
	Commercial loans

5.6. Second-stage model

While gauging branch performance is essential for branch managers to buy-into the program, being able to rank their overall performance is a requirement by senior management. They claim that a ranking scheme enables senior management to target branches in most need of assistance. The application of a scheme that encompasses different performance measures clearly improves branch ranking accuracy. A non-parametric index approach is used to evaluate a branch's ability of performing well in all dimensions through aggregating the efficiency scores obtained in the first stage. The main reason for the use of a DEA model instead of other summary ratios/indices is the difficulty of determining suitable weights for each efficiency component a priori. A DEA model shows a strong ability to choose weights objectively and generate a scalar-valued indicator.

The three obtained efficiency scores are the outputs in the second stage DEA model. On the input side, we assume that the Bank fairly and equally supports all branches for providing financial products and generating profits. Therefore, a dummy variable with value 1 is employed as the input for all branches. Manandhar and Tang [64] used a no-input BCC model, proposed by Lovell, Knox, and Pastor in 1997 to evaluate a branch's overall performance based on production and profitability efficiency. The main drawback of their model is that it cannot incorporate all the sources of inefficiency; therefore, the overall efficiency obtained from this model is only suitable for situations where the non-radial slacks are not important.

After discussions with Bank management, as well as other experts in the field, we concluded that all three performance dimensions are equally important to a branch, since the Bank does not intentionally place a greater emphasis on any of the three performance dimensions. As the weights are allowed to move freely, the BCC model is inappropriate here. As there is the same input value and the output results are somewhat similar for each branch, the BCC model would essentially give weights of zero to the two lower output scores and simply maximize the weight of the highest one. This would have resulted in two lower scores being ignored. It should be noted that for specific situations, such as when there is no DMU scored as 1.00 in all three performance dimensions, the BCC model may not completely ignore other two lower scores (i.e. the corresponding weights may not be zero). Given this consideration, the Slacks Based Measure (SBM) Additive model is used to provide a more representative assessment of efficiency, because the SBM model is a summary measure including all identified inefficiency sources. The reader is encouraged to consult [11] for a more detailed description of the SBM method. A modified output-oriented VRS SBM model with a unique constant input is developed here to achieve our efficiency combination objective. Because all outputs in the second stage model are in the similar range, there is no scale effect in the results. Therefore, the results obtained from VRS and CCR model are in fact the same.

$$\text{Minimize}: \ \rho = \left(\frac{1}{s} \sum_{r=1}^{s} \frac{y_{r0} + s_r^+}{y_{r0}} \right)^{-1} \tag{8}$$

$$\text{Subject to}: \ y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \tag{9}$$

$$1 = \sum \lambda_j \tag{10}$$

$$\lambda_j \geq 0, \text{ for } j = 1,2,\ldots,n \tag{11}$$

$$s_r^+ \geq 0, \text{ for } r = 1,2,\ldots,s \tag{12}$$

The advantages of using this SBM model become clearer if we compare it with other methods such as the BCC and arithmetic means. A group of 15 DMUs are chosen here for testing, and the obtained results from the three models are compared in Table 4. It is found that the numbers of efficient DMUs identified by different models are the same, but the SBM model presents more power of discrimination indicated by the widest score spread and the highest standard deviation, which helps senior management differentiate the branches' performance. It should be pointed out that if the information about the relative importance of different performance aspects is available, the BCC or CCR model can also be applied and generate acceptable results.

The results demonstrate that the BCC model intends to assign the best single performance indicator of a branch as its overall performance measure and ignores the other two indicators. That means the BCC model deems a branch overall efficient as long as it is efficient in any one single area. Obviously, this result is in conflict with our goal of developing an index that can reflect a branch's overall performance. The arithmetic average method actually corresponds to an equally weighted BCC model. This method cannot show the performance differences between two branches if they have the same average efficiency. For example, DMU #3 with scores of 0.9, 0.9 and 0.9 and #2 with scores of 1.0, 1.0, and 0.7 have the same average efficiency of 0.9 when using the Average model. However, because the objective of the SBM model is to find the maximal slacks and assign the highest weight to the most disadvantageous variable, DMU #2 with a score of 0.7 is penalized for performing poorly in one area and given an overall efficiency of 0.88. The capability of generating a scalar-valued index that aggregates all performance indicators without requiring a priori weights along with a strong discriminative ability shows that this modified SBM ranking model can be used as a complement to various index analyses.

Table 4
Descriptive statistics of the SBM, BCC, and arithmetic mean model.

DMU	E1	E2	E3	BCC	Average	SBM
1	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	0.70	1.00	1.00[a]	0.90	0.88
3	0.90	0.90	0.90	0.90	0.90	0.90
4	0.98	0.72	0.54	0.98[a]	0.75	0.70
5	0.72	0.72	0.69	0.72[a]	0.71	0.71
6	0.44	1.00	0.75	1.00[a]	0.73	0.65
7	0.85	0.80	0.70	0.85[a]	0.79	0.78
8	0.59	0.91	0.44	0.91[a]	0.65	0.59
9	0.97	0.72	0.64	0.97[a]	0.78	0.76
10	0.78	1.00	0.93	1.00[a]	0.90	0.89
11	0.64	0.92	0.49	0.92[a]	0.68	0.64
12	1.00	0.87	0.67	1.00[a]	0.85	0.82
13	0.76	0.82	1.00	1.00[a]	0.86	0.85
14	0.92	0.67	0.81	0.92[a]	0.80	0.79
15	0.86	1.00	0.87	1.00[a]	0.91	0.91
Average				0.95	0.81	0.79
Std.				0.08	0.10	0.11
Min.				0.72	0.65	0.59
# Eff.				1	1	1

[a] Results showing slacks.

All efficiency analyses are carried out using the DEA-Solver-Pro software in combination with Microsoft Excel 97 and 2000 spreadsheet software.

6. Results and discussions

6.1. General analysis

The average DEA scores for the 816 branches are listed in Table 5. Based on the BCC models (the pure technical efficiency), the results suggest that, on average, the whole branch system could reduce its staffing by 23%, their operational expenses by 13%, and their assets and low quality loans by 19%. Given average branch expenses of just under a million dollars and the potential for efficiency improvement of up to 13% (from the BCC profitability model results), the Bank could theoretically save over $100 million dollars annually. While this is a very hypothetical calculation, the potential for real efficiency savings are clearly there, especially over such a large branch network. From past practice, 30–40% of the potential savings are most easily achieved (the low hanging fruit), another 30–40% is still achievable and worth the effort, while the last 20–40% will not see a positive return for the investment. Cook et al. [52] also investigated Canadian bank branch production performance with a nation-wide distribution network, but they just presented the results of a selected group of 20 branches, which makes comparisons with this study difficult. The only other Canadian study to be found using the profitability model was Yang and Paradi [59], but the results are not comparable due to the significant differences in number of branches (70 branches in their case) and their branches data were derived from three different banks.

Due to the property of being distribution free, Spearman's rank correlation coefficient is employed to investigate the relationships between the BCC scores in three performance dimensions, and the results are listed in Table 6. The correlation of profit vs. production efficiency is 0.12 and profit vs. intermediary is 0.35. Although, both of these correlations are statistically significant at the 5% significance level, the strength of the relationships are very weak, since less than 2% and 15% of the variance in the production and intermediary efficiencies, respectively, could be explained by the changes in profitability efficiency, or vice versa. Moreover, no statistically significant relationship is found between the intermediary and production efficiency, e.g. a branch's intermediary efficiency may be independent of its production performance. This hypothesis is demonstrated by an example, the DMU #853 is ranked 792nd in terms of production efficiency (0.40), however, when evaluated with respect to

Table 5
Average efficiency scores—whole branch system.

First-stage analyses	**CCR model**				**BCC model**			
	Average	**Median**	**Min**	**% Eff.**	**Average**	**Median**	**Min**	**% Eff.**
Production	0.71	0.69	0.25	21	0.77	0.77	0.28	33
Profitability	0.82	0.83	0.26	26	0.87	0.90	0.32	38
Intermediation	0.76	0.75	0.29	20	0.81	0.82	0.34	29

Profitability and Intermediary efficiency, it is ranked 489th (0.84) and 261st (0.97), respectively. This is not unreasonable, since the higher number of transactions completed per FTE could not, with any certainty lead to a larger volume of lending.

A detailed analysis of problematic branches in different dimensions can provide more evidence for the necessity of a multi-dimensional performance evaluation program. Three groups of one-dimensional problematic branches are identified separately from the three models. The problematic branches are defined here as the ones, whose efficiency scores fall into the bottom 10% (about 81 branches). The average efficiencies of the bottom 10% of the branches in each dimension and their corresponding average efficiencies in the other two dimensions are listed in Table 7. For example, those branches ranked in the bottom 10% with respect to their production efficiency (0.42 at average) have the average score of 0.80 and 0.83 for their profitability and intermediary efficiency, respectively. Since the DEA score is a relative efficiency, the percentage rank of these corresponding average efficiencies are also provided in Table 7. For example, a branch with an intermediary efficiency level of 0.83 is ranked higher than 52% of the Bank's branches. The results confirm that those branches that perform poorly in one dimension do not predictably perform worse in the other dimensions, and comparing the three lists of bottom 10% branches, there are only 8 branches falling into all three groups.

Our results appear to be in conflict with some of previous studies, which generally find a stronger relationship between a branch's different performance models. Portela and Thanassoulis [47] reported a correlation of 0.3 between profit and operational DEA efficiency. Giokas [62] reported a correlation of 0.5 between transaction and intermediary efficiency. Berger et al. [68] found a correlation of 0.40 between production and intermediation efficiency obtained from a trans-log cost function. But we still cannot predict a branch's performance in the other dimensions based only on these correlation coefficients, because less than 25% variance in one performance dimension can be explained by the other one. Furthermore, we believe that this difference may be mostly attributable to comparability problems for different model variables employed. Probably due to data availability issues, all of the models developed in these prior studies [47,62,68] suffer to some extent. Portela and Thanassoulis [47] used the total number of staff and rent cost as two inputs of their operational model, and used the number of staff and supply costs as the inputs to a profit model. Similar aggregations are found in Giokas's models [62]. For the transaction model, the total personnel costs and other operating costs are the only two inputs, as for the intermediary model interest costs and non-interest costs serve as two inputs and the interest income and non-interest income as two outputs. Because a parametric model was used in Berger et al. [68], there was only one output, operating expenses and operating expenses plus interest expenses, in their production and intermediation model, respectively. Obviously, these aggregated models did not recognize the differences within staffing types, cost, fund and revenue resources, therefore cannot fully reflect the different levels of complexity, difficulty and risks involved in completing transactions and investments in a branch. Another problem with this aggregation is that the model's ability to identify the sources of inefficiency may be reduced.

Table 6
Correlation coefficients between pairs of efficiencies.

Spearman's rank correlation	Production	Intermediary	Profitability
Production	1		
Intermediary	NA[a]	1	
Profitability	0.12	0.35	1

[a] No statistical significant correlation.

6.2. Analyses by different regions

When all efficiencies are split out by region, the average BCC scores for each region are presented in Fig. 1. Kruskal–Wallis and the *t*-test are conducted to examine the differences across the regions, and for all tests the significance level is set at 5%. Strong variations are found among the averaged regional efficiencies in all three dimensions. These variations can be contributed to the significant differences in average transactions per staff, bad loans as a percentage of assets, and average revenue and expenses per employee.

With respect to production efficiency, the branches in Quebec show better performance than the average, and B.C. exhibits the worse performance with pure technical inefficiency of only 29%. When more detailed analyses of the input/output levels in each region is taken, it is found that Quebec exhibits the best performance in the Commercial and Corporate banking areas with 5% less staff but being able to complete 35% and 90% more Commercial and Corporate transactions than the national average, respectively. On the other hand, it is found that although B.C. branches show better results on Commercial banking transactions than the national average (40% higher), this advantage is balanced by the over-staffed branches, as much as 55% more staff than the national average. Furthermore, about half of the B.C. branches show production efficiency lower than 0.67. Based on these findings, bank management should pay more attention to B.C.'s inefficient branches in order to improve their overall branch network efficiency, especially their staffing arrangements.

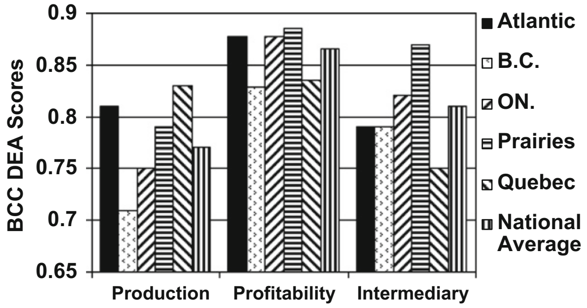

Fig. 1. Average BCC scores for each region.

Table 7
Average BCC scores of bottom 10% branches.

Bottom 10% branches	Production	Intermediary	Profitability
Based on production efficiency ranking	***0.42***	0.83 (52%)[a]	0.80 (33%)[a]
Based on intermediary efficiency ranking	0.79 (53%)[a]	***0.51***	0.75 (25%)[a]
Based on profitability efficiency ranking	0.71 (42%)[a]	0.71 (32%)[a]	***0.56***

[a] The percentage rank of the corresponding efficiency.

In terms of intermediary efficiency, the Prairies branches get the highest efficiency scores, which may be contributed to their strong economies, especially in their low loan loss experience that is 32% lower than the national average. The lowest Non-performing loans make Ontario branches present better performance than the other regions. The relatively poor intermediary score for B.C. is due to its serious Loan Loss Experience and high Other Liabilities. However, B.C. branches are identified as the best performers in handling Wealth Management and Homeowner Mortgages. The increasing bankruptcy experience in Quebec [69,70] is reflected by its extremely high net NPL, 80% higher than national average, which leaves the Quebec branches with the lowest intermediary efficiency score.

It is interesting to note that, on average, the branches in Atlantic, Ontario, and the Prairie provinces show strong profitability with an average efficiency of around 0.88. The relatively lower profitability of B.C. and Quebec branches is consistent with their unusually high Non-performing loans.

6.3. Analyses by different market sizes

The effects of market size on branch performance are investigated by evaluating all the branches together and then split out by market size, the average BCC efficiency scores are shown in Fig. 2. The Rural market is found to be performing better than Major Urban and Small Urban markets in both production and profitability efficiency (at a 5% statistical significance). This advantage of the Rural market can be contributed to the higher transactions/FTE than the average, possibly due to less staff specialization (i.e. they all could do everything needed). This agrees with Frei et al. [71], where they observed that a branch with high levels of cross training between employee types and minimal role differentiation had better productivity (i.e. higher customer transactions/FTE) than a branch that did not. Another possibility for the better production scores is a lower staff turnover leading to more experienced (and thus faster) employees. Employees of the Rural branches often remain with the branch for a significant period of time and may know their customers well, so transactions can be done faster. The higher profitability score for the Rural branches could be contributed to its lower bad loans. The Intermediation results (which are directly related to lending ability) remain almost consistent across all three market sizes, suggesting that branch's lending ability is not impacted by the size of the market.

6.4. Scale efficiency analysis

Scale efficiency for the branches is calculated by taking the ratio of the CCR to the BCC efficiency ratings. Combining with the returns to scale (RTS) indicators, it can be observed whether these scale inefficiencies are due to increasing (IRS) or decreasing (DRS) returns to scale. For those branches not on the production frontier, the RTS is based on the projection of the inefficient unit onto the efficient frontier. While there are studies on Canadian banking; few of them examined the scale efficiency at the branch level. Schaffnit et al. [51] reported an average scale efficiency of 0.97 based on 291 branches located in Ontario and among these branches 72% were identified as CRS, 21% as IRS and 18% as DRS. Wu et al. [55] analyzed the production efficiency of 808 branches cross three provinces and also claimed most of the branches were operating under CRS with an average scale efficiency of 0.9. To our best knowledge, there is no published paper that examines in further detail the nature of the branch size-efficiency relationship in the Canadian banks.

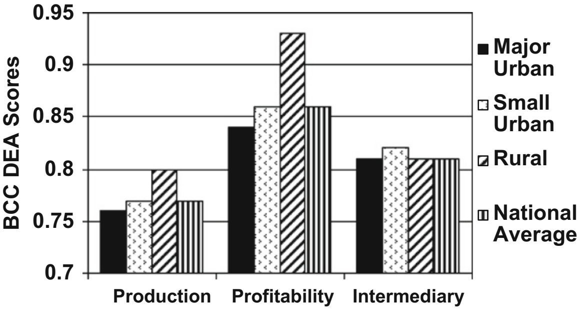

Fig. 2. Average BCC scores by market size.

The returns to scale results are presented in Table 8. The majority of the branches (73–79%) are considered to operate under CRS, 18–23% of the branches are classified as DRS, and there are only 1–4% IRS branches. Moreover, 76–84% of the inefficient branches are classified to be CRS and only 2% belong to IRS, which means that a decrease in the branches' inputs may enable them to operate under their optimal operating scale. In order to gain a more accurate perspective on the size–efficiency relationship, the branches are split into 4 quartile groups based on their asset sizes. The composite of the return to scale within each asset group are listed in Table 8. In all three dimensions, increasing asset size results in a larger percentage of branches being classified as DRS. For example, when production efficiency is concerned, the Small group has 93% CRS branches and only 4% DRS, while the X-Large group has 58% CRS branches and 42% DRS, and no IRS branch is found. Similar trends can be found in both the Profitability and Intermediary models.

The existence of efficient DRS in all branch size groups suggests that the branch size may not be the only influential factor on a branch's returns to scale. This hypothesis is supported by the fact that when comparing to the efficient CRS and IRS branches in the same size group, the majority of DRS branches are found narrowly focusing on particular outputs and/or having a significantly uneven resource allocation. This implies that the DRS branch managers may not improve their scale efficiency only through the scale efficiency ratio, hence, restructuring/rationalizing of the input combination is required.

Table 8
Composite percentages of returns to scale branches.

Asset size (quartiles)	Production			Profitability			Intermediary		
	CRS (%)	IRS (%)	DRS (%)	CRS (%)	IRS (%)	DRS	CRS (%)	IRS (%)	DRS (%)
Small									
Efficient	27	1	3	38	5	0	19	6	1
Inefficient	66	2	1	49	7	1	72	2	0
Medium									
Efficient	21	1	9	27	2	4	19	1	1
Inefficient	59	0	9	62	2	3	75	0	3
Large									
Efficient	14	0	14	22	0	7	19	1	5
Inefficient	59	0	13	53	0	18	62	0	13
X-large									
Efficient	21	0	22	19	0	30	24	0	23
Inefficient	37	0	20	23	0	28	26	0	27
Total	76	1	23	73	4	23	79	3	18

Table 9
Average scale efficiency results by branch asset sizes.

Asset size (quartiles)	Production			Profitability			Intermediary		
	CCR	BCC	SE	CCR	BCC	SE	CCR	BCC	SE
Small	0.74	0.77	0.95	0.86	0.89	0.96	0.75	0.80	0.93
Medium	0.74	0.78	0.95	0.85	0.87	0.98	0.76	0.78	0.97
Large	0.68	0.73	0.94	0.79	0.82	0.96	0.76	0.79	0.96
X-large	0.69	0.79	0.88	0.76	0.87	0.88	0.79	0.87	0.90

Descriptive statistics for overall technical efficiency (CCR), pure technical efficiency (BCC), and scale efficiency (SE) are presented in Table 9. This table indicates clearly that branch size has an obvious influence on branch efficiency. In general, for the Bank's branches the pure technical inefficiency is a much more serious problem than scale inefficiency, especially for the Small and Medium branches. And not surprisingly, the X-Large branches present the highest scale inefficiency (0.1–0.12) in all three dimensions.

In terms of Production and Profitability, the Small and Medium branches can be considered as the relatively efficient groups as all of these branches scored better on overall technical efficiency (CCR). This appears to be consistent with the findings of Drake and Howcroft [41] who examined the relationship between production efficiency and scale size at the UK bank branch level and reported that the optimum branch size fell into the medium size group classified according to the total value of branch lending. However, the relationship between the branch size and Intermediary efficiency is different. The highest overall and pure technical efficiency of X-Large group implies that the X-L asset size has more advantages in terms of intermediary services. No significant difference in this context is found among the Small, Medium, and Large groups.

It is worth noting that the Large group exhibits relatively lower levels of performance in all three dimensions and the bulk of inefficiency is attributable to pure technical inefficiency rather than scale inefficiency. This result has an important policy implication that, while a branch may derive productivity gains from expanding and thus achieves better economies of scale, these gains may be offset by the increased operating complexity, especially when production and profitability efficiency are concerned. According to this limited study, we might suggest that the relatively inefficient Large group is due for management review. As for the X-L group, the reconstituting of their input combination for the DRS branches is important for efficiency improvement.

6.5. *Second stage analysis*

In order to provide a comprehensive performance indicator for each branch, an output-oriented SBM model illustrated in Section 4 is used in the second stage analysis. Only 58 of the 816 branches (7%) are considered overall efficient (efficient in all three dimensions) and the average efficiency score for the whole sample set is 0.78. It should be kept in mind that as DEA scores reflect a relative efficiency, this low number of efficient branches (7%) indicates that they are more efficient in all dimensions when compared to the rest of an already highly performing group. Compared with the high proportions of efficient branches identified using the Production model, Profitability model and Intermediary model (33%, 38%, and 29%, respectively), it is evident that the two-stage efficiency analysis helps to discriminate between the branches' comprehensive performance and rank the branches more effectively. The outcome of the second stage assessment shows that, on average, B.C. has the lowest efficiency (0.75) among the five regions, while the Prairies represents the best overall performance with an average efficiency of 0.82. When the branches are compared under the market size category, the Rural market presents a better overall performance (0.82) than the other two markets, and no significant difference is found between the Major Urban (0.78) and the Small Urban market (0.79).

The top 10% of the branches based on the combined model have average scores of 0.99 in all three dimensions. These branches could be used to develop "branch templates" or used as "benchmarks" for what new branches should be modeled after. The bottom 10% of the branches has average Production, Profitability, and Intermediary efficiency scores of 0.61, 0.63, and 0.65, respectively. Those under-performing branches should receive immediate attention, and typically these are the branches where efficiency improvements could see the most significant and immediate results.

When the combined model scores are separated out, as presented in Fig. 3 the majority of the branches (231 branches) fall into the 0.70–0.79 range and only seven branches have scores below 0.50. Of the seven branches, only one has all three performance measures below 0.50. When including branches with scores less than 0.60, the vast majority score poorly in the Production model, which is actually a good sign, since staffing polices for branches is the one area where management can make an immediate impact by either eliminating staff or restructuring their assigned tasks (i.e. broader range of work to increase utilization). In both of the other models, although management can also affect outcomes, the time frame can be significantly longer (i.e. restricting consumer lending). This overall ranking process offers the Bank an opportunity to prioritize their efforts and helps identify the truly problematic branches.

While no weight restrictions are applied, in the future the Bank could give a certain performance aspect (i.e.: production scores) a heavier weighting. This weighting could be used to reflect the case that management is able to make changes or to reflect the aspect that is the most cost effective to improve.

6.6. *Comparison with the Bank's internal metrics*

For the DEA efficiency scores (or any other new metrics) to be acceptable by management, the estimated scores should be consistent with the current measurements used by the decision makers. Statistical analyses are conducted here to examine if there are significant relationships between the obtained DEA efficiency scores and the profitability ratio (revenue to expenses) augmented with two customer satisfaction scores, used by the Bank for branch comparison or rating. But it must be kept in mind

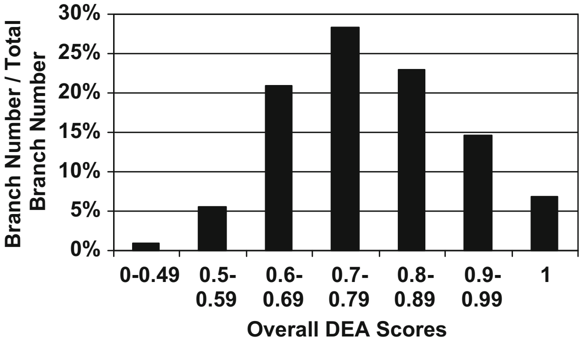

Fig. 3. Second stage overall DEA scores.

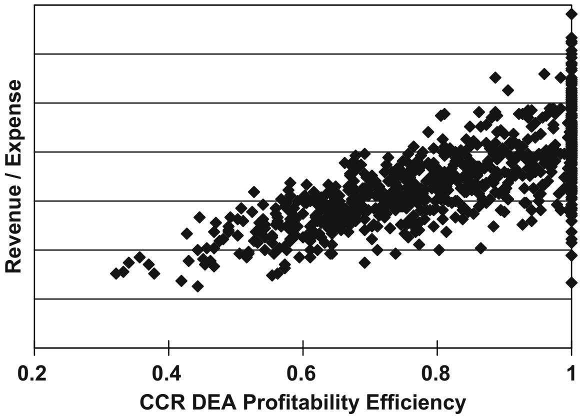

Fig. 4. CCR profitability efficiency vs. revenue/expense ratio.

that single ratios cannot appropriately represent the complex production process that banking is.

No significant correlation is found between the customer satisfaction scores and Production efficiencies. This is not unexpected, since no customer service factors are considered in our DEA Production model, and the branch efficiency measure is based on the most number of transactions performed by the fewest staff. Moreover, it is not clear whether “faster” service is certain to translate to “better” service by customers. A time lag might even exist between production efficiency and service quality, which could be explored with windows analysis in the future.

When the Profitability CCR and BCC efficiency scores are compared against the Bank’s Revenue/Expense ratio, a strong positive correlation is identified with Spearman’s rank correlation of 0.71 and 0.58, respectively. The higher correlation between the CCR efficiency and the Revenue/Expense ratio is consistent with their constant returns to scale assumption. Those branches in the top 10% of the Revenue/Expense ratio have an average CCR score of 0.98, while those in the bottom 10% have an average CCR score of only 0.60. Similar results are found when the DEA scores are compared against net profit as a percentage of revenue. When presented graphically in Fig. 4, it is clear that the results of the Profitability model are quite consistent with those of Profit/Revenue ratio, increasing the Bank’s confidence in our DEA results.

7. Conclusions

This paper presents a two-stage DEA analysis approach applied in a Canadian bank’s national branch network to assess, in detail, the main source of branch inefficiency and meet the needs of Bank management at all levels.

In the first stage 816 branches across three different market sizes and five different geographical regions are analyzed using both BCC and CCR input-oriented models from three dimensions —production (staffing), profitability, and intermediation (Lending). Comparing with previous branch studies, this three-dimensional efficiency analysis shows a significantly more comprehensive evaluation of bank branch performance that is also likely to be better accepted by branch level management. Results show that poor performance in one aspect does not predict similar poor results in the other two aspects. This suggests the possibility that branch managers could, and would, choose to focus on specific areas of performance likely due to their particular operating environments. But a significant effect is the willingness to accept the results as the managers are able to take some credit where they do well while acknowledge where they need improvements. Strong correlation between the results of the Profitability model and the Bank’s current internal measures confirms the reliability of these DEA models from the bank’s point of view.

When the branches are split out by market size and geographic region, significant differences in performance are noted, and these correlate well with the actual economic climate in such regions. Scale efficiency analysis indicates that the majority of the branches operate at constant returns to scale and the scale inefficiency increases with branch size. DRS branches are found in all branch groups, implying that the branch size is not the only influential factor affecting the branch’s scale efficiency, rationalization of the input combination is also needed for branches to reach their most productive scale sizes. Moreover, the relationship between the branches’ pure technical efficiency and asset size is non-linear. Small and Medium branches are more efficient in the Production and Profitability dimensions, X-Large branches exhibit the best in terms of Intermediation efficiency, while, the Large branch group is found exhibiting relatively lower levels of efficiency in all three dimensions. These results suggest that the efficiency gains from a strategy of mergers and acquisitions founded on potential cost cutting benefits may be offset by the increased operating complexity.

The second stage in the study is accomplished by using a modified output-oriented SBM model that incorporates the efficiency scores of the three first-stage models as outputs with unity as input. This combined model produces the overall ranking for bank branches and it is a senior management oriented model first introduced here. The application of such comprehensive technique also aids in marketing the DEA approach inside the banking industry.

This is a valuable opportunity to evaluate several different performance aspects of a significant number of branches from both a regional and a national perspective. Given the comprehensive database for a large set of branches that is made available from the Bank, there is still an excellent opportunity for further investigations in future.

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