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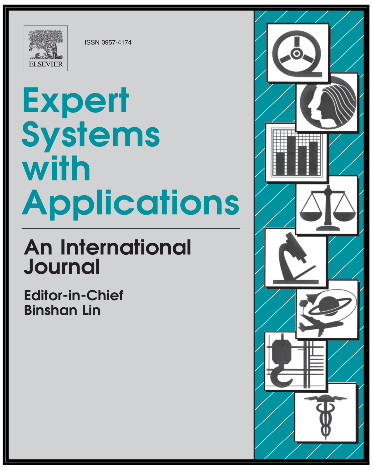

Bank Branch Operational Performance: A Robust Multivariate and Clustering Approach

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Highlights

- Integration of robust clustering analysis and DEA to study bank branch performance
- Detection of influential branches, i.e., exhibiting extreme operating behaviors
- Detection of influential branches affecting the clustering and efficiency performance
- Exploration of how peer selection is affected by influential branches
- Influential-based and cluster profiles that inform network design decisions

Bank Branch Operational Performance: A Robust Multivariate and Clustering Approach[1]

Oscar Herrera-Restrepo[a], oscar84@vt.edu, Konstantinos Triantis[a], triantis@vt.edu, William L. Seaver[b], wseaver@utk.edu, Joseph C. Paradi[c], paradi@mie.utoronto.ca, Haiyan Zhu[d], haiyanzhu29@gmail.com

[a]Grado Department of Industrial and Systems Engineering, System Performance Laboratory, Virginia Tech, Falls Church, VA 22043, USA
[b]Business Analytics & Statistics Department, Haslam College of Business, The University of Tennessee, Knoxville, TN 37996-0532, USA
[c]Centre for Management of Technology and Entrepreneurship University of Toronto, 200 College Street, Toronto, Ontario, M5S 3E5, CANADA
[d]Rogers Communications Inc., Toronto, Ontario, M4W 1G9, CANADA
*Corresponding Author: 7054 Haycock Rd, R442; Falls Church, VA, 22043, USA; (571) 2127006.

Abstract

This paper proposes a multi-step procedure that integrates robust methods, clustering analysis and data envelopment analysis (DEA) to identify bank branch managerial clusters and to study efficiency performance. By applying robust techniques based on principal component analysis, we look for (1) the detection of influential branches, i.e., exhibiting extreme operating behaviors, and (2) the clustering of branches based on operating characteristics. Our premise is that influential branches affect both the clustering and the determination of efficiency performance. The application of the procedure yields various aggregate influential-based branch profiles along with cluster profiles. These aggregate profiles provide valuable insights on the determinants of branch efficiency performance and operating patterns. Using the profiles as contextual information, DEA input-oriented slack-based models are applied to study branch efficiency performance from meta-frontier and cluster-frontier perspectives. Branch performance is characterized in terms of influential-based and cluster profiles, and efficiency designations. This allows for the understanding of how efficiency and peer selection are affected by influential branches, and how the profiles can be used to inform design decisions.

Keywords

Data envelopment analysis; Influential observations; Robust principal component analysis; Meta-frontier; cluster-frontier; Bank branch performance.

1. Introduction

This paper discusses a unique augmentation and implementation of a multivariate approach (Triantis, Seaver, & Sarayia, 2010) for efficiency analysis accounting for influential observations (Seaver & Triantis, 1992; Seaver & Triantis, 1995; Seaver, Triantis & Hoopes, 2004). This paper expands on this approach by including (1) the study of efficiency performance from both meta-frontier and cluster-frontier (i.e., a frontier computed from a cluster based analysis) perspectives, and (2) influential-based and cluster profiles to guide bank branch network design decisions, e.g., how to group branches, how to change the input/output structure of branches, etc. Our multi-step procedure can be considered as an expert system that informs decision making at the network and branch levels and is implemented using a dataset of bank branch data (Paradi, Zhu, & Eldestein, 2012). Our research objectives are threefold. First, we augment and implement a multi-step procedure to identify managerial clusters of bank branches, as well as the challenges and intuition associated with its execution. Our approach in this paper differs from the Triantis, et al. (2010) approach in that robust principal component analysis is conducted to obtain an in-depth influential observation evaluation with a data set that is over five times larger than that of Triantis, et al. (2010). Based on this outlier evaluation and in the absence of specific contextual variables, we use the inputs and outputs to conduct both density and centroid based clustering analyses. We acknowledge that our proposed approach is heuristic but provides a wealth of information that lends to the investigation of bank branch profiles both from an influential observation and clustering perspectives. Second, we investigate how the concepts of meta-frontier and cluster-frontier along with the identification of influential observations improve the understanding of bank branch efficiency performance and design decisions. Third, we compare and contrast the bank branch performance results of Paradi et al. (2012) with the results reached by implementing our procedure. This allows the identification of alternative ways to cluster bank branches and to obtain new or complementary managerial insights.

The impact of influential observations on efficiency measurement is an ongoing research issue. While many approaches that investigate this impact are highlighted in the DEA literature (e.g., Beguin & Simar, 2004), our contention over the years is that the integration of DEA with robust, fuzzy and multivariate approaches (Seaver & Triantis, 1995; Seaver & Triantis, 1992; Seaver, et al., 2004; Triantis et al., 2010) offer a unique perspective of the masking that occurs due to influential observations along with a different understanding of efficiency extremes (efficient versus very inefficient). Additionally, the meta-frontier concept hinges in part on the consideration of the contextual features of the DMUs that are used in the analysis. These features are typically used to arrange DMUs into homogenous groups. The cluster frontiers are formed by more similar DMUs, offering an additional perspective of efficiency performance along with the identification of performance targets and peers, and the discovery of best practices and design insights (see Section 5.1).

Bank branch performance is of continued interest especially in the context of technological and socio demographic shifts. While the study of a specific data set does not allow for complete generalizations on bank branch clustering and performance especially since the available dataset is from the year 2004, and consequently dynamic considerations (Fallah-Fini, Triantis, & Johnson, 2014) cannot be incorporated, our multi-step procedure allows us to obtain practical and technical managerial insights summarized in Section 5. We consider this implementation as a point of departure from the literature as a means to analyze more recent banking data in the future. We provide information that can be useful not only when understanding ex-post bank branch operational performance but also when considering future network design decisions (see Section 5.1). Our approach allows for a comprehensive meta-analysis of the data provided. In its core, it is a heuristic analysis dealing with a host of issues, e.g., influential observations; meta-frontier and cluster-frontiers.

2. Bank Branch Performance: Context and Previous Study

Retail banks perform two operations: the provision of financial products and services, and financial intermediation and risk management (Mukherjee, Nath, & Nath, 2002). They operate in a network fashion through branches across a country. Branches might have similar portfolios, but they might differ in terms of size, market orientation, operating environment, etc. (Paradi & Zhu, 2013). Their largest source of expenses is their operational inputs used to provide financial products and services (Paradi & Zhu, 2013). These costs range from 60 to 70% of the total expenses (McKinsey and Company, 2010), involving personnel, rent and supplies. When evaluating branch performance two types of efficiencies are of interest: profit and operational (Paradi & Zhu, 2013). Profit efficiency relates to the intermediation and risk management operations. Typical variables of interest are: interest revenues/costs and bank fees (Hannan, 2006). Operational efficiency focuses on the provision of financial products and services, minimizing operational inputs while maximizing the products/services volume. Profit efficiency is of interest to shareholders, and operational efficiency to stakeholders, e.g., branch managers. Branch performance has been measured using financial ratios (Mukherjee et al., 2002), e.g., return on investment. They compare few variables, making them easy to calculate. The criticism against them is their inability to measure performance as a multidimensional construct including non-financial variables (Berger & Mester, 1997).

To overcome the shortcomings of financial ratios, the efficiency measurement literature proposes parametric methods, such as stochastic frontier analysis (SFA), and non-parametric ones, such as data envelopment analysis (DEA). These methods allow the evaluation of bank branch performance by including multiple dimensions, i.e., inputs and outputs (Sherman & Gold, 1985; Berger & Humphrey, 1997; Paradi & Zhu, 2013). DEA has been used to address both profit and operational efficiency. Two approaches are typically followed: intermediation and production (Paradi & Zhu, 2013; Avkiran, 2009). The intermediation approach manifests itself when funds are raised, e.g., from deposits, and money is lent to customers through credit lines (Mukherjee et al., 2002; Schaffnit, Rosen, & Paradi, 1997). Collecting and lending money imply an intermediation process, which allows banks to generate profits from the interest charged on credits minus the interest paid on deposits (Paradi & Zhu, 2013). The goal is to maximize profits while minimizing or maintaining the interest costs; i.e., to achieve profit efficiency. In contrast, the production approach focuses on the provision of financial products and services given certain physical (e.g., layout), informational (e.g., technology) and human (e.g., employees) resources (Yang, 2009). Financial products and services include deposits, over-the-counter transactions, etc. (Cook & Zhu, 2006). The goal is to minimize the use of resources while maximizing or maintaining product or service volumes; i.e., to achieve operational efficiency.

We focus on operational efficiency. Table 1 depicts typical inputs/outputs used in the literature for the production approach. It suggests that: (1) Facilities-related inputs are fixed in the short term since they are not likely to change under the branch managers' control and banks do not change their fixed costs frequently. Capturing their contribution to branch performance, in terms of output production, is difficult; (2) the use of costs for inputs and transaction values for outputs implies the use of prices, representing profitability. In this case, separating technical from price efficiency is a challenge; (3) the use of output transaction duration raises the issue of the appropriate metric to measure time, e.g., is the average time a reliable metric? The efficiency results will differ given the metric. In this context, we pursue a production approach with a model specification using personnel-related inputs and volumes for outputs, avoiding market prices and time in the analysis (see Table 2).

Table 1. The Production Approach: Literature-Related Typical Inputs and Outputs

Inputs	Outputs
Personnel-related: services, sales, management, and other staff measured in Full-Time Equivalents (FTEs).	**Transaction volume (units)**: over-the-counter transactions (e.g., withdrawals, checks cashed, treasury checks), personal/business deposits, personal/business loans, insurance and mortgages, etc.
Facilities-related: rent cost, layout space in ft^2, number of ATMs and computers.	**Transaction value (dollars)**: deposits, personal/business loans, personal/business investments, and mortgages, etc.
Supply-related: cost of supplies, cost of ATMs and computer maintenance.	**Transaction duration (time)**: over-the-counter transactions, personal/business deposits, personal/business credits, etc.

Grouping branches is crucial for retail banks. Efficiency performance comparisons cannot be completed if branches are dissimilar. Strategies (e.g., initiatives to attract customers) and network design decisions (e.g., to have more sales-oriented branches, which branches to keep open based on efficiency performance) cannot be taken studying each branch due to cost and time constraints. Branches should be grouped into clusters composed of comparable branches, promoting a reasonable efficiency performance benchmarking process (Athanassopoulos, 1998). Homogeneous clusters would make it easier to suggest strategies and support network design decisions. Also, clusters would allow for the identification of differentiated needs and improvement actions. Banks use location and or size variables to group branches and compare efficiency performance (e.g., Yang, 2009). These variables fall short in capturing other characteristics such as the operating environment (customer age, income distribution, etc.), and operating patterns (product or service orientation and sales or service personnel focus). Recognizing that branches might share similar features beyond location and size, banks would require more reliable ways to group branches to (1) focus the design of strategies; (2) foster multidimensional performance comparisons; and (3) make informed network design decisions.

2.1 Background on Canadian Banking

The Canadian Banking System is composed of: 29 domestic and 24 foreign banks, 27 full-service and 3 foreign lending branches (Canadian Bankers Association, 2014). The Office of the Superintendent of Financial Institutions regulates the system through the Canadian Bank Act (S.C. 1991, c.46). Domestic banks operate through networks, reporting 6,321 branches, over 275,000 employees, and 18,500 Automatic Banking Machines-ABMs (Canadian Bankers Association, 2014). Since two decades ago, Canadian bank networks experienced major changes due to regulatory and technological reasons. The introduction of the National Interact Debit Card in 1994, the first full-service virtual bank in 1997, internet banking, and online shopping in 2000 and 2001, and the Bill C-8, which introduced changes to financial legislation are some examples (Canadian Bankers Association, 2014). The movement towards a multichannel approach (branches, ABMs, and internet) has changed the way Canadians do banking. Recent statistics (Canadian Bankers Association, 2014) show that 55% of Canadians used the internet as the primary banking choice in 2014 versus 8% in 2000. Although banking at branches has decreased over time, branches are still necessary for small town economic development since they provide access to financial markets, especially for towns in remote areas where the access to internet is not given. Also, some people prefer the personal touch that branches provide to customers. Despite the global trends on closing brank branches (e.g., U.S. branch closures in 2012 were 2,267 (Sidel, 2013)), Canadian banks show a positive growth in the number of branches, i.e., from 5,902 branches in 2006 to 6,321 in 2013 (Canadian Bankers Association, 2014). This growth is the product of re-designing branches within a multichannel approach, making them more specialized through customized products and services and expert advice.

2.2 Selected Study on Bank Branch Clustering and Performance

Paradi et al. (2012) identify bank branch managerial groups with similar operating patterns. The authors use data from a large Canadian bank, 962 out of 966 branches are analyzed after identifying four outliers. The dataset includes three inputs and four outputs. The inputs are: Full-time equivalent (FTE) service, sales, and management employees. The outputs relate to the number of new account openings and transactions: day-to-day (personal/small business accounts), investment (personal/small business terms; money funds; fixed income and wealth accounts), borrowing (mortgages; personal and small business loans; and lines of credit), and over-the-counter transactions (bill payments; deposits; withdrawals). Following a production approach, Paradi et al. (2012) execute the following multi-step procedure: **Step 1**: Identify efficient branches through a non-oriented slack-based measure-SBM model. **Step 2**: Establish reference peers using an additive DEA model (Charnes, Cooper, Golany, Seiford and Stutz 1985) through lambda values (λ), indicating the degree of closeness of an inefficient branch to an efficient one. **Step 3**: Determine operating patterns. The premise is that efficient branches follow different operating patterns. To identify the operating patterns, vectors of inputs and outputs are compared to standard input/output vectors using the dot product. A standard vector is one with components equal to one or zero. A component equal to one designates a specific input focus (e.g., service FTEs) or output orientation (e.g., investments). The resulting measure of similarity is the cosine of the angle formed by the vectors. If the cosine value is closer to 1, the branch follows an operating pattern similar to the one proposed by the standard vector. **Step 4**: Conduct K-means clustering. The K-means clustering uses the cosine measures to cluster efficient branches. Six clusters are selected. **Step 5**: Provide an inefficient branch allocation where the approach uses the lambdas to allocate inefficient branches to clusters. A max function determines the within-group membership, e.g., if an inefficient branch has a peer in Cluster A and Cluster B, the branch belongs to Cluster A if the sum of the lambdas related to it is greater than the one related to Cluster B. Paradi et al. (2012) highlight several managerial insights: (1) inefficient branches may not find their peers or role models within groups of branches located in similar geographical areas; (2) branches can be grouped by similar operating patterns (i.e., input focus/output orientation), leading to business specialization; (3) the effect of managerial staff on branch performance is not clear. This is due to the low correlation between the management input and the outputs; and (4) inefficient branches may find their peers in clusters that do not represent their exact operating patterns. This cross-referencing provides the opportunity to evaluate alternatives and change branch operating patterns. Alternatives include scaling the branch size up in terms of all or individual inputs and/or outputs.

3. Data and Methodology

3.1 Data Description and Multi-step Procedure

The data belongs to a Canadian Bank with 966 branches and are the same used in the Paradi, et al. (2012) study. Branches are spread across the country and, in theory, follow the same processes under varied socio-demographic conditions, i.e., operating environments. The variables are divided into three inputs and four outputs, which are presented in Section 2.2. The cross-sectional data correspond to a 10 month period in 2004. Even though more recent data is not available, we use the data as a means to explore the capabilities of our multi-step procedure in identifying managerial clusters, studying branch performance, and informing network design decisions. Table 2 provides descriptive statistics of the data. The large data variability confirms the heterogeneity of operating patterns. The multi-step procedure is divided in two major steps and four sub-steps shown in Figure 1.

Table 2. General Descriptive Statistics (966 branches)

	Inputs (in FTEs)			Outputs (in Units)			
	Service	**Sales**	**Mgmt.**	**Day-to-Day**	**Investments**	**Borrowing**	**OTC**
Mean	8.16	5.48	0.82	2,867.20	3,414.25	1,855.27	248,459.33
Std. Dev.	4.41	3.34	0.21	1,832.77	2,244.85	1,028.97	172,969.65

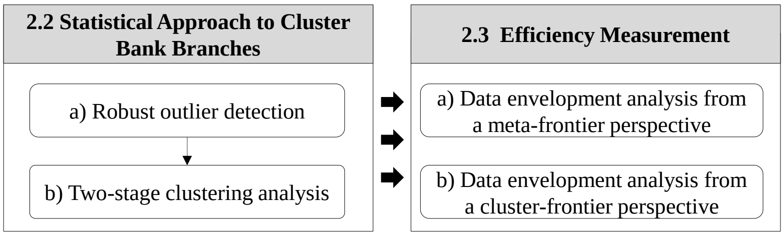

Figure 1. The Multi-step Procedure

3.2 Statistical Approach to Cluster Bank Branches

This step integrates various statistical techniques to find a sound way of clustering branches. Two sub-steps are followed. Sub-step a) corresponds to **robust outlier detection**. Outliers might come from contaminated or incorrect data (e.g., bad measurement) or just from observations exhibiting extreme but valid behaviors (Seaver & Triantis, 1992). Since benchmarking depends on the results coming from the data used in the analysis (Seaver & Triantis, 1995), it is important to identify extreme observations before pursuing other analyses. Paradi, Yang and Zhu (2011) point out that under the assumption of correct data, outlier detection can identify whether some branches are different from others with respect to business orientation (e.g., output orientation) or structure (e.g., input focus). In other words, outlier detection can inform different operating patterns. This sub-step deals with the detection of outliers through the application of robust principal component analysis-ROBPCA (Hubert, Rousseeuw, & Vanden Branden, 2005). Robustness implies stable results in the presence of outliers (Triantis et al., 2010). The influence that extreme observations exert on others is accounted for and isolated. ROBPCA allows for dimensionality reduction, so that data can be represented by a number of linear combinations that are lower than the number of variables of a dataset. The resulting linear combinations are called Principal Component (PC) hyper-planes (Triantis et al., 2010) and they explain fractions of the dataset variability. The first PC explains the largest proportion of the variability, the second PC the second largest proportion, etc. To verify the proportion of variability explained by each PC, we apply oblique rotation (for correlated data: Oblimin, Promax) or orthogonal methods (for uncorrelated data: Varimax, Quartimax). These methods prove useful when determining if the sizes of the PCs hide other PC structures; i.e., if other PCs explain dissimilar proportions of the variability. Not all PCs are selected for further analyses. The number of PCs selected depends on the fraction of variability explained by each PC, i.e., the more variability explained, the better. This decision can be tied to the Kaiser rule (Kaiser, 1960) that suggests that a PC should be selected if its eigenvalue (i.e., variability explained by a PC) is greater or equal than 1.0 for the correlation matrix, or greater or equal than 0.7 rule for simulation results.

ROBPCA classifies observations in four categories: regular, good leverage, orthogonal, and bad leverage (Hubert, Rousseeuw, & Vanden Branden, 2005) while the robust PCA with m-estimation used by Triantis et al. (2010) only indicated outliers but not type. According to Hubert and Engelen (2004), regular observations are a consistent group horizontally and vertically close to the PC hyper-planes. They do not show extreme behaviors. Good leverage observations are vertically close to the PC hyper-planes, but horizontally far away from them. Their variability is still well captured by the PC hyper-planes. Orthogonal outliers are observations with a large vertical distance to the PC hyper-planes and their projection on them is close to the regular observations. Their variability is harder to explain when compared to other observations. Finally, bad leverage observations have both large vertical and horizontal projections on the PC hyper-planes. They exhibit extreme behaviors and increased variability. The robust PCA used by Triantis et al (2010) creates a weight (between 0 and 1 inclusive) for each observation that is inversely proportional to the outlying-ness of the observations that affects the mean vector and covariance matrix while ROBPCA provides more information by classifying observations into the four categories above. Our contention is that there is something to be learned from each type of observation. We believe that the most interesting observations are those that are extreme. For example, bad leverage observations could represent extreme occurrences. Thus, they might provide insights on the determinants of performance (inputs and outputs) generating extreme behaviors, and would also inform what a 'bad leverage' branch means in banking terms. This is why our approach looks at the classification of outliers by keeping as many observations as possible rather than discarding them. Although we recognize the variability within each group of observations, it is our intent to come up with **aggregate profiles** of the outlier-based classification as means to explore what we can learn from the data. Also, this sub-step provides the robust PC scores used for clustering. The PC scores are the new coordinates of the observations regarding the PC hyper-planes. Since the ROBPCA eigenvalues represent the variability explained by each PC, the PC scores are multiplied by the square root of their eigenvalues to weigh them for further clustering analysis.

Sub-Step b) pertains to a **two-stage clustering analysis**. Branches might share similarities regarding operating environments, and hence, it is possible to cluster branches through statistical techniques (e.g., Prior & Surroca, 2006). Clustering allocates observations into several clusters (Paradi et al. 2012). Observations within clusters are 'similar' (i.e., low within-group variability) and to a certain degree, different from others belonging to other clusters (i.e., high between-group variability). In banking, clustering might be used as a pre or post-assessment efficiency performance technique (Thanassoulis, 1999). Clustering as a pre-assessment tool defines clusters first, and then its results are used for performance analyses. Thanassoulis (1999) indicates that pre-assessment makes sure that branches within clusters are really comparable, so that the efficient ones are appropriate benchmarks. Pre-assessment clustering often uses socio-demographic or contextual variables. Clustering as a post-assessment tool seeks to group branches using efficiency results, e.g., efficiency scores (Prior & Surroca, 2006). Efficiency branch performance is evaluated first, and then branches are grouped using performance results. Post-assessment clustering does not allow the drawing of inferences beyond efficiency performance, masking the influence of operating environments.

For our research, the available dataset is bounded to internal data for inputs and outputs. This means that no contextual variables are available to pursue pre-assessment clustering based on external variables. Considering this limitation and the intention of using pre-assessment clustering, we use the branch operating patterns, i.e., input focus and output orientation, as proxies to represent the heterogeneity of branch operating environments. Clustering can use raw or pre-processed data. We use the latter to avoid scaling issues, to concentrate on significant variables, and to reduce dimensionality (Han, Kamber, & Pei, 2012). Thus, the PC scores obtained in sub-step a) are used as the inputs for clustering. They are robust and account for high variability. For the clustering analysis, we include all the observations derived from sub-step a). This aligns with our premise to explore what we can learn from all observations in terms of efficiency performance. With respect to clustering methods, we use the two-stage clustering method proposed by Seaver and Triantis (1992). The first stage allocates observations to clusters using the k-NN algorithm (i.e., density-based method), providing robustness and less spherical cluster shapes. The second stage uses the hard allocated results as inputs to implement a k-means clustering method (i.e., centroid-based method) and obtain **cluster profiles**. Future research will show how a fuzzy clustering approach brings more clarity to the understanding of **cluster profiles** of banks (Triantis et. al., 2010). We tested a number of clusters from 4 to 8. It is our experience that a number greater than eight makes clusters more difficult to evaluate. The 'best' number of clusters is obtained from the jackknife error, which yields the minimum classification error possible when using a discriminant analysis for classifying observations into their clusters. To get the jackknife error, linear discriminant functions under several combinations of the raw variables are computed. Only one combination yields a minimum jackknife error.

3.3 Efficiency Measurement

We evaluate efficiency performance using data envelopment analysis -DEA (Charnes, Cooper, & Rhodes, 1978). We execute two sub-steps. Sub-step a), where we use **DEA from a meta-frontier perspective**. We analyze performance comparing each branch to all branches and in this way have an evaluation based on an overall meta-frontier. The model specification adopts a production model, where a bank branch represents a service provider using personnel-related inputs to provide sales and service-related outputs. We select an input oriented DEA model because at the operational level, branch managers have more control over inputs than outputs. Given that no contextual variables are available; this paper takes a traditional view of DEA using internal data for inputs and outputs. This leads to the assumption of personnel disposability for input minimization (e.g., hourly or part-time employees) in response to the demand for financial services and products. The relationships between inputs and outputs are not expected to be proportional (Avkiran, 2014). For example, a 10% reduction on service FTEs does not imply 10% reduction on the over-the-counter transactions (OTC). This is because some OTCs might be absorbed by the remaining service FTEs. Within this context, we then assume variable returns to scale. The Slack-Based Measure-SBM model by Tone (2001) is used for efficiency measurement. This model assumes a non-radial reduction or increase in inputs and outputs respectively. Thus, the rate at which inputs or outputs can be adjusted to achieve performance targets, is not proportional for all input or outputs (Avkiran, Tone, & Tsutsui, 2008). The model provides an efficiency score between 0 and 1, where 1 means fully efficient branches and 0 fully inefficient branches. Efficient branches determine the efficient frontier and serve as peers for the inefficient ones. The model formulation is shown in Equations (1)-(5), where ρ is the efficiency score, x_{i0} is the input i of the evaluated branch 0, y_{r0} is the output r of the evaluated branch 0, λ_j is the weight assigned to branch j (reference peer), x_{ij} is the input i for branch j, y_{rj} is the value of output r for branch j, and s_i^- is the input excess associated with input i. For more modeling details see Tone (2001).

$$\textit{Min} \qquad \rho = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}} \quad (1)$$

$$\textit{Subject to} \qquad x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \quad (2)$$

$$y_{r0} \leq \sum_{j=1}^{n} y_{rj}\lambda_j \quad (3)$$

$$1 = \sum_{j=1}^{n} \lambda_j \quad (4)$$

$$\lambda_j \geq 0,\ \textit{for}\ j = 1, 2, \ldots n, \textit{and}\ s_i^- \geq 0,\ \textit{for}\ i = 1, 2, \ldots m, \quad (5)$$

Sub-step b) pertains to efficiency measurement using **DEA within each cluster**. The performance evaluation is conducted for each cluster where the cluster frontier is computed. To ensure consistency, the same SBM model presented above is applied. Considering branches within clusters as comparable and relatively homogeneous, the efficiency performance evaluation aims to (1) better discriminate branch efficiency, (2) ensure that the reference peers are appropriate role models, and (3) make sure that improvement targets are achievable. In the meta-frontier perspective, we address branch performance in relation to a common frontier where all branches compose a single production possibility set (O'Donnell, Prasada Rao, & Battese, 2008). Conversely, when looking at the cluster-frontier perspective, we address efficiency performance with respect to different cluster-frontiers where branches compose production possibility sets only within those clusters. According to O'Donnell et al. (2008), the meta-frontier envelops the cluster-frontiers. Thus, efficiency performance results vary depending on the perspective used for the efficiency evaluation. We consider that it is important to compare both perspectives so that the efficiency performance evaluation is informed.

4. Results

The results are presented in the following six sub-sections. The first five present the results from applying the multi-step procedure described in Section 3, and the last sub-section compares and contrasts our results to the ones obtained by Paradi et al. (2012). In order to successfully guide the reader through our findings, we provide an overview of the first five sub-sections. Figure 2 provides a diagram of the sequential empirical processes. In **sub-section 4.1** (robust outlier detection), our purpose is to identify influential branches and characterize them into **aggregate profiles** based on their input focus and output orientation; 86 out of 965 branches are influential (8.91%). This sub-section provides the PC's scores for the clustering, the ROBPCA branch classification, and branch profiles. In **sub-section 4.2** (clustering results), our intention is to cluster branches into managerial groups. Four clusters are obtained. This sub-section discusses the cluster composition and their profiles. In **sub-section 4.3** (meta-frontier efficiency), our objective is to identify the efficient branches that form the meta-frontier; 78 out of 965 branches are efficient (8.08%). Efficient branches show high variance, and high out-of-cluster peer referencing exists. This sub-section provides the efficiency designations for the meta-frontier. In **sub-section 4.4** (cluster-frontier efficiency), our purpose is to identify the efficient branches that form the individual cluster-frontiers; 202 out of 965 branches are efficient (20.93%). The cluster-frontiers yield more condensed frontiers by isolating the effect of influential branches with different operating patterns. This sub-section provides the cluster-frontier efficiency designations along with their ROBPCA classification. **In sub-section 4.5** (influential branches and DEA designations), we study the effect of cluster-frontiers on the number and type of influential branches referenced as peers. As one would expect, the effect of influential branches on the inefficient ones is reduced when going from a meta-frontier to a cluster-frontier perspective. The combined use of the ROBPCA classification and the efficiency designation provides a means to improve peer selection and inform network design decisions.

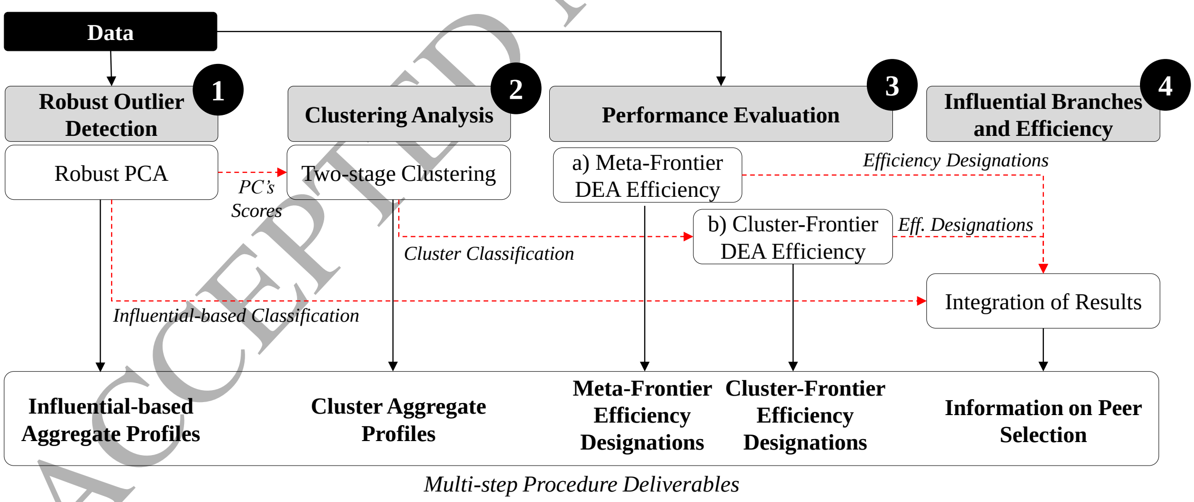

Figure 2. The Multi-step Procedure: Sequential Empirical Processes

4.1 Robust Outlier Detection

We apply ROBPCA as a means to classify branches into bad leverage, good leverage, orthogonal, and regular branches. We define the group of bad leverage, good leverage and orthogonal branches as influential ones. Influential branches deviate from regular operating patterns. By initially applying

ROBPCA to all 966 branches, we obtain 81 influential (28 bad leverage, 48 good leverage, and 5 orthogonal) and 885 regular branches. Branch #1020 is classified as a bad leverage and exhibits very extreme behavior. Its average inputs FTEs for sales and services are 7 times greater than the overall average (10.4 standard deviations), and its average outputs are 6.9 times greater than the overall average (9.1 standard deviations), reaching a peak for the over-the-counter transactions (OTC) output with a value 12.8 times greater than the overall average (16.9 standard deviations). When comparing branch #1020 to branch #1104 (next most extreme branch) branch #1104 shows average input FTEs 3.5 times greater than the overall average (4.5 standard deviations), and average outputs 3.3 times greater than the overall average (3.7 standard deviations) with no peak in any output. The remaining extreme branches, e.g., #1440, #9400 and #78, show similar behaviors to the one exhibited by branch #1104. This implies that they are not as isolated as branch #1020. Table 3 shows the inputs and outputs of the subset of the extreme branches above mentioned. We removed branch #1020 from the dataset due to its extreme characteristics, which would distort the results of subsequent analyses.

Table 3. Inputs and Outputs of Most Extreme Observations

	Inputs (in FTEs)			Outputs (in Units)			
Branch #	**Service**	**Sales**	**Mgt.**	**Day-to-Day**	**Investments**	**Borrowing**	**OTC**
1020	53.63	40.72	1.61	15,721	17,135	8,222	3,186,208
1104	37.37	13.52	1.74	12,967	9,385	4,785	929,742
1440	30.96	15.04	1.31	9,272	13,057	5,188	913,592
9400	28.01	20.21	0.89	18,308	11,156	4,110	869,825
78	24.10	15.50	0.85	6,876	10,971	5,030	941,487

The ROBPCA analysis is run again yielding 86 influential (30 bad leverage, 53 good leverage, and 3 orthogonal) and 879 regular branches. The first PC accounts for 82.56% of the data variability with an eigenvalue equal to 4.07, while the second PC accounts for 6.16% of the data variability with an eigenvalue equal to 0.21. In essence, the results show that only one PC accounts for the majority of data variance. To confirm this finding, we perform oblique rotation and random partitions. Since the dataset is highly correlated for all variables[1], Oblimin and Promax methods are applied. The results from both methods suggest that the size of the first PC is not hiding other PC structures, and hence, the first PC is dominant. This finding is supported by the random partitions, where the dataset is randomly partitioned into four equally sized datasets. The results show that on average the first PC explains 82% of the data variability. In all the previous analyses, the loads of the management input are extremely low in the first five PCs, and very high only in the sixth PC (explaining ~87% of the variability). This implies that the management input does not allow for branch differentiation, at least for the data we are dealing with. Based on the Kaiser rule, only the first PC should be kept for further analyses (i.e., its eigenvalue is greater than 1). However, we also keep the second PC since it does not add any complication, and in turn, it increases the total variability explained to 88.72%. Table 4

[1] Except for the management FTEs input. This variable has a correlation lower than 0.4 with all remaining inputs and outputs.

provides the classification of branches considering the outlier analysis on the first two PCs along with their means. The classification suggests that we need to identify aggregate branch profiles. The profiles are investigated through the examination of the inputs and outputs. The examination is in part conducted using the Tukey honestly significant difference test for comparison of means (Salkind & Rasmussen, 2007).

From Table 4, the bad leverage branches have the highest average and variance (not reported) values for all inputs and outputs. However, Table 5 provides the mean service and sales per FTEs in an aggregate fashion. Taking the aggregate results to draw insights, one might think that the bad leverage branches are not exemplary in relation to service and very poor with respect to borrowing service. They are only high on investments and day-to-day account openings. A design decision in this case might consider rethinking the allocation of service personnel, and or verifying the existence of measurement problems related to the service FTEs input. The good leverage branches aggregate results have the second highest sales FTEs and the second highest average outputs, except for OTC. Again adjusting for FTEs, there is a dichotomy. These branches have the highest outputs per service FTEs, except for OTC, but the lowest outputs for sales FTEs. The emphasis for these branches is service.

Table 4. ROBPCA Results: Classification and Means

		Inputs (in FTEs)			Outputs (in Units)			
Type	**#Branches**	**Service**	**Sales**	**Mgt.**	**Day-to-Day**	**Investments**	**Borrowing**	**OTC**
Bad Leverage	30	19.70	12.73	0.94	7,415	8,919	4,067	657,026
Good Leverage	53	11.85	11.38	0.87	5,456	6,653	3,720	340,410
Orthogonal	3	15.49	8.54	0.94	5,075	5,199	3,767	598,723
Regular	879	7.47	4.83	0.81	2,533	3,009	1,653	224,433

Table 5. ROBPCA Results: Mean Service and Sales Per FTEs

		Outputs/FTEs for Service				Outputs/FTEs for Sales			
Branch Type	**# Branches**	**Day-to-Day**	**Invest-ments**	**Borrow-ing**	**OTC**	**Day-to-Day**	**Invest-ments**	**Borrow-ing**	**OTC**
Bad Leverage	30	376	453	206	33,352	583	701	320	51,612
Good Leverage	53	460	561	314	28,727	479	585	327	29,913
Orthogonal	3	328	336	243	38,652	594	609	441	70,108
Regular	879	339	403	221	30,044	525	623	342	46,467

For the orthogonal branches, their aggregate service FTEs are second highest with respect to average borrowing and OTC. Although just three branches fall into this category, we explore what we can learn from them regarding their determinants of performance, and how they compare to the other groups in aggregate terms. Once again adjusting for service FTEs, these branches have the lowest aggregate outputs for day-to-day operations and investments and the highest with respect to OTC. As to sales FTEs, these branches have highest aggregate outputs in all categories, except investments. The weakest link for these branches is in services with respect to day-to-day operations and investments. These branches when considering the outputs adjusted for service could have the following situations: (1) the FTEs might be masking administrative activities that do not have direct impacts on the outputs, e.g., training people for other branches; (2) the existence of qualified people to handle investments; or (3) a measurement problem with respect to the service metric.

With respect to regular branches, they have the lowest aggregate average input FTEs and the lowest aggregate average outputs. When one adjusts the outputs for service and sales FTEs, these branches are not top-tiered. They are ranked second when considering investments and borrowing with respect to sales FTEs. These branches seem to be in the middle of the spectrum with respect to outputs. However, a quick glance at Table 5 suggests that changes in sales FTEs and in the day-to-day output could move these branches into a favorable top tiered position for sales. Table 6 provides a quick glance at the aggregate profiles of the types of branches.

Table 6. ROBPCA Results: Branch Aggregate Profiles

Bad Leverage Branches	**Good Leverage Branches**	**Orthogonal Branches**	**Regular Branches**
Large service and sales per FTEs generating more outputs but low borrowing in relation to service and sales FTEs.	Highest outputs per FTEs for service except for OTC and worse outputs per FTEs for sales	Very poor service per FTEs for day-to-day and investments but good for borrowing and OTC per FTEs for sales.	Basically in the middle ground for service and sales per FTEs, i.e., nothing exceptional.

4.2 The Clustering Results

Branches are grouped using the two-stage clustering method described in Section 3.2. As input for the clustering, we use the product between the PC scores and the square root of the eigenvalues of each PC from Section 4.1. Table 7 shows the clustering results with respect to jackknife errors for k=4-8 clusters, where the appropriate number of clusters is k=4 due to its low jackknife error equal to 9.43%[2]. Branches are hard or crisply allocated to clusters as follows: 320 branches to Cluster 1, 71 branches to Cluster 2, 195 branches to Cluster 3, and 379 branches to Cluster 4. This cluster composition is contingent on the number of observations used for classification. In our case, it includes influential observations. The cluster composition would change if some of the influential observations are removed, which is not the approach we follow in this research. At this point one could also argue that once the branches are clustered, the problem of outliers reproduces itself within the clusters. Following this logic would imply looking at various iterations of outlier detection, adding more complexity than clarity on practical managerial decisions. The clusters are shown in Figure 3, and it is important to note that there seem to be overlapping clusters suggesting the need for fuzzy clustering (Seaver & Triantis, 1992). Table 8 depicts the results in terms of the cluster means.

[2] The minimum classification error comes from the optimal combination Sales FTEs, OTC, Borrowing, and Investments respectively.

Table 7. Clustering Results: Jackknife Errors

	k=4 clusters	k=5 clusters	k=6 clusters	k=7 clusters	k=8 clusters
Jackknife Error	0.0943	0.1300	0.1973	0.1970	0.1309

Using the resulting clusters, we provide cluster profiles. To do so, we apply a Tukey test for the comparison of means. This test suggests that all clusters are statistically differentiated for all inputs and outputs as far as their means are concerned, except for the management FTE input. Figure 4 shows a representation on the cluster differentiations based on the ratios of the clusters' means to the overall means. From Figure 4 and Table 8, one can classify branches based on scale (i.e., FTEs and transaction volumes) instead of operating patterns, except for Cluster 2. There are no differences between clusters 1, 3, and 4, except their scale. These clusters comprise 93% of the total branches, which is quite likely since banks run a very tight ship and control all aspects of their operations. A pertinent question relates to the real differentiation regarding operating patterns. Based on the results, differentiation is more a matter of scale. It is our contention that fuzzy cluster assessment would allow for better differentiation in terms of operating patterns. Further research will address this issue. For the moment, it seems that hard or crisply allocated clusters somehow mask this differentiation.

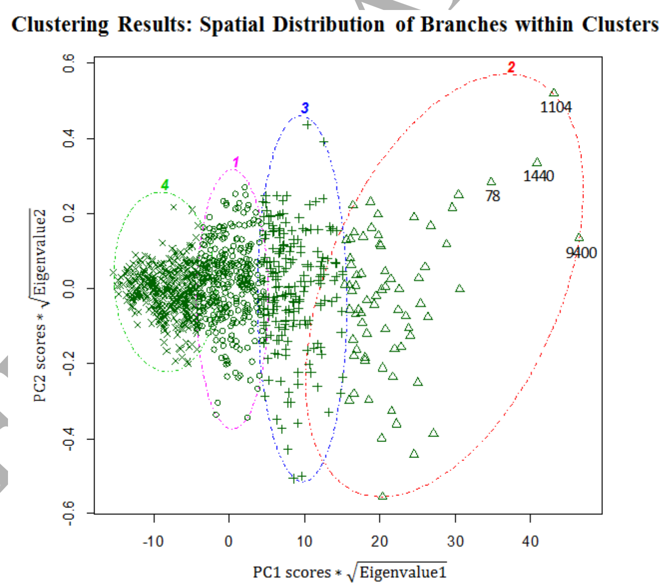

Figure 3. Clustering Results: Spatial Distribution of Branches within Clusters

Table 8. Clustering Results: Cluster Means

Cluster	# Branches	Inputs (in FTEs)			Outputs (in Units)			
		Services	Sales	Mgt.	Day to Day	Invest-ments	Borrow-ing	OTC
1	320	8.25	5.28	0.86	2,805	3,264	1,813	250,531
2	71	17.03	12.54	0.90	6,808	8,440	3,963	542,280
3	195	11.75	8.15	0.88	4,287	5,035	2,752	375,341
4	379	4.45	2.87	0.75	1,416	1,728	1,017	118,632

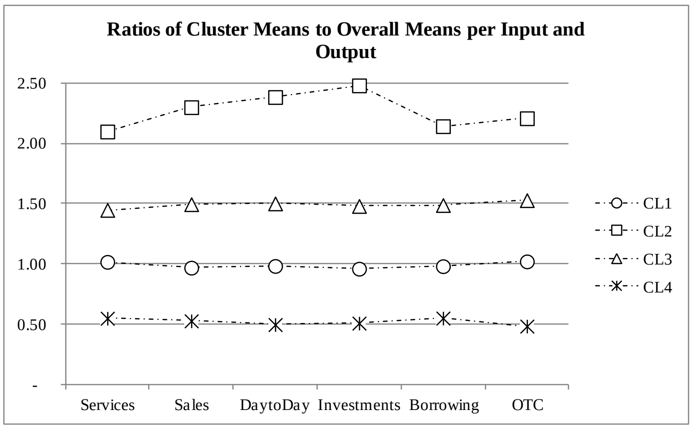

Figure 4. Clustering Results: Ratios of Cluster Means to the Overall Means per Input and Output

In terms of FTEs (inputs) and transaction (output) volumes, hereinafter operational levels, Clusters 4 and 1 contain the branches with the lowest operational level. They show an aggregated average service and sales FTEs equal to 7.3 and 13.5 respectively. Cluster 4 contains 44 out of the 45 branches with no management FTEs. The operational level of these branches imply that there is no need for management FTEs; managerial activities might be covered by service sales FTEs; or the way this variable is measured needs to be revised. The FTEs mix of Clusters 1 and 4 is similar (~61% of service FTEs, ~39% of sales FTEs). Cluster 1 has a slightly higher proportion of service FTEs when compared to Cluster 4; and its OTCs are a little bit higher than Cluster 4. Cluster 4 has a slightly higher proportion of sales FTEs when compared to Cluster 1; and its day-to-day, investment, and borrowing transactions are a little bit higher than Cluster 1. In reality, there is no significant differentiation in the input-output mix for these clusters. Differentiation pertains more to scale rather than to operating patterns. We label branches grouped in Cluster 4 as low-operational level branches, while branches falling in Cluster 1 as medium-operational level branches.

Table 9. Clustering Results: Mean Service and Sales per FTEs

		Outputs/FTEs for Service				Outputs/FTEs for Sales			
Cluster	**Branches**	**Day-to-Day**	**Invest-ments**	**Borrow-Ing**	**OTC**	**Day-to-Day**	**Invest-Ments**	**Borrow-ing**	**OTC**
1	320	340	396	220	30,367	531	618	344	47,449
2	71	400	496	233	31,843	543	673	316	43,244
3	195	365	429	234	31,944	526	618	338	46,054
4	379	318	388	229	26,659	494	602	354	41,336

From Tables 8 and 9, Clusters 3 and 2 contain branches with higher FTEs and transaction volumes. Both clusters have an aggregate average of service FTEs and sales FTEs of 19.9 and 29.6 respectively. The proportion of sales FTEs in Cluster 3 is slightly higher than in Cluster 1 (40.9% vs 39%). The mix of inputs and outputs when comparing Clusters 3, 1 and 4 is not very different. However, Cluster 2 has the highest aggregate outputs per service and sales FTEs of all of the clusters, except for borrowing and OTC on the sales side while Cluster 3 would rank second for outputs corrected for FTEs. Cluster 3 seems to consist of high-operational level branches since these branches have higher FTEs and transaction volumes than those in Clusters 1 and 4. Meanwhile, Cluster 2 is the one with the largest branches but with the greatest input and output variation (see Table 8). It has a high proportion of sales FTEs (42.4% vs. ~39.7% on average in other clusters). This makes the sales outputs higher for this cluster than in the other clusters (3.42% vs. ~3.19% on average in other clusters). The largest branches are more oriented to sales outputs (e.g., day-to-day, investment) than to service ones (i.e., OTC). They might be regional or headquarter branches, where more sales-strategic activities take place. According to the patterns in Figure 4, Cluster 2 is not as homogenous in terms of its input and output mix as the other clusters. It uses more sales FTEs. Branches in Cluster 2 are labelled as very high-operational level branches since they differentiate from others with respect to scale and operating patterns. Table 10 provides an overview of the cluster profiles.

Table 10. Clustering Results: Cluster Profiles

Criteria	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Operational level	Medium	Very high	High	Low
Avg. sales and service inputs	6.76	14.78	9.95	3.66
Avg. sales-related outputs (day-to-day, investment, borrowing)	2,627.88	6,404.25	4,025.16	1,387.33
Avg. service-related outputs (OTC)	250,531.50	542,280.90	375,341.80	118,632.70
Operating pattern	No specific input focus or output orientation	Targeting sales-related outputs	No specific input focus or output orientation	No specific input focus or output orientation

Table 11. Clustering Results: Cluster Composition regarding ROBPCA Classification

	Type of Branch				
Cluster	Bad Leverage	Good Leverage	Orthogonal	Regular	Total
1	0	6	0	314	320
2	28	25	2	16	71
3	2	22	1	170	195
4	0	0	0	379	379
Total	30	53	3	879	965

Branches within clusters possess different classifications regarding their ROBPCA categories. Table 11 shows the number of influential and regular branches within each cluster. 63.95% (55 out of 86) of the influential branches are grouped into Cluster 2. This cluster gathers 93.3% (28 out of 30) of all bad leverage branches, 47.16% (25 out of 53) of all good leverage branches, and 66.6% (2 out of 3) of all orthogonal branches. Conversely, Cluster 4 is composed of 100% regular branches, Cluster 1 has 98.1% (314 out of 320), and Cluster 3 has 87.17% (170 out of 195) regular branches. When studying these results we observe that the two-stage clustering method is able to isolate, as much as possible, the branches that exhibit extreme behaviors. Actually, the most extreme branches in the dataset are in Cluster 2, i.e., bad leverage branches #78, #1104, #1440, and #9400.

4.3 Efficiency Results Including all Branches (the Meta-Frontier)

The input-oriented SBM model discriminates 78 branches as efficient (8.08%) and 887 as inefficient (91.92%) when using the entire dataset. Table 12 provides a descriptive summary of the efficient branches. They show high variability for almost all inputs and outputs, demonstrating the existence of branch heterogeneity regarding operating patterns. It would not be fair to compare inefficient branches to efficient ones possessing dissimilar features.

Table 12. Efficiency Results with All Data: Descriptive Statistics of Efficient Branches

	Inputs (in FTE)			**Outputs (in Units)**			
	Services	**Sales**	**Mgmt.**	**Day to Day**	**Investments**	**Borrowing**	**OTC**
Mean	7.84	5.19	0.64	3,299	3,588	2,104	269,187
Std. Dev.	7.40	4.53	0.41	3,408	3,555	1,705	255,688

Table 13. Percentage of Inefficient Branches Referencing Efficient Peers across Clusters

			Peers (Efficient Branches)			
	Cluster	**# Branches**	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Inefficient Branches	1	313	57.19%	0.32%	2.88%	39.62%
	2	54	1.85%	53.70%	44.44%	0.00%
	3	185	58.38%	9.19%	27.57%	4.86%
	4	335	8.36%	0.00%	0.00%	91.64%

In Table 13 we present a comparison between the number of inefficient branches that are hard or crisply allocated to the clusters obtained in Section 4.2 and the percentage of those branches referencing efficient branches within the same or different clusters. The intention in studying the efficiency results using all data (the meta-frontier) with the branch groupings that are derived from the clustering is to investigate the peer designation from the DEA analysis in relation to where these peers exist using the clustering analysis. From Table 13, a high percentage of inefficient branches have peers from other clusters (i.e., high out-of-group references), especially inefficient branches that are allocated in Cluster 1 (39.62% of peers in Cluster 4), Cluster 2 (44.44% of peers in Cluster 3) and Cluster 3 (58.38% of peers in Cluster 1). This indicates that performance comparisons based on lambda values do not capture all the similarities that branches share in terms of operating patterns across clusters. In contrast, 91.6% of the inefficient branches in Cluster 4 have their peers within the same cluster.

As an example, let us analyze inefficient branch #12 allocated to Cluster 1. The meta-frontier results suggest the efficient branch #7288 from Cluster 4 as the primary peer for branch #12. Figure 5 depicts the efficiency performance of inefficient branch #12, efficient branch #7288, the average performance of efficient branches in Cluster 1 and Cluster 4. For normalization purposes, the values shown in Figure 5 correspond to the ratios of the branch's input and output values to the overall mean for each input and output of interest. The figure shows how the inefficient branch #12 does not really compare to either its peer branch #7288 or the average of the efficient branches in Cluster 4. Indeed, the pattern of the inefficient branch #12 is more similar to the average of the efficient branches within its own cluster, i.e., Cluster 1. If the inefficient branch #12 uses branch #7288 as a role model for best practices, it would need to drastically change its operating patterns to emulate branch #7288. Besides costs and time, it would suggest considering the short and long term feasibility of the changes.

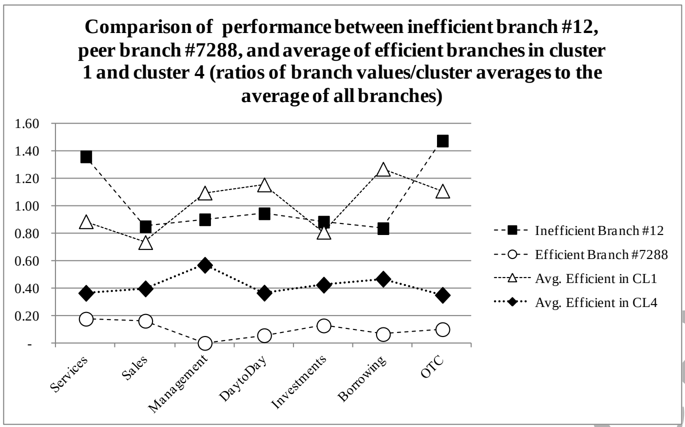

Figure 5. Comparison between Inefficient Branch #12 and Efficient Peer Branch #7288

4.4 Efficiency Results within Each Cluster

The input-oriented SBM model is applied to each cluster. The results are provided in Table 14. As expected, the number of efficient branches identified (202 out of 965) exceeds the number of efficient ones from the meta-frontier approach (78 out of 965), i.e., almost 2.6 times more efficient branches. In this case, inefficient branches find all their peers within their clusters. Table 15 provides descriptive statistics for the efficient branches. By comparing the variability in Table 15 and Table 12, the efficient branches in clusters show less variability in all inputs and outputs compared to the meta-frontier approach. Branches within clusters are more similar. Revisiting branch #12 for example, we find that it remains inefficient when evaluating its performance within Cluster 1. However, the branch has branch #131 from Cluster 1 as its peer instead of branch #7288 from Cluster 4 as described in Section 4.3. In Figure 6, we identify how the branches within the same cluster (#12 and #131) are more similar with respect to operating patterns. Thus, any improvements performed by branch #12 are more reasonable to attain using efficient branch #131 as a peer rather than efficient branch #7288.

Table 14. Cluster Efficiency Results: Efficiency Classification per Cluster

Designation	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total
Efficient	50	23	43	86	202
Inefficient	270	48	152	293	763
Total	320	71	195	379	965

In Table 14, the proportion of efficient branches is 20.93% (202/965) versus 8.08% (78/965) using the meta-frontier. This proportion increases in the cluster-frontiers because each branch is compared to a smaller set of more similar branches. The cluster-frontier perspective allows for the definition of more reasonable efficient frontiers by isolating the effect of influential branches with different operating patterns. With respect to influential branches, we find that the meta-frontier is formed by 78 efficient branches classified into 57 regular and 21 influential (13 bad leverage, 7 good leverage and 1 orthogonal). The efficient frontiers from the cluster-frontier perspective are represented by four frontiers. Figure 7 shows the cluster composition. In this figure, the majority of efficient branches in Clusters 1, 3 and 4 are regular branches: 94% in Cluster 1 (47/50), 72% in Cluster 3 (31/43), and 100% in Cluster 4. Influential branches are not associated with these clusters. However, Cluster 2 contains the most influential branches (28 bad, 25 good, 2 orthogonal). Out of the 71 branches composing cluster, 23 are efficient. Three are classified as regular branches and 20 as influential ones (12 bad leverage[3], 7 good leverage and 1 orthogonal); 17 out of the 20 influential efficient branches in Cluster 2 are contained in the set of influential efficient branches found in the meta-frontier perspective. The cluster-frontier approach classifies a higher proportion of efficient influential branches in a particular cluster.

Table 15. Cluster Efficiency Results: Efficient Branch Means per Cluster

		Inputs (in FTEs)			Outputs (in Units)			
Cluster	**Statistic**	**Services**	**Sales**	**Mgt.**	**Day-to-Day**	**Investments**	**Borrowing**	**OTC**
1	Mean	8.12	5.14	0.84	3,168	3,649	2,052	279,615
	Std. Dev.	1.78	1.50	0.11	865	1,299	589	83,145
2	Mean	17.82	11.59	0.89	8,067	8,699	4,415	613,705
	Std. Dev.	6.40	3.18	0.29	2,888	3,258	880	166,063
3	Mean	11.64	7.99	0.87	4,793	5,429	3,005	392,228
	Std. Dev.	2.43	2.24	0.18	1,190	1,879	770	103,988
4	Mean	3.95	2.76	0.58	1,442	1,763	1,058	117,012
	Std. Dev.	1.76	1.10	0.40	729	892	521	57,548

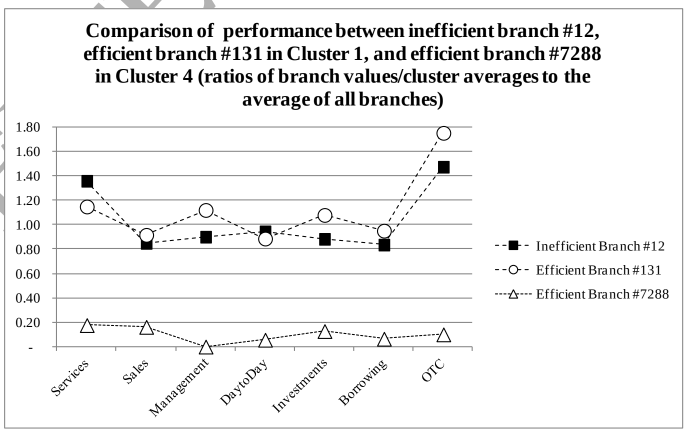

Figure 6. Comparison among Inefficient Branch #12 and Efficient Branches #131 and #7288

[3] This set includes the most extreme branches of the entire bank network: branches #78, #1104, #1440 and #9400.

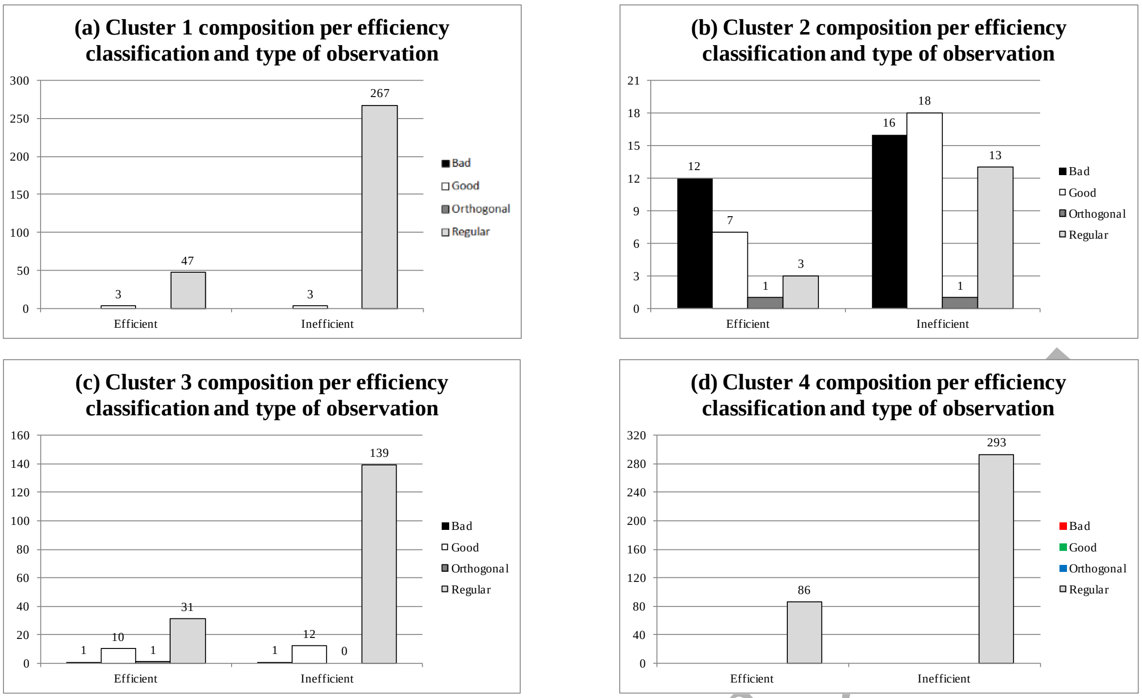

Figure 7. Composition with respect to Efficiency Designation and Branch Type

4.5 Influential Branches and DEA Efficiency Performance Measurement

From the previous analysis, one can gain insights with respect to the reduction of the number of influential branches used as peers when using cluster-frontiers. As a matter of comparison, Table 16 shows the number and type of branches used as primary peers in both the meta-frontier and cluster-frontiers. It also shows the number of inefficient branches referencing primary peers falling into each ROBPCA category. Looking at the meta-frontier, 13 out of 30 bad leverage branches (43.3%) are used as primary peers by 25 inefficient branches, and a total of 84 inefficient branches (out of 887: 39 regular, 11 bad, 33 good, and 1 orthogonal) reference influential branches as primary peers. In other words, efficient influential branches are peers for 9.47% (84/887) of the inefficient branches. A valid question to ask is if it is reasonable that inefficient branches choose efficient influential branches as peers. To some degree, there is no a clear answer to this question. It depends on the correspondence between inputs and outputs. For instance, 88% of the peers of the 33 good leverage branches referencing influential branches as primary peers are good leverage branches; meanwhile, 12% are bad leverage branches. Thus, cross-referencing is numerically possible, but the appropriate peer selection must be carefully studied by the analyst in a meta-analysis.

By analyzing the cluster-frontiers shown in Table 16, 13 out of 30 bad leverage branches are used as primary peers by 34 inefficient branches. From these 13 efficient and bad leverage branches, 12 belong to Cluster 2 (92.3%) and one to Cluster 3 (7.7%). A total of 61 inefficient branches (out of 763) reference influential branches as primary peers. Thus, efficient influential branches are peers for 7.99% (61/763) of the inefficient branches. These results must be decomposed per cluster to investigate the real impact. From the 61 inefficient regular branches referencing influential branches as peers, 8 belong to Cluster 1 (1.04% out of 763), 46 to Cluster 2 (6.02% out of 763), 7 to Cluster 3 (0.91% out of 763), and 0 to Cluster 4 (0% out of 763). Thus, there is a reduction in the number of influential branches serving as peers when using the cluster-frontiers versus the meta-frontier.

Table 16. Number of Branches used as Efficient Peers per ROBPCA Classification

Category	Details	Meta-Frontier	Cluster-Frontier
Bad Leverage	# Bad leverage branches used as peers	13	13
	# Inefficient branches using bad leverage branches as peers	25	34
Good Leverage	# Good leverage branches used as peers	7	20
	# Inefficient branches using good leverage branches as peers	58	24
Orthogonal	# Orthogonal branches used as peers	1	2
	# inefficient branches using orthogonal branches as peers	1	3
Regular	# Regular branches used as peers	57	167
	# inefficient branches using regular branches as peers	803	702

The discrimination of branches based on their ROBPCA classification and efficiency designation provides a means to improve peer selection. For example, from the 25 inefficient branches that have efficient bad leverage ones as peers in the meta-frontier, 10 are regular. Recalling the aggregate profile in which a bad leverage branch is where more outputs but low borrowing are produced in relation to service and sales FTEs, this implies that the 10 branches might follow peers that do not address their performance in a meaningful way. The targets might be infeasible, misrepresent the correspondence between sales and service inputs and outputs, and exert pressure towards unreachable goals. To confirm this, the analyst would need to compare the input and output mix of the 10 inefficient regular branches and the mix of the bad leverage branches referred to as peers. Special attention must be given to bad leverage and orthogonal branches referenced as peers. A solution might be to select as peers efficient branches (not bad or orthogonal) with the second highest lambda. Good leverage peers exhibit better operating conditions (more service outputs using less service inputs); thus, their use as peers would not lead to unreasonable targets.

4.6 Comparing and Contrasting with Paradi et al. (2012)

We select the study by Paradi et al. (2012) to compare and contrast how different multi-step procedures provide varying results for managerial groups in bank branch networks. Our intent is not to suggest methodological superiority but to investigate how different methodologies lead to different clusters of bank branches, their study of efficiency and managerial insights. (1) ***Point of departure:*** Paradi et al (2012) use clustering as a post-assessment tool based on **efficient** branches and cosine similarity measures. Our approach clusters **all** branches first and then applies DEA analysis to each cluster, ensuring similarity between inefficient and efficient branches so that performance targets are achievable. ***(2) Treatment of Outliers:*** Paradi et al. (2012) use a rule of thumb approach to remove four extreme branches. The rule consists on removing branches for which at least two out of three of their inputs have values larger than the input mean plus three times the input standard deviation of all branches. No additional discussion is provided. In contrast, our approach attempts to keep the outliers throughout the analysis to understand their influence in terms of the clustering and efficiency analysis. We apply ROBPCA to classify influential branches into profiles defining bad leverage, good leverage, and orthogonal branches. Only branch #1020 (bad leverage) is removed given its extreme behavior. ***(3) Number of Clusters:*** Paradi et al. (2012) obtain six clusters based on the **efficient** branches. The clusters are differentiated given certain inputs and outputs. Inefficient branches are allocated to the clusters based on their DEA lambda values. Our approach yields four clusters composed of **efficient** and **inefficient** branches. Only one cluster shows specific patterns in terms of the inputs and/or outputs. Clusters 1, 3 and 4 are composed of branches following homogeneous operating patterns (no specific input focus and/or output orientation), while Cluster 2 targets more sales-related outputs with more sales FTEs. ***(4) Efficiency Classification:*** The non-oriented DEA model applied by Paradi et al. (2012) identifies 78 efficient branches out of 962. Our cluster-frontier input-oriented DEA approach identifies 202 efficient branches out of 965. This is because the influential efficient branches are mainly grouped into one cluster, increasing the discrimination of efficient branches in other clusters. ***(5) Managerial Insights:*** The study developed by Paradi et al. (2012) provides several managerial insights discussed in Section 2.2. Our approach provides alternative insights by including influential-based and cluster profiles, which expand the characterization of branches beyond operating patterns and include the analysis of reasonable correspondences between inputs and outputs. This provides managers with both aggregate and detailed information to support decision making in terms of shifting operating patterns, new branch openings, and operational improvements. Furthermore, our approach clearly identifies the low contribution of the management input to branch performance differentiation and characterization. This is evident by means of both the robust principal component analysis and the two stage clustering. This finding reinforces the need of revising the way the management input is measured. Contrary to Paradi et al. (2012), our approach informs managerial stakeholders about the suitability of using peers or role models within the same cluster. In other words, using peers within a group of branches that share the same operating patterns. As a result, our approach yields 0% cross-referencing and ensures the formulation of performance targets that are more feasible and logical with respect to current operating patterns of the inefficient branches.

5. Conclusions

5.1 Practical Remarks from the Analysis

Despite the limitation of this research in terms of accessing more recent bank branch data and the non-availability of contextual variables for clustering, our multi-step procedure offers a set of capabilities that bank branch stakeholders might take advantage of when considering grouping branches, studying their performance, and informing bank network design decisions. These capabilities are: ***(1) Address operational performance from a multidimensional viewpoint***. As supported by previous studies (e.g., Avkiran, 2014; Yang, 2009; Thanassoulis, 1999), multiple inputs and outputs can be included for efficiency performance evaluation, overcoming the limitations of financial ratios. It is important to recall the importance of the selection of an appropriate input and output model specification, since the use of different inputs and outputs leads to alternative realizations of operational or profit efficiency. ***(2) Ensure fairer comparability***. Our multi-step procedure views branches as entities sharing similarities regarding operating patterns and environments. Clustering by similarities promotes fairer comparisons among branches. This challenges the tendency of grouping branches based on size or geographical location, which usually benefits branches serving big markets surrounded by favorable environmental conditions. Operating patterns that are not fully scale-driven will be further explored when using fuzzy methods (Seaver & Triantis, 1992). ***(3) Fully characterize branches at the individual level***. Stakeholders can characterize each individual branch in relation to (a) its branch type (influential, regular), (b) its operating patterns (cluster allocation), (c) its efficiency designation (efficient or inefficient) for both the bank network (meta-frontier) and within clusters, and (d) its closest and most appropriate peer. This characterization provides a level of detail that is not usually found in efficiency banking studies, delivering as much information as can be extracted from the available data. ***(4) Fully characterize branches at the aggregate level***. Individual information allows for pattern aggregation. Stakeholders are provided with two kinds of aggregate profiles. The influential-based branch profiles lead to an understanding of what bad leverage, good leverage, orthogonal, and regular branches mean based on the determinants of efficiency performance, i.e., key inputs and outputs. Bank networks might use these profiles as guidance for the identification of best practices and expected input-output correspondences. The cluster profiles identify the input focus and output orientation (operating patterns) of each cluster. Our multi-step procedure is replicable to other banking and non-banking networks***. (5) Get a big picture on bank branch performance***. By combining individual and aggregate information, stakeholders get a better understating of bank branch efficiency performance and are able to inform better network design decisions. Stakeholders thinking on re-designing branches, e.g., changing their output orientation, might use the branches' current cluster profiles to determine the feasibility of future changes (e.g., adaptation to other operating pattern(s), costs, and time). Aggregate information would also allow for the discovery of measurement issues. For example, in this research we do not encounter a reasonable contribution of management FTEs on efficiency, which is not really expected. This is probably due to the difficulty of obtaining appropriate measurements for this variable. This is an opportunity to investigate how efficiency performance is measured in terms of specific variables using different methods, and to demonstrate how bad measurement affects network design decisions.

5.2 Technical Remarks from the Analysis and Future Research

We discuss technical insights along with further research challenges. ***(1) The need for consensus on model specifications.*** It is worth to note that there is no consensus in the literature as to what the appropriate model specification for bank branch operational performance is (Luo, Bi, & Liang, 2012).

The selection of model specifications should be informed by research on input-output correspondences contingent by the availability of data. ***(2) Building on the integration of Operations Research and robust statistical techniques***. Current literature on bank branch operational performance usually concentrates on identifying efficient and inefficient branches, formulating improvement targets, and recommending peers. Besides these contributions, this paper augments and implements the Triantis et al. (2010) integrated approach in a bank branch network setting and complements it by adding aggregate profiles for influential observations and clusters. This unique implementation provides capabilities to investigate bank branch efficiency performance as it relates to the deviation of bank branches from normal operating patterns, the clustering of branches based on similarity, and the influence of clusters and influential branches on efficiency evaluation. ***(3) Number of clusters***. Clustering results depend on both the method used to cluster and the selected number of clusters. We explored four to eight clusters, selecting four clusters based on the minimum jackknife error. This decision should be complemented with feedback from bank stakeholders through face-validation. ***(4) Meta-frontier versus cluster-frontiers***. In Sections 4.3 and 4.4, we explore how efficiency designations change when using a meta-frontier versus cluster-frontiers. Less variability, more efficient branches, and fairer benchmarking conditions are some of the benefits. ***(5) The effect of the robust clustering approach on efficiency designations***. Figure 8 shows how the efficient branches identified by the meta-frontier are allocated into clusters along with their branch ROBPCA classification. We can see how none of the efficient branches change their efficiency designations, and particularly, how the majority of the influential branches (17 out 21) are allocated in Cluster 2. This captures the essence of what we refer to in Section 4 as the power of isolation of the robust two-stage clustering method. This isolation increases the discriminatory power of efficient branches in all clusters and reduces the number of influential branches referenced as peers. ***(6) Use of results for an ex-ante perspective***. Our approach might be used for bank network design. This implies looking at clustering and efficiency performance as a means for ex-ante interventions as opposed to the classical ex-post approach of the efficiency performance literature. Designing a bank network can imply decisions on restructuring, reengineering, closing or opening branches. The individual and aggregate branch characterizations can support and guide these decisions. Further research on linking efficiency performance measurement and bank network design is encouraged. ***(7) Additional future research***. Some issues to address are: the analysis of more recent banking datasets along with the inclusion of contextual variables; the automation of the proposed multi-step procedure in a unified code so that analysts interested in its capabilities can use it as a single expert system to support clustering, efficiency evaluation, and bank network design decision making; the comparison of bank branch performance realities of different countries; and the exploration of the effect on operational performance by Full-Time Equivalent employees when breaking them down into full and part-time employees. Other critical issues should investigate the effect of mobile banking channels on branch performance and to examine a **fuzzy clustering** approach based on our previous research. With respect to the latter, our intuition is that branches share similarities with more than one cluster, which affect their efficiency classification and the classification of other branches in the clusters.

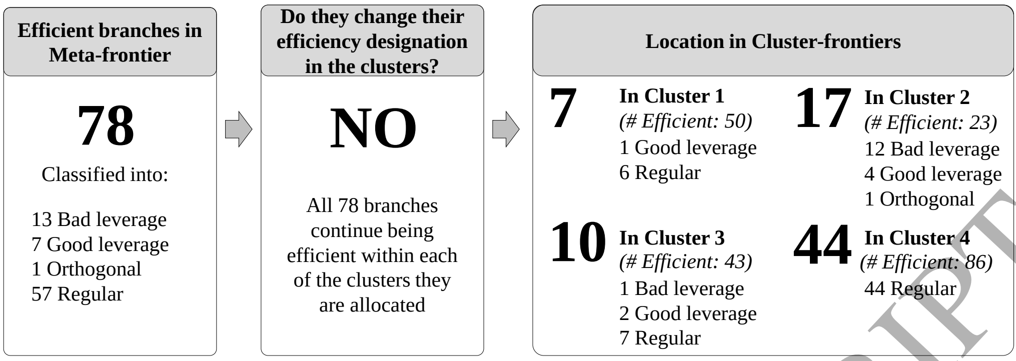

Figure 8. Effect of Clustering on Efficiency Designations

References

Athanassopoulos, A. (1998). Nonparametric frontier models for assessing the market and cost efficiency of large-scale bank branch networks. *Journal of Money, Credit, and Banking*, 30, 172-192.

Avkiran, N. (2009). Opening the black box of efficiency analysis: An illustration with UAE banks. *Omega*, 37, 930-941.

Avkiran, N. (2014). An illustration of dynamic network DEA in commercial banking including robustness tests. *Omega*, In Press, Corrected Proof — Note to users.

Avkiran, N., Tone, K., & Tsutsui, M. (2008). Bridging radial and non-radial measures of efficiency in DEA. *Annals of Operations Research*, Volume 164, Issue 1, pp 127-138.

Beguin, C., & Simar, L. (2004). Analysis of the Expenses Linked to Hospital Stays: How to Detect Outliers. *Health Care Management Science*, 7, 2, 89-96.

Berger, A., & Humphrey, D. (1997). Efficiency of financial institutions: International survey and irections for future research. *European Journal of Operational Research*, 98, 175-212.

Berger, A., & Mester, L. (1997). Inside the black box: what explains differences of financial institutions? *Journal of Banking and Finance*, Vol 21, Issue 7, 895-947.

Canadian Bankers Association. (2014). *Canadian Bankers Association*. Retrieved 2014, from http://www.cba.ca/en/component/content/publication/69-statistics

CBC News. (2013, 01 25). *Banks misleading clients on mutual funds*. Retrieved from http://www.cbc.ca/news/canada/banks-misleading-clients-on-mutual-funds-1.1415027

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, vol. 2, no. 6, pp. 429–444.

Charnes, A., Cooper, W., Golany, B., Seiford, L., & Stutz, J. (1985). Foundations of data envelopment analysis and Pareto-Koopmans emprical production functions. *Journal of Econometrics*, 30, 91-107.

Cook, W. D., & Zhu, J. (2006). Incorporating Multiprocess Performance Standards into the DEA framework. *Operations Research*, Vol. 54, No. 4, 656-665.

Fallah-Fini, S., Triantis, K., & Johnson, A. (2014). Dynamic Efficiency Assessment: The State of the Art. *Journal of Productivity Analysis*, 41(1): 51-67.

Han, J., Kamber, M., & Pei, J. (2012). Data processing. In J. Han, M. Kamber, & J. Pei, *Data Mining: Concepts and Techniques* (pp. 83-123). Waltham, MA: Elsevier Inc.

Hannan, T. H. (2006). Retail deposit fees and multimarket banking. *Journal of Banking & Finance*, Vol. 30, Issue 9, 2561-2578.

Hubert, M., & Engelen, S. (2004). Robust PCA and classification in biosciences. *Bioinformatics*, Vol. 20, No. 11, pp. 1728–1736.

Hubert, M., Rousseeuw, P. J., & Vanden Branden, K. (2005). ROBPCA: a new approach to robust principal. *Technometrics*, 47, 64–79.

Kaiser, H. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, 20, 141-151.

Luo, Y., Bi, G., & Liang, L. (2012). Input/output indicator selection for DEA efficiency evaluation: An empirical study of Chinese commercial banks. *Expert Systems with Applications*, 39, 1118–1123.

McKinsey and Company. (2010). *The Future of Retail Banking.* McKinsey & Company.

Mukherjee, A., Nath, P., & Nath Pal, M. (2002). Performance benchmarking and strategic homogeneity of Indian banks. *International Journal of Bank Marketing*, 20/3, 122-139.

Mukherjee, A., Nath, P., & Nath, M. (2002). Performance benchmarking and strategic homogeneity of Indian banks. *International Journal of Bank Marketing*, 20/3, 122-139.

O'Donnell, C. J., Prasada Rao, D. S., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, Vol. 34, Issue 2, 231–255.

Paradi, J. C., & Zhu, H. (2013). A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega*, 41, 61-79.

Paradi, J. C., Yang, Z., & Zhu, H. (2011). Assessing Bank and Bank Branch Performance. In W. W. Cooper, L. M. Seiford, & J. Zhu, *Handbook on Data Envelopment Analysis* (pp. 315-361). Springer Science+Business Media, LLC.

Paradi, J. C., Zhu, H., & Eldestein, B. (2012). Identifying managerial groups in a large Canadian bank branch network with a DEA approach. *European Journal of Operation Research*.

Prior, D., & Surroca, J. (2006). Strategic groups based on marginal rates: An application to the Spanish banking industry. *European Journal of Operational Research*, Vol. 170, 1, 293–314.

Salkind, N. J., & Rasmussen, K. (2007). *Encyclopedia of Measurement and Statistics.* Sage Publications.

Schaffnit, C., Rosen, D., & Paradi, J. C. (1997). Best practice analysis of bank branches: An application of DEA in a large Canadian bank. *European Journal of Operation Research*, 98, 269-289.

Seaver, B., & Triantis, K. (1992). A Fuzzy Clustering Approach Used in Evaluating Technical Efficiency measures in Manufacturing. *The Journal of Productivity Analysis*, 3, 337-363.

Seaver, B., & Triantis, K. (1995). The impact of outliers and leverage points for technical efficiency measurement using high breakdown procedures. *Management Science*, Vol. 41, No. 6, 937-956.

Seaver, B., Triantis, K. P., & Hoopes, B. J. (2004). Efficiency Performance and Dominance in Influential Subsets: An Evaluation using Fuzzy Clustering and Pair-wise Dominance. *Journal of Productivity Analysis*, 21, 201-220.

Sherman, H. D., & Gold, F. (1985). Bank Branch Operating Efficiency. *Journal of Banking and Finance*, 9, 297-315.

Sidel, R. (2013, 03 31). After Years of Growth, Banks Are Pruning Their Branches. *The Wall Stree Journal*. Retrieved 2014, from http://www.wsj.com/articles/SB10001424127887323699704578326894146325274

Sterngold, J. (2014, 09 02). Banks' Fee Bonanza Dries Up. *The Wall Street Journal*.

Thanassoulis, E. (1999). Data Envelopment Analysis and Its Use in Banking. *Interfaces*, 29, 3, 1-13.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, Vol. 130, Issue 3, 498–509.

Triantis, K., Seaver, B., & Sarayia, D. (2010). Using Multivariate Methods to Incorporate Environmental Variables for Local and Global Efficiency Performance Analysis. *Informational Systems and Operational Research*, Vol. 48, No. 1, pp. 39-52.

Yang, Z. (2009). Assessing the Performance of Canadian Bank Branches Using Data Envelopment Analysis. *Journal of the Operational Research Society*, 60, 771-780.