# Evaluating productive efficiency

*comparative study of commercial banks in Gulf countries*

Abdel Anouze

# Evaluating Productive Efficiency: Comparative Study of Commercial Banks in Gulf Countries

Abdel Latef Anouze

Thesis submitted to the University of Aston in part fulfilment of the requirements of the degree of Doctor of Philosophy

**ASTON UNIVERSITY**

August 2010

# Acknowledgements

I would like to express my sincerest thanks and gratitude to my advisors, Dr. Ali Emrouznejad and Prof. Emmanuel Thanassoulis. It was their initial encouragement that began my doctorial research and it has been their patience and support that has helped to continue my research efforts. Also it is with their insight and discussions my understanding of these topics has become much richer. I would also like to thank for their assistance and frequent conversations. It is their open door which allows so many students to connect with this department and feel a genuine concern and interest of the faculty. This dissertation would not have been possible without all the assistance I have received. Special thanks to Gary Simpson, Dr. Ozren Despic, and Dr. David Saal for their assistance and advice in helping me in this research.

I also thank my dearest parents their unconditional love and support on all the decisions I have made. I wish to give my hearty thanks to them for their continuous support and encouragement throughout my studies and my entire life, even though the value of my appreciation cannot compare with everything they have done for me. To my brothers and sisters who shared with me my dream, it is with them by my side that life is more enjoyable.

# Contents

## List of Figures

# List of Tables

**Evaluating Efficiency: Comparative Study of Commercial Banks in Gulf Countries**

# Summary

Financial institutes are an integral part of any modern economy. In the 1970s and 1980s, Gulf Cooperation Council (GCC) countries made significant progress in financial deepening and in building a modern financial infrastructure. This study aims to evaluate the performance (efficiency) of financial institutes (banking sector) in GCC countries. Since, the selected variables include negative data for some banks and positive for others, and the available evaluation methods are not helpful in this case, so we developed a Semi Oriented Radial Model to perform this evaluation. Furthermore, since the SORM evaluation result provides a limited information for any decision maker (bankers, investors, etc...), we proposed a second stage analysis using classification and regression (C&R) method to get further results combining SORM results with other environmental data (Financial, economical and political) to set rules for the efficient banks, hence, the results will be useful for bankers in order to improve their bank performance and to the investors, maximize their returns.

Mainly there are two approaches to evaluate the performance of Decision Making Units (DMUs), under each of them there are different methods with different assumptions. Parametric approach is based on the econometric regression theory and nonparametric approach is based on a mathematical linear programming theory. Under the nonparametric approaches, there are two methods: Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). While there are three methods under the parametric approach: Stochastic Frontier Analysis (SFA); Thick Frontier Analysis (TFA) and Distribution-Free Analysis (DFA).

The result shows that DEA and SFA are the most applicable methods in banking sector, but DEA is seem to be most popular between researchers. However DEA as SFA still facing many challenges, one of these challenges is how to deal with negative data, since it requires the assumption that all the input and output values are non-negative, while in many applications negative outputs could appear e.g. losses in contrast with profit. Although there are few developed Models under DEA to deal with negative data but we believe that each of them has it is own limitations, therefore we developed a Semi-Oriented-Radial-Model (SORM) that could handle the negativity issue in DEA.

The application result using SORM shows that the overall performance of GCC banking is relatively high (85.6%). Although, the efficiency score is fluctuated over the study period (1998-2007) due to the second Gulf War and to the international financial crisis, but still higher than the efficiency score of their counterpart in other countries. Banks operating in Saudi Arabia seem to be the highest efficient banks followed by UAE, Omani and Bahraini banks, while banks operating in Qatar and Kuwait seem to be the lowest efficient banks; this is because these two countries are the most affected country in the second Gulf War. Also, the result shows that there is no statistical relationship between the operating style (Islamic or Conventional) and bank efficiency. Even though there is no statistical differences due to the operational style, but Islamic bank seem to be more efficient than the Conventional bank, since on average their efficiency score is 86.33% compare to 85.38% for Conventional banks. Furthermore, the Islamic banks seem to be more affected by the political crisis (second Gulf War), whereas Conventional banks seem to be more affected by the financial crisis.

**Keyword**: Productivity and Efficiency, GCC bank performance, Parametric Approach, Nonparametric Approach, Semi-parametric Approach

# CHAPTER 1 : INTRODUCTION AND STRUCTURE

## 1. Introduction

Financial institutions are an integral part of any modern economy. In the 1970s and 1980s, Gulf Cooperation Council (GCC) countries made significant progress in financial deepening and in building a modern financial infrastructure. Excess oil revenues led to the accumulation of sizable foreign assets and private wealth, part of which were intermediated by the banking sector. The Iraqi attack of 1990-1991 profoundly affected the GCC economy and its financial sector. After that banks strengthened their deposit base and improved productivity by acquiring advanced technologies and developing profitable consumer-based services (Eltony and Al-Mutairi , 2001).

Today, commercial banks in GCC countries are facing many challenges that are likely to affect their ability to grow and operate within a more competitive environment. However, the GCC commercial banks will be exposed to even more competition by the time they become more integrated within the recently announced GCC economic and monetary union. As well, they are expected to face high competitive pressure when they open up their domestic markets to foreign banks. Thus, commercial banks of GCC countries not only need the proper regulatory framework to play the role of universal banks, but they also have to face stiff competition from well-established domestic investment and insurance companies.

Over the last decade, GCC countries' banking sector has experienced many regulatory changes. The most important of these has been the gradual removal of interest rate ceiling on loans and deposits, which commenced from the mid 1990s onwards. The aim of these regulatory changes was to bring about a more competitive environment and foster improved efficiency in the banking sector (Shamsi, 2003). The ability of GCC commercial banks to meet these challenges depends on how efficiently they are run. Therefore, the analysis of their efficiency will be the focus of this study.

## 2. Aims of the study

The aim of this study is to evaluate the performance (efficiency) of the banking sector in GCC countries. Furthermore, since, the selected variables include negative data for some banks and positive for others, and the available evaluation methods are not helpful in this case, so we aim to develop or amend the current Models to deal with the negativity issue. Moreover, to study the impact of the economic and financial factors on bank efficiency in the countries under study as the available Models provides a limited information about bank performance to decision makers (bankers, regulators, investors, etc...), therefore, we aim to integrate more than one measurement tools to get further useful results for bankers in order to improve their bank performance and for the investors to maximize their benefits.

Also, the study aims to compare the efficiency of GCC commercial banks according to their operating style (Islamic or Conventional) and to their geographical location. Thus, it provides empirical evidence about efficiency differences across various GCC banking sector and across various types of operating style. Although, an extensive literature has examined efficiency, especially in the US banking sector and other European markets and the empirical research on financial sectors in developing countries including GCC is limited, therefore, this study ultimately aims to extend the established literature on bank efficiency in developing countries.

## 3. Data and Methodology

### a. Data

The empirical part of this study is based on all banks operating in GCC countries over the period 1998- 2007 using BankScope database. The reasons behind this selection for GCC banking sector are; the banking sector in these countries is the largest in the Arabian region, also, the lack of relevant information about banking sectors in other Arabian countries is the main reason for excluding them from our sample.

### b. Methodology

There is a substantial body of the literature discussing different methods applied to performance evaluation. Reviewing 130 studies of efficiency of financial institutions Berger and Humphrey (1997) classified them according to the technical approach employed into parametric and nonparametric. Parametric methods such as; stochastic frontier approach (SFA), distribution free approach (DFA) and thick frontier approach (TFA), and nonparametric such as data envelopment analysis (DEA), free disposal hull (FDH). The number of methods has been increased to include; multivariate statistical analysis (Huang, 1986; Chen, 1991); fuzzy set theory (Ho and Tan, 2004); grey relation analysis (Ho, 2006); balanced scorecard (Norreklit, 2000); artificial neural network and so on. Therefore, choosing a viable method to evaluate the performance of decision making units (DMUs) is not an easy task (Ho, 2006).

A further problem faced by researchers studying banks' efficiency relates to difficulties in the definition of bank inputs and outputs variable. There are two main approaches to define banks inputs-outputs: production and intermediation approach. However, there is no agreement on the clear definition for banks inputs and outputs under each approach. Berger and Humphrey (1997) pointed out that although there is no perfect approach for evaluating banks efficiency, the intermediation approach might be more appropriate. For the purposes of this study we reviewed the literature on bank efficiency to propose a comprehensive approach that takes into account the different aims of banks managers, which includes three major aims; business motivator, risk taker and profit maker. Bank as business motivator could have different inputs and outputs than banks as risk taker or profit (value added) maker.

Nevertheless, before reviewing the methodological part it is worth to briefly introduce the Islamic banks and highlight some of the differences between the two operating Models, Islamic and Conventional.

## 4. Islamic and Conventional Banks

Islamic banks are commercial banks, which tend to comply with the religious injunctions of Islam (Noman, 2003). The Islamic financial rules encourage risk- and profit sharing in the sphere of financial activities, as the essential principle of interest-free banking is profit/loss sharing (Metwally 1997). Also, it prohibits interest or usury, gambling and Gharar (undue risk taking), involvement in trading in such goods and services that are unlawful in themselves (El-Gamal 2001). Thus, Islamic banks are commercial banks operating with interest free rate (no interest rate). Interest free banks are new proposition that began in the seventies of the last century. Dubai Islamic Bank is the first modern private Islamic bank, established in 1975 in Dubai, United Arab Emirates (UAE). An international development bank called Islamic Development Bank based in Jeddah (Saudi Arabia) started operating in the same year, followed by the establishment of several other banks mainly in the Middle East and North Africa. Prior to these initiatives, there is evidence of earlier efforts to mobilize and invest savings based on interest-free principles in Egypt and Malaysia during the 1960s (Ahmed 1995). To highlight the differences between Islamic and Conventional banks, the following table summarizes the similarities and differences between both operating styles.

Table 1: Comparison Islamic banks with Conventional banks

| Islamic Bank | Conventional Bank |
|---|---|
| Deposit Mechanism | |
| Al Wadiah Current Deposit<br>Bank guarantees the full return of the deposits and the depositors are not paid any share of the profit or any other return. | Current Deposit<br>It is same to Al Wadiah current deposits of Islamic banks. |
| Mudaraba Savings Deposit<br>Bank uses the funds at its own risk, but guarantees full return of deposits and shares any profits. | Savings Deposit<br>Bank accepts deposits as a safe custodian of the customer's money, on a declared rate of interest to be paid. The depositors can withdraw the balance. |
| Mudaraba Term Deposit<br>Deposit holders participate in the share of the profit / loss of the bank; therefore they do not receive any interest and do not have the right to withdraw from this account<br>The return is determined according to the actual profits earned from the investment operations of the bank. | Fixed or Term Deposit<br>Usually these accounts are opened for a specific period.<br>Deposit holders receive interest at different rates of interest for different terms of fixed deposits.<br>Generally the depositors cannot withdraw the money from these accounts. But, withdrawals can be made under special circumstances. |
| Investment Mechanism | |
| Murabaha<br>The client request the bank to finance his specific requirement like purchase raw materials.<br>The bank informs the client about the margin profit the bank would like to make on the original price.<br>The final price is deferred to a payment on an instalment basis.<br>The sale item is in the possession of the bank before sale to the client. | Cash Credits<br>The bank allows borrower to draw cash up to the limit of the credit by issuing cheque.<br>Interest is charged on the daily balance of the account.<br>Overdrafts<br>The bank allows borrower to overdraw money in excess of his credit balance, up to a certain limit. |
| Bai-Muajjal<br>The client approaches the bank for financing the purchase of goods; the bank purchases them and resells them to the customer at an agreed price to be paid later.<br>The agreed price includes the cost of goods plus the bank's margin of profit with other incidental costs. | Advances for Hire-purchase<br>Advances are made to the client under the condition that repayment of principal would be made in instalments along with interest charged.<br>The immovable properties might be kept as security. |

| Islamic Bank | Conventional Bank |
|---|---|
| Bai-Salam<br>It is a sale of commodity, the delivery of which would be in a future date for cash price.<br>Price is advanced in cash to the seller, who makes the delivery of commodity of determined specification on a definite due date.<br>Generally, agricultural products are purchased under this mode of investment. | Purchase or Discount of Bills<br>A customer at the time of opening a Letter of Credit signs an agreement with the bank assuring that the latter will pay the bill received on the former on a certain date onward in exchange for a specific rate of interest determined at the time of agreement.<br>If the bill happens to reach well ahead of the date mentioned, the bank might purchase the bill, if requested, with a discount.<br>In this case, the bank has made the return twice: firstly, by charging interest and then by discounting the bill. |
| Qard Hasan<br>It is loan without interest that plays a socially useful role engaging in income generating activities. | |
| Mudaraba<br>It is a contract between two parties, in which one party supplies capital to other party carrying on some trade on the condition that the resulting profits be distributed in a mutually agreed proportion, while all losses be borne by the provider of the capital | Loans<br>A loan is an advance sanctioned in lump sum.<br>Borrower can draw it at a time or by pre-agreed instalment.<br>The bank debits the money to the loan account opened in the name of the borrower.<br>Interest is usually calculated and charged |
| Musharaka<br>Under this mode of finance, one or more entrepreneurs approach an Islamic bank for the finance required for a project. The bank provides total finance, and has the right to participate in the project.<br>The profits/ losses are distributed according to an agreed ratio or as per the capital proportion. | |

Sources: Adopted from different sources, i.e.; Alam (2003), Noman (2003), Hussein (2004) and Ahmad and Hassan (2007)

The above table shows that Conventional Banks and Islamic Banks finance the same transactions under different titles, but they projects for the same customers. The key difference between Islamic and Conventional banks is that the Islamic banking is consider a loan to be given or taken, free of charge (no interest); it is more oriented towards profit/loss (risk) sharing products, which is not the same for Conventional banks where the transaction are based on the interest. The relation between investor and the bank leads one to a very fundamental concept; in Islamic banking their relationship is conceived as a partnership whereas in Conventional banking it is that of creditor – investor.

## 5. Banking Sector in Gulf State countries

Gulf Cooperation Council (GCC) is a group of six countries; Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates (UAE), formed in May 1981 (Mazhar, 2003). These countries are located on the Persian Gulf and share certain characteristics such as same historical development. In the ancient world, gulf peoples established trade connections with India. Later on, in the middle ages, they went as far as China and around Southeast Asia. In the twentieth century, the discovery of massive oil deposits in the gulf made the area once again a crossroads for the modern world. Also, people of these countries are mostly Arabs and Muslims, they live in basically tribal societies, and family and clan connections underlie most political and economic activity.

However, within these common characteristics it is still some distinction among the six countries. Bahrain is an island; Kuwait is separated from the others by Saudi Arabia while high mountain ranges effectively cut off the Oman hinterland from the rest of the region. Since a well-developed efficient banking sector is an important prerequisite for saving and investment decisions for rapid economic growth, GCC countries developed a strong and healthy environment for their banking sector. Therefore, next section briefly introduces the GCC and their banking system.

## 6. Bank Development in GCC countries

This section presents a brief description of banking in GCC countries. Early banking in the GCC countries experienced a lot of foreign ownership mostly by British Bank where their braches extended across all six GCC countries. Local banks were not common as there was not sufficient experience. Later on, governments adopted central banking systems to eliminate foreign involvement. For example, Saudi banking system allows a maximum of 40% foreign ownership, while the 60% should be local ownership. In other GCC countries however, foreign ownership is still permitted with no requirement of local ownership, but they must abide to the central banking rules and regulations (Iqbal and Molyneux, 2005). Today there are 68 local banks operating in GCC countries; out of them there are 18 Islamic banks and 50 Conventional banks. The following table summarize some financial data of the Conventional banks.

Table 2: Conventional banks in GCC countries (Million US$- 2007)

| Countries | Bahrain | Kuwait | Oman | Qatar | S. Arabia | UAE | All GCC |
|---|---|---|---|---|---|---|---|
| Total Assets | 108,307 | 108,174 | 22,259 | 56,429 | 239,095 | 224,542 | 758,809 |
| Deposits | 76,305 | 89,937 | 16,208 | 40,272 | 19,7111 | 161,837 | 581,673 |
| Off-Balance Sheet | 22,009 | 39,720 | 6,742 | 29,767 | 66,671 | 102089 | 266,999 |
| Net Profit | 414.07 | 2,736.5 | 540.45 | 1,408.1 | 6,322.6 | 4,382.0 | 15,803.8 |

Table 2 shows that, Saudi Arabia is the largest investor in GCC, shares 32% of the total assets, with 9 Conventional banks and 2 Islamic banks and had a total asset of $239,095 Million in 2007. UAE with 15 Conventional and 5 Islamic banks and a total asset of $224,542 Million in 2007 is the second largest investor in the area. Bahrain with 9 Conventional and 6 Islamic banks and a total asset of $108,307 Million and Kuwait with 7 Conventional and 3 Islamic banks and a total asset of $108,174 Million are placed in the 3rd position. Then, Qatar with 4 Conventional and 2 Islamic banks and a total asset of $56,429 Million represents only 7% of the total assets. Finally, Oman with only 6 Conventional banks and a total asset of $ 22,259 Million represents only 3% of the total assets. The following, the above general description following parts analyze in more details banking sector in each country

### a. Kingdom of Bahrain

Bahrain is a small size country, located in the centre of Persian Gulf countries; it lies some 15 miles off the northeast coast of Saudi Arabia and 13 miles to the northwest of the Qatar Peninsula. Bahrain's first commercial bank, a branch of the British owned Eastern Bank, opened in 1921. Two decades passed before a second bank, the British bank of the Middle East, set up an office. It was not until 1957 that the first bank wholly owned by National bank of Bahrain. Once the Bahraini Dinar in 1965 replaced the Indian Rupee, banks began to find the island a more attractive location; by 1974 fourteen commercial banks operated in Bahrain. As an increase in the number of banks after independence Bahraini government, in 1973, established the Bahrain Monetary Agency (BMA). In 1975 BMA promulgated regulations for the creation of offshore banking units (OBUs) Modelled on those operating in Singapore. OBUs are branches of international commercial banks exempted from foreign-exchange controls, taxes on interest paid to depositors, and banking income taxes that are required of other banks in Bahrain.

The civil war in Lebanon stimulated the OBU boom, since several international banks based in Beirut transferred their Middle East operations to Bahrain after 1975. By the early 1980s, a total of seventy-five OBUs having assets in excess of $62 billion were operating out of Bahrain. Beginning in 1985, falling oil prices and a corresponding decline in oil revenues dramatically reduced the funds deposited in both onshore banks and OBUs. Several banks decided not to renew their OBU licenses, resulting in a net loss of OBUs. However, a majority of OBUs continue to operate from Bahrain-based offices. In 1990 a total of fifty-five OBUs were located on the island. Despite the fluctuations in gulf financial markets of the 1980s, Bahrain is well established as the principal banking and financial centre of the gulf region.

### b. The State of Kuwait

Kuwait is located in the northeast Arabian Peninsula at the head of the Persian Gulf. Settled by Arab tribes in the early 18th century, it became a British protectorate in 1897 and an independent in 1961. Iraq invaded and occupied the country in 1990, sparking the Persian Gulf War (1991), which ended with Iraqi troops being driven out by a coalition of Arab and Western forces. With its major oil reserves, discovered in 1938, it has one of the highest per capita incomes in the world. The first bank in Kuwait was established in 1941 by British investors. Subsequent laws prohibited foreign banks from conducting business in the country. When the British bank's concession ended in 1971, the government bought 51% ownership of this bank. In 1952 the National bank of Kuwait was founded. Later on several other banks was established; the Credit and Savings bank, established in 1965. By the 1980s, Kuwait's banks were among the region's largest and most active financial institutions (Federal Research Division, 2004).

The large revenues of the 1970s left many private individuals with substantial funds at their disposal. These funds prompted a speculation boom in the official stock market in the mid-1970s that culminated in a small crash in 1977. The government's response to this crash was to bail out the affected investors and to introduce stricter regulations. This response unintentionally contributed to the far larger stock market crash of the 1980s by driving the least risk-averse speculators into the technically illegal alternate market, the Suq al Manakh. The Suq al Manakh had emerged next to the official stock market, which was dominated by several older wealthy families who traded, largely among themselves, in very large blocks of stock. The Suq al Manakh soon became the market for the new investor and, in the end, for many old investors as well. Share dealings using post-dated cheques created a huge unregulated expansion of credit. The crash of the unofficial stock market finally came in 1982, when a dealer presented a post-dated cheque for payment and it bounced. The crash prompted a recession that rippled through society as individual families were disrupted by the investment risks of particular members made on family credit. The debts from the crash left all bank in Kuwait technically insolvent held up by support from the Central Bank.

Only the National Bank of Kuwait, the largest commercial bank, survived the crisis intact. In the end, the government stepped in, devising a complicated set of policies, embodied in the Difficult Credit Facilities Resettlement Program. The implementation of the program was still incomplete in 1990 when the Iraqi invasion changed the entire financial picture (Federal Research Division, 2004).

### c. Sultanate of Oman

Oman is located in the south-eastern quarter of the Arabian Peninsula. The land area is composed of varying topographic features: valleys and desert mountain ranges and the coastal plain. The sultanate is flanked by the Gulf of Oman, the Arabian Sea, and Saudi Arabia, all of which contributed to Oman's isolation. Historically, the country's contacts with the rest of the world were by sea, which not only provided access to foreign lands but also linked the coastal towns of Oman (Federal Research Division, 2004).

The Omani banking sector is largely the product of a November 1974 banking law that established the Central Bank of Oman (CBO). The law also facilitated the entry of foreign-owned banks and permitted an increase in the number of local banks in the sultanate. As of September 1992, there were twenty-one commercial banks in addition, there were three specialized development banks: the Oman Development bank (1977); the Oman Housing bank (1977); and the Oman Bank for Agriculture and Fisheries (1981). However, the Omani banking market is the smallest in the GCC. Of the twenty-one commercial banks, eleven are foreign owned and concentrate primarily on financing trade. Ten are local banks operating in an increasingly competitive market.

### d. The State of Qatar

Qatar is a small country; surrounded on three sides by the waters of the Arabian Gulf and connected to the south by land to Saudi Arabia. Traditionally poor and populated by nomadic peoples, the country’s economy, originally dominated by pearl-diving, was in ruins by the end of the 1930s when cultured- pearl production took off in Japan. In the 1940s, the discovery of oil marked a turn in Qatar’s fortunes and over time the country has taken advantage of its natural resources to emerge as one of the fastest developing economies in the world.

The Indian Rupee was the principal currency until 1959, when the government replaced it with a special gulf Rupee in an effort to halt gold smuggling into India. In 1966 Qatar and Dubai jointly established a currency board to issue a Qatar-Dubai Riyal. In 1973 Qatar introduced its own Riyal, which was pegged to the International Monetary Fund's (IMF) special drawing rights. The exchange rate is tied to the United States Dollar at a rate of QR3.64 per US$1.00. Qatar Monetary Agency (QMA), established in 1973, has most of the traditional powers and prerogatives of a central bank. The QMA regulates banking, credit, and finances; issues currency; and manages the foreign reserves necessary to support the Qatari Riyal. Unlike many central banks, the agency shares control over the country's reserves with what was in 1973 the Ministry of Finance and Petroleum (Federal Research Division, 2004).

The banking sector is supervised by Qatar Central Bank (QCB), which was incorporated in 1993 when it took over the responsibilities of QMA. The QCB has introduced major international standards applicable to banking supervision and regulations based on the Basle Accord. QCB has set the minimum capital adequacy regulations applicable to Qatari banks at 10%, compared to the Basle rate of 8%. In February 2001, the QCB removed its ceiling on interest rates for local currency deposits, thereby freeing the banking system from all interest rate policy restrictions. Today Qatari banking sector comprises of a combination of national and foreign banks. A total of 15 banks currently operate in Qatar, seven of which are Qatari owned, including five commercial and two Islamic banks.
As a result of the Iraqi invasion of Kuwait, banks in Qatar lost an estimated 15 to 30% of deposits in late 1990 (Federal Research Division, 2004).

### e. Kingdom of Saudi Arabia

Saudi Arabia is the largest country on the Arabian Peninsula. Much of the land is flat or slightly undulating, although the Hijaz and Asir mountains form a backbone along the west of the kingdom, with a 14-65 km wide coastal plain. Over half of the territory is desert, with the great sand sea of the Empty Quarter covering much of the south.

Until the mid-twentieth century, Saudi Arabia had no formal money and banking system. A few banking functions existed, such as money changers (largely for pilgrims visiting Mecca), who had informal connections with international currency markets. A foreign bank was established in Jiddah in 1926, but its importance was minor. Foreign and domestic banks were formed as oil revenues began to increase. The government issued a silver Riyal in 1927 to standardize the monetary units then in circulation. By 1950 the sharp increase in government expenditures, foreign oil company spending, and regulation of newly created private banking institutions necessitated more formal controls and policies. With United States technical assistance, in 1952 the Saudi Arabian Monetary Agency (SAMA) was created, designed to serve as the central bank within the confines of Islamic law (Federal Research Division, 2004).

In 1966 a major banking control law clarified and strengthened SAMA's role in regulating the banking system. Applications for bank licenses were submitted to SAMA, which submitted each application and its recommendations to the Ministry of Finance and National Economy. The Council of Ministers set conditions for granting licenses to foreign banks, however. The law also established requirements concerning reserves against deposits. Several restrictions continued to inhibit SAMA's implementation of monetary policy. It could neither extend credit to banks nor use a discount rate because these measures were forms of interest. By the 1980s, new regulations were introduced, based on a system of service charges instead of interest to circumvent Islamic restrictions. As of the early 1990s, banks were subject to reserve requirements. A statutory reserve requirement obliged each commercial bank to maintain a minimum of non-interest-bearing deposits with SAMA. Marginal reserve requirements applied to deposits exceeding a factor of the bank's paid-in capital and reserves. Moreover, banks had to hold additional liquid assets such as currency, deposits with SAMA beyond the reserve accounts, and Government Development Bonds equal to part of their deposit liabilities. Twelve private commercial banks operated in Saudi Arabia, providing full-service banking. Eight of the banks were totally Saudi-owned. Four were joint ventures with foreign banks. The commercial banks operated more than 1,000 branches throughout the country and a widespread network of automated teller machines. (Federal Research Division, 2004)

### f. United Arab Emirates

The United Arab Emirates (UAE) is situated on the Arabian Peninsula between Oman and Saudi Arabia and bordering the Gulf of Oman and the Persian Gulf (Peterson, 2003). The UAE is a federation of seven emirates; Abu Dhabi, the political capital of the federation; Dubai, its free-trading commercial hub; Sharjah; Ajman; Fujairah; Umm Al-Qawayn; and Ras Al-Khaymah. The federation formed in 1971, after Britain announced that it would no longer be able to ensure security in the Gulf, and six of these states, at the time called the Trucial States, decided to merge. Ras Al-Khaymah joined the federation in 1972. Each of the seven maintains substantial autonomy and has its own ruler, although Sharjah and Ras al-Khaymah share a ruling family.

Last 40 years since oil was first discovered the UAE has been transformed from a region of small country, subsisting on pearling, and fishing to a modern state with a high per capita income. Abu Dhabi, the largest and wealthiest emirate, is the principal petroleum producer and financier of the federation. Dubai, the second largest emirate, thrives on wealth derived from a services-based economy (tourism, construction, telecommunications, and financial services). Together, the two emirates provide more than 80% of the UAE's income, while the northern emirates remain relatively undeveloped (Federal Research Division, 2004).

The UAE Central Bank was established in 1980 to direct monetary, credit, and banking policy. It maintains the UAE government's reserves of gold and foreign currencies, acts as the bank for banks operating in the UAE, and acts as the state's financial agent at international financial institutions. In response to pressure from the World Trade to open the banking sector to more foreign competition, in late 2004 the UAE Central Bank stated that it would consider allowing new foreign banks to establish themselves in the UAE for the first time in 20 years, but as of late 2005 no new licenses had been issued. Relative to its population and gross domestic product, the UAE has an unusually high number of banks—21 local, 25 foreign, 2 specialized, and approximately 50 representative offices of other foreign banks. The Dubai International Financial Centre (DIFC) opened officially in September 2004. The DIFC is a self-regulating financial free zone, operated independently of the UAE Central Bank and including more than a dozen international financial institutions. In September 2005, it established the Dubai International Financial Exchange, which provides markets for equities, bonds, funds, Shariah-compliant products, and derivatives and is fully open to foreign investment (Federal Research Division, 2004).

From the above introduction we can note that the history of the banking industry in the GCC countries is relatively young. The pioneer banks were opened in the early 1950s. Subsequently, there was a tremendous growth in the number and diversity of financial institutions. The Gulf banking industry prospered following the vast prosperity of the economies. Islamic banks as one of the financial institutions emerged in GCC countries especially in Bahrain, Kuwait, Saudi Arabia, Qatar and UAE towards the end of the 1970s and operated on a parallel basis with the Conventional banks.

## 7. The main Contribution of the Study

The main contribution of the study are summarised as follows:

It includes the survey of the published academic articles in the field of banking efficiency. Also, it develops a new DEA based model (SORM) that provides a framework for measuring efficiency of DMUs with negative data. Furthermore, it proposes to use Classification and Regression (C&R) tree technique as a second stage analysis to investigate the influence of environmental factors in efficiency measurement (Internal, bank specification) or external factors (country specification), finally this thesis uses the methodology developed for assessing bank in Gulf Cooperation Countries (GCC) .

## 8. Structure Plan

The structure of this study is as follows; chapter 1 is an introduction to the thesis, which includes the aims of the study, the data and methodology, a brief introduction and comparison between Islamic and Conventional banks and brief introduction of the banking sector in GCC countries. Chapter 2 introduces the theoretical background of efficiency measurement methods: parametric (econometric) and non-parametric (mathematic) approaches. Chapter 3 reviews the literature in banking efficiency. Chapter 4 focuses in the application of DEA in banking sector. Chapter 5 proposes a new Model to deal with negative data in DEA, and chapter 6 presents data and analysis. Chapter 7 concludes and proposed some future works.

# CHAPTER 2 : EFFICIENCY MEASUREMENT

## 1. Introduction

Mainly there are two approaches to measure the efficiency of any DMU: nonparametric and parametric. Although, both approaches are based on the same seminal paper of Farrell (1957), but unlike nonparametric, parametric method counts for the noise, hence, any deviation from the outlier is treated as noise and inefficiency; while nonparametric treats them as inefficiency. This fundamental difference motivates us to compare these approaches and point out the most applicable one for banking sector. The outline of the following sections is as follow: Section 2 introduces the two approaches and their main methods; parametric approaches like; goal programming Model, stochastic Models, while, the nonparametric approaches like; DEA and FDH. Section 3 for the conclusion where it compares parametric approach with nonparametric approach.

## 2. Methods of efficiency measurement

This section introduces the main approaches for evaluating the efficiency and presents the bases for the methodological framework that will be used for the subsequent empirical analysis. The root of efficiency definition and measurement referred to the work of Koopmans (1951), Debreu (1951) and Shepherd (1953). Koopmans (1951) defined a DMU as efficient whenever it is impossible to produce more of any output without producing less of some other output or using more of some input. Debreu (1951) and Shepherd (1953) introduced distance functions as a way of Modelling multiple-output technology, but more importantly as a way of measuring the radial distance of a DMU from a frontier, in either an output-expanding direction (Debreu, 1951) or an input-conserving direction (Shepherd, 1953).

However, the production function is never known in practice; therefore, Farrell (1957) suggests estimating the production function from observed data using a nonparametric or a parametric function. Different Models were developed based on these two approaches; the choice between any of them depends on the purpose of efficiency measurement and, in many instances, on the availability of data. Next section, introduces these two approaches and there major developed methods.

## a. Parametric Approach

There are two main groups under parametric or econometric approaches: deterministic and stochastic. Deterministic methods include: ordinary least squares (OLS); corrected ordinary least squares (COLS) and modified ordinary least square (MOLS), whereas, stochastic methods include: stochastic frontier analysis (SFA); thick frontier Analysis (TFA) and distribution free analysis (DFA). Although, regression analysis is the basis of these methods, and each method has the same basic idea of efficiency analysis, which is to make a comparison among a group of DMUs, in order to evaluate how the resources (inputs) are used to obtain the outputs, each of them has a different set of assumptions about the probability distributions of the inefficiency differences and random error.

To introduce the parametric approach, consider a set of n observed DMUs, $\{DMU_j; j=1,2,\ldots,...,n\}$, is associated with m inputs, $\{X_{ij} ; i=1,...,m\}$, and s single output, $\{Y_j\}$. All inputs ($x_{ij}$) and outputs ($y_j$) are positive and represents the observed inputs and outputs of the $j^{th}$ DMU. Since the efficiency score of $DMU_j$ represented by it is outputs to inputs therefore we can write the production function of each DMU as follows;

$$y_j = f(x_{ij}, \beta) \times TE_j \quad (1)$$

Where; $y_j$ is the output that produced by $j^{th}$ $DMU_j$, ($j=1\ldots n$), $x_{ij}$ is a vector of $m$ inputs used by $DMU_j$, $f(x_{ij}, \beta)$ is the production function, $\beta$ is a vector of technology parameters to be estimated, and $TE_j$ is the technical efficiency of $DMU_j$. Assuming that $TE_j$ is an output-oriented technical efficiency, therefore

$$TE_j(x, y) = \frac{y_j}{f(x_{ij}, \beta)} \quad (2)$$

Now, equation (2) defines $TE_j$ as a ratio of observed output ($y_j$) to maximum feasible output ($f(x_{ij}, \beta)$). Equation (2) shows that $y_j$ achieves its maximum feasible value of $f(x_{ij}, \beta)$, if and only if, $TE_j = 1$, whereas, $TE_j < 1$ represents a measure of the shortfall of observed output from maximum feasible output. Based on this equation any shortfall in the observed output is attributed to technical inefficiency. However, equation (1 and 2) ignores the fact that output can be affected by random shocks (external noise such as error) that are not under the control of the DMU. To incorporate for the random shocks into the analysis, it requires the specification of a stochastic production frontier. Hence, to account for the random shocks we could be rewrite equation (1) as follow;

$$y_j = \underbrace{f(x_{ij},\beta)}_{\text{Deterministic component}} \times \underbrace{\exp(v_j)}_{\text{Noise}} \times \underbrace{TE_j}_{\text{Efficiency}} \qquad (3)$$

In equation (3) the right hand side of equation (3) is the stochastic production frontier and it is consisting of two parts: a deterministic part $f(x_{ij},\beta)$ common to all DMUs, and $\exp(v_j)$, which is DMU specific part that captures the effect of external noise on each DMU. Therefore the technical efficiency as given by equation (3) becomes:

$$TE_j(x,y) = \frac{y_j}{f(x_{ij},\beta) \times \exp(v_j)} \qquad (4)$$

Now equation (4) defines the technical efficiency as a ratio of observed output to maximum feasible output in the environment characterized by $\exp\{v_j\}$.

Therefore based on parametric method, technical efficiency can be estimated using either the deterministic production frontier Model given by equation (1) and (2) or the stochastic production frontier Model given by equation (3) and (4). Next part will more analyze these equations

### b. Deterministic Production Frontier

Assuming that $TE_j = exp\,\{-u_j\}$, thus we can rewrite equation (1) as follow; $y_j = f(x_{ij},\beta) \times exp\{-u_j\}$, where, $u_j \geq 0$ is a measure of technical inefficiency and $TE_j = exp\{-u_j\}$. Furthermore, assume that $f(x_{ij},\beta)$ takes the log-linear Cobb-Douglas form, now, the deterministic production frontier Model becomes

$$lny_j = \left[\alpha + \sum_{j=1}^{n} \beta_j lnx_{ij}\right] - u_j \qquad (5)$$

Equation (5) is a linear regression Model with a non-positive disturbance, where $u_j \geq 0$ guarantees that $y_j \leq f(x_{ij},\beta)$. The objective is to estimate $\beta$ and estimates the $TE_j$ for each DMU by means of $TE_j = exp\{-u_j\}$. Three methods have been proposed to obtain this estimation; ordinary least squares (OLS), corrected ordinary least squares (COLS) and modified ordinary least squares (MOLS) (Cazals, *et al*., 2008).

## Ordinary least squares (goal programming)

Aigner and Chu (1968) showed that the deterministic production frontier Model (1) could be converted to either of a pair of mathematical programming Models. The first Model is a linear programming Model; such Model can be expressed as (Greene, 2008, p 20);

| **Model 1: OLS linear programming Model** |
|---|
| $Min_{\alpha,\beta} \sum_{j=1}^{n} u_j$ <br> $Subject\ to$ <br> $\left[\alpha + \sum_{j=1}^{n} \beta_j lnx_{ij}\right] - lny_j \leq 0$ |

Once the parameter values are calculated from Model (1), the technical efficiency of each DMU can be calculated as the difference in the functional constraint. Thus $TE_j = ex\,p\{-u_j\}$, where

$$u_j = \left[\alpha + \sum_{j=1}^{n} \beta_j lnx_{ij}\right] - lny_j \qquad (6)$$

The second Model is a quadratic programming Model; this Model can be expressed as (Greene, 2008, p 20)[1];

| **Model 2: OLS quadratic programming Model** |
|---|
| $Min_{\alpha,\beta} \sum_{j=1}^{n} u_j^2$ <br> $Subject\ to$ <br> $\left[\alpha + \sum_{j=1}^{n} \beta_j lnx_{ij}\right] - lny_j \leq 0$ |

Also, once the parameter values are calculated from Model (2), the technical efficiency of each DMU can be calculated as the difference in the functional constraint. Thus $TE_j = ex\,p\{-u_j\}$, where

[1]) Greene, W.H. (2008) The Econometric Approach to Efficiency Analysis, in: H. Fried, C.A.K. Lovell, S. Schmidt (eds) *The Measurement of Productive Efficiency and Productivity Growth*, Oxford University Press, Oxford

$$u_j = \left[\alpha + \sum_{j=1}^{n} \beta_j lnx_{ij}\right] - lny_j \qquad (7)$$

A non-negativity constraints on the parameters *β*, *j= 1,…,n* could be added to each Model. Once parameter values are calculated from either Model, the technical efficiency of each DMU is calculated from the slacks in the function constraints in Model (1) and (2).

As pointed by Schmidt (1976) Model (1) and (2) give a statistical interpretation if a distributional assumption is imposed on the $u_j$. Therefore the linear programming estimates are maximum likelihood estimates of the parameters of the deterministic production frontier if $u_j \geq 0$, follow an exponential distribution: $f(u_j) = \frac{1}{\sigma_u} \times exp\left\{-\frac{u}{\sigma_u}\right\}$ in which case the log likelihood function is

$$lnL = lnI\sigma_u - \frac{1}{\sigma_u}\sum_{j=1}^{n}|u_j| \qquad (8)$$

While the quadratic programming estimates is maximum likelihood estimates of the parameters of the deterministic production frontier if the $u_j \geq 0$ follow a half normal distribution (Coelli, et al. 2005)

$$f(u_j) = \frac{2}{\sqrt{2\pi\sigma_u^2}} \times exp\left\{-\frac{u^2}{2\sigma_u^2}\right\} \qquad (9)$$

## Corrected Ordinary Least Squares (COLS)

Winsten (1957) suggested that equation (9) could be estimated in two steps: in the first step ordinary least square (OLS) is used to obtain consistent and unbiased estimates of the slope parameters and a consistent but biased estimate of the intercept parameter. In the second steps, the biased OLS intercept $\beta_0$ is shifted up (corrected) to ensure that the estimated frontier bounds the data from above.

## Modified Ordinary Least Squares (MOLS)

Afriat (1972) and Richmond (1974) suggested that equation (9) could be estimated by OLS under the assumption that the disturbances follow an explicit one-sided distribution, such as exponential or half-normal. A motivation for such assumption that technical efficiency might reasonably be expected to follow one of these distributions, with increasing degrees of technical inefficiency being increasingly less likely. The MOLS procedure is very similar to the two-step COLS procedure. After estimation by OLS, the estimated intercept is modified by the mean of the one-sided distribution. Although MOLS is easy to implement, there is no guarantee that the modification of OLS shifts the estimated intercept up by enough to ensure that all DMUs are bounded from above by the estimated production frontier.

After reviewing the deterministic Models, it is useful to compare them and highlight their advantage and limitations. Figure 1**Error! Reference source not found.** illustrates the differences between the deterministic methods.

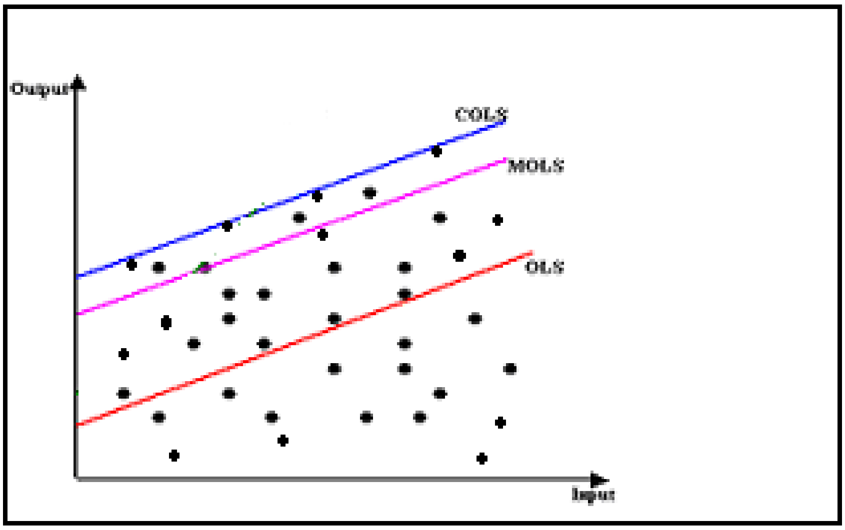



Figure 1: OLS Production Frontier Estimators

COLS and MOLS as **Error! Reference source not found.** shows attribute all deviation from the production frontier to inefficiency. Thus, they did not make allowance for the effect of measurement error, which might also contribute (positively or negatively) to variation in output. Furthermore, both methods are adjusted the OLS estimate of the intercept, leaving the remaining elements of $\beta$ unchanged from their OLS estimates (Fried, *et al*., 1993). As a result, the structure of efficient frontier is the same as the structure of technology of less efficient DMU. Consequently MOLS and COLS assign the same efficiency ranking as OLS does, so a justification of MOLS or COLS techniques must be made on the ground that the magnitudes, as well as a ranking, of efficiency scores are of interest.

On the other hand, the predicted values resulting from a regression Model provides the average level of outcome given certain inputs, instead of the maximum achievable outcome (Ray, 1991). Also, most regression Models use a single output production function, which may be unrealistic (Bowlin, 1998). However, Saal *et al*. (2007) and Giuffrida and Gravelle (2001) proposed to use canonical regression to allow for multiple output production processes or more importantly input distance function.

### c. Stochastic Production Frontiers

After introducing and analysing the deterministic Models, this part introduces and analyzes another regression based method, taking into account the effect of random shocks (external noise such as error).

## Stochastic Frontier Analysis (SFA)

The stochastic frontier Model was proposed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). The main motivation behind SFA is the idea that deviations from the production 'frontier' might not be entirely under the control of the firm being studied. Therefore Aigner *et al.* Meeusen and van den Broeck added an additional random error $v_i$ to the non-negative random variable $u_i$. They assumed that the $v_i$ is independent and identically distributed (*i.i.d*) normal random variables with mean zero and constant variance $\sigma^2$ independent of the $u_i$, which is also assumed to be *i.i.d* exponential or half-normal random variables.

To reach to the stochastic Model, assume in equation (1) that $f(x_{ij}, \beta)$ takes the log-linear Cobb-Douglas form, then the given in equation (3) could be rewritten as follow;

$$lny_j = \beta_0 + \sum_{j=1}^{n} \beta_n lnx_{ij} + v_j - u_j \qquad (10)$$

where:

$y_j$ is the production (or the logarithm of the production, output) of the j^th DMU

$x_{ij}$ is the input (or the logarithm of the resources) used by j^th DMU

$\beta$ is unknown coefficients to be estimated

$v_j$ is a random variable which is assumed to be $iid.N(0, \sigma_u^2)$, and independent of

$u_j$ which is a non-negative random variable which is assumed to account for technical inefficiency in production and is often assumed to be $iid.N|(0, \sigma_u^2)|$.

Since the error term has two components, the stochastic production frontier Model is often referred to as a "composed error" Model. The random error $v_i$ can be positive or negative and so the stochastic frontier outputs vary about the deterministic part of the frontier Model $exp(x_{ij}\beta)$ (Coelli *et al.* 2005). Therefore, equation (10) is called the stochastic frontier function, because the output values are bounded above by the stochastic (random) variable $exp(x_{ij}\beta + v_i)$. This original specification has been used in an enormous number of empirical applications. These extensions include: specification of more general distributional assumptions for $u_j$, (i.e. truncated normal or two-parameter gamma distributions); the consideration of panel data and time-varying technical efficiencies; and so on. The following some of these estimation technique and there distributional assumptions, readers can find more details in Greene (2008), Kumbhakar and Lovell (2000).

### The Normal-Half Normal Model

Based on this Model, the following distribution assumptions are made (Kumbhakar and Lovell, 2000):

1- $-v_i \sim iid\ N(0, \sigma^2)$;

2- $u_i \sim iid$ that is, a nonnegative half normal and

3- $u_i$ and $v_i$ are distributed independently of each other, and of the regressors.

Assumption (1) is conventional, and is maintained throughout. Assumption (2) is based on the plausible proposition that the modal value of technical inefficiency becoming increasingly less likely. It is also based on tractability, since it is relatively easy to derive the distribution of the sum $v_i$ and $u_i$ under distributional assumption (1) and (2). The first part of assumption (3) seems innocuous, but the second part is more problematic, since if DMUs know something about their technical efficiency, this may influence their choice of inputs (Kumbhakar and Lovell, 2000).

Based on the given density function of $u_i \geq 0$ in equation (9), and the density function of $v, f(v) = \frac{1}{\sqrt{2\pi\sigma_v}} . exp\left\{-\frac{v^2}{2\sigma_v^2}\right\}$. The joint densities function of u and v based on the independence assumption can be represented as follow;

$$f(u, v) = \frac{2}{\sqrt{2\pi\sigma_v\sigma_u}} . exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\} \qquad (11)$$

Furthermore, since $\varepsilon = v - u$, then the joint density functions for $u$ and $\varepsilon$ is

$$f(u, \varepsilon) = \frac{2}{\sqrt{2\pi\sigma_v\sigma_u}} . exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon + u)^2}{2\sigma_v^2}\right\} \qquad (12)$$

Now the marginal density function of $\varepsilon$ could be obtained by integrating $u$ out of $f(u,\varepsilon)$ which yields:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \frac{2}{2\pi\sigma}.\left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right].exp\left\{-\frac{\varepsilon^2}{2\sigma^2}\right\}$$

$$= \frac{2}{\sigma}.\phi\left(\frac{\varepsilon}{\sigma}\right).-\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right) \qquad (13)$$

Using equation (7), the log likelihood function for a sample of *I* DMU is

$$lnL = constant - Iln\sigma + \sum_{i=1}^{n} ln\Phi(-\frac{\varepsilon\lambda}{\sigma}) - \frac{1}{2\sigma^2}\sum_{i=1}^{n} \varepsilon_i^2 \qquad (14)$$

The log likelihood function in the above equation can be maximized with respect to the parameters to obtain maximum likelihood estimates of all parameters. The next step is to obtain estimates of the technical efficiency of each DMU. If $\varepsilon_i > 0$, chances are that $u_i$ is not larger which suggest that the DMU is relatively efficient, whereas if $\varepsilon_i < 0$, chances are that $u_i$ is larger, which suggest that the DMU is relatively inefficiency. The problem is to extract the information that $\varepsilon_i$ contains on $u_i$. A solution to the problem is obtained from the conditional distribution of $u_i$given $\varepsilon_i$, which contains whatever information $\varepsilon_i$contains concerning $u_i$

### The Normal-Exponential Model

Based on this Model, the following distribution assumptions are made to estimate the inefficiency at the firms (DMUs) level (Kumbhakar and Lovell, 2000):

1- $-v_i \sim iid\ N(0,\sigma^2)$;

2- $u_i \sim iid$ Exponential and

3- $u_i$ and $v_i$ are distributed independently of each other, and of the regressors.

The above assumptions show that the difference here concerning to the distributional assumptions underlying the normal (half normal Model applies with equal force to the normal) exponential Model. The log likelihood function for a sample of DMU can be written as:

$$lnL = constant - Iln\sigma_u + I\left(\frac{\sigma_v^2}{\sigma_u^2}\right) + \sum_{i=1}^{n} ln\Phi(-A) + \sum_{i=1}^{n} \frac{\varepsilon_i}{\sigma_u} \qquad (15)$$

Where $A = \frac{-\tilde{\mu}}{\sigma_v}$ and $\tilde{\mu} = -\varepsilon - \left(\frac{\sigma_v^2}{\sigma_u}\right)$, $InL$ can be maximized with respect to the parameters to obtain maximum likelihood estimates of all parameters, these parameters can be used to estimate the inefficiency at the firms (DMUs) level.

## Thick Frontier Analysis

Thick frontier approach, introduced by Berger and Humphrey (1991, 1992) as a way of avoiding the restrictive assumptions required in conventional approaches. One implication of the normal-half-normal specification of the composed error term commonly assumed in stochastic frontier estimation is that most of the observations should be clustered near full efficiency. But as they noted, at least for bank data, the distribution of costs has a thicker tail than is permitted with the normal-half-normal frontier Model.

TFA, as suggested by Berger and Humphrey, specifies a functional form and assumes that deviation from predicted performance values within the highest and the lowest performance quartiles of observations represents random error, while deviations in predicted performance between the highest and lowest quartiles represents inefficiencies. However, this method does not introduce any assumption regarding either inefficiencies or random error. Also, TFA provides efficiency for the overall DMUs and not for individual ones

To address this problem Berger and Humphrey introduced the concept of a thick frontier that is a frontier based only on the lowest quartile of average costs in each of several size categories. The advantage of TFA rather than an explicit cost frontier approach is that, TFA does not require restrictive distributional and independence assumptions on error components. It is based on an estimable version of the Translog cost function with a conventional error structure. Meanwhile, TFA does not generate cost efficiency estimates for each DMU in the sample. It generates only (1) cost efficiency estimate, for the hypothetical mean DMU in the high-cost quartile relative to the hypothetical mean DMU in the low-cost quartile. Thus TFA is likely to be useless to management and of limited value to policy-makers. Also, it is arbitrarily based on average cost quartiles and estimated cost, inefficiency would increase if equally arbitrary quintiles were used instead, and it uses only half of the data (or 40% of the data if quintiles are used). However, there is no theoretical justification for the number of size categories to use, and the fraction of data to use to determine the frontier. This drawback could have implications about the distance between the highest and lowest efficiency score, or in other world the distance between the low and high cost DMUs (Caudill, 2002).

## Distribution-Free Approach

DFA Introduced by Berger (1993) to estimates the cost inefficiency for each DMU in each time period based on a Translog system of cost and input cost share equations. Unlike TFA, DFA specifies a functional form of the frontier, but separates the inefficiencies from random error in a different way. The DFA assumes that the efficiency of each DMU is stable over time, whereas, the random error tends to average out to zero over time. The estimate of efficiency for each DMU is determined as the difference between its' average residual and average residual of the DMU on the frontier.

However DFA requires panel data and allows the structure of production function to vary flexibly through time. A disadvantage of DFA is the requirement that cost efficiency to be time invariant, and this assumption becomes less tenable as time increases. If time is short the random noise terms (*v*) may not average zero, and substantial amounts of random noise will appear in the cost inefficiency error component (*u*). On the other hand if time is long the time invariant assumption on (*u*) is likely to be violated. This suggests that there may be exist an optimal value of time on which to base the DFA approach.

Both TFA and DFA can be based on a Translog function consisting of a cost equation and its associated input cost share equations. However neither approach attempts to decompose estimated cost efficiency into its technical and allocative components. Although, TFA is easy to implement using either cross sectional data or panel data, it does not require a one-side error term.

### d. Non-Parametric Approaches

As it is stated before that the nonparametric approach is based on the linear programming analysis. Mainly there are two nonparametric methods; data envelopment analysis (DEA) and free disposal hull (FDH. The next part introduces both methods and their main modifications.

### e. Data Envelopment Analysis (DEA)

Since its conception by Charnes *et al.* (1978), the original DEA Model has undergone many modifications and developments. Most of these developments occurred when some of the deficiencies of the original Model were exposed during its application to solving real life problems. This section focuses on the most basic Models of DEA rather than it is modifications.

Cooper *et al*. (2004) considered constant return to scale (CRS) and variable return to scale (VRS) Models as the basic Models in DEA literature. The constant returns to scale (CRS) Model developed by Charnes *et al*. (1978), implying that DMU size doesn’t matter for efficiency.

The CRS assumption is only appropriate when all DMUs are operating at an optimal scale and yields an objective evaluation of overall technical efficiency and identifies the sources of inefficiency. Imperfect competition or constraints on finance, among others, may cause a DMU not to operate optimally. The use of the CRS specification, when not all DMUs are operating at the optimal scale, will result in measures of total efficiency (TE). However, factors like imperfect competition and constraints on finance may cause a DMU not to be operating at optimal scale. As a result, the use of the CRS specification when some DMUs are not operating at optimal scale will result in measures of technical efficiency (TE) which are confounded by scale efficiencies (SE).

The variable returns to scale (VRS) Model, introduced by Banker *et al*. (1984), is similar to CRS Model, since it is based on radial minimization / maximization of all inputs / outputs. However, the VRS Model ensures that an efficient DMU is only benchmarked against DMUs of similar size, while in the CRS Model a DMU may be benchmarked against DMUs which are substantially larger (smaller) than it. The following part explains in more detail each of these Models, firstly it introduces the technical efficiency, and then explains the Models in more details.

## Technical efficiency

In the production process, banks turn inputs into outputs (e.g. assets and equity as inputs and profit as output). The relationship between inputs and outputs can be expressed by a production function which illustrates the maximum outputs feasible for a given level of inputs. For each bank suppose, for example, the inputs are assets and equity and the output is profit in a specific period of time. This production function can be depicted graphically as shown in Figure 2 using an isoquant (CD), i.e. a curve that shows all the possible combinations of inputs that yield the same level of output. PQ is the isocost, i.e. the minimum cost line.

Technical efficiency is a measure to show how the maximum/minimum amount of output/input is obtained from the available inputs/output. Banks C, D and E are technically efficient because they are operating on the production function (sometimes referred to as efficient frontier). Their efficiency scores are one (or 100%). Banks A and B are technically inefficient because they are using more assets and equity to produce the same level of profit as banks C, D and E. The extent of technical inefficiency of bank A can be expressed as $1-\frac{OE}{OA}$ which is the amount by which all inputs could be proportionately reduced without a reduction in the output level. This definition of technical efficiency measurement proposed by Farrell (1953) and generalized through the use of mathematical programming by Charnes *et al.* (1978).

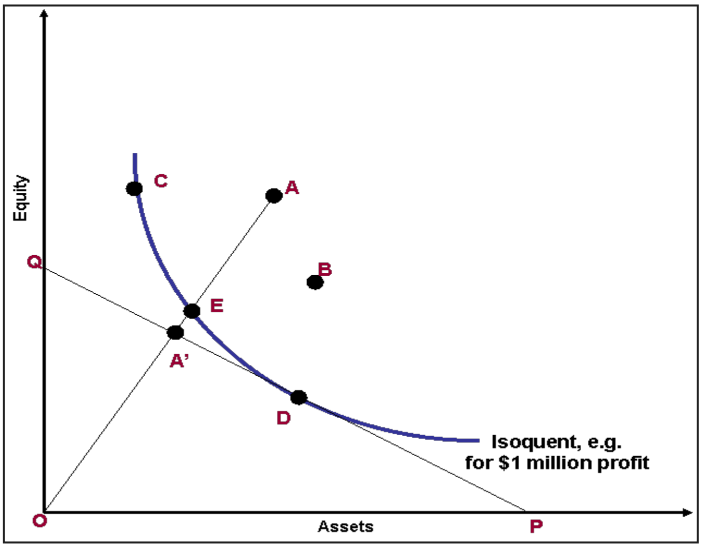



Figure 2: Technical efficiency; a graphical illustration

## Technical efficiency for multi-inputs and multi-outputs

Assume there are n banks (j=1, …n) using m inputs ($x_{ij}$ i=1,…m) and producing s outputs ($y_{rj}$, j=1,…s). DEA measures the technical efficiency of bank $j_0$ compared with *n* peer group of banks as follows:

| **Model 3: Technical efficiency: a fractional programming Model** |
|---|

$$Max\ \ h_0 = \frac{\sum_{r=1}^{s} u_r y_{rj0}}{\sum_{i=1}^{m} v_i x_{ij0}}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad ; \mathrm{j} = 1, \ldots \mathrm{n}$$

$$u_r \geq \varepsilon \quad ; \mathrm{r} = 1, \ldots \mathrm{s}$$

$$v_i \geq \varepsilon \quad ; \mathrm{i} = 1, \ldots \mathrm{m}$$

where:

$h_0$ = efficiency score of $j_0^{th}$ bank,
$\varepsilon$ = a non-Archimedean value to enforce strict positivity of the weights
$y_{rj}$ = observed amount of $r^{th}$ output produced by bank j,
$x_{ij}$ = quantity of $i^{th}$ input used by bank j,
$u_r$ = the weight given to output r as determine by the linear programming,
$v_i$ = the weight given to input i as determine by the linear programming,
n = the number of banks,
m = the number of inputs used by each bank,
s = the number of outputs produced by each bank and
$j_0$ is the bank being assessed in the set of j=1,…,n banks.

The above fractional programming implies that the technical efficiency of bank $j_0$ is maximized subject to efficiency of all banks being less than or equal to one, hence the relative efficiency of all banks is constrained between 1 (relatively efficient) and less than 1 (relatively inefficient).

Assuming constant returns to scale, the above Model can be rewritten in the form of the following linear programming.

**Model 4: Technical efficiency: a linear programming Model for CRS**

$$Max\ h_0 = \sum_{r=1}^{s} u_r y_{rj_0}$$

subject to:

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad ; \quad j = 1,\ldots,n$$

$$u_r, v_i \geq \varepsilon \quad ; \ i = 1,\ldots m,\ \&\ r = 1,\ldots s$$

In this Model the first constraint indicates that the weighted sum of inputs for the $j_0^{th}$ bank equals one. The second constraint implies that all banks are on or below the frontier, that is, the efficiency of all banks has an upper bound of one. The weights $u_r$ and $v_i$ are treated as unknown variables and they are obtained in the linear programming solution. This Model usually refers to the CCR Model (Charnes, Cooper, and Rhodes). To allow calculation of technical efficiency that is free from the scale efficiency effects, Banker *et al*. (1984) proposed a variable returns to scale (VRS) Model by introducing an extra variable as indicated in the following Model.

| **Model 5: Technical efficiency: a linear programming Model for VRS** |
|---|
| $Max\ h_0 = \sum_{r=1}^{s} u_r y_{rj_0} + u_0$<br>subject to:<br>$\sum_{i=1}^{m} v_i x_{ij_0} = 1$<br>$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \le 0 \quad ; \quad j = 1,\ldots,n$<br>$u_r, v_i \ge \varepsilon \quad ;\ i = 1,\ldots m,\ \&\ r = 1,\ldots s$<br>$u_0$ *free in sign.* |

In this Model, the sign of $u_0$ determines the returns to scale;

- If $u_0$ takes negative values in all optimal solutions to Model (5) then locally at $DMUj_0$ increasing returns to scale hold;
- If $u_0$ takes a zero value in some optimal solutions to Model (5) then locally where $DMUj_0$ lies or is projected on the efficient boundary CRS hold; and
- If $u_0$ takes positive values in all optimal solutions to Model (5) then locally at $DMUj_0$ decreasing returns to scale hold.

This mathematical program measures the distance of non-efficient banks from the best frontier (i.e. from the set of efficient banks). Technically inefficient banks are given a score between zero and less than one, the higher the score, the greater the efficiency, and vice versa.

Model (5) is a weight Model; by duality this problem is equivalent to the linear programming problem (6).

| **Model 6: Technical efficiency: a linear programming Model for variable returns to scale, envelopment Model, input orientation** |
|---|
| $Min\ h_0 - \varepsilon(s_r^+ + s_i^-)$<br>subject to:<br>$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = h_0 x_{ij_0} \quad ; \quad \forall i = 1, \ldots, m$ |

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rj_0} \qquad ; \qquad \forall r = 1, \dots, s$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0 \qquad ; \qquad \forall j = 1, \dots, n$$

This Model identifies a benchmark DMU which uses as low a proportion of the inputs of $j_0$ as possible while at least matching its output levels. The second constraint signifies that the output levels of inefficient observations are compared to the output levels of a reference DMU that is composed of a convex combination of observed outputs. The third constraint allows for variable returns to scale. The last constraint ensures that all values of the production convexity weights are greater than or equal to zero so that the hypothetical reference DMU is within the possibility set. $\mathrm{DMU}_{j_0}$ is efficient if only if $h_0 = 1$ and all slacks ($s_r^+ \forall r$ & $s_i^- \forall i$) are zero.

We should point out that Model (5) and (6) involving the ratio of outputs to inputs is referred to as the input-oriented Model. One could, as well, invert this ratio and solve the corresponding output-oriented problem as formulated in Model (7). We will generally deal with the output-oriented Model in this section.

**Model 7: Technical efficiency: a linear programming Model for VRS, envelopment Model, output orientation**

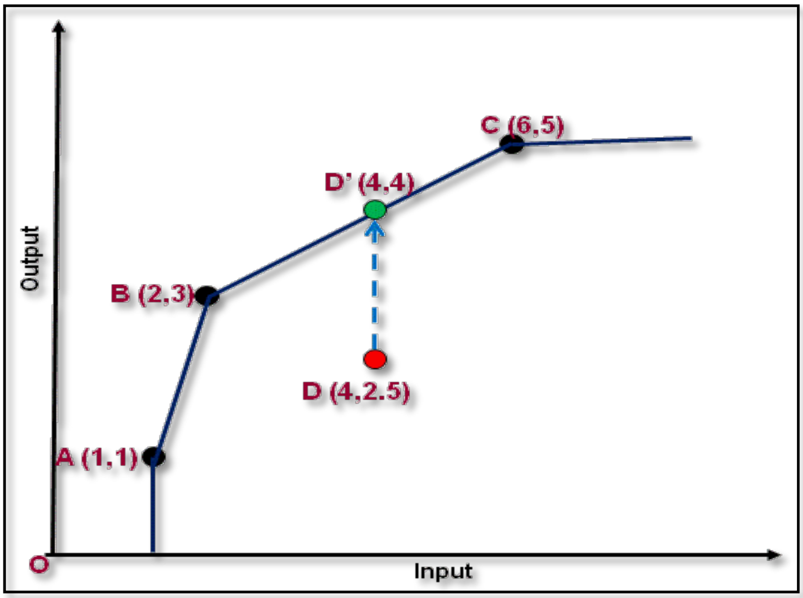
$$Max\ h_0 - \varepsilon\,(s_r^+ + s_i^-)$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ij_0} \qquad ; \qquad \forall i = 1,\dots,m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = h_0 y_{rj_0} \qquad ; \qquad \forall r = 1,\dots,s$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0 \qquad ; \qquad \forall j = 1,\dots,n$$

To get a geometric view for the DEA Model, one can represent Model (7) in a form such as Figure 3. This figure provides an illustration of a single output single input case for 4 DMUs. If we solve Model (7) for DMU D, we will obtain the amount that DMU D should increase its output to be placed on the frontier, i.e. target point of D', hence the efficiency of DMU D is $\frac{2.5}{4}$=0.75 or 75%.

Figure 3: A graphical illustration of DEA, single output/ single input




An alternative geometric view of Model (5) is provided in Figure 4. Here, there are 4 DMUs with two outputs and a single common input value for all DMUs. In solving Model (5) we find that DMUs A, B and C are efficient, i.e. $h_A = h_B = h_C = 1$. For DMU D $h_D = 0.80 \text{ or } 80\%$ hence DMU D is inefficient and its target on the DEA frontier is D'= (37.5, 62.5).

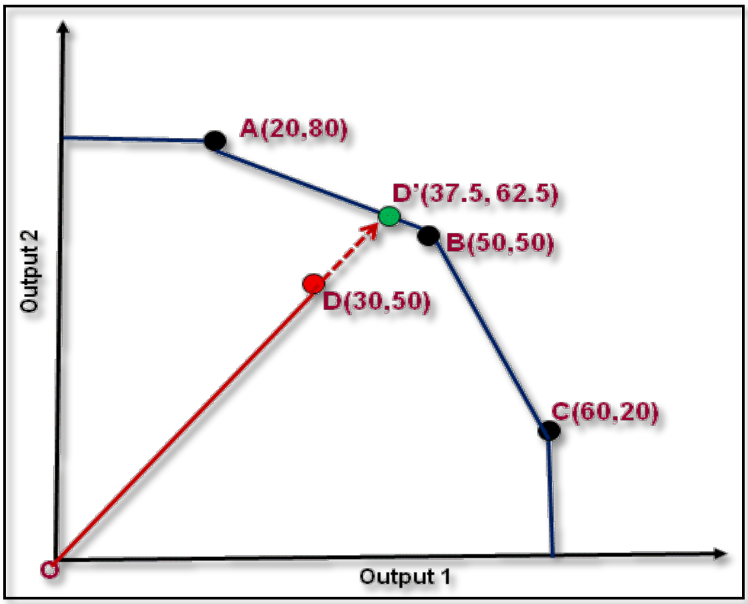



Figure 4: A graphical illustration of DEA, two outputs/ common input

## Decomposition of Technical efficiency

It is interesting to investigate the sources of inefficiency that a DMU might have. The CRS efficiency score is called global technical efficiency (TE), while the VRS is the local pure efficiency (PTE). However the ratio of CRS efficiency scores to VRS efficiency scores is called scale efficiency (SE) score. Hence SE is equal to $(\frac{CRS\ score}{VRS\ score})$.

## Mix Efficiency

The presented radial Model (CRS and VRS) are the classical best adopted measurers. However, they do not capture slack inefficiency. Hence the following measure has also been proposed.

**Model 8 Slack based Model (SBM): Input oriented**

$$Min\, \tau = \quad \mathrm{t} - \frac{1}{\mathrm{m}} \sum_{j=1}^{n} \frac{ts_i^-}{x_{i0}}$$

subject to:

$$\mathrm{t} + \frac{1}{\mathrm{s}} \sum_{j=1}^{n} \frac{ts_r^+}{y_{r0}} = 1$$

$$\sum_{j=1}^{n} \lambda_j\, x_{ij} + s^- = x_{i0}$$

$$\sum_{j=1}^{n} \lambda_j\, y_{rj} - s^+ = y_{r0}$$

$$\lambda_j \geq 0, s^- \geq 0\; s^+ \geq 0 \;\; and\; t > 0;$$

Where; t is a scalar variable greater than zero $(t > 0)$, m and s are the number of inputs and outputs respectively$s_i^-$ $and$ $s_r^+$ represents the slacks (input excesses and output shortfalls respectively). The same thing we can obtain the slack based Model output oriented. A DMU is SBM efficient if and only if the efficiency score of $\tau^* = 1$.

### f. Free Disposal Hull Model (FDH)

The basic motivation behind this Model is to ensure that efficiency evaluations are effected from only actually observed performance. Therefore it could be considered as a more general version of the DEA Model as it relies only on the free disposability assumption, and hence does not restrict itself to convex technologies. This seems an attractive property of FDH since it is frequently difficult to find a good theoretical or empirical justification for assuming convex production sets in efficiency analysis.

Figure 5 illustrates FDH, where y-axis and x-axis represent the value of input ($x_1$ and $x_2$) used to produce the output ($y$). The dashed line linking the DMUs (A, B, C and D) represents the efficiency frontier as determined by the VRS Model. The solid line represents the frontier developed using the FDH Model. The efficiency of $DMU_p$ is the ratio of $\frac{OP''}{OP}$, whereas it is $\frac{OP'}{OP}$ based on FDH assumption.

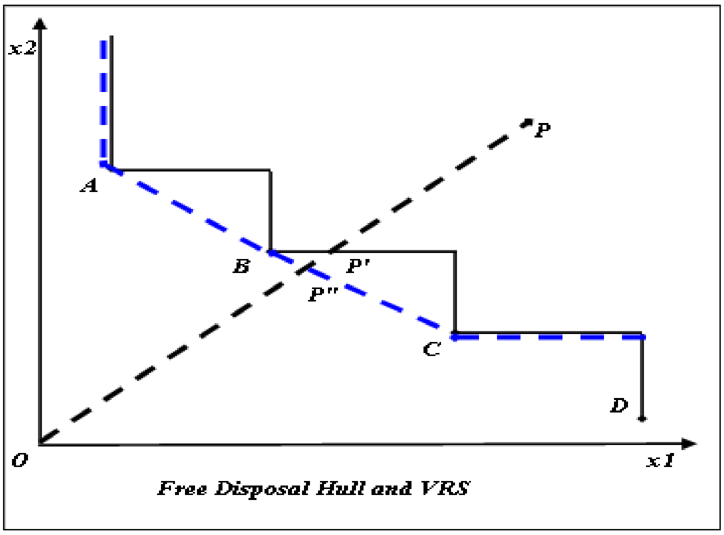



Figure 5: Free Disposal Hull representation

As **Error! Reference source not found.** shows that the boundary set and its connection represent the hull defined as the smallest set that encloses all of the production possibilities that can be generated from the observation. This could be presented mathematically as follow,

| **Model 9: Free disposal hull Model as proposed by Deprins *et al*. (1984)** |
|---|

$$Min\ h$$

subject to:
$$\sum_{j=1}^{n} \lambda_j\, x_{ij} \leq h x_{ij_0}\,; \qquad \forall i = 1, \dots, m$$
$$\sum_{j=1}^{n} \lambda_j\, y_{rj} \leq y_{rj_0}\,; \qquad \forall r = 1, \dots, s$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \in \{0,1\} \quad \forall j = 1, \dots, n$$

Where x and y contain the given inputs and outputs variables and $\lambda_j \in \{0,1\}$ means that the components of $\lambda_j$ are constrained to be bivalent, that is all must have values of zero or unity so that together with the condition $\sum_{j=1}^{n} \lambda_j = 1$ of the performance actually observed can be chosen. This gives rise to the staircase (or step) function, which is portrayed by the solid line.

## 3. Comparisons Parametric with Nonparametric Approaches

Previous sections introduce different methods for evaluating the efficiency of DMUs, now we are in a position to compare them. Reviewing the literature shows that, SFA is the most used parametric method whereas DEA is the most popular nonparametric method. Both methods are suggested as alternatives to OLS, as each solves a different drawback implicit in OLS. Therefore this part is dedicated to compare between OLS, SFA and DEA methods. It is important to note that the purpose of this comparison is to select the most proper method in order to use it in our study. The following table highlights a theoretical comparison between these methods.

Table 3: The differences between Parametric and nonparametric

| Comparative factor | OLS | SFA | DEA |
|---|---|---|---|
| Theoretical bases | Regression theory | Regression theory | Linear programming theory |
| Production function (Model) | $y = f(x\ ;\beta) + u$ | $y_i = f(x\ ;\beta) + w$<br>$w = v + u$ | $y = f(x)$ |

| Comparative factor | OLS | SFA | DEA |
|---|---|---|---|
| Assumption; functional form | require more assumptions about the production or cost function and about the distribution of the errors | require more assumptions about the production or cost function and about the distribution of the errors | Not required |
| Sample size | Can cope better with large sample | Can cope better with large sample | Can cope also with small and medium sample |
| Noise | Accounting for noise | Accounting for noise | Not accounting for noise |
| Frontier estimation | Assume structure then fit curve | Assume structure then fit curve | Determined by the best external fit given convexity constraints |
| Incorporate categorical variables | Not easy | Not easy | It is possible |
| Possibility for further constrain | Not easy | Not easy | It is possible |
| Applied on cross-section or panel data | Can be applied | Can be applied | Can be applied |

**Sources:** Adopted from different sources; Delgado (2005), Smith (1997)

Table 3 shows a mixed result from OLS, SFA and DEA since each method has advantages and limitations. OLS and SFA mostly have the same characteristics while DEA is completely different. Both SFA and OLS are regression based analysis, accounting for noise, easy to test the hypothesis about causal relationships holding in the production context being Modelled, allowing for environmental differences and have the ability to provide a Model for predicting. Meanwhile, they cannot provide the sources for inefficiency; have low flexibility and need to specify the form of production function and need more specific assumptions. On the other hand DEA as a nonparametric approach where doesn't required functional form of the production frontier, has the ability to handle multi-input output variables. Also, it provides the sources and the amount of inefficiency as well as it is more fixable and doesn't require any specified assumptions. With all of these advantages, DEA is not accounting for noise in the data. Therefore the results could be biased if important inputs or outputs are excluded.

Based on the above comparison it is difficult to recommend one technique as being superior to any other. Therefore, for further investigation and analysis, we reviewed some academic literature that presents different results produced by using different methods. Cubbin and Tzanidakis (1998) results show that the mean efficiency score based on DEA is higher than OLS analysis. Also the regression rankings are relatively stable compared to DEA. Ruggiero (1998) finding is that compared canonical regression with DEA, canonical regression estimates are highly correlated with the DEA efficiency. Thanassoulis (1993) found that DEA outperforms regression analysis on accuracy of estimates, but that regression analysis offers greater stability of accuracy. On the other hand SFA and DEA studies for the same data set shows mixed results. Ferrier and Lovell (1990); Bauer *et al*. (1998) and Weill (2004) use both approaches, finding are mixed in terms of efficiency estimates. Gong and Sickles (1989; 1992) find the same results, but as the misspecification of the functional form becomes more serious, DEA estimates become more accurate. Hjalmarssone *et al*. (1996) find that each method gives similar trends in efficiency over time. Wadud and White (2000) find some correlation between SFA and DEA estimates. Read and Thanassoulis (1995) found that SFA estimates of efficiency are worse than DEA. Resti (1997) results shows that both scores do not differ substantially, moreover, the rank correlation is statistically significant. Bauer *et al*. (1998) compare SFA, DEA, TFA and DFA. The result shows that DEA shows better stability. Casu and Girardone (2002) compared SFA, DFA and DEA and find that DFA efficiency estimates are consistent with the DEA scores rather than with the SFA. Weill (2004) results for the same methods shows that there are positively correlated between SFA and DFA. At the same time, there is no positive relationship between SFA and DFA with DEA. Beccalli *et al*. (2006); Fiorentino *et al*. (2006); Bauer *et al*. (1998) Resti (1997) and Sharma *et al*. (1997) result shows that the mean efficiency of parametric techniques is higher than DEA; since in DEA any random error in the sample appears as inefficiency; thus the DEA results should show a higher amount of inefficiency compared to SFA.

Although, the related literature gives a mixed result in comparing the parametric with the nonparametric methods and the best selection would be depended on the situation and the main question of interest, therefore, banks are using multi-input to produce multi-output, and the sample size is relatively small; therefore the selected Model should be capable of handling this situation. Furthermore, banking managers are in need to know the source and the amount of their inefficiency and their performance in comparison to their peers. DEA could easily handle these requirements; therefore, DEA will be used as a methodology to evaluate the efficiency of banking sector in GCC countries. However, DEA method for evaluating bank efficiency still faces some limitations such as the existence of negative data. Therefore, this study will tackle this issue and develop a new DEA

Model that could handle such situation where we have negative variable for some banks and positive for others.

## 4. Conclusion

This chapter is about evaluating main measurement approaches nonparametric and the parametric of efficiency. The following the introducing to the main approaches for evaluating the performance of DMUs, it is clear that the comparison and the selection the most proper Model is difficult. Thus it is difficult to recommend one technique as being superior to any other. Furthermore, reviewing the previous literature that compares the results of each method shows that the results are mixed too, but some advantage was given to DEA over OLS and SFA. Hence, it is useful to look to the application part of these methods in banking sector; this could help us to pick the most popular method in evaluating banking sector efficiency. Therefore, next chapter reviews the related literature in this field.

# CHAPTER 3 : LITERATURE REVIEW

## 1. Introduction

The discussion so far has addressed the theoretical approaches to the efficiency assessment. Also, the previous chapter summarises the strengths and weaknesses of each technique. It is clear that the selection of any particular technique to measure the efficiency is likely to be subject to both theoretical and empirical considerations. Therefore, the emphasis here is not on selecting a superior theoretical approach, rather than to survey the previous literature in banking sector to point out the most popular method in this field. Although, there is no agreement over the best method, but reviewing the previous literature could help to find the most used method.

The studies of efficiency using frontier approaches on banking started with Sherman and Gold (1985), where they applied DEA to a sample of USA savings bank branches by focussing on operating efficiency. Subsequently, there are extensive studies on bank efficiency. Berger and Humphrey (1997) review 130 studies that examine the efficiency of financial institutions over the period 1985-1997. Their conclusion mentioning that out of the 130 studies there are 69 of the studies used nonparametric methods and 61 used parametric methods. Mokhtar *et al*. (2006) reviewed 47 bank efficiency studies; their finding shows that there is no estimation techniques dominate over the other. DEA widely used to measure the technical efficiency, while SFA mostly used to measure the cost efficiency. Berger (2007) discussed the more recent applications of frontier techniques but his survey focused only on studies that provide international comparisons of bank efficiency. Emrouznejad *et al*. (2008) count more than 175 studies used DEA in the banking sector. Fethi and Pasiouras (2009) reviewed a total of 179 studies. Their finding shows that DEA is the most commonly used technique in assessing bank performance and they identified 136 studies that use DEA-like techniques to estimate various measures of bank efficiency and productivity growth.

We further reviewed literature for the years to 2009 and we found that there are more than 400 studies that focus on the efficiency and productivity of banking sectors. Since not all of the 400 studies are fully accessible therefore, this chapter provides an in depth analysis for the 204 published studies in this field that representing 62 countries and six continents. It is important to note that the survey does not include bank branch studies since they have a different operating style, and they require different set of inputs and outputs. We only included all studies published in refereed journals or books that were either published or available in pre-print. However, to keep our survey project within resource constraints, technical reports and proceedings were excluded, as well as, studies published in a language other than English. The essential features of each study such as: choice of input and output categories; type of efficiency measured; time frame considered (single year vs. multiple years); and the chosen function are summarized in the next sections. The pattern of bank efficiency studies over time is presented in Figure 6 from 1985–2009.

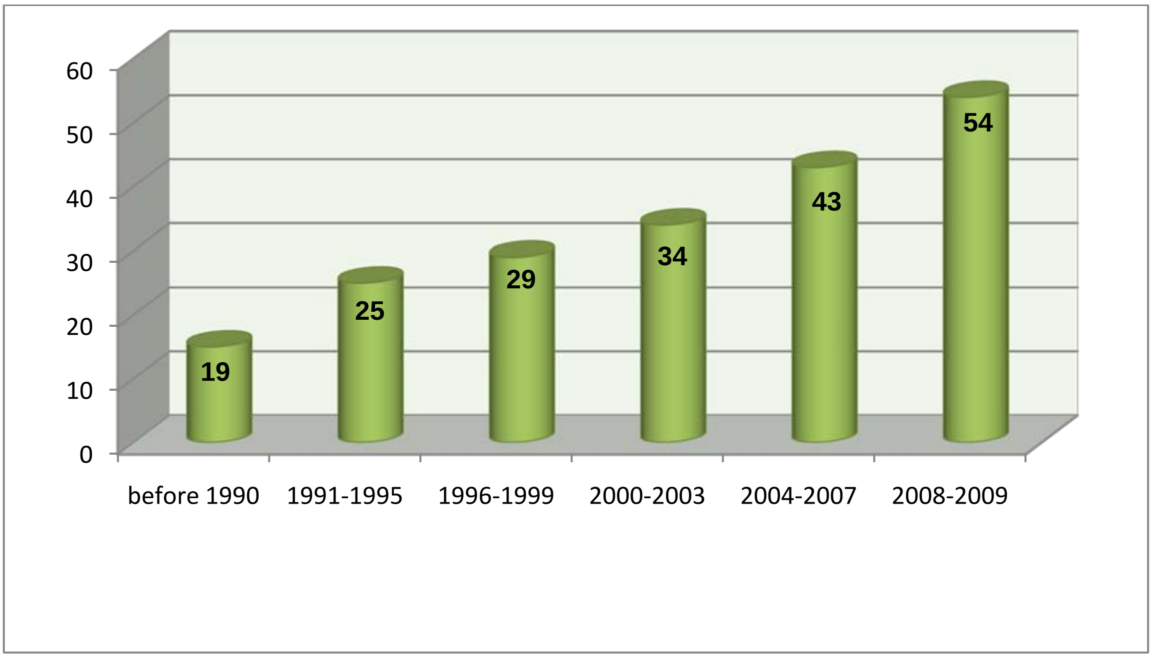



Figure 6: Number of bank efficiency studies over time

Figure 6, shows that the number of studies was increased over the time from 19 studies over six years (1985-1990) to reach 54 studies in two years only (2008-2009. By the late 2008-2009, the number of such studies seemed to have peaked. Although the first study of European banks (Vassiloglou and Giokas, 1990 and Field) did not appear until 1990, such applications spread rapidly thereafter. Beginning in 1993, several studies from other countries have appeared, most of the newer studies continue to analyze banks in the different nations, particularly the U.S. and Europe.

Nonetheless, the list of nations covered has increased tremendously. There has been an expansion to additional developed nations such as Australia (Allenand and Rai, 1996; Avkiran, 2009; Pastor and Tortosa-Ausina, 2008), Canada (Allenand and Rai, 1996; Ismail *et al*., 2009; Pastor and Tortosa-Ausina, 2008; Asaftei, 2008), European countries (Allenand and Rai, 1996; Ashton, 2001; Battese *et al*, 2000; Bos and Kolari, 2005; Carbo *et al*, 2002; Avkiran, 2009; Bos *et al*, 2009; Huanga and Chen, 2009; Delis *et al* 2009; Bos and Schmiedel, 2007; Grifell-Tatje and Lovell, 1997; Hahn, 2007; Girardone *et al* 2004; Koetter, 2008; Casu and Molyneux, 2003; Ismail *et al*., 2009) and Japan (Hirofumi, 1993; Pastor and Tortosa-Ausina, 2008, Fukuyama *et al*, 1999; Altunbas *et al*, 2000; Drake and Hall, 2003) and to developing nations such as: Algeria (Benamraoui, 2008), Argentina (Hermes and Nhung, 2008; Delfino, 2007; Forster and Shaffer, 2005), Bahrain (Čihák and Hesse, 2008; Al-Jarrah and Molyneux, 2003; Shams and Molyneux, 2003), Brazil (Hermes and Nhung, 2008; Forster and Shaffer, 2005), China (Sufian, 2009; Chen, 2001), Egypt (Čihák and Hesse, 2008; Al-Jarrah and Molyneux, 2003), India (Sahoo and Tone, 2009; Zhao *et al* 2008; Debnath and Shankar, 2008; Mahesh and Meenakshi, 2008), Jordan (Čihák and Hesse, 2008; Al-Jarrah and Molyneux, 2003), Kuwait (Čihák and Hesse, 2008; Shams and Molyneux, 2003), Mexico (Hermes and Nhung, 2008; Pastor and Tortosa-Ausina, 2008), Malaysia (Suhaimi, 2008; Mahadzir, 2004; Sufian and Abdul Majid, 2007; Sufian,2009; Batchelor and Wadud, 2004; Čihák and Hesse, 2008), Namibia (Ikhide, 2008), Oman (Shams and Molyneux, 2003), Pakistan (Hermes and Nhung, 2008; Ataullah *et al* , 2004; Burki and Niazi, 2009), the Philippines (Hermes and Nhung, 2008), Qatar (Čihák and Hesse, 2008; Shams and Molyneux, 2003), Russia (Pavlyuk and Balash, 2004), Saudi Arabia (Čihák and Hesse, 2008; Al-Jarrah and Molyneux, 2003; Shams and Molyneux, 2003), Singapore (Sufian and Abdul Majid, 2007), South Africa (Ismail *et al*., 2009;), South Korea (Hermes and Nhung, 2008; Pastor and Tortosa-Ausina, 2008), Taiwan (Kaoa, and Liu, 2009; Wang and Huang, 2007; Lin , 2005; Chiu *et al* 2008; Chiu *et al* 2009), Tanzania (Okeahalam, 2008), Tunisia (Reisman *et al*, 2003; Čihák and Hesse, 2008), Turkey (Oral and Yolalan, 1990; Osman, 1995; Ozkan-Gunay and Tektas, 2006; El-Gamal and Inanoglu, 2005) and the United Arab Emirates (Al-Tamimi and Lootah , 2007; Al Shamsi *et al*, 2009; Čihák and Hesse, 2008; Shams and Molyneux, 2003).

However, for a full analysis of the surveyed literature, the proposed taxonomy is presented in Figure 7. The studies were classified into six groups according to the method employed.

**Group 1**: Out of the 109 studies that employed DEA, which represent 53% of the total surveyed studies, 83 studies in this group used the standard DEA Model, as defined previously. Novel applications and extensions include: additive Model (Yue, 1992), cone ratio (Charnes *et al*, 1990), distance function (Weber and Devaney, 1998 and Weber and Devaney, 1999), dynamic DEA (Wang and Huang, 2007), fuzzy DEA (Uemura, 2006 and Kao and Liu, 2004), sensitivity analysis (Chen, 1998), slack-based method (SBM) (Avkiran, 2009 and Hahn, 2007), super SBM (Chiu *et al*, 2008; Chiu *et al* 2009; Chiu *et al* 2008 and Chiu *et al* 2009) and window analysis (Webb, 2003; Sufian, 2009 and Reisman *et al*, 2003).

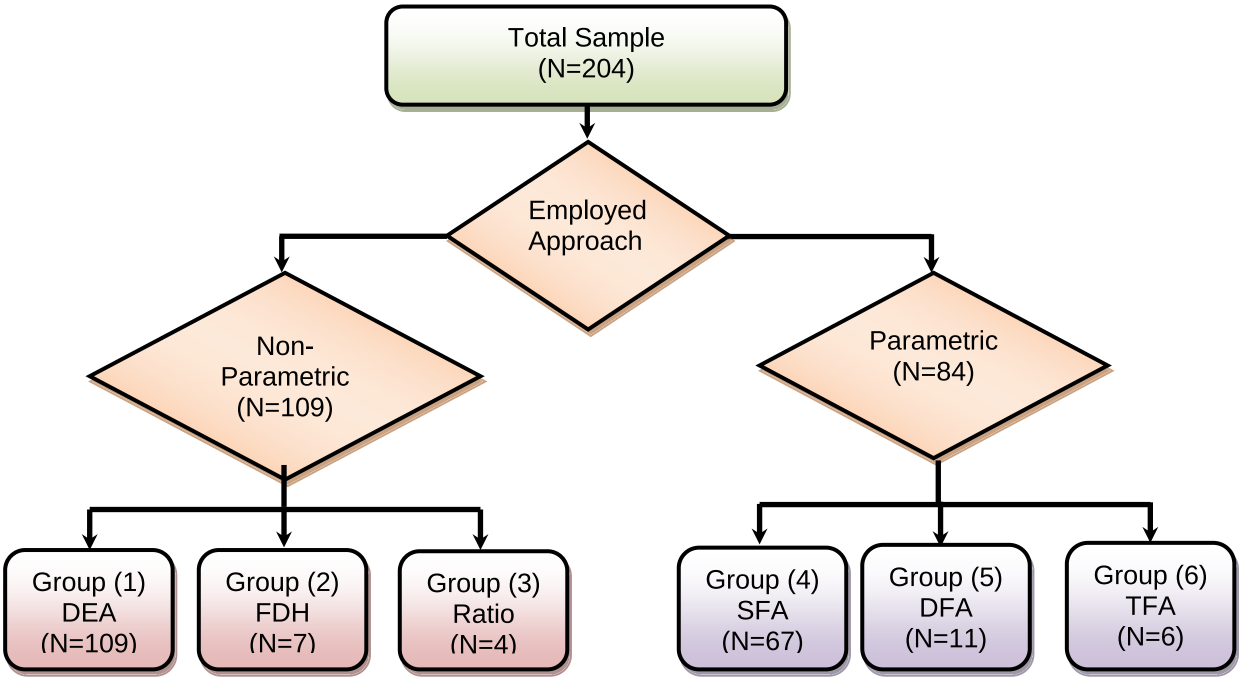



Figure 7: Categorization of bank efficiency studies

**Group 2**: There are only 7 out of 204 studies that used FDH (De Borger *et al*, 1998; Tulkens, 1993; Tulkens and Eeckaut, 1991; De Borger, 1995; Fried *et al* 1993). This reflects the unpopularity of this method between researchers.

**Group 3**: Only 4 studies used only financial ratios to measure the performance of banks (Haslem *et al*., 1984; Ismail *et al* 2009; Forster and Shaffer, 2005; Swamy *et* *al*, 2003) however, a few studies incorporated the financial ratios with other methods, such as (Yao *et al*, 2008; James, 1984; Didar, 2004).

**Group 4**: Out of 84 studies that used the parametric method to measure the efficiency of banks, 67 studies employed SFA, which represent 32% of the reviewed studies.

**Group 5**: There are only 11 out of 204 studies that used DFA (Akhavein *et al*, 1997; Allenand and Rai, 1996; Ashton, 2001; Bauer *et al*, 1998; Berger and Hannan, 1998; DeYoung, 1997; Shen, 2005; Ashton, 2001; Nikiel and Opiela, 2002; Wheelock and Whilson, 1999). This reflects the unpopularity of this method between researchers.

**Group 6**: Only 6 out of 204 studies used TFA (include: Bauer *et al*. 1998; Berger and Mester, 2003; Sherrill, 1993; Noulas, 1997; Avkiran, 1999), which also reflect the unpopularity of this method with the researchers.

Beside the above groups, there are a few studies that compared the result of more than one method: Allenand and Rai (1996) compared the banks' efficiency score using SFA and DFA; Shen (2005) compared SFA and OLS results; Al-Sharkas *et al*. (2008), Olgu and Weyman-Jones (2008), Figueira and Nilles (2009), Schure *et al*. (2004) and Huang and Wang (2002) compared SFA and DEA results, whereas, Bauer (1998) compared the results of SFA, DFA, TFA and DEA.

## 2. Results of Cross-National Comparisons

Out of the 204 studies, there are 66 studies on Asian commercial banks, which represent 32%, followed by USA commercial banks with 57 studies, which represent 28% of the surveyed studies. There are 46 on European commercial banks, which represent 23%, and 17 studies on the South American and African banking sectors. There are 18 studies that compared the efficiency of different countries' commercial banks.

Table 4: Summary of some bank efficiency studies

| Study ID | Study period | Country | Method | No. of Observation | No. of input | No. of output | Efficiency Score |
|---|---|---|---|---|---|---|---|
| Akhavein *et al*. (*et al*. (1997) | 1981–89 | USA | DFA | 2944 | 2 | 2 | 46–73% |
| Ila and Semenick (2001) | 1980–89 | USA | DEA | 112 | 4 | 6 | 82% |
| Al-Sharkas *et al*. (2008) | 1987–99 | USA | SFA & DEA | 440 | 3 | 4 | 83–89% |
| Ashton (2001) | 1984–97 | UK | DFA | 11 | 3 | 3 | 82–99% |
| Battese *et al* (2000) | 1984–95 | Sweden | SFA | 1275 | 2 | 3 | 88% |

| Study ID | Study period | Country | Method | No. of Observation | No. of input | No. of output | Efficiency Score |
|---|---|---|---|---|---|---|---|
| Berger & DeYoung (1997) | 1985–94 | USA | SFA | 46504 | 2 | 5 | 92% |
| Berger & Hannan (1998) | 1980–89 | USA | DFA | 5263 | 2 | 5 | 65–70% |
| De Borger *et al*. (1998) | 1984 | USA | FDH | 575 | 2 | 5 | 77–97% |
| Bos & Kolari (2005) | 1995–99 | International | SFA | 995 | 3 | 3 | 72–95% |
| Carbo *et al*. (2002) | 1989–96 | Europe | SFA | 4086 | 3 | 3 | 78% |
| Chen *et al*. (2009) | 1997–04 | USA | DEA | 3000 | 6 | 2 | 67% |
| Kaoa & Liu (2009) | 1997—01 | Taiwan | DEA | 25 | 3 | 3 | 34–70% |
| Mahesh & Rajeev (2008) | 1985–04 | India | SFA | 94 | 3 | 3 | 75% |
| Yao *et al*. (2008) | 1998–05 | China | DEA | 15 | 3 | 2 | 85% |
| Wang & Huang (2007) | 1982–01 | Taiwan | DEA | 22 | 3 | 3 | 79% |
| Bos & Schmiedel (2007) | 1993–04 | Europe | SFA | 9544 | 3 | 3 | 42–63% |
| Sufian & Abdul Majid (2007a) | 1993–03 | Singapore | DEA | 189 | 2 | 3 | 95% |
| Elyasiani & Mehdian (1990a) | 1985 | USA | COLS | 144 | 4 | 2 | 64% |
| Fukuyama (1993) | 1990 | Japan | DEA | 143 | 3 | 2 | 87% |
| Elyasiani *et al*. (1994) | 1983 & 87 | USA | DEA | 203 | 3 | 5 | 75–86% |
| Hunter & Timme (1995) | 1985–90 | USA | DFA | 317 | 5 | 4 | 46–70% |
| Grifell-Tatje & Lovell (1997) | 1986–1993 | Spain | DEA | 174 | 3 | 3 | 82–84% |
| Mester (1997) | 1991–92 | USA | SFA | 6630 | 3 | 3 | 84% |
| DeYoung (1997) | 1984–94 | USA | DFA | 618 | 3 | 3 | 77–79% |
| Ozkan & Tektas (2006) | 1990–01 | Turkey | DEA | 580 | 3 | 3 | 62–89% |
| Hahn (2007) | 1995–02 | Austria | DEA | 800 | 3 | 3 | 74–78% |
| Lang & Welzel (1999) | 1987–97 | Germany | SFA | 6731 | 3 | 5 | 92% |
| Hermes & Nhung (2008) | 1991–00 | International | DEA | 4002 | 3 | 2 | 58–94% |
| Ataullah & Le (2006) | 1992–98 | India | DEA | 566 | 2 | 3 | 57–84% |
| Girardone *et al*. (2004) | 1993–96 | Italy | SFA | 1958 | 3 | 2 | 85–87% |
| Ariss (2008) | 1990–01 | Lebanon | SFA | 322 | 3 | 3 | 84% |
| Sufian (2009) | 1997–06 | China | DEA | 307 | 3 | 2 | 86–92% |
| Koetter (2008) | 1993–04 | Germany | SFA | 29960 | 3 | 4 | 51–79% |
| Casu & Molyneux (2003) | 1993–97 | Europe | DEA | 750 | 2 | 2 | 59–69% |
| Fitzpatrick & McQuinn (2007) | 1996–00 | Europe | SFA | 385 | 3 | 3 | 61–80% |
| Chen (1998) | 1996 | Peru | DEA | 34 | 6 | 4 | 98% |
| Burki & Niazi (2009) | 1991–00 | Pakistan | DEA | 366 | 4 | 2 | 75% |
| Chen & Yeh (2000) | 1995–96 | Taiwan | DEA | 34 | 3 | 3 | 93% |
| Lin *et al*. (2007) | 2002–03 | Taiwan | DEA | 37 | 2 | 3 | 59% |

Table 4 summarizes some of the bank efficiency studies. Although, different methods used to measure the efficiency and different study period will affect in banks efficiency scores, this efficiency score could give some information about bank performance. On average the efficiency scores of efficient banks were slightly higher for USA studies than their counterpart in European. Furthermore, the DEA frontier is sensitive to the number of observations, but reviewing the literature shows that there is no agreement over the number of the inputs and outputs in relation to the number of DMUs. According to the DEA rule of thumb, the sample should have at least three times as many DMUs as the total number of output and input variables. Table 4 shows that most of the studies satisfied this rule; only few studies had a ratio of fewer than three observations per variable (Ashton, 2001; Yao *et al*, 2008 and Chen, 1998).

## 3. Methodological Consideration

A huge number of theoretical and empirical studies have been published on banking efficiency. Despite this attention, it is very difficult to determine from the literature the appropriate answer for some issues – specification of production function, bank behavioural approach, input variables and output variables – but reviewing the literature could identify the most popular treatment for such issues. Therefore, the next sections attempt to provide a survey of the reviewed literature.

### a. Returns to Scale Assumption in DEA

The two most frequently applied Models used in DEA are the CRS and VRS Models. The CRS assumption is appropriate when all the banks are operating at an optimal scale. However, (Debnath and Shankar, 2008; Wheelock and Whilson, 1999 and McAllister and McManus, 1993) believe that, in the case of the banking sector, there are several reasons such as imperfect competition, financial constraints, banking regulation and supervision, concentration, market structure and other factors existing in the real environment that may not allow banks to operate at an optimal scale. Nevertheless, other studies (Avkiran, 1999; Noulas, 1997) among others argue that the CRS assumption is appropriate to study bank efficiency rather than VRS since it allows the comparison between small and large banks. Under the VRS assumption each bank is compared only against other banks of a similar size, instead of against all of them. Furthermore, it claims that, in a sample where a few large banks are present, in the other hand using VRS Model raises the possibility that these large banks will dominant the small ones and appear efficient for the simple reason that there are no truly efficient banks of that size (Berg *et al*., 1991). Reviewed the related literatures show that the majority of the studies report the results obtained from both CRS and VRS assumptions (i.e. Ila and Alam, 2001; Yao *et al*, 2008; Sensarma, 2006; Hermes and Nhung, 2008; Figueira and Nellis, 2009; and Chen, 1998). Consequently, there is no agreement over the operating scale assumption in banking studies. About half of the reviewed studies that used the standard DEA Models are based on VRS assumption (55%) compare to (45%) are based on CRS assumption. Surely, whether or not we used VRS depends on the input–output variables used as well as to the DEA Model oriented (input oriented or output oriented).

## b. The Orientation Approach in DEA

Bank technical efficiency using DEA can be estimated under either an input-oriented or an output-oriented approach. This again depends on the input–output set chosen. So far, bank managers and policy makers seem to have relatively less control over their inputs than their outputs, and, in a majority of countries, the emphasis is on increasing demand for bank products rather than controlling inputs. Hence, as Figure 8 shows, relatively, the majority of studies analysed here used the output-oriented DEA Model. Although both the input-oriented and output-oriented measures provide the same value under constant returns to scale, based on this assumption 49 applications used output-oriented compared with 46 applications that used the input-oriented DEA Model. Based on the VRS assumption, 61 applications used the output-oriented approach compared with 56 applications that used the input-oriented approach.

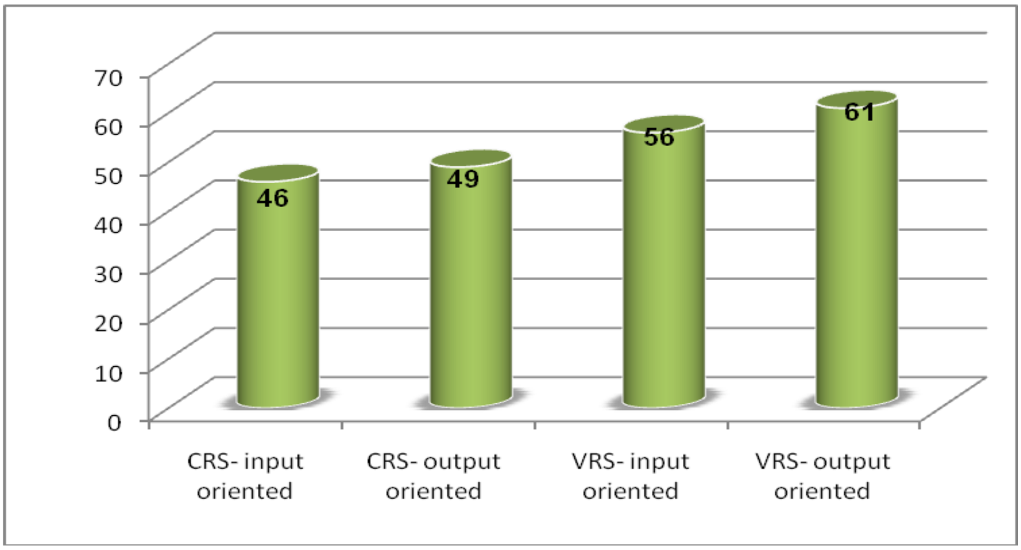



Figure 8: Input- vs. output-oriented DEA Model

Nevertheless, there are some studies that reported the results from both approaches, such as: Gonza'lez, 2009; Figueira and Nellis, 2009 and Casu and Molyneux, 2003. The following figure summarizes the results of the surveyed studies. However, since DEA does not suffer from statistical problems, the choice of an appropriate orientation is not as important as in the case of econometric approaches (Coelli *et al*., 2005). Moreover, in many cases, the choice of orientation has only a minor influence upon the scores obtained (Coelli and Perelman, 1996).

### c. Production Specification

In the econometric methods, having chosen the frontier approach, the next step is to select the suitable functional form to be used in the estimation. There are three main different functional forms: the Translog function, the Cobb–Douglas and the Fourier flexible form. The Translog function form is one of the most widely used functional forms in the empirical literature on bank efficiency. It is a flexible form in the sense that it imposes few restrictions on the production technology. The Cobb–Douglas method implies a stronger restriction on the set of technologies that can be borne out by the data. The Fourier flexible form represents a semi-nonparametric approach, which combines a standard Translog form with a non-parametric Fourier form; hence, it is more flexible than the Translog form.

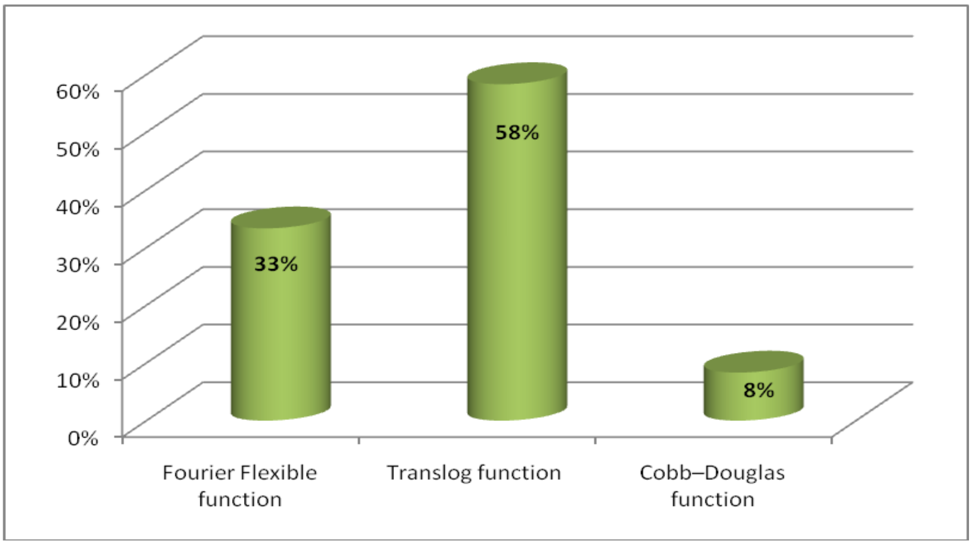



Figure 9: Popularity of production functions with researchers

Figure 9 shows that the Translog form is by far the most popular function used in bank efficiency literature; it is used by 58% of the studies that employed the parametric methods. The Fourier flexible form is the next most popular with 33%, whereas the Cobb–Douglas form is the least popular one (8%).

### d. Bank Production Approach

Recently, substantial research efforts have been devoted to measuring the efficiency of the banking sector. Much attention has been focused on estimating an efficient frontier and measuring the average differences between banks (Aziz and Lennart, 2002). Despite the increasing number of bank efficiency studies, the major shortcoming of these studies is their failure to define inputs and outputs in the banking sector. There are few attempts to define this concept (Sealey and Lindley, 1977; Colwell and Davis, 1992; Berger and Humphrey, 1997). Nevertheless, there is still a lack of a theoretical basis for these definitions. Reviewing the literature shows that mainly there are two main approaches: production approach or service provision approach and intermediation approach or asset approach, which has two major sub-groups: the profit approach and the risk management approach.

According to the production approach, efficiency can be analysed by comparing the quantity of services given the quantity of resources used. Berg *et al*. (1991) identified five activities performed by a bank: supplying demand and facilitating deposit services; short- and long-term loan services; brokerage and other services; property management; and the provision of safe deposit. Based on the intermediation approach, a bank accepts deposits from customers and transforms them into loans to clients. The inputs are labour, materials and deposits, and the outputs are loans and other income-generating activities. In the profit approach, the bank manager's purpose is to maximize the bank's profit function. The risk-management approach translates into input and output classification by considering the management decision-making process and its implementation on one side as the inputs and shareholders' value and bank profit as the outputs on the other side (Mlima and Hjalmarsson, 2002).

However, neither of these two main approaches is perfect because they cannot fully capture the dual role of financial institutions as providers of transactions/document processing services and also being financial intermediaries (Berger and Humphrey, 1997). Therefore, we could argue that the production approach may be somewhat better for evaluating the efficiencies of bank branches, whereas the intermediation approach may be more appropriate for evaluating financial institutions as a whole. Reviewing the literature, as presented in Figure 10 shows, the intermediation approach is the most favoured approach between researchers as it is used by 63% of the total applications, followed by the production approach with 10% and the value added and financial ratio approaches with 5% and 3%, respectively. A few studies, such as (Kaoa and Liu, 2009; Asaftei, 2008; Suhaimi, 2008; Mahesh and Rajeev, 2008 and Battese *et al*, 2000), used a combination of more than one approach; we call this a mixed approach and it represents 19% of the total applications.

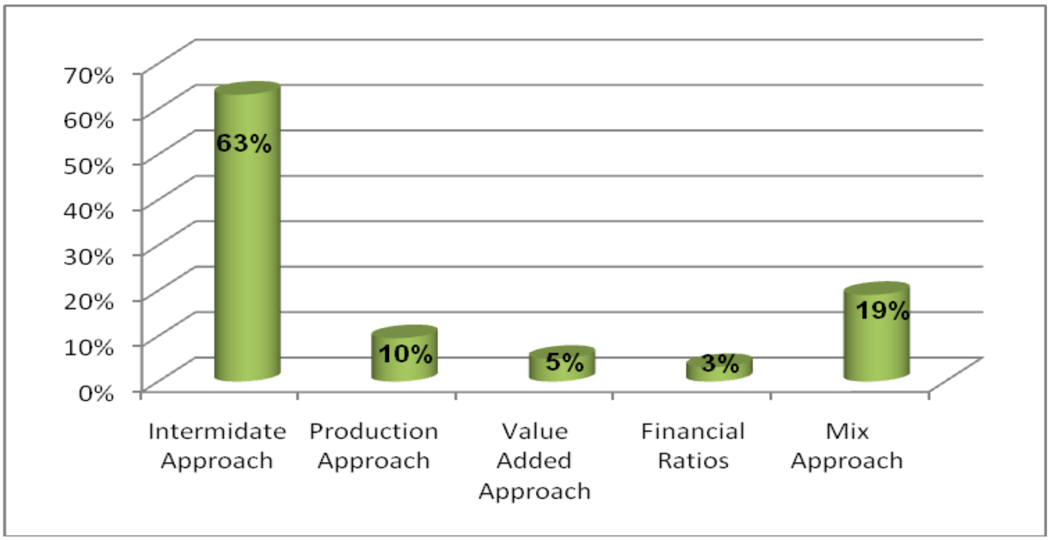



Figure 10: Popularity of production functions with researchers

The surveyed literature shows that the financial statement is the main source for these variables. Table 5 summarizes the major categories and sub-categories of each statement and how frequently they are used as an inputs or outputs variable by researchers.

Table 5: Summary of input–output categories*

| Categories | Sub-Categories | Frequency as | |
|---|---|---|---|
| | | Input | Output |
| **Balance Sheet Items** | | | |
| **Assets** | Current/Liquid Assets | - | 16 |
| | Loans Less than One Year | 8 | 230 |
| | Long-Term Loan | - | 6 |
| | Fixed Assets/Physical Capital | 99 | 2 |
| | Investments | 1 | 45 |
| | Other Assets | - | 4 |
| | Security | 1 | 34 |
| | Off-Balance Sheet (OBS) | - | 11 |
| | Total Assets | 10 | 1 |

| Categories | Sub-Categories | Frequency as | |
|---|---|---|---|
| | | Input | Output |
| **Liability/ Deposit** | Current Liabilities/Deposits | 148 | 48 |
| | Long-Term Liabilities | - | - |
| **Equity/Share Capital/Financial Capital** | | 1 | 1 |
| **Income Statement Items** | | | |
| **Income** | Interest Income | 1 | 39 |
| | Non-Interest Income | 1 | 41 |
| | Total Income | - | 3 |
| **Expenses** | Interest Expense | 26 | - |
| | Non-Interest Expense | 171 | - |
| | Total Expense | 2 | - |
| **Profit** | Operating Profit | | 2 |
| | Net Profit | | 5 |
| **Others** | Number of Transactions | 1 | 11 |
| | Other Input/ Output Category | 9 | 7 |

This result is based on a review of 204 studies; the total frequency of the inputs and outputs variable used is more than 204 since some studies used more than one Model with different input and output variables. The same goes for the other findings.

Table 5 shows that in general there is relatively semi agreement over the input and output variables to evaluate bank efficiency. The only problematic item is the deposit; there are 148 applications in bank efficiency that used the deposit as an input, whereas only 48 applications used it as an output. Reviewing these 48 applications shows that some applications, such as: Berger and Mester, 2003; Mahesh and Rajeev, 2008 and Färe *et al*, 2004 used the expenses as inputs and deposits as one of their outputs.

Moreover, based on the analysis in Table 5, one can safely conclude that, regardless to the bank approach, the input variables fall into three broad categories: assets (fixed assets), deposits and expenses. Likewise, the most commonly used outputs fall into four broad categories: assets (liquid assets), Liability (loan) Sales (income or profit) and the number of produced transactions. This supports the above conclusion where we conclude that the intermediation approach is the most frequently employed approach to define the banks' inputs and outputs. In general banks' input categories could be further classified into the following sub-categories: assets, deposits, labour, other expenses and atypical and specific input categories. Furthermore, the output categories could be further classified into the following sub-categories: assets, investments, securities, loans, income, number of produced transactions and atypical and specific output categories.

## Input Categories

As stated above, banks' input falls into three broad categories; it is, furthermore, classified into five sub-categories: assets, deposits, labour, other expenses and atypical and specific input categories. The following sections review these groups in more detail.

## Assets (Fixed Assets)

Assets are anything of value that is owned by the bank and range from cash, inventory and other 'current assets' to real estate, equipment and other 'fixed assets'. Intangible items of value to the bank, such as exclusive use contracts, copyrights and patents, are also regarded as assets. Among asset items, fixed assets or physical capital are widely used as an input; they are used in 97 applications, followed by total assets with 10 applications. There are a few uncommon assets items used by researchers as inputs such as: securities (Zaim, 1995), investments (Chiu *et al*, 2009) and risky weighted assets (Hahn, 2007).

Deposits

Deposits are an amount of money placed with a bank and it is divided into: current account, savings account, money market deposit account and time deposit. A current account is a deposit for the purpose of securely and quickly providing frequent access to funds on demand. A savings account is an account maintained by banks that pays interest but cannot be used directly as money. A money market deposit account is a deposit account with a relatively high rate of interest and short notice (or no notice) required for withdrawals. Time deposit is a money deposit at a bank that cannot be withdrawn for a preset fixed 'term' or period of time. Table 6 summarizes the results of the surveyed literature.

Table 6: Summary deposit items results

| Deposit Items | Frequency |
|---|---|
| Total Deposits | 96 |
| Demand Deposit | 8 |
| Non-Transaction Deposit | 6 |
| Transaction Deposit | 5 |
| Safe Deposit | 5 |

| | |
|---|---|
| Other Deposit | 4 |
| Time Deposit | 3 |
| Core Deposit | 3 |
| Deposit More than $100,000 | 2 |
| Deposit Less than $100,000 | 2 |
| Non-Deposit Fund | 1 |
| Net Fund | 1 |
| Large Certificate and Time and Saving Deposit | 1 |
| **Total Applications** | **137** |

As Table 6 shows, apart from the total applications, deposits are used as input in 137 cases; the total deposit is the most commonly used among the deposit categories with 96 applications, followed by demand deposit with 8 applications and non-transactional, transaction and safe deposits with 6, 5 and 5 applications, respectively. There are a few uncommon deposit items used by researchers as inputs: other deposit (Lin, 2005), time deposit (Al Shamsi *et al*, 2009 and Worthington, 2001), core deposit (Suhaimi, 2008; Al-Sharkas *et al*, 2008 and Asaftei, 2008), deposit more than $100,000 and deposit less than $100,000 (Kaparakis *et al*, 1994 and Wheelock *et al*, 1995), non-deposit fund (Gonza'lez, 2009), net fund (Favero and Papi, 1995) and large certificate and time and saving deposit (Elyasiani and Mehdian, 1995)

## Labour

Labour is included in 129 applications as an input variable; out of these 34 applications only used the number of full-time equivalent (FTE) labour whereas 95 applications used labour expenses (salary as input).

## Other expenses

Other expenses include all the expenses except the labour cost, such as: interest expenses; non-interest expenses or operational expenses; occupancy and equipment costs; expenditures on materials; rental expenses; computer hardware rental; administration expenses and total expenses. Non-interest expenses are widely used as input with 29 applications, followed by interest expenses with 26 applications. Table 7 summarizes the surveyed literature results.

Table 7: Expense items as inputs

| Expenses Item | Frequency |
|---|---|

| | |
|---|---|
| Non-interest expenses | 29 |
| Interest expenses | 26 |
| Occupancy and equipment costs | 4 |
| Expenditures on materials | 4 |
| Rental expenses | 3 |
| Computer hardware rental | 1 |
| Administration expenses | 1 |
| Total expenses | 2 |
| **Total applications** | **70** |

Table 7 shows that there are a few uncommon expenses items such as: occupancy and equipment costs, expenditures on materials, rental expenses, computer hardware rental, administration expenses and total expenses.

## Atypical and specific input categories

Atypical input categories were found in a few studies such as: exchange transactions, interest revenue, non-interest revenue, service quality, performed loans, federal funds purchased, certificate of deposit. Other studies defined non-performing loans, provision for bad debt, loans and office space as inputs. In general, however, the use of this factor as an input should be avoided since it is more a characteristic of bank outputs.

### e. Output categories

In order to handle the variety of banks' output categories found in the literature, we identified four sub-categories: assets (liquid assets), Liability (loans), Revenue (income) and the number of produced transactions. Furthermore, we further classified these four categories into the following sub-categories: assets, investments, securities, loans, income, the number of produced transactions and atypical and specific output categories.

## Assets (Liquid Assets)

A liquid asset is simply cash or any asset that can be converted into cash. The typical bank assets that are liquid according to that definition include cash, reserves, securities (e.g. government debt, commercial papers) and interbank loans with very short maturity. Liquid assets can also include mortgages, tax refunds, certificates of deposit (CDs), court settlements and trust fund monies, since all of these items can be converted into cash as well. Among asset items, liquid or earning assets are widely used items as inputs; they are used in 16 applications, followed by off-balance sheet (OBS) with 10 applications and other assets with 4 applications. Furthermore, there are a few uncommon asset items used by researchers as outputs, such as total assets, fixed assets and assets' value at risk (VAR).

## Investment

Investment is any use of resources intended to increase future production output or income. Reviewing the literature shows that investment is used as an output in 45 applications.

## Securities

Securities are any form of ownership that can be easily traded on a secondary market, such as stocks and bonds. These also include their derivatives, such as futures contracts, options or mutual funds. Reviewing the literature shows that the total securities are used as an output in 34 applications, and 4 studies disaggregated the securities into security transactions, short-term securities and long-term securities and bonds.

## Loans

The vast majority of studies included loans as an output category. Twenty-six studies disaggregated the loans into personal, business (commercial and industrial loans, agricultural loans and loans to other financial institutions) and real estate loans. Four studies disaggregated the loans into household and business loans, while others disaggregated the loans into personal, business and real estate loans. Weber and Devaney (1999) disaggregated the loans according to their risk weight (0% risk loan, 20%, 50 and 100% risk loan). A few studies disaggregated the loans into other categories, such as commercial, real estate, personal, business, agriculture and interbank loans.

## Income

In terms of income, the non-interest income (including transaction fees, the revenue on securities investment and other business revenues) is the more widely used between the income categories as an output with 41 applications, followed by interest income with 36 applications, while the total revenue is used as an output in 3 applications. The profit is used less as an output; there are only 6 applications that used profit after tax and 3 applications that used the operating profit as output.

### Number of Produced Transactions

Reviewing the literature shows that only three studies used the number of produced transactions as an output. Borger *et al*. (1998) and Wheelock and Wilson (1995) used the number of demand deposits, number of time deposits, number of installations and number of commercial deposits; furthermore, Wheelock and Wilson (1995) used the number of real estate loans. Al-Tamimi and Lootah (2007) used the number of counter transactions as one of their outputs. This means that the number of produced transactions is uncommonly used by researchers.

### Atypical and Specific Output Categories

Atypical output categories were found in a few studies. Deposits were used in 48 applications as an output. Chen (2002) used a three-stage efficiency approach and defined equity and exchange transactions as one of the outputs. Other studies used financial ratios as one of the outputs such as: return on equity (ROE), return on assets (ROA). Other outputs used were guarantees, the number of bank branches and number of counter sales. In general, these variables could be used as an output but with caution, since there is no agreement over them.

## 4. Additional Influences on Bank Performance

Nevertheless, the process of producing outputs from inputs can also be influenced by environmental variables or explanatory variables such as location, which are often not controllable by managers. Hall and Winsten (1959) were the first to recognize and name environmental variables in a frontier Model, where they identified social efficiency for which environmental variables are treated as any other input or output variable. Later on, Banker and Morey (1986) introduced a single-stage method for handling environmental variables through including them directly in the DEA Model formulation along with the traditional inputs and outputs. While, Ray (1988) introduced a two-stage Model where at the first stage DEA is used to calculate the efficiency and in the second stage the efficiency estimates are regressed against the environmental variables using an OLS Model. Afterwards, Ray (1991) used a regression Model rather than the SFA Model. Lovell (1994) presented a Model for handling uncontrollable inputs (similar to Banker and Morey, 1986) by constraining the comparison set to units with the same or a lower value for uncontrollable inputs. The primary advantage of this method is that the second stage allows for sensitivity analysis and different sets of non-discretionary inputs can be tested.

However, there are several possible problems that can arise with either the two-stage or the one-stage method. As McCarty and Yaisawarng (1993) warned, the two-stage approach could be problematic when there is strong correlation between the independent variables in the two stages and they claim that the second stage incorporates fundamentally different types of inputs, controllable and uncontrollable variables, becoming untenable. The reviewed literature identified two main groups treated as environmental variables: the internal (bank-specific variables) and external (environmental) variables. Commonly found bank-specific factors are size, profitability, capitalization, ownership type, loans to assets, age, risk profile, return on assets and return on equity. Country-specific factors include market concentration, presence of foreign banks, ratio of private investments to GDP, fiscal deficits to GDP, GDP growth, regulations related to capital adequacy, private monitoring, banks' activities, deposit insurance schemes, supervisory power and bank entry into the industry. The following table summarizes the results of the surveyed literature.

Table 8: Summary of explanatory variables' results

| Explanation of the variables | Reviewed studies' results |
|---|---|
| **Bank type**<br>This will indicate whether there is any difference in efficiency. | • Islamic banks are more efficient than commercial and investment banks (Al-Jarrah and Molyneux, 2003)<br>• No evidence that joint equity outperforms state-owned banks (Yao *et al*, 2008) |
| **Bank size**<br>• To examine whether size would be the determinant of bank efficiency.<br>• The natural log of total assets is used to examine the relationship between efficiency and bank size. | • Positive relation (Mahesh & Rajeev, 2008; Ataullah *et al*, 2004; Akhigbe and McNulty,2003 and Allen & Rai, 1996)<br>• Medium-size banks have higher efficiency (Avkiran, 2009)<br>• Negative relation (Sufian & Abdul Majid 2007and Sufian, 2009)<br>• No significant relation (Yao *et al*, 2008 and Chen & Yeh, 2000)<br>• Weakly correlated (Forster & Shaffer, 2005) |
| **Bank age**<br>Assessed by the number of years the bank has been in operation. | • The older banks could better manage their operations and might become more efficient (Loretta, 1994 and Okeahalam, 2008) |
| **Political stability** | • Positive relationship (Figueira *et al*, 2009) |
| **Ownership status**<br>An analysis of different ownership statuses will indicate whether there is any efficiency difference between different kinds of ownership status. | • Positive relation with foreign and private banks (Osman, 1995 and Chen & Yeh, 2000)<br>• Positive relation with domestic and foreign banks (Elyasiani *et al*, 1994)<br>• Positive relation with private banks (Osman, 1995 and Lin *et al* 2007)<br>• Positive relationship with foreign banks (Kraft *et al*, 2006)<br>• No significant relation (Yao *et al*, 2008 and Figueira, 2009)<br>• Negative relationship with foreign banks (Ataullah & Le, 2006) |
| **Geographical region** | • New Zealand banks are more efficient than Australian banks (Bos *et al*, |

| Explanation of the variables | Reviewed studies' results |
|---|---|
| | 2009)<br>• Positive relationship with geographic location (Casu & Molyneux, 2003)<br>• Brazilian banks are more efficient than Panama banks (Figueira, 2009) |
| **Government effectiveness** | Political influence<br>• Negative relation (Chen & Yeh, 2000) |
| **Regulatory quality** | • Liberalization policies have encouraged a more efficient use of resources in the banking industry (Osman, 1995; Hermes & Nhung, 2008; Ataullah *et al* 2004; Figueira *et al*, 2009 and Huang *et al*, 2007)<br>• No significant influence (Huang *et al*, 2007) |
| **Rule of law** | • The more the government interferes, the less well banks perform (Figueira, 2009) |
| **Voice and accountability** | • Negative relationship (Figueira, 2009) |
| **GDP growth rate** | • Positive relation (Hermes & Nhung, 2008) |
| **Inflation rate** | • No significant influence (Hermes & Nhung, 2008) |
| **Privatization** | • Positive relationship (Chen,1998)<br>• No significant influence (Yao *et al*, 2008 and Kraft *et al*, 2006) |
| **Market concentration**<br>Hirshman–Herfindahl index | • Positive relation (Akhigbe & McNulty, 2003 and Figueira, 2009) |
| **Market Share**<br>The bank share of deposit market | • Positive relation (Osman, 1995) |
| **Stock price** | • No significant influence (Sufian & Abdul Majid, 2007) |
| **Market power** | • Very little effect (Berger & Mester, 2003) |
| **Competition** | • Positive relationship (Ataullah & Le, 2006)<br>• No significant influence (Kalish & Gilbert, 1973) |
| **Merger** | • Increase in merger activity had a negative relation (Berger & Mester, 2003)<br>• No significant influence (Lang & Welzel, 1999) |
| **Capital adequacy**<br>Capital adequacy can be proxied by the ratio of equity to total assets. | • Positive relationship (Chiu *et al*, 2008 and Casu & Molyneux, 2003)<br>• The higher capital-asset ratio is the less efficient (Mester, 1994) |
| **Bank expenses**<br>The ratio of total costs to total assets | •<br>• Negative relation (Allen & Rai, 1996) |
| **Loan quality**<br>The ratio of loan loss reserve to total loans. | • Positive relation between asset qualities, loans to deposit ratio (Chen & Yeh, 2000) |
| **Total loans/total assets** | • Negative relation (Chen & Yeh, 2000[2]) |
| **Capitalization**<br>Book value of stockholders' equity as a fraction of total assets. | • Negative relation (Hermes & Nhung, 2008) |
| **Portfolio composition**<br>Total loans over total assets and total deposits over total assets | • No significant influence (Hermes & Nhung, 2008) |
| **Profitability** | • Positive relation (Kraft *et al*, 2006) |
| **Return on equity (ROE)** | • Positive relation (Elyasiani *et al*, 1994; Hermes & Nhung, 2008 and Casu & Molyneux, 2003) |
| **Return on assets (ROA)** | • Positive relation (Carbo *et al*, 2002 and Elyasiani *et al*, 1994) |
| **EP behaviour** | • Negative relation (Akhigbe & McNulty, 2003) |
| **Share price** | • Positive relation (Sufian and Abdul Majid (2007[3]) |
| **Number of branches** | • Positive relation (Elyasiani & Mehdian, 1990)<br>• Negative relation (Chen & Yeh, 2000) |
| **Fiscal deficits** | • Negative relationship (Ataullah & Le, 2006) |

---

[2] ) It is noted that bank efficiency is decreased if the ratio of non-performing to total loans is increased.

[3] ) The stock price tends to reflect cost efficiency albeit with small degree of reaction.

The above Table 8 summarizes the frequently used bank-specific and environmental variables. Those variables are used to explain the differences in efficiency according to the selected variables. Although there are conflicts in the results, using such variables could help bankers or any interested parties to take their decisions.

## 5. Other Methodological Issues

The reviewed literature shows that there are unsolved issues in bank efficiency needing more investigation and analysis, such as negativity issues and the incorporating the environmental factors (external and internal) in DEA Models. DEA requires the assumption that all the input and output values are non-negative. Al-Sharkas *et al*. (2008) handled this problem by adding a constant value to every bank with variable values less than zero, whereas Asaftei (2008) Bos and Kolari (2005) and Batchelor and Wadud (2004) among others excluded the observations that have variable values less than zero.

Other problems face researchers investigating the effect of external variables; reviewing the literature shows that it is common to analyse efficiency in two stages: in the first stage to evaluate the bank efficiency while in the second stage to employ: regression test (i.e. Akhigbe and McNulty, 2003; Berger and Mester, 2003; Ataullah and Le, 2006; Lensink *et al*, 2008; Sahoo and Tone, 2009; Figueira *et al*, 2009), logistic regression (i.e. Carbo *et al*, 2002; Girardone *et al*, 2004 and Chiu *et al*, 2008) and Tobit regression (i.e. Avkiran, 2009; Sufian, 2009 (a &B) and Casu and Molyneux, 2003). Other tests have been used, such as correlation (i.e. Yao *et al*, 2008 and Mester, 1994), ANOVA and Kruskal–Wallis test (i.e. Fukuyama, 1993 and Elyasiani and Mehdian, 1995), Mann–Whitney test (i.e. Chen, 1998 and Lin *et al*, 2007) and Wilcoxon test (Bos *et al*, 2009). However, McDonald (2009) argued that Tobit regression is an inappropriate estimation procedure, since it is an inconsistent estimator and the best that can be said for it is that Tobit estimates are often similar to OLS estimates. The literature shows that these challenges are still uncovered and even need greater efforts to handle them. For further analysis, next chapter tackles these two issues and proposes new method to evaluate the performance of the banking sector.

## 6. Conclusion

Following the first study on banking efficiency measurement published by Sherman and Gold (1985), many efficiency studies have been conducted. One can read and learn from them before embarking on an empirical analysis. Since the best way to learn about banking efficiency is to learn from reviewing the literature, this chapter provided an insight analysis into the process by which research ideas spread. This analysis can serve as a helpful tool for researchers and policy makers in a step-by-step process: from the selection of the measurement method, to the choice of the input and output categories and, finally, to analyse and present the results. Looking forward, the question arises as to what sort of work remains to be carried out? In our view, DEA has yet to make significant inroads into several important areas where it could be of real value, e.g. in support of managerial decision making within the banking industry.

Although there is a lack of agreement among researchers over the preferred frontier method, DEA seems to be the most popular method; additionally, the output-oriented variable returns to scale is the most familiar approach. The most popular parametric method is SFA; the Translog function is the wider used form among the researchers. Nevertheless, the results show that the intermediation approach is a common approach used to decide the appropriate input and output variables. However, a few problems still face researchers in banking efficiency, such as variables with negative values.

# CHAPTER 4 : DEA WITH NEGATIVE DATA[4]

## 1. Introduction

The DEA approach requires the assumption that all the input and output values are non-negative, while in many applications negative outputs could appear as loss in contrast with profit. In the literature, there have been various approaches to deal with negative data, but there is not any standard Model dealing with variables that are positive for some DMUs and negative for others.

Many researchers such as: Pastor (1994); Lovell (1995) and Seiford and Zhu (2002) in order to handle negative values in DEA used data transformations so that all negative data was turned positive. An example of this approach is to substitute a very small positive value for the negative output. This approach is based on the fact that the DEA Model shows each DMU in the best possible light and therefore, emphasizes those outputs on which the DMU performs best. Because of this, an output variable with a very small positive value would not be expected to contribute to the efficiency rating of the DMU concerned.

Depending on the approach adopted, the results could be different. For example treating a negative output as an input would generally lead to different results compared to substituting it with a small positive output. There are, however, certain DEA Models which can cope in an objective manner with negative data. A case in point is the additive DEA Model of Charnes *et al.* (1985) under variable returns to scale. This Model can be applied either directly to negative data or to the resulting data after a sufficiently large positive value has been added to render all data positive. The Model correctly identifies Pareto efficient and inefficient DMUs. The additive Model of Charnes *et al.* (1985), is thus said to be *translation invariant* as demonstrated by Ali and Seiford (1990) (see also Lovell and Pastor; 1995 and

[4]) This chapter is adopted from our published papers:

- Ali Emrouznejad, **Abdel Latef Anouze** and Emmanuel Thanassoulis (2010), A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA, *European Journal of Operational Research*, **200**(1): 297-304.
- Ali Emrouznejad, Reza Amin, Emmanuel Thanassoulis and **Abdel Latef Anouze** (2010), On the boundedness of the SORM DEA models with negative data, *European Journal of Operational Research*, **206**(1): 265-268

Pastor; 1996). They have shown that an absolute constant can be added to any input or output in the additive Model without changing the results.

However the disadvantages of additive Models are that (1) while they estimate efficient input-output levels (targets) for inefficient units they do not provide any measure of efficiency and (2) the results are units-dependent in that they depend on the unit of measurement of the inputs and outputs. Models which can provide efficiency measures under translation of inputs or outputs exist in certain restricted cases. For example output oriented Models under variable returns to scale can be shown to be input-translation invariant and the other way round for input oriented VRS Models (see Cooper *et al.* 2000).

Scheel (2001) suggested an approach for handling negative data in DEA whereby the absolute values of negative outputs are treated as inputs and the absolute values of negative inputs are treated as outputs. Sharp *et al.* (2006) introduced a modified slack-based measure (MSBM) in which both negative outputs and negative inputs could be handled. Portela *et al.* (2004) have also tackled variables which can take positive and negative values in DEA. They have developed two variants of a *range directional measure* (RDM) Model. One version, labelled $RDM^+$, is for cases where targets are sought to improve those variables where the DMU is furthest from best attainable levels while a second, labelled $RDM^-$, is for cases where improvement is prioritised for variables where the DMU is closest to best attainable levels. The advantage of the RDM over the additive Model is that it yields an efficiency measure that is very similar to those obtainable from radial Models.

In this section we propose a semi-oriented radial measure (SORM) which can yield a measure of efficiency and can handle variables that take positive values for some and negative values for other DMUs. The section is organised as follows. Next part gives a brief explanation of the recent approaches that deal with negative data in DEA and are closest to our own approach in philosophy, followed by introduction to the SORM Model. Then it provides numerical examples to compare the results with previous Models. It ends with the advantages and drawbacks of SORM and conclusion.

## 2. Some recent approaches to deal with negative data in DEA

Consider a set of n observed DMUs, {DMU j; j=1,...,n}, using m inputs, {$X_{ij}$ ; i=1,...,m}, to secure s outputs, {$Y_{rj}$ ; r=1,...s}.

### a. Range directional measure (RDM+)

Portela *et al.* (2004) have developed this Model for the case when some inputs and/or outputs can take negative as well as positive values. Their approach is applicable to negative data without the need for any transformation and it can yield a measure of efficiency akin to the radial measures in traditional DEA. It uses a modified version of the generic directional distance Model (see Chambers *et al.*; 1996 and 1998). The generic directional distance Model to assess DMU $j_0$ under variable returns to scale and with inputs ($X_i$ ; i=1,...,m) and outputs ($Y_r$ ; r=1,...s) is presented as:

**Model 10: Generic directional distance Model (Chambers *et al*.; 1996 &1998)**

$$Max\ \beta_0$$

subject to:

$$\sum_{j=1}^{n} \lambda_j\, y_{rj} \geq y_{r_0} + \beta_0 g_{yr} \qquad ; r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j\, x_{ij} \geq x_{i_0} - \beta_0 g_{xi} \qquad ; i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j, \beta_0, g_{yr}, g_{xi} \geq 0$$

When data are positive a usual choice for the direction vectors ($g_{xi}$, $g_{yr}$) is the observed input and output levels respectively of DMU $j_0$. But when some data are negative, the use of observed input and output levels would violate the non negativity constraints of the Model. Portela *et al.* (2004) modified the above Model using an ideal point (I) where I = ($\underset{j}{Max}$ {$Y_{rj}$, r = 1,…,s}, $\underset{j}{Min}$ {$X_{ij}$, i=1,…,m}) to identify direction vectors ($g_{xi}$, $g_{yr}$). The direction from DMU $j_0$ to the ideal point I is ($g_{xi}$, $g_{yr}$) = ($R_{i0}$, $R_{r0}$) where

$$R_{i0} = X_{i0} - \underset{j}{Min}\{X_{ij} \quad ; \mathrm{j} = 1, \ldots \mathrm{n}\}, \quad \mathrm{i} = 1, \ldots, \mathrm{m}$$

and

$$R_{r0} = \underset{j}{Max}\{Y_{rj} \quad ; \mathrm{j}=1,...\mathrm{n}\} - Y_{r0}\,, \qquad \mathrm{r}=1,...,\mathrm{s} \quad .$$

The directions ($R_{i0}$, $R_{r0}$) are used by Portela *et al.* (2004) in two alternative ways. When it is desired to identify targets for $DMU_{j0}$ so that priority is given for it to improve in areas where it performs worst (in terms of distance from the efficient boundary) Model 11 is solved. The Model is referred to as $RDM^{+}$. When on the other hand it is desired to identify targets for $DMU_{j0}$ so that priority is given for it to improve in areas where it performs best (in terms of distance from the efficient boundary) Model 11 is solved using instead of the direction ($R_{i0}$, $R_{r0}$) the direction ($1/R_{i0}$, $1/R_{r0}$), the resulting Model being referred to as $RDM^{-}$.

| **Model 11: Rang directional measure (RDM+) (Portela *et al*., 2004)** |
|---|
| $Max\ \beta_0$<br>subject to:<br>$\sum_{j=1}^{n} \lambda_j\, y_{rj} \geq y_{r_0} + \beta_0 R_{r_0} \qquad ; r = 1, \ldots., s$<br>$\sum_{j=1}^{n} \lambda_j\, x_{ij} \geq x_{i_0} - \beta_0 R_{ir_0} \qquad ; i = 1, \ldots., m$<br>$\sum_{j=1}^{n} \lambda_j = 1$<br>$\lambda_j, \beta_0 \geq 0$ |

One advantage of the RDM Models ($RDM^{+}$ and $RDM^{-}$) over the additive Model is that they yield targets which attempt to reflect the priorities for improvement of inputs and outputs of a DMU while the additive Model yields targets which are furthest from $DMUj_0$ to the efficient boundary. A second advantage is that the RDM Models yield efficiency measures that are similar to those obtained from radial Models while the additive Model yields no efficiency measure.

### b. Modified slacks based measure (MSBM)

Tone (2001) introduced a slacks-based measure of efficiency (SBM), reflected in the optimal value of p in Model 12.

| **Model 12: Slack-based measure Model (SBM) (Tone, 2001)** |
|---|

$$Max\ \ \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i_0}}}{1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{r_0}}}$$

subject to:

$$\sum_{j=1}^{n}\lambda_j\, x_{ij} + s^- = x_{i0}$$

$$\sum_{j=1}^{n}\lambda_j\, y_{rj} - s^+ = y_{r0}$$

$$\sum_{j=1}^{n}\lambda_j = 1$$

$$\lambda_j \geq 0, s^- \geq 0\ s^+ \geq 0$$

In the case of positive inputs we have $s_i^- \leq X_{i0}$ as $X > 0$ and $\lambda \geq 0$. However, as noted by Sharp *et al.* (2006) this is not necessarily the case for negative inputs and therefore there is a possibility that the efficiency measure becomes negative. Sharp *et al.* (2006) modified the above Model drawing upon the RDM$^+$ approach of Portela *et al.* (2004) so that it will yield a measure of efficiency between 0 and 1 while also being units and translation invariant. The Model developed by Sharp *et al.* (2006) is as follows.

**Model 13: Modified SBM (fractional Model) (Sharp *et al.*, 2006)**

$$Min\quad p = \frac{1 - \sum_{i=1}^{m}\frac{w_i s_i^-}{R_{i0}}}{1 + \sum_{r=1}^{s}\frac{v_r s_r^+}{R_{r0}}}$$

subject to:

$$\sum_{j=1}^{n}\lambda_j Y_{rj} - s_r^+ = Y_{r0} \qquad ;\mathrm{r} = 1,\ldots,\mathrm{s}$$

$$\sum_{j=1}^{n}\lambda_j X_{ij} + s_i^- = X_{i0} \qquad ;\mathrm{i} = 1,\ldots,\mathrm{m}$$

$$\sum_{j=1}^{n}\lambda_j = 1,\quad \sum_{i=1}^{m} w_i = 1,\quad \sum_{r=1}^{s} v_r = 1$$

$$\lambda_j\ , w_i\ , v_r\ , s_r^+, s_i^- \geq 0 \quad ;\forall \mathrm{j} = 1,\ldots,\mathrm{n}\ \&\ \ \mathrm{r} = 1,\ldots,\mathrm{s}\ \ \&\ \ \mathrm{i} = 1,\ldots,\mathrm{m}$$

Where $w_i$ and $v_r$ are user specified weights to reflect the strength of preference for improving the value of the input or output concerned. Notation is otherwise as in the RDM$^+$ Model 11. Sharp *et al.* (2006) convert this fractional Model to the linear Model 14.

| **Model 14: Modified Slack-Based Model (MSBM) (Sharp *et al*.; 2006)** |
|---|
| $Min \quad \tau = t - \sum_{i=1}^{m} \frac{w_i s_i^-}{R_{i0}}$ <br> subject to: <br> $\sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = tY_{r0} \quad ; r = 1,...,s$ <br> $\sum_{j=1}^{n} \lambda_j X_{ij} + s_i^- = tX_{i0} \quad ; i = 1,...,m$ <br> $\sum_{r=1}^{s} \frac{v_r s_r^+}{R_{r0}} + t = 1$ <br> $\sum_{i=1}^{m} w_i = 1, \ \sum_{r=1}^{s} v_r = 1 \ \sum_{j=1}^{n} \lambda_j = t$ <br> $t, \lambda_j, w_i, v_r, s_r^+, s_i^- \geq 0, \quad ; \forall j = 1,...,n \ \& \ r = 1,...,s \ \& \ i = 1,...,m$ |

The efficiency of $DMU_{j0}$ is the optimal value of $\tau$ in Model 5 which can be shown to equal the optimal value of p in Model 13. The optimal values of the remaining variables in Model 13 can also be readily derived through simple division of those of Model 14 by the optimal value of t as explained in Sharp *et al.* (2006).

It is important to note that the MSBM Model was devised for what Sharp *et al*. (2006) called “naturally negative” inputs. Therefore the MSBM Model is more limited in it is application than the RDM and the SORM Models.

## 3. A semi-oriented radial measure (SORM) to deal with negative data

The standard input and output oriented DEA Models to assess $DMU_{j0}$ under variable returns to scale are presented in Model 15a and Model 15b, respectively, where the efficiency of $DMU_{j0}$ is the optimal value of *h* in Model 15a and 1/h in Model 15b (Thanassoulis; 2001).

| **Model 15a: Standard input oriented DEA - VRS Model** | **Model 15b: Standard output oriented DEA - VRS Model** |
|---|---|

| $Min\ h$ | $Max\ h$ |
|---|---|
| subject to $\sum_{j=1}^{n} \lambda_j x_{ij} \leq hx_{ij_0}$ ; $\forall i$ <br> $\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_0}$ ; $\forall r$ <br> $\sum_{j=1}^{n} \lambda_j = 1$ <br> $\lambda_j \geq 0$ ; $\forall j, h$ free | subject to $\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij_0}$ ; $\forall i$ <br> $\sum_{j=1}^{n} \lambda_j y_{rj} \geq hy_{rj_0}$ ; $\forall r$ <br> $\sum_{j=1}^{n} \lambda_j = 1$ <br> $\lambda_j \geq 0$ ; $\forall j, h$ free |

One of the key concerns when we have a variable that takes positive values for some and negative values for other DMUs is that its absolute value should rise or fall for the DMU to improve its performance depending on whether the DMU concerned has a positive or negative value on that variable. For example in the case of an output variable, if the DMU has a positive value the output should rise to improve further but it should fall in absolute value so long as it continues to be negative. To overcome this problem we shall treat each variable that has positive values for some and negative for other DMUs as consisting of the sum of two variables as follows.

Let us take an output variable $Y_k$ which is positive for some DMUs and negative for others. Let us define two variables $Y^1{}_k$ and $Y_k^2$ which for the j$^{th}$ DMU take values $Y^1{}_{kj}$ and $Y^2{}_{kj}$ such that.

$$Y^1{}_{kj} = \begin{cases} Y_{kj} & ;\text{if } Y_{kj} \geq 0 \\ 0 & ;\text{if } Y_{kj} < 0 \end{cases} \quad \& \quad Y^2{}_{kj} = \begin{cases} 0 & ;\text{if } Y_{kj} \geq 0 \\ -Y_{kj} & ;\text{if } Y_{kj} < 0 \end{cases}$$

Note that we have $Y^1{}_{kj} \geq 0$ and $Y^2{}_{kj} \geq 0$ while $Y_{kj} = Y^1{}_{kj} - Y^2{}_{kj}$ for all j. To assess $DMU_{j0}$ we construct Model 16.

| **Model 16: Input oriented VRS SORM, when DMUs have positive and negative values in output variables** |
|---|
| $Min\ h$<br>subject to<br>$\sum_{j=1}^{n} \lambda_j x_{ij} \leq hx_{ij_0} \quad ; \forall i \quad (C1)$<br>$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_0} \quad ; \forall r \neq K \quad (C2)$<br>$\sum_{j=1}^{n} \lambda_j y_{kj}^1 \geq y_{kj_0}^1 \quad ; \forall k \in K \quad (C3)$<br>$\sum_{j=1}^{n} \lambda_j y_{kj}^2 \leq y_{kj_0}^2 \quad ; \forall k \in K \quad (C4)$<br>$\sum_{j=1}^{n} \lambda_j = 1 \quad (C5)$<br>$\lambda_j \geq 0 \quad ; \forall j, h \text{ free}$ |

On the face of it what we have done is to create two variables from a single variable that takes positive values for some and negative for other DMUs. This enables us to treat the negative output values as inputs in that the Model seeks improved solutions which reduce the absolute value of the negative output. Note that this happens only for DMUs that have a negative value on the output concerned while the same variable is treated as a normal output for those DMUs that have a positive level on that variable.

To be more precise we have constructed two non-negative variables out of $Y_k$, one as an output $Y^1_k$ and the second as an input $Y^2_k$ and so that the resulting Production Possibility Set (PPS) when these two variables are introduced is the same as that obtained when we apply DEA without disaggregating $Y_k$. This can be readily shown to be true. If in Model 16 we multiply constraint (C4) by -1 and add it to constraint (C3) the result will be $\sum_j \lambda_j Y^1_{kj} \geq Y^1_{kj_0} + \sum_j \lambda_j (-Y^2_{kj}) \geq (-Y^2_{kj_0})$ which reduces to $\sum_j \lambda_j (Y^1_{kj} - Y^2_{kj}) \geq Y^1_{kj_0} - Y^2_{kj_0}$ and since we have $Y_{kj} = Y^1_{kj} - Y^2_{kj}$ we have created the initial Model 15a as obtained before disaggregating $Y_k$. Thus any solution feasible in Model 16 will also be feasible in Model 15a and so obeys the axioms for creating the PPS in DEA under VRS. The converse, however, is not true.

That is to say any solution that is feasible in Model 6a (the original Model) is not necessarily feasible in Model 16. This can be readily seen by a simple example. Let us assume that $Y_{kj0}$ is positive and that at the optimal solution to Model 15a some $\lambda$ relating to a negative $Y_{kj}$ is positive while all other positive $\lambda$s relate to DMUs which have positive $Y_{kj}$. Then Constraint (C4) in Model 16 cannot be satisfied because its RHS will be 0 while its LHS will be positive.

Thus the feasible region of Model 16 is a subset of that of Model 15a. This has two corollaries:

- Model 16 cannot yield an efficiency rating *h* lower than that yielded by Model 15a.
- Model 16 may not identify all Pareto efficient solutions to Model 15a.

The aim of Model 16 is primarily to lead to improved targets for $DMU_{j0}$, notwithstanding the fact that they may not be on the efficient part of the original PPS. The solutions of Model 15a that are not feasible in Model 16 are those which violate constraints of the type in (C4) as illustrated above. It is intuitively acceptable to exclude the related peers for $DMU_{j0}$. $DMU_{j0}$ offering a positive value on the output concerned will see a peer that offers a negative value on that output as having an inferior performance, which in terms of utility may not be possible to compensate for by good performance in other variables. E.g. a DMU making a profit, however, low, will find it hard to accept as a peer to emulate one that is making a loss because a loss has a non-linear disutility with profit. E.g. a firm may survive with low profits but it may not do so in the long term with losses, however low.

Clearly Model 16 can be readily modified to include more than one output variable k which takes positive values for some DMUs and negative for others. The Model can also be readily modified to handle input variables which take positive values for some DMUs and negative for others. Thus assume the input variable $X_i$ $, i \in I$ and the output variable $Y_r$, $r \in R$ are positive for all DMUs. Further, assume that the input variable $X_\ell$, $l \in L$ is positive for some DMUs and negative for others and $Y_k$, $k \in K$ are outputs which take positive values for some DMUs and negative for others. (Note that $I \cup L = \{1,...,m\}, I \cap L = \phi, R \cup K = \{1,...,s\}, R \cap K = \phi)$ . Let us define

$Y^1_{kj}$ and $Y^2_{kj}$ as above. Similarly let us define $X^1_{\ell j}$ and $X^2_{\ell j}$ such that $X_{\ell j} = X^1_{\ell j} - X^2_{\ell j}$ and so that $X^1_{\ell j} \geq 0$ and $X^2_{\ell j} \geq 0$ for all j as follows.

$$X^1_{\ell j} = \begin{cases} X_{\ell j} & ;\ \text{If } X_{\ell j} \geq 0 \\ 0 & ;\ \text{If } X_{\ell j} < 0 \end{cases} \qquad \& \qquad X^2_{\ell j} = \begin{cases} 0 & ;\ \text{If } X_{\ell j} \geq 0 \\ -X_{\ell j} & ;\ \text{If } X_{\ell j} < 0 \end{cases}$$

To assess $DMU_{j0}$ we formulate Model 17.

| **Model 17: Input oriented VRS SORM, when DMUs have positive and negative values in input and output variables** |
|---|
| $Min\ h$ <br> subject to <br> $\sum_{j=1}^{n} \lambda_j x_{ij} \leq hx_{ij_0} \quad ; \forall i \in \mathrm{I}$ <br> $\sum_{j=1}^{n} \lambda_j x^1_{\ell j} \leq hx^1_{\ell j_0} \quad ; \forall \ell \in L$ <br> $\sum_{j=1}^{n} \lambda_j xy^2_{\ell j} \geq hx^2_{\ell j_0} \quad ; \forall \ell \in L$ <br> $\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_0} \quad ; \forall r \in R$ <br> $\sum_{j=1}^{n} \lambda_j y^1_{kj} \geq y^1_{kj_0} \quad ; \forall k \in K$ <br> $\sum_{j=1}^{n} \lambda_j y^2_{kj} \leq y^2_{kj_0} \quad ; \forall k \in K$ <br> $\sum_{j=1}^{n} \lambda_j = 1$ <br> $\lambda_j \geq 0 \quad ;\ \forall j, h \text{ free}$ |

Model 17 represents the general case for an input oriented VRS DEA Model which has both inputs and outputs which take positive values for some DMUs and negative for others. The aim in Model 17 as in Model 16 is to lead to improved targets for $DMU_{j0}$. The Model also yields a measure of efficiency for $DMU_{j0}$, which is the optimal value of *h*. This measure reflects the radial contraction of the positive valued inputs. However, for each input that takes positive and negative values the Model creates two variables, one for negative values and one for positive values. Negative input values are in effect treated as outputs in that the Model seeks improved solutions which can raise the absolute value of the negative input. Note that this happens only for DMUs that have a negative value on the input concerned while the same variable is treated as a normal input for those DMUs that have a positive level on that variable. The efficiency measure of Model 17 will then reflect radial contraction only of absolute input values and then only when there is no slack in either one of the constraints in Model 17 which relate to the two auxiliary variables created from the original variable. For this reason we refer to the efficiency measure *h* in Model 17 as "*input reduction semi-oriented radial measure* (SORM)".

Following the reasoning of Model 16 we can readily demonstrate that the feasible region of Model 17 is a subset of that of Model 15a. Thus as with Model 16 Model 17 too cannot yield an efficiency measure below that yielded by Model 6a and it may not lead to a Pareto efficient solution of Model 15a. It is noteworthy that when $DMU_{j0}$ has a negative input level on some input $l \in \mathrm{L}$ its efficient peers in Model 17 can only be other DMUs which also have a negative or zero level on that input. This is acceptable at the intuitive level. $DMU_{j0}$ could find it hard to use efficient peers with positive levels on an input in which it itself has a negative level. A negative input level (e.g. contributory rather than competing sales outlets where competing establishments are a positive input) is a good thing and targets which suggest replacing contributory with competing sales outlets would not be seen as sensible.

Model 17 can be readily modified to assess $DMU_{j0}$ in the output orientation. This is done in Model 18 which yields an "*output augmentation semi-oriented radial measure* (SORM) of efficiency" *1/h** where *h** is the optimal value of *h* in Model 18.

The reasoning expounded in respect of Model 17 can be readily transferred to Model 18 to show that the feasible solutions to Model 18 are a subset of those of Model 15b. Hence Model 18 can never lead to an efficiency value *1/h** below that of the output oriented version of Model 15b and it may not lead to a Pareto efficient solution of that Model.

**Model 18: Output oriented VRS SORM, when DMUs have positive and negative values in input and output variables**

$Max\ h$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij_0} \qquad ; \forall i \in \mathrm{I}$$

$$\sum_{j=1}^{n} \lambda_j x_{\ell j}^1 \leq x_{\ell j_0}^1 \qquad ; \forall \ell \in L$$

$$\sum_{j=1}^{n} \lambda_j xy_{\ell j}^2 \geq x_{\ell j_0}^2 \qquad ; \forall \ell \in L$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq hy_{rj_0} \qquad ; \forall r \in R$$

$$\sum_{j=1}^{n} \lambda_j y_{kj}^1 \geq hy_{kj_0}^1 \qquad ; \forall k \in K$$

$$\sum_{j=1}^{n} \lambda_j y_{kj}^2 \leq hy_{kj_0}^2 \qquad ; \forall k \in K$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \qquad ; \forall j, h \text{ free}$$

## 4. Illustration of the SORM Models and comparison with alternative DEA Models for dealing with negative data

This section presents two examples. The first example shows how the SORM Model can be used when an assessment involves a variable which takes positive values in some DMUs and negative in others. The second example compares the results of the SORM Model with those obtained from the approaches by Portela *et al.* (2004) and Sharp *et al.* (2006) for dealing with negative data in DEA.

### a. Example 1:

Table 9 shows data for 10 hypothetical DMUs with one input (X) and two outputs (Y and Z). The output (Y) is positive for some DMUs and negative for others.

Table 9: Input-Output Data for 10 DMUs

| DMU | (X) (input) | (Y) (output) | (Z)(output) |
|---|---|---|---|
| DMU1 | 12 | 15 | 11 |

| | | | |
|---|---|---|---|
| DMU2 | 35 | 18 | 6 |
| DMU3 | 25 | 20 | 13 |
| DMU4 | 22 | 12 | 20 |
| DMU5 | 40 | -10 | 25 |
| DMU6 | 50 | -8 | 27 |
| DMU7 | 35 | -18 | 6 |
| DMU8 | 40 | -10 | 22 |
| DMU9 | 25 | -7 | 19 |
| DMU10 | 16 | 26 | 8 |

In this example we shall use SORM, RDM and MSBM, all in output orientation. We do not include the Scheel's approach since it cannot be used for cases where some DMUs have positive and others negative values on a variable. First, to formulate SORM Model, we introduce in respect of variable (Y) two variables: $Y^1$ & $Y^2$ as follows:

$Y^1 = Y$ and $Y^2=0$ ; if $Y \geq 0$

$Y^2 = -Y$ and $Y^1=0$ ; if $Y<0$.

Then we solve the output oriented SORM Model 19 as follows.

| **Model 19: An output oriented VRS SORM Model** |
|---|
| $Max\ h$<br>subject to<br>$$\sum_{j=1}^{n} \lambda_j X_j \leq X_{j_0}$$<br>$$\sum_{j=1}^{n} \lambda_j Z_j \geq hZ_{j_0}$$<br>$$\sum_{j=1}^{n} \lambda_j Y_j^1 \geq hY_{j_0}^1$$<br>$$\sum_{j=1}^{n} \lambda_j Y_j^2 \leq hY_{j_0}^2$$<br>$$\sum_{j=1}^{n} \lambda_j = 1$$<br>$\lambda_j \geq 0 \quad ; \forall j, h \text{ free}$ |

We have also applied to the data in Table 12 the $RDM^+$ Model 20 based on the approach by Portela *et al.* (2004). Note that in this Model we set $R_{x0}=0$ and have β only for Z and Y. This enables us to compare output oriented SORM with output oriented RDM+.

**Model 20: RDM+ Model**

$$
\begin{aligned}
Max \quad \{\beta_0 \mid \; & \sum_{j} \lambda_j Z_j \geq Z_{j_0} + \beta_0 R_{Z0} \\
& \sum_{j} \lambda_j Y_j \geq Y_{j_0} + \beta_0 R_{Y0} \\
& \sum_{j} \lambda_j X_j \leq X_{j_0} \\
& \sum_{j} \lambda_j = 1 \\
& \lambda_j \geq 0 \;\; ; \forall j, \beta_0 \geq 0 \,\}
\end{aligned}
$$

Furthermore, we applied to the data in Table 12 the output oriented MSBM Model 21 based on the approach by Sharp *et al.* (2006).

**Model 21: MSBM Model**

$$
Max \quad h = \sum_{r=1}^{s} \frac{v_r s_r^{+}}{R_{r0}}
$$

$$
\begin{aligned}
s.t.& \\
& \sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^{+} = Y_{r0} \qquad ; r = 1,\ldots,s \\
& \sum_{j=1}^{n} \lambda_j X_{ij} + s_i^{-} = X_{i0} \qquad ; i = 1,\ldots,m \\
& \sum_{j=1}^{n} \lambda_j = 1, \quad \sum_{r=1}^{s} v_r = 1 \\
& \lambda_j, v_r, s_r^{+}, s_i^{-} \geq 0 \quad ; \forall j = 1,\ldots,n \;\&\; r = 1,\ldots,s \;\&\; i = 1,\ldots,m
\end{aligned}
$$

Models 19 and 21 yield the efficiency rating 1/h* for DMUj0, where h* is the optimal value of h in that Model. In the case of Model 20 the efficiency rating of DMUj0 is $(1-\beta^*)$ where $\beta^*$ is the optimal value of $\beta$ in that Model. In all cases an efficiency of 1 (100%) means that $DMU_{j0}$ is boundary in the sense that at least one input or output or the negative component of output Y cannot improve further. However, when the efficiency rating is below 100% the three Models give measures of different distances. The SORM Model 19 as noted earlier captures the radial distance of the observed outputs from their target levels only in absolute terms and only when there are no slacks in the constraints relating to the Y1 and Y2 variables, while $1 - \beta^* < 1$ captures the distance of the observed outputs from their target levels but expressed as a fraction of the range for that output as defined in the RDM$^+$ Model. Thus to compare the results of the three Models we use the efficiencies when they are 100% and otherwise compare the target output levels they yield. Table 10 shows the results of the efficiencies.

Table 10: The efficiencies yielded by the RDM+, MSBM and SORM Models

| DMU | RDM+ | MSBM | SORM |
|---|---|---|---|
| DMU1 | 100 | 100 | 100 |
| DMU2 | 68.20 | 64.61 | 70.77 |
| DMU3 | 99.25 | 98.63 | 99.53 |
| DMU4 | 100 | 100 | 100 |
| DMU5 | 100 | 100 | 100 |
| DMU6 | 100 | 100 | 100 |
| DMU7 | 38.36 | 59.72 | 25.41 |
| DMU8 | 76.69 | 72.62 | 88.03 |
| DMU9 | 84.21 | 73.27 | 91.21 |
| DMU10 | 100 | 100 | 100 |

Clearly RDM$^+$, MSBM and SORM agree on boundary units in that the same DMUs are 100% efficient in all Models. Note that the RDM$^+$ Model captures in full the PPS constructed in ordinary DEA while SORM may capture only a subset of the ordinary PPS. This suggests that the SORM PPS in this case does include the boundary of the true PPS as reflected in RDM$^+$.

Table 11 shows the target output levels yielded by the three Models we have used for the DMUs that are not boundary by either method. It is important to note that the target of Y in SORM is the difference of the targets of $Y^1$ and $Y^{2,}$ i.e. ($Y^1$-$Y^2$).

Table 11: Target output levels for non-boundary DMUs

| **DMU** | **(Z)** | | | | **(Y)** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Observe** | **RDM$^+$** | **MSBM** | **SORM** | **Observed** | **RDM$^+$** | **MSBM** | **SORM** | | |
| | | | | | | | | **$Y^1$** | **$Y^2$** | **$Y = (Y^1 - Y^2)$** |
| DMU2 | 6 | 2.7 | 8 | 8.48 | 18 | 20.5 | 26 | 25.4 | 0 | 25.4 |
| DMU3 | 13 | 3.1 | 13 | 13 | 20 | 20 | 20.17 | 20.1 | 0 | 20.1 |
| DMU7 | 6 | 0.14 | 20 | 23.6 | -18 | 11.6 | 12 | 3.4 | 7.2 | -3.8 |
| DMU8 | 22 | 3.64 | 24.5 | 25 | -10 | 1.6 | 0 | 0 | 10 | -10 |
| DMU9 | 19 | 0.85 | 20.75 | 20.9 | -7 | 8.26 | 12.3 | 9.86 | 1.7 | 8.3 |

Firstly we note how all methods can estimate suitable improved targets for variables which take negative values. As can be seen in Table 14 while the observed value of Y for $DMU_9$ is negative all three Models estimate a positive target. For $DMU_7$ with negative observed value of Y only SORM estimates a negative target. For $DMU_8$ with negative observed value of Y only RDM estimate a positive target. In the case of SORM the target is identical with the observed value but in the case of MSBM and $RDM^+$ an improved target is obtained.

In order to better compare the methods we derive where possible efficiency scores which are comparable for the methods. The efficiency scores are derived as the ratio of observed to target output where the observed output and its target are both positive. If observed output and its target are both negative then the ratio of absolute value of target to absolute value of observed level is used. Finally where the target is positive but the observed output level is negative no efficiency measure is possible. The efficiency measures obtained, converted to percentages, appear in Table 12.

Table 12: The efficiency measure of inefficient DMUs

| DMU | Average Efficiency | | |
|---|---|---|---|
| | $RDM^+$ | MSBM | SORM |
| DMU2 | 67.52 | 72.12 | 70.81 |
| DMU3 | 99.62 | 99.58 | 99.75 |
| DMU7 | 29.79 | 30.00 | 23.27 |
| DMU8 | 93.06 | 89.80 | 94.00 |
| DMU9 | 67.52 | 72.12 | 70.81 |

The efficiency scores reported in Table 12 are the average efficiency across Y and Z. The efficiency measures are remarkably similar across the three methods. Though the methods yield different targets on different input/output variables on average, in percentage terms, the methods estimate a similar potential for improvement for each DMU.

### b. Example 2:

In this further example we use the data set of “the notional effluent processing system” as extracted from Sharp *et al.* (2006) and presented in Table 13.

Table 13: Notional effluent processing system

| DMU | ($I_1$) Cost | ($I_2$) Effluent | ($O_1$) Saleable | ($O_2$) CO2 | ($O_3$) Methane |
|---|---|---|---|---|---|

| DMU | ($I_1$) Cost | ($I_2$) Effluent | ($O_1$) Saleable | ($O_2$) CO2 | ($O_3$) Methane |
|---|---|---|---|---|---|
| DMU1 | 1.03 | -0.05 | 0.56 | -0.09 | -0.44 |
| DMU 2 | 1.75 | -0.17 | 0.74 | -0.24 | -0.31 |
| DMU 3 | 1.44 | -0.56 | 1.37 | -0.35 | -0.21 |
| DMU 4 | 10.8 | -0.22 | 5.61 | -0.98 | -3.79 |
| DMU 5 | 1.3 | -0.07 | 0.49 | -1.08 | -0.34 |
| DMU 6 | 1.98 | -0.1 | 1.61 | -0.44 | -0.34 |
| DMU 7 | 0.97 | -0.17 | 0.82 | -0.08 | -0.43 |
| DMU 8 | 9.82 | -2.32 | 5.61 | -1.42 | -1.94 |
| DMU 9 | 1.59 | 0 | 0.52 | 0 | - 0.37 |
| DMU 10 | 5.96 | -0.15 | 2.14 | -0.52 | -0.18 |
| DMU 11 | 1.29 | -0.11 | 0.57 | 0 | -0.24 |
| DMU 12 | 2.38 | -0.25 | 0.57 | -0.67 | -0.43 |
| DMU 13 | 10.3 | -0.16 | 9.56 | -0.58 | 0 |

In the comparison set there are 13 DMUs with one positive input (cost), one non-positive input (effluent), one positive output (saleable) and two non-positive outputs (Methane and $CO_2$). Consider the following 4 output oriented VRS Models:

(1) Scheel: Undesirable inputs/outputs Model in which we treat the absolute values of negative outputs as inputs and the absolute values of negative inputs as outputs (Scheel; 2001). Therefore the inputs are cost, absolute value of Methane and absolute value of $CO_2$ and the outputs are saleable and absolute value of effluent.

(2) MSBM: Modified Slack-based Model (Sharp *et al.*; 2006); we used the output oriented MSBM. Similar to Sharp *et al.* (2006) we used weight of 0.33 for each output in the objective function.

(3) $RDM^+$: Range directional measures (as developed by Portela *et al.*; 2004). An output oriented was solved, setting $R_{x0}=0$ and $\beta = 0$ for input-related constraints.

(4) SORM: Semi-oriented radial measure (as developed in this section).

In this example we solve an output oriented VRS-SORM as in Model 22.

**Model 22: An output oriented SORM - VRS Model***

$Max\ h$

subject to

$$\sum_j \lambda_j Cost_j \le Cost_{j_0}$$
$$\sum_j \lambda_j Effluent^2{}_j \ge Effluent^2{}_{j_0}$$
$$\sum_j \lambda_j Saleable_j \ge h\, Saleable_{j_0}$$
$$\sum_j \lambda_j Methane^2{}_j \le h\, Methane^2{}_{j_0}$$
$$\sum_j \lambda_j CO2^2{}_j \le h\, CO2^2{}_{j_0}$$
$$\sum_j \lambda_j = 1$$
$$\lambda_j \ge 0 \qquad ; \forall j.$$

$*$ *Note that* $Effluent^1{}_j = 0$ *and* $Methane^1{}_j = 0$ & $CO2^1{}_j = 0$ $(\forall j)$ *since Effluent, Methane and CO2 are negative for all DMUs.*

*Hence,* $Effluent^2{}_j = |Effluent_j|$ *and* $Methane^2{}_j = |Methane_j|$ & $CO2^2{}_j = |CO2_j|$

The results are reported in Table 14.

Table 14: Efficiencies (%) for the Scheel, MSBM, RDM+ and SORM Models

| DMU | Scheel | MSBM | RDM$^+$ | SORM |
|---|---|---|---|---|
| 1 | 64 | 88 | 97 | 63 |
| 2 | 47 | 74 | 91 | 45 |
| 3 | 100 | 100 | 100 | 100 |
| 4 | 61 | 56 | 50 | 59 |
| 5 | 41 | 70 | 92 | 41 |
| 6 | 86 | 78 | 97 | 86 |
| 7 | 100 | 100 | 100 | 100 |
| 8 | 100 | 100 | 100 | 100 |
| 9 | 91 | 89 | 99 | 91 |
| 10 | 39 | 72 | 65 | 39 |
| 11 | 100 | 100 | 100 | 100 |
| 12 | 33 | 68 | 81 | 25 |
| 13 | 100 | 100 | 100 | 100 |

Interestingly, Table 14 shows that the Scheel, MSBM, RDM$^+$ and SORM Models are agreed on DMUs that are boundary and have efficiency of 100%. However, we cannot generalise this as the authors have found cases where a DMU can be boundary in SORM but not so in other methods.

However, the correlation between SORM and RDM is fairly strong (with 62.6%), MSBM is also poorly correlated with RDM (with 60.2%).

Table 15: The correlation between different methods

| | Undesirable | MSBM | RDM | SORM |
|---|---|---|---|---|
| **Undesirable** | 1 | | | |
| **MSBM** | 87.89 | 1 | | |
| **RDM** | 62.58 | 60.19 | 1 | |
| **SORM** | 99.79 | 87.90 | 62.46 | 1 |

As it can be seen in Figure 11 SORM and the undesirable method results are moderate efficiency values.

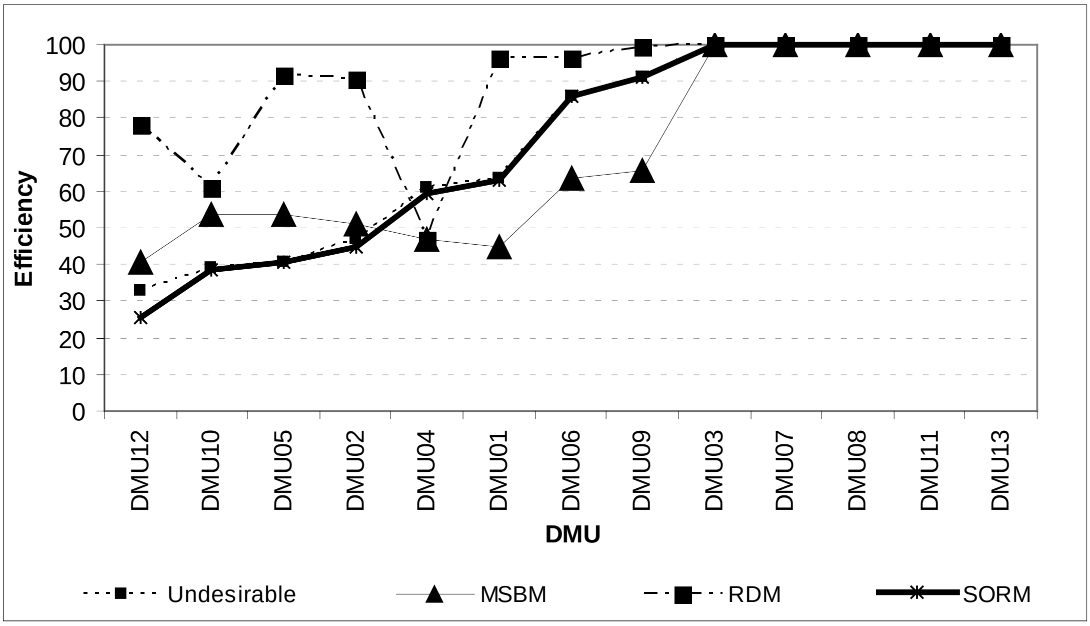



Figure 11: Comparison of undesirable, MSBM, RDM and SORM models

One may argue that the efficiency scores from the above methods are not directly comparable. Interestingly all four methods give the same ranks for all DMUs. Therefore extra attempts have been made to enhance the comparison using rank and target in each method.

Each one of the above Models uses a different measure of efficiency, and so all but the efficiencies of 100% are not directly comparable. Thus to compare the Models we first compare the targets they yield for non-boundary units and then we compute efficiency measures using those targets by using the procedure outlined in respect of Table 14 above. Table 16 shows the targets for the output variables yielded by each Model. We have not used the inputs targets here as all Models were solved in an output orientation.

Table 16: Target level for inefficient DMUs

| | | | Saleable | CO2 | Methane |
|---|---|---|---|---|---|
| DMU1 | Observed→ | | 0.56 | -0.09 | -0.44 |
| | Target | Scheel | 0.88 | -0.09 | -0.42 |
| | | MSBM | 0.77 | -0.07 | -0.39 |
| | | $RDM^+$ | 0.88 | -0.09 | -0.42 |
| | | SORM | 0.89 | -0.06 | -0.08 |
| DMU2 | Observed→ | | 0.74 | -0.24 | -0.31 |
| | Target | Scheel | 1.58 | -0.24 | -0.31 |
| | | MSBM | 0.74 | -0.05 | -0.23 |
| | | $RDM^+$ | 1.53 | -0.22 | -0.28 |
| | | SORM | 1.33 | -0.18 | -0.29 |
| DMU4 | Observed→ | | 5.61 | -0.98 | -3.79 |
| | Target | Scheel | 9.19 | -0.66 | -0.18 |
| | | MSBM | 9.45 | -0.60 | -0.05 |
| | | $RDM^+$ | 8.96 | -0.84 | -0.32 |
| | | SORM | 9.45 | -0.6 | -0.05 |
| DMU5 | Observed→ | | 0.49 | -1.08 | -0.34 |
| | Target | Scheel | 1.21 | -0.27 | -0.28 |
| | | MSBM | 0.58 | 0.00 | -0.24 |
| | | $RDM^+$ | 1.21 | -0.27 | -0.28 |
| | | SORM | 1.21 | -0.27 | -0.28 |
| DMU6 | Observed→ | | 1.61 | -0.44 | -0.34 |
| | Target | Scheel | 1.87 | -0.36 | -0.20 |
| | | MSBM | 1.61 | -0.23 | -0.21 |
| | | $RDM^+$ | 1.86 | -0.36 | -0.20 |
| | | SORM | 1.87 | -0.36 | -0.20 |
| DMU9 | Observed→ | | 0.52 | 0.00 | -0.37 |
| | Target | Scheel | 0.57 | 0.00 | -0.24 |
| | | MSBM | 0.57 | 0.00 | -0.24 |
| | | $RDM^+$ | 0.57 | 0.00 | -0.24 |
| | | SORM | 0.57 | 0.00 | -0.24 |
| DMU10 | Observed→ | | 2.14 | -0.52 | -0.18 |
| | Target | Scheel | 5.50 | -0.48 | -0.13 |
| | | MSBM | 5.25 | -0.31 | -0.11 |
| | | $RDM^+$ | 5.31 | -0.34 | -0.12 |
| | | SORM | 5.55 | -0.47 | -0.10 |
| DMU12 | Observed→ | | 0.57 | -0.67 | -0.43 |
| | Target | Scheel | 1.85 | -0.47 | -0.40 |
| | | MSBM | 1.85 | -0.17 | -0.20 |
| | | $RDM^+$ | 2.24 | -0.34 | -0.19 |
| | | SORM | 2.27 | -0.37 | -0.19 |

As can be seen in Table 16 all methods generally yield improved targets on all the outputs, which is what we would expect. It is noteworthy that the two 'negative' outputs Methane and $CO_2$ are outputs whose reduction is desired and so the lower the absolute values of these outputs in a target set the better the targets. However, the methods differ on the actual targets they determine.

The efficiency scores reported in Table 17 are the average efficiency over the three output variables Saleable, $CO_2$ and Methane using the procedure outlined in respect of Table 16 above.

Table 17: The efficiency measure of inefficient DMUs

| DMU | Average Efficiency | | | |
|---|---|---|---|---|
| | Scheel | MSBM | RDM | SORM |
| DMU1 | 86 | 78 | 86 | 49 |
| DMU2 | 82 | 66 | 77 | 63 |
| DMU4 | 55 | 41 | 52 | 51 |
| DMU5 | 49 | 52 | 49 | 49 |
| DMU6 | 76 | 71 | 76 | 76 |
| DMU9 | 52 | 85 | 85 | 52 |
| DMU10 | 68 | 55 | 57 | 61 |
| DMU12 | 65 | 35 | 42 | 42 |

Table 17 suggests that each method can serve different level of improved performance.

## 5. SORM: advantages and drawbacks

The SORM method represents an instrument for arriving at targets for improved performance when some of the variables in a DEA framework take negative values. One key feature that distinguishes SORM from other methods such as RDM and MSBM, also capable of handling negative data within DEA, is that it treats each input-output variable essentially as being the sum of two variables, one taking its negative value and the other its positive value and so that the sum of the two leads to the initial value of the variable. This approach creates an advantage but also a drawback.

The advantage is that the negative part of a variable can be dealt with in absolute value terms and thus in positive format without arbitrary changes of origin as might otherwise be necessary to achieve positive values. The preservation of the origin means a form of radial pursuit of targets can be engaged in which could have intuitive appear for the user, albeit radial in terms of the positive or negative part of a variable but not necessarily radial for their sum. The radial targets mean in turn that a form of a radial efficiency measure can be obtained though it is noted that this is radial on the positive and negative parts of each variable rather than on the original variables. The measure and indeed the targets SORM yields reduce to those of traditional DEA if no variable takes negative values. Thus in a sense SORM generalises the original radial DEA Models (Charnes *et al.*; 1978 and Banker *et al.*; 1984) leading to the original notion of targets and to efficiency measures which are relatively easy to interpret in terms of implications.

The disadvantage is that the increase in dimensionality of the problem, consequent on treating negative parts of a variable as a distinct variable, means that part of the original production possibility set is deleted and the method may not necessarily determine Pareto efficient targets. However, the method cannot lead to targets that are worse than the observed input-output levels of the unit.

## 6. Conclusion

The standard DEA Model cannot be used for efficiency assessment of decision making units with negative data. The additive Model, undesirable DEA, Range Directional Measures (RDM) and Modified Slack-Based Model (MSBM) could be used for this case with some limitations. For example the additive Model does not give an efficiency measure. The main drawback of the $RDM^+$ Model is that it cannot guarantee projections on the Pareto efficient frontier, as happens with the classical radial DEA Model.

The Semi-Oriented Radial Measure (SORM) overcomes some of the foregoing difficulties, but not all. The SORM Model can be used in cases where some DMUs have positive and others negative values on a variable. Further, it can be used for DMUs with negative input and negative output at the same time. Finally, as other Models in this area, the SORM Model will lead to improved targets and never to a worsening of any input or output.

# CHAPTER 5 : INTERGRATED DEA WITH C&R TREE[5]

## 1. Introduction

Chapter 3 reviewed the literature on banking efficiency. It is clear that DEA is the most popular method in evaluating bank efficiency. This chapter deals with some issues that still faced researchers in banking efficiency. Two issues are discussed and two Models are proposed with illustrating examples. The first issue is how to deal with the environmental factors (exogenous factors) in DEA context and the second issue is how to deal with negative data.

To address the first issue, several studies attempt to answer the question of how to examine the relationship between continuous variables limited between 0 and 1 (efficiency score) and selected environmental factors. These environmental factors could be continuous (bank established date), categorical (country) or classificatory (bank operating style). Most of the previous studies dealt with these factors using two stage analyses, at the first stage to evaluate the DMUs efficiency score using DEA Models. A common approach to second stage is two limits Tobit regression, which is suitable when the dependent variables are either censored or corner solution outcomes, of which DEA scores falls within the second category. However, Hoff (2007) noted that Tobit regression is misspecified when applied to DEA scores. Furthermore, McDonald (2009) shows that, Tobit regression is an inappropriate estimation procedure since it is an inconsistent estimator and it is often similar to OLS estimates. Therefore, in this study we propose a three stage analysis using classification and regression (C&R) tree as a third stage tool to investigate the effects of the environmental factors.

This chapter is organized as follow; Next section introduces current methods to deal with the environmental factors, proposes a new method to deal with such factors and provides a real example to highlight the advantage of the proposed method. However, this part has been published before developing the SORM Model, therefore, the banks with negative data (profit) are excluded, only we include in this example all banks with nonnegative data (profit). The full dataset that includes banks

---

[5]) This chapter partially is adopted from our forthcoming paper:
Ali Emrouznejad and **Abdel Latef Anouze** (in press), Data envelopment analysis with classification and regression tree – a case of banking efficiency, *Expert Systems*,

with negative and positive profit is included in the next chapter, as we employed the SORM Model to get the efficiency score for each bank. Some conclusions are offered in the final section.

## 2. The proposed method

In this chapter we propose a two stage performance analysis using DEA, a DEA is used to measure banks efficiency while, C&R tree, a nonparametric data mining technique for classification and regression is used to set rules for the efficient banks. For illustrative purposes, we use this methodology to evaluate the performance of 36 banks in Gulf Cooperation Council (GCC). Since the sample size is limited by 36 banks and to run C&R tree analysis needs a large dataset, therefore we introduced a re-sampling technique as a third stage, to evaluate the banking performance and incorporate the environmental factors. DEA scores provides valuable information for the performance of banks while C&R tree revealed additional facts that have not been identified from previous studies.

### a. Classification and regression tree (C&R)

Data mining techniques allow DMUs to explore and discover meaningful, previously hidden information from huge databases. C&R is the commonly used decision tree in data mining that was developed by Breiman, *et. al.* (1984) and further improved by Ripley (1996). A tree structure represents the given decision problem such that each non-leaf node is associated with one of the decision variables, each branch from a non-leaf node is associated with a subset of the values of the corresponding decision variable, and each leaf node is associated with a value of the target (or dependent) variable. For each leaf the tree associates the mean value of the target variable, thus, a tree is an alternative approach to continuous linear Models for regression problems and to linear logistic Models for classification problems (Clark and Pregibon, 1992). In principle, C&R tree is similar to regression analysis since both are used for prediction. However, C&R tree uses a step function and the regression analysis uses continuous functions (Clark and Pregibon, 1992).

Generally, C&R tree has some advantages over the regression Model. First, a Model generated by a C&R tree is easier to understand and relatively simple to interpret for non-statisticians (Breiman *et al*., 1984; Torgo, 1997; Edelstein, 1996; Han *et al*., 2001). Secondly, It is inherently non-parametric that means no assumptions need to be made regarding the underlying distribution of values of the predictor variables. Thus, C&R tree can handle numerical data that are highly skewed or multi-modal, as well as categorical predictors with either ordinal or non-ordinal structure. This is an important feature; generally, it eliminates analyst time which would otherwise be spent determining whether variables are normally distributed and making transformation if they are not, specifically, it is important for using it with DEA since DEA scores are skewed to one side.

Furthermore, C&R tree has sophisticated methods for dealing with missing variables as compared with the regression that omit data that has any missing values automatically. Thus, C&R tree can be generated even when important predictor variables are not known for some decision making units. DMUs with missing predictor variables are not dropped from the analysis but, instead, substitute variables containing information similar to that contained in the primary splitter are used (Torgo, 1997). When predictions are made using a C&R tree, predictions for DMU with missing predictor variables are based on the values of substitute variables as well. Finally, C&R tree is a relatively automatic “machine learning” method. C&R trees provide computational efficiency since they take less time in computation and require less storage.

To generate a C&R tree, the dataset is partitioned into at least two parts: the training dataset and the validation dataset (commonly referred to as the test dataset) (Han and Kamber, 2001). Then it goes into two major phases of process: the growth phase and the pruning phase (Kim and Koehler, 1995). In the growth phase the C&R constructs a tree from the training dataset. In this phase, either each leaf node is associated with a single class or further partitioning of the given leaf would result in the number of cases in one or both subsequent nodes being below some specified threshold. In the pruning phase the generated C&R tree in the growth phase is improved in order to avoid over-fitting. In this phase, the C&R tree is evaluated against the validation (or test) dataset in order to generate a sub-tree with the lowest error rate against the validation dataset.

There are several criteria for measuring performance of C&R trees. The predictive accuracy of a C&R tree is commonly measured by R-squared (average squared error); however simplicity and stability are also important measures for a C&R tree. Simplicity refers to the interpretability of the C&R tree and is often based on the number of leaves in the C&R tree. Stability of a C&R tree refers to obtaining similar results for the training and validation datasets. One way to assess the stability of the C&R tree can be achieved by comparing the predicted mean value of the target variable (based on the training dataset) and the corresponding value for the validation dataset for each rule of the C&R tree (Han and Kamber, 2001). Next section introduce in more details the C&R tree methodology

## Introduction to classification and regression (C&R) tree

As stated before that the C&R tree is a nonparametric technique introduced by Breiman et al. (1984) for explaining and/or predicting both categorical and continuous responses. It uses historical data to construct so-called decision tree (rules) by selecting those variables and their interactions that are most important in determining a dependent variable (target). If the target variable is continuous, C&R tree produces regression trees; whereas, if it is categorical, C&R tree produces classification trees. C&R algorithm learns attributes (input factors) by constructing them top-down manner starting with selecting the best attribute to test at the root of the tree. To find the best attribute, each instance attribute is put into a statistical test to determine how well it alone classifies the training examples. The best feature is selected and used as a test node of the tree. A child of the root node is then created for each possible value of the attribute namely two children for ordered features as $x_i \leq c$ and $x_i > c$ , and m children for unordered feature as $x_i = c_1, x_i = c_2, \ldots, x_i = c_m$ where m is the number of different possible values of the feature $x_i$. The splitting of the parent nodes continues until their child nodes are homogeneous, that is the objects in the node are very similar or a predefined number of objects in the Terminal nodes is reached (Caetano et al, 2007). Following figure shows the partition process.

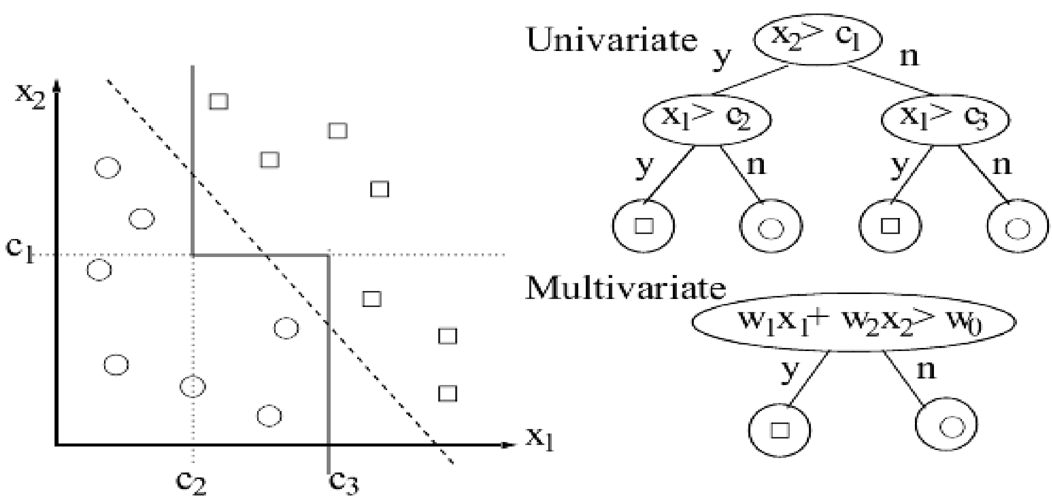


Figure 12: The construction of multivariate decision trees

## C&R tree computational methods

C&R tree methodology mainly consists of three steps: it starts by *tree building step*: an over-large tree is grown by recursive partitioning of the data hence, this tree will have a large number of terminal nodes and, though it describes the dataset perfectly. However, it will have a low predictive ability since it over-fits the data. The second step called *pruning step*, the sequence of nodes that should be eliminated to obtain a set of smaller trees is found. The last stage of this procedure is called *selection step*, the selection of the optimal tree taking into account the predictive error of the trees which is obtained using cross-validation (CV).

### Tree Building (Growing)

C&R tree searches for the best possible variable (splitter) to divide the root node (initial dataset) into two more homogeneous child nodes. The goodness of the split (impurity reduction), $\Delta(s,t)$, can be determined using the following equation:

$$\Delta(s,t) = i(t) - p_L i(t_L) - p_R i(t_R)$$

where $s$ is the candidate split of a variable ($v$, $t$) the parent node, $i(t)$ the impurity of the node $t$, $p_L$ and $p_R$ the proportions of objects going to the left $(t_L)$ or right $(t_R)$ child nodes, respectively, and $i(t_L)$ and $i(t_R)$ their impurities. Several impurity measures have been proposed as splitting criteria, for classification trees to choose the best split such as: deviance and Gini indexes. The deviance index allows forming groups where the diversity within them is minimized, and the impurity of the node is determined as:

$$i(t) = -\sum_{j=1}^{k} p_j(t)\ln(p_j(t))$$

In the above equation: $i(t)$ is the impurity of node $(t)$, $p_j(t)$ the fraction of objects in node $(t)$ that belong to the $j^{th}$ class of the $(k)$ classes present in the dataset. Contrary to the deviance index, Gini aims to isolate a single class of the dataset. The reason of this behavior lies on the fact that the Gini index reaches its minimum value when the node contains only objects of the same class (pure node).

The impurity is then determined as

$$i(t) = 1 - \sum_{j=1}^{k} \left(p_j(t)\right)^2$$

By using one of the splitting criteria mentioned above an over-large tree is built by a recursive division of the nodes.

## Tree pruning

The resulting tree, built on the first step is usually a large tree and describes the initial dataset perfectly, such tree often is difficult to interpret and their predictive ability for new observations is generally poor. Accordingly, selecting of a smaller tree with better predictive ability without losing much accuracy is then necessary for predictive purposes. Therefore, prune the resulting tree from the first step is essential to generate a sequence of smaller trees, which are obtained by removing successively branches of the maximal tree. The optimal tree size is found by pruning, that is, by successive cutting back branches of the over-large tree. This procedure determines a sequence of smaller trees and establishes which is the most accurate by calculating its cost-complexity. The cost complexity measure, $\mathrm{R}_\beta$ is defined as a linear combination of the cost of the tree and its complexity

$$\mathrm{R}_\alpha = \mathrm{R(T)} + \beta|\breve{\mathrm{T}}| \Leftrightarrow \beta = \frac{\mathrm{R}_{\beta -}\mathrm{R(T)}}{|\breve{\mathrm{T}}|}$$

Where R(T) is the resubstitution estimated error, which for a classification tree is given by the misclassification error, $|\breve{\mathrm{T}}|$ is the size of the sub-tree (number of terminal nodes) and $\beta$ is the complexity parameter. During the pruning procedure $\beta$ takes values between 0 and 1, and a sequence of nested trees of decreasing size is found. It was proved by Breiman et al. (1984) that for one $\beta$ value, among all sub-trees of the same size, only one is found that minimizes the above equation.

## Optimal tree selection

The final step starts with selecting the optimal tree from the generated sequence of sub-trees through evaluating the predictive error of the trees. This is often estimated using cross validation technique where, some samples are randomly drawn from the dataset, to test the tree, which is built with the rest of the data. For a ten-fold cross validation, the original dataset is divided into ten equal parts (test sets), each containing a similar distribution for the response variable. A tree is then built using 70% of the observations (learning set), while the remaining 30% (test set) are used to test the tree. This step is repeated different times (usually

10 times) using each time a different test set and the remaining observations as the learning set. The optimal tree is the one having the minimal cross validation error (most accurate tree). However, in the practice, the optimal tree is chosen as the simplest tree with a predictive error estimate within one standard error (SE) of minimum (1-SE). In this way, the chosen tree is the simplest with an error estimate comparable to that of the most accurate one.

We employ C&R trees to explore the impact of internal and external factors such as country, operational style, size, price book value, capital structure, market share, etc on productivity of GCC banks. The target value for the tree is the efficiency score obtained by DEA, Therefore DMUs are divided to two efficient and inefficient groups, and hence our tree target is a discrete (categorical) variable.

### b. DEA with C&R methodology

A C&R tree proposed in this study consists of four main components. The first component is the outcome variable or “dependent” variable. In general, this variable is the characteristic which we hope to predict, based on the predictor or independent variables. In our study the outcome variable is the DEA efficiency score classified as efficient (target=1) and non-efficient (target=0). The second component of a C&R tree is the predictor variable. There are many possible predictor variables depend on the aim to achieve. In this study the predictor variables are internal and external factors as listed in Table 2. The third component of the C&R tree is the learning dataset. This is a dataset which includes values for both the outcome and predictor variables, from a group of DMUs to those for whom we would like to be able to predict outcomes. The fourth component of the C&R tree is the test or further dataset, which consists of decision making units for which we would like to be able to make accurate predictions. This test dataset may or may not exist in practice. While it is commonly believed that a test or validation dataset is required to validate a classification or decision rule, a separate test dataset is not always required to determine the performance of a decision rule. Figure 13 illustrates the steps for banking efficiency using DEA/C&R.

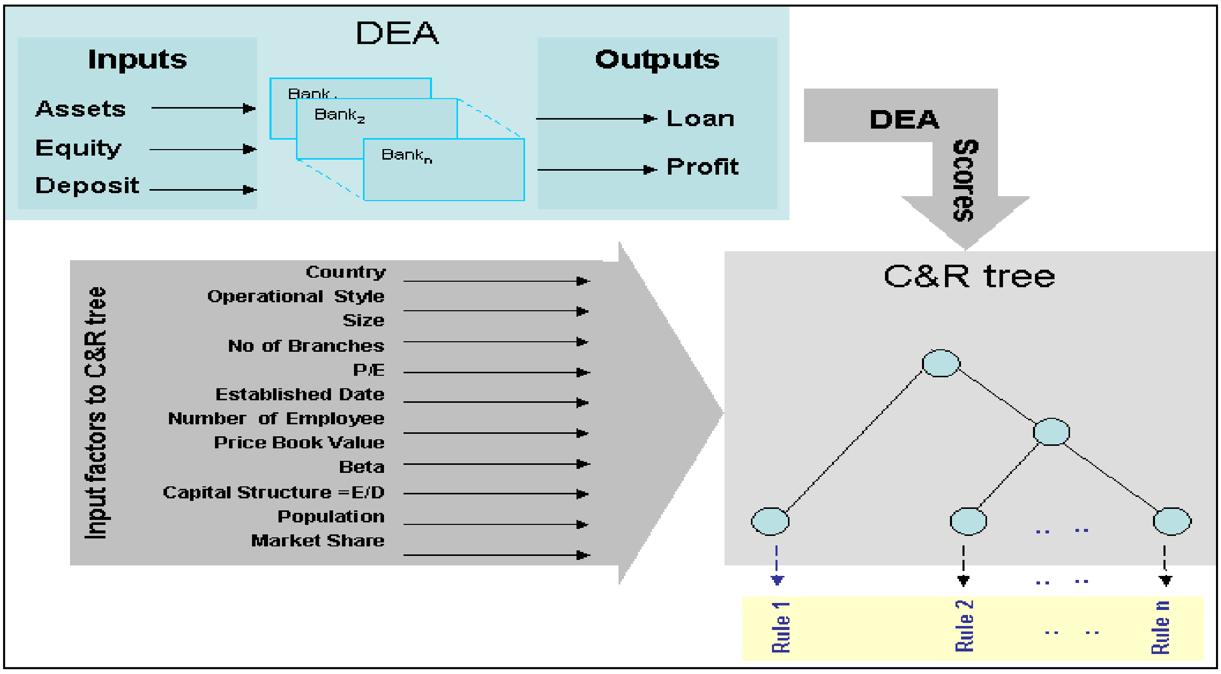



Figure 13: DEA/C&R methodology for GCC banks

Figure 13 illustrates the three stages analysis; stage 1 is to compute the efficiency score of each bank using DEA. Accordingly, the banks are categorized into two groups; (efficient banks, target =1 and inefficient banks, target =0). As an accurate C&R requires a large dataset, so at the second stage we increase the original dataset by bootstrapping technique. Hence stage 2 is to randomly select (x) units (by replacement) and we repeat this sampling (n) time to get a large number of units. After re-sampling the original data set the dataset is divided, into two groups of train and test (validation), by ratio of 7:3 (Zhou and Jiang, 2003). Stage 3 is to use the classified efficiency score (0 or 1) as the target variable of the C&R tree and the other uncontrollable variables explanatory variables. Next part illustrates these stages using 36 banks operating in GCC countries.

## 3. Empirical Study: DEA with C&R: a case of GCC banking efficiency

### a. Data Description

Due to presence of negative profit (loss) and unavailability of the data, in this example we included only 36 commercial banks with total assets of $312,591.30 Million. Islamic banks share by $64,851.94 Million, which represent 20.75%. Figure 14 shows the share of bank assets within each country. Saudi Arabia, the largest investor in GCC, shares 40% of the total assets with 9 conventional banks and 1 Islamic bank and had a total asset of $132,733.54 Million in 2002. UAE with 6 conventional and 3 Islamic banks and a total asset of $63,571.01 Million in 2002 is the second largest investor in the area. Bahrain with 8 conventional and 3 Islamic banks and a total asset of $60,776.73 Million and Kuwait with 8 conventional and 1 Islamic banks and a total asset of $57,157.27 Million are placed in the 3rd position. Finally, Qatar with 4 conventional and 2 Islamic banks and a total asset of $15,145.79 Million represents only 4% of the total assets.

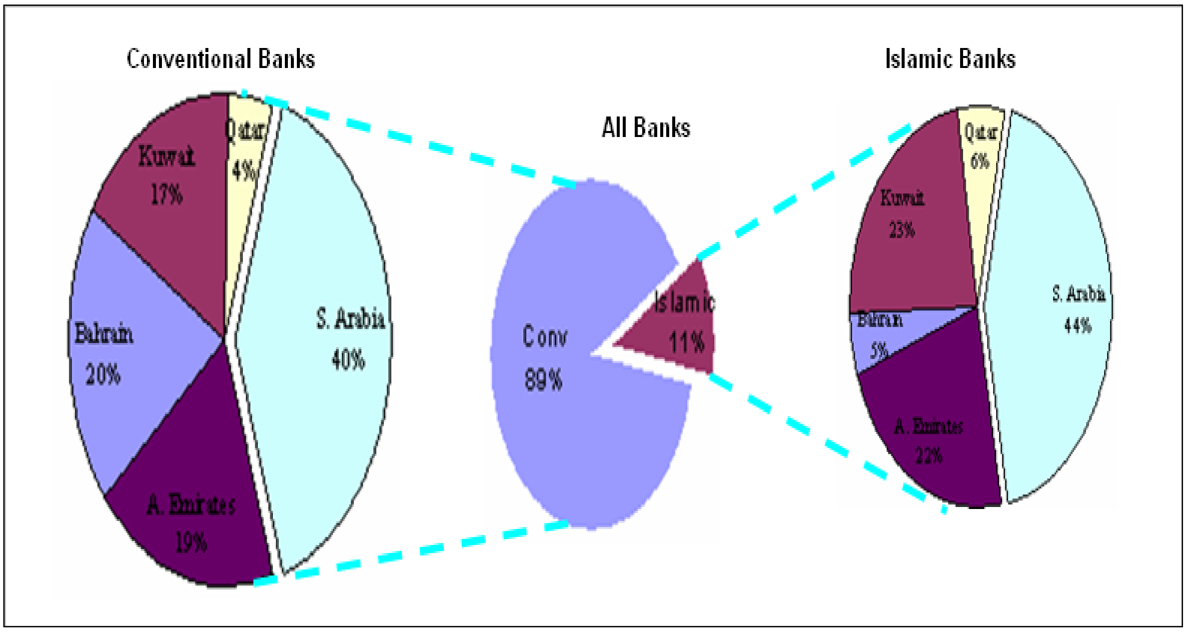



Figure 14: Share of assets; GCC commercial banks

## b. Stage 1: DEA analysis

In this section we employ the intermediation approach with three inputs; total assets, capital, and deposits, and two outputs; loans and net profit. The data used in this section is obtained from BankScope database, which is global database containing information on public and private banks. Table 18 shows the descriptive statistics of the selected variables.

Table 18: Input/output variables in DEA

| Variable ( Million $) | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| **Inputs** | | | | |
| Assets | 731.25 | 29313.00 | 8683.09 | 7515.12 |
| Equity | 66.37 | 2381.04 | 876.58 | 664.27 |
| Deposit | 549.36 | 25251.31 | 7140.03 | 6287.32 |

| Variable ( Million $) | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| **Outputs** | | | | |
| Loan | 150.66 | 15379.00 | 4146.32 | 3681.61 |
| Profit | 13.56 | 486.29 | 111.19 | 119.45 |

The efficiency of GCC commercial banks are computed and reported in Table 19 using an output oriented DEA Model with variable returns to scale assumption as outlined in Model (7). Twelve banks are fully efficient and the overall average efficiency of 79.92% indicates that, in general, the GCC banks could produce on average 20% higher outputs with the same level of inputs.

Table 19: DEA-scores, GCC bank efficiency

| Bank | Efficiency Score | | Bank | Efficiency Score |
|---|---|---|---|---|
| **Bahrain** | | | **Saudi Arabia** | |
| Al-Ahli United Bank | 60 | | Arab National Bank | 62 |
| Bahraini Saudi Bank | 45 | | Bank Al Jazira | 59 |
| Bank of Bahrain & Kuwait | 50 | | Banque Saudi Fransi | 82 |
| National Bank of Bahrain | 76 | | Riyadh Bank | 89 |
| **Bahrain Average** | **57.75** | | Saudi American Bank | 100 |
| | | | Saudi Hollandi Bank | 71 |
| **Kuwait** | | | Saudi Investment Bank | 74 |
| Al Ahli Bank of Kuwait | 100 | | Al-Rajhi Banking | 100 |
| Bank of Kuwait & ME | 100 | | **Saudi Arabia Average** | **79.63** |
| Burgan Bank | 53 | | **UAE** | |
| Commercial Bank of Kuwait | 100 | | Bank of Sharjah | 100 |
| Gulf Bank | 70 | | Commercial Bank of Dubai | 100 |
| Kuwait Real State Bank | 67 | | Emirates Bank Intern. | 98 |
| National Bank of Kuwait | 100 | | First Gulf Bank | 100 |
| Kuwait Finance House | 81 | | Investment Bank | 100 |
| **Kuwait Average** | **83.88** | | Mashreq Bank | 77 |
| | | | National Bank of Abu Dhabi | 82 |
| **Qatar** | | | National Bank of Fujairah | 51 |
| Commercial Bank of Qatar | 100 | | National Bank of RAK | 69 |
| Doha Bank | 91 | | Union National Bank | 100 |
| Qatar-Inter. Islamic Bank | 32 | | Abu Dhabi Islamic Bank | 91 |
| Qatar Islamic Bank | 82 | | Dubai Islamic Bank | 65 |
| **Qatar Average** | **76.25** | | **UAE Average** | **86.08** |
| **GCC average (all banks)** | | | | **79.92** |

### c. Stage 2 – Re-sampling

One of the difficulties with using DEA/C&R is that in many DEA studies there is not enough data available to generate the decision tree. Hence the following Re-sampling method is proposed to increase the number of DMUs prior to construction of the C&R tree. As an accurate C&R requires a large dataset, and we have only 36 banks, so we increase the original dataset to 100 times by re-sampling re-sampling technique. Hence in stage 2 we randomly select 36 units (by replacement) and we repeat this sampling 100 times to get 3600 units, this will ensure we get a better accuracy on the predicted tree. After re-sampling the original data set 100 times the dataset is divided, into two groups of train and validation, by ratio of 7:3

### d. Stage 3 – C&R analysis

According to DEA, banks have been divided into two groups, efficient (DEA score=100) and inefficient (DEA score<100). These groups are used as the target variable in the C&R tree. Table 20 shows all the factors that were included in the C&R algorithm.

Table 20: Input factors in C&R tree

| Variable | Variable type | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Country[1] | Categorical | 1 | 5 | | |
| Operational style[2] | Categorical | 1 | 2 | | |
| Size[3] | Numerical | 0.23 | 9.38 | 2.78 | 2.40 |
| No of branches | Numerical | 3 | 505 | 55 | 107 |
| Price earning index (P/E)[4] | Numerical | 6.04 | 49.56 | 18.78 | 8.02 |
| Established date[5] | Categorical | 1952 | 2000 | | |
| Number of employees | Numerical | 97.00 | 3557.00 | 1042.28 | 788.14 |
| Price book value[6] | Numerical | 1.28 | 15.36 | 4.57 | 2.79 |
| Beta[7] | Numerical | -0.07 | 1.38 | 0.71 | 0.33 |
| Capital structure (E/D)[8] | Numerical | 0.08 | 0.31 | 0.15 | 0.06 |
| Population[9] | Numerical | 2.14 | 68.27 | 21.21 | 25.75 |
| Market share[10] | Numerical | 0.21 | 9.82 | 2.78 | 2.45 |

1) 1=Bahrain; 2 = UAE; 3= Kuwait; 4= Qatar and 5= Saudi Arabia
2) 1=Conventional bank and 2=Islamic bank
3) Size of the bank is proportion of the bank assets to the total Assets
4) P/E: Price earning index helps in evaluating the attractiveness of an investment. It is calculated as “last closing price” divided by “latest trailing 4-quarter earnings” per share.
5) The date of establishment is the date on which that bank chooses to claim as its starting point.
6) It is the ratio of market price to book value, and indicates a growth prospects and calculated as “last closing price” divided by “latest book value”.
7) It is a relative measure of the systematic return of the stock to the overall market. Stocks with

| Variable | Variable type | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|

Betas greater than 1.0 are highly volatile and have a positive correlation with the market; such stocks are termed aggressive securities. Stocks with Betas less than 1.0 are either more stable than the average or have a low correlation with the market or both (defensive securities). Stocks with a negative Beta move in the direction opposite to that of the market. Beta 1.5 means the stock moves 50% more than the overall market in the same direction. Beta 0.5 means the stock moves 50% less than the overall market. Beta (-1.0) means the stock tends to move in a direction opposite from the overall market.

8) Capital structure refers to the way a bank finances itself through some combination of equity sales, equity options, bonds, and loans. A bank's capital structure is then the composition or 'structure' of its liabilities
9) Population of the country as percentage of the total population.
10) It shows the extent of bank's risks, as higher ratios of loans to total assets reveals the aggression of lending by the bank to increase profits.

## e. Results and discussion

We built two C&R trees with a different selection of input variables. First we included country, operational style, number of branches, price earning index (P/E), price book value, beta, capital structure, and market share as inputs and efficiency classification as output. Note that the data shows size, number of branches and number of employees are highly correlated hence we included only a number of branches to reflect the size of banks. Figure 15 shows the importance of variables.

| Variable | Score |
|---|---|
| PRICEBVAL | 100.00 |
| P_E | 76.10 |
| COUNTRY__S$ | 67.75 |
| BETA | 53.83 |
| MARKETSHARE | 35.77 |
| CAPTAILSTRU | 34.50 |
| BRANCHES | 23.54 |
| OPSTYLE__S$ | 9.06 |

Figure 15: Importance of variables

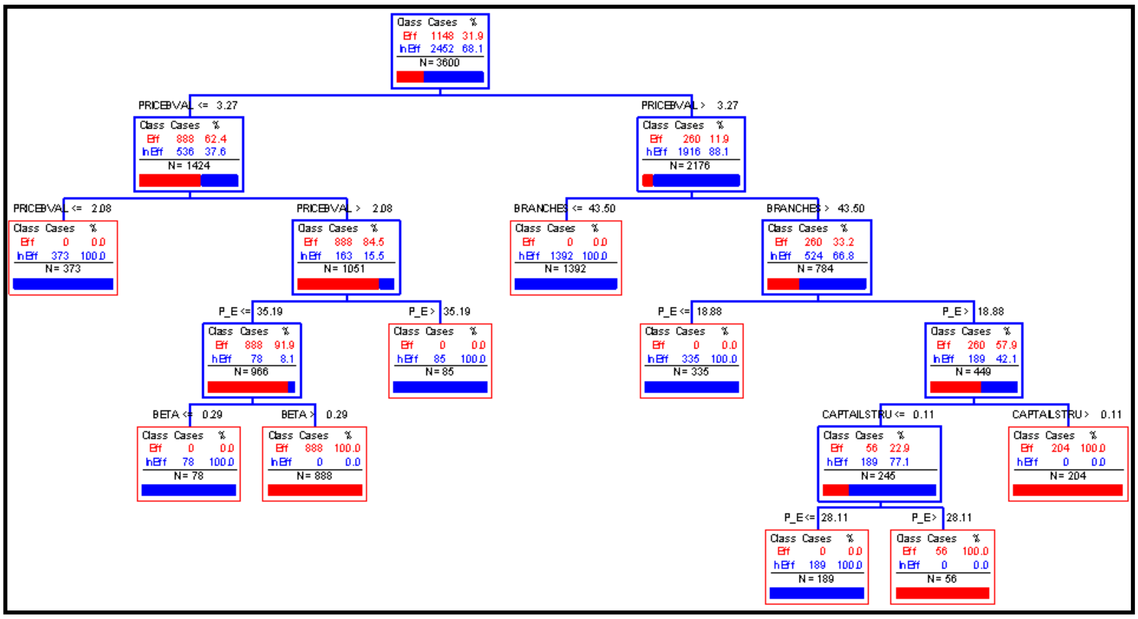
As it can be seen in this figure, the price book value is the most important variable in determining the classification, price earning index (76.10%) and country (67.75%) are the second and third important variables. The number of branches and the operation style seem to be less important in the classification.

Figure 16 shows the predicated accuracy of the generated tree. Out of 3,600 cases 1,148 cases are predicted to be efficient with accuracy of 100%. 2,452 cases are predicted to be inefficient. However in total there are 2374 inefficient banks in the dataset, hence the accuracy in predicting the inefficient banks is 96.82%. The overall accuracy level of the predicted C&R tree is 97.83%, which represents a high level of confidence.

Figure 16: Predicated accuracy of the tree

| Actual Class | Total Cases | Percent Correct | Predicted Class: Eff N=1226 | Predicted Class: InEff N=2374 |
|---|---|---|---|---|
| Eff | 1,148 | 100.00 | 1,148 | 0 |
| InEff | 2,452 | 96.82 | 78 | 2,374 |
| Total: | 3,600.00 | | | |
| Average: | | 98.41 | | |
| Overall % Correct: | | 97.83 | | |

Figure 17 illustrates the generated C&R tree




*The red color indicate the efficient cases whereas, the blue color indicates the inefficient cases, the same for all C&R tree figures

Figure 17: C&R tree for GCC banks

According to this tree the following 9 rules can be extracted:

Rules for efficient banks: Banks are efficient (total of 1148 cases) if:

**Rule one**: Price book value is greater than 2.08 but less than or equal 3.27, price earning index is less than or equal 35.19 and beta is greater than 0.29 (888 cases).

**Rule two**: Price book value is greater than 3.27, number of bank branches is greater than 44, price earning index is greater than 28.11 and capital structure is less than or equal 0.11 (56 cases).

**Rule three**: Price book value is greater than 3.27, number of bank branches is greater than 44, price earning index is greater than 18.88 and capital structure is greater than 0.11 (204 cases).

Rules for inefficient banks: The banks are inefficient (total of 2452 cases) if:

**Rule four**: Price book value is less than or equal to 2.08 (373 cases).

**Rule five**: Price book value is greater than 2.08 but less than 3.27, price earning index is less than or equal to 35.19 and beta is less than or equal to 0.29 (78 cases).

**Rule six**: Price book value is greater than 2.08 but less than or equal to 3.27 and price earning index is greater than 35.19 (85 cases).

**Rule seven**: Price book value is greater than 3.27 and number of bank branches is less than or equal to 44 (1392 cases).

**Rule eight**: Price book value is greater than 3.27 and number of bank branches is greater than 44 and price earning index is less or equal than 18.8 (335 cases).

**Rule nine**: Price book value is greater than 3.27, number of bank branches is greater than 44, price earning index is greater 18.8 but less than or equal to 28.11 and capital structure is less than or equal 0.11 (189 cases).

With limitation of the number of banks and because of the large number of input variables included in the C&R tree it can be seen that only price book value, price earning index, beta and capital structure are enough to extract the rules. To investigate the impact of other factors that are not included in the above decision tree, a second C&R tree is drawn by including input variables of country, operational style, number of branches, and market share. In this case Figure 18 shows the importance of variables.

| | | |
|---|---|---|
| MARKETSHARE | 100.00 | |
| BRANCHES | 85.76 | |
| COUNTRY__S$ | 50.26 | |
| OPSTYLE__S$ | 23.59 | |

Figure 18: Importance of variables

It can be seen that market share is the most important variable while operation style is the least important variable in the classification of the banks. Interestingly the accuracy of this tree is 100% as shown in Figure 19.

| Predicted Class | | | | |
|---|---|---|---|---|
| Actual Class | Total Cases | Percent Correct | Eff N=1148 | InEff N=2452 |
| Eff | 1,148 | 100.00 | 1,148 | 0 |
| InEff | 2,452 | 100.00 | 0 | 2,452 |
| Total: | 3,600.00 | | | |
| Average: | | 100.00 | | |
| Overall % Correct: | | 100.00 | | |

Figure 19: Predicated accuracy of the tree

Fourteen rules can be extracted from the generated C&R tree (see Figure 20). Some of these rules are:

**Rule one**: Banks are inefficient if they are located in Bahrain, Qatar and Saudi Arabia, and their number of branches is less than or equal to 15 (393 cases).

**Rule two**: Banks are inefficient if they are located in UAE or Kuwait, their number of branches is less than or equal 15 and their market share is greater than 2.25 (85 cases).

**Rule three**: Banks are efficient if they are located in UAE or Kuwait, their number of branches is less than or equal to 15 and their market share is less than or equal to 2.25 but greater than 0.61 (210 cases).

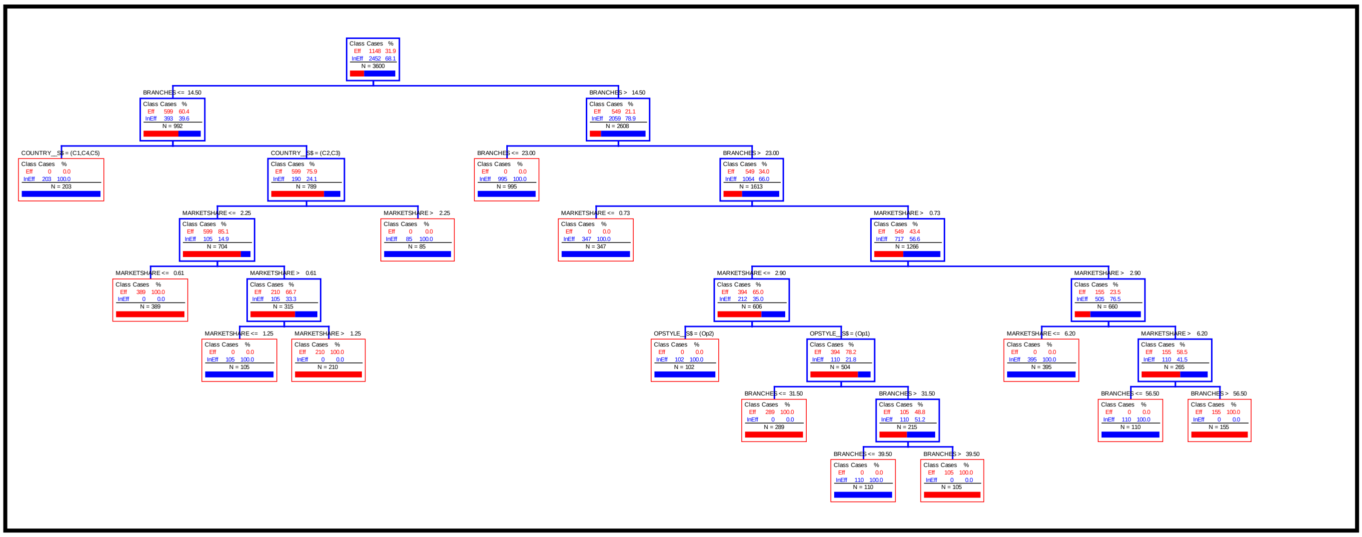


Figure 20: C&R tree

## 4. Conclusion

In General we conclude that, DEA is a managerial tool for measuring efficiency and productivity of decision making units. This section introduces a framework that combined DEA with classification and regression analysis. While the use of DEA has provided valuable results, our C&R-based analysis revealed additional findings that were not identified in the previous studies. For example unlike the econometric-based studies that identify a uniform impact of market share on efficiency, our C&R-based analysis suggests that the level of the impact of the market share on efficiency depends on the bank size and the operation style, even within each of the two major banking systems, Islamic and conventional banks, the impact of market share is not uniform. On the other hand we found that capital structure, price book value and price earning index could be used to identify the efficiency of selected banks. Unlike the previous DEA applications that focused only on numeric fields to calculate the efficiency scores, this study used C&R to further investigate any rules that can be obtained for being an efficient or an inefficient DMU using both numerical and categorical variables. Obviously the rules are more useful to policy makers.

There are a number of additional topics, although of practical importance to those using C&R tree analysis, are beyond the scope of our analysis. These include the choice of independent factors for banking sector and the use of different splitting rules and accuracy measures as well as improving Re-sampling technique. These could be areas for future development in DEA/C&R.

# CHAPTER 6 : DATA DESCRIPTION AND ANALYSIS

## 1. Introduction

A new methodology for measuring efficiency of decision making units with negative data was developed in the previous chapter. This chapter aims to evaluate the performance of the GCC commercial banks over the study period 1998-2007. Also, it aims to compare the performance of Islamic with Conventional banks and to investigate the effect of environmental factors (internal (bank) and external (country) specification) on bank performance.

SORM Model and C&R tree technique are used: SORM is used to measure the performance of GCC commercial banks and C&R tree is used to investigate the effect of environmental factors on bank performance. Therefore, the structure of this chapter is as follow; section two describes the data and section three presents the first stage empirical results. Section four presents the second stage empirical results and section five draw some conclusions.

## 2. Banking Industries in Gulf State Countries

Commercial banks in GCC as stated early are divided into groups according to their operating style: Islamic and Conventional banks. The most important difference between the two operating style is that Islamic banks are running their financial transactions with free of interest. This means there is no interest rate to be taken or given against any financial transaction, while it is an interest based transactions in Conventional banks case.

### a. Data Description

The data used in this study are a cross-country bank-level data, compiled from income statements and balance sheets of 60 banks each year in the 1998-2007 periods in GCC countries. The main data source is BankScope database, which is the most comprehensive available database of banking sector, where the financial statement data are converted into common international standards to facilitate comparisons. However, we largely rely on BankScope for data quality. There are a number of important issues with this database. It is argued that data obtained from

BankScope need to be dealt with carefully in order to ensure that a reliable sample has been constructed (Bonin *et al.*, 2005). This means that the data still required substantial editing, in order to avoid problems associated with double counting of institutions to ensure consistent accounting standards and to ensure those nonbank financial institutions were excluded from the sample. In our study we have done a basic crosschecking and also excluded banks with insufficient data.

Although, our sample consists of banks from various countries with differing accounting regulations, we believe the accounting data are comparable across the whole sample since the financial statements data optioned from BankScope are reported in a unified global format. Furthermore, the data that we collected from other sources was added to the database; hence it was converted automatically and instantly to the same unified global format. Furthermore, our empirical analysis relies to a large extent on unconsolidated bank statements. Ideally, we would have opted for using only consolidated statements for all banks. We therefore use consolidated data when available, but when consolidated data are not available for a bank, we use unconsolidated data instead. Moreover, since Islamic banks are based on interest free principles, the problem raised relating to the definitions of financial indicators for Islamic banks, for example what to include in capital, or how to measure (the equivalent of) interest income. To deal with this issue, the variables adopted in this study are based on the equivalence of the inputs and outputs which follow closely to the conventional bank. Whatsoever, this database has been used extensively in research into banking internationally and can produce useful results, provided data entry is undertaken with care. A brief statistical descriptive of the input and output variables are presented in Table 21.

Table 21: Descriptive analysis of input and output variables[6] (in Million US$)

| Inputs/Outputs | Variables | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Inputs | Fixed Assets | 7.28 | 24.16 | 0.03 | 413.34 |
| | Non-earning assets | 21.86 | 55.08 | 0.00 | 609.61 |
| | Deposits | 424.11 | 940.28 | 0.00 | 11,161.00 |
| Outputs | Investments | 226.01 | 525.43 | 0.00 | 5,766 |
| | Loans | 256.26 | 531.37 | 1.27 | 7,528.63 |

[6] ) Original data was expressed in nominal each country's currency. We converted the data to real terms using Consumer Price Index (CPI), with 1997 as the base year. We then converted all of the variables to real 1997 US$ using the real exchange rate for 1997, which is the base year for GCC and US CPIs.

| Inputs/Outputs | Variables | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| | Off-balance sheet | 166.87 | 423.91 | 0.00 | 4,619.70 |
| | Net profit | 8.70 | 21.52 | -289.01 | 195.97 |

Table 21 shows that our Model consists of 3 inputs and 4 outputs; these variables vary over the study period, the minimum value of fixed assets which is one of the inputs is US$ 0.03 Million whereas the maximum value is US$ 413.34 Million, with average US$ 7.28 Million and standard deviation US$ 24.16 Million. The same thing for other variables, take for example the net profit, the minimum net loss is US$ 289.01 Million, and the maximum value is US$ 195.97 Million, with average US$ 8.70 Million and standard deviation US$ 21.52 Million. This variation and the high standard deviation for all variables relatively reflect the heterogeneity among the selected banks. Given the long time period of analysis, it is expected to find such variation, Therefore, since DEA Models are sensitive to observations it is likely to find significant levels of variation in the efficiencies as well.

## 3. Empirical Results

Based on SORM Model 19 technical efficiency is computed for all GCC commercial banks. The intermediate banking approach is employed to measure the performance GCC commercial banks. The input variables include; fixed assets, non-earning assets, and deposits, while the outputs are; loans, investments, net profit and off-balance sheet. The technical efficiency measure from SORM is tested with five (Bauer *et al*. 1998) consistency checks; the efficiency estimates should be consistent in the efficiency levels, rankings, identification the best and worst efficient banks, the stability of efficiency score over the study period and it is relation with non-frontier measures of performance.

### a. First stage: SORM analysis

We calculate bank efficiency scores at the individual bank level, using three input and four output variables, and then aggregate annual average efficiency scores of all banks at the country level. We believe that there is a reasonable degree of homogeneity between GCC banking systems and technology, which could justify use of a common frontier. Hence, we use one common frontier for all countries to calculate efficiency scores, rather than separate frontier for each country.

Furthermore, since grand-frontier approach provides a trend in the efficiency of banks, which would not be available if we calculated the efficiency of banks using a separate frontier for each year therefore, we used the grand-frontier since it provides a best practice benchmark against which the efficiency of each bank in each year. The employed approach, therefore, provides variations in the efficiency of banks over both time and space. This comparison across time and countries is on the same principles as the use of global frontier in Portela and Thanassoulis (2010).

For comparison of GCC commercial banking efficiency, we defined the common frontier based on the traditional approach, i.e., building a common frontier by pooling the bank data of all the countries and considering a DEA Model with different banking inputs and outputs. VRS-output-oriented Model is used to measure GCC commercial banks efficiency, since; CRS is not possible in technologies where negative data can exist (Portela *et al*, 2004). An input-oriented Model would be inappropriate as the underlying assumption is the desirability to maximize bank output rather than minimize the used resources, since we believe that the initial inputs which include fixed assets and non earning assets are results of long term decisions rather the short ones (annual).

Table 22 and Table A-1 in the appendix show that the average of the efficiency score has turned out to be 85.6% for 60 commercial banks; this suggests that, by adopting best practices, GCC commercial banks can be, on an average, increase their outputs by 14.4 % with the same level of inputs. However, the potential increment in outputs from adopting best practices varies from bank to bank. In general, GCC commercial banks have the scope of producing 1.17 times (i.e.$\frac{1}{0.856}$) as much outputs from the same level of inputs.

Table 22: summary of banks technical efficiency

| Bank Code | Efficiency score | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
| Average | 89 | 88 | 89 | 88 | 87 | 86 | 92 | 77 | 81 | 79 | 85.6 |
| No of efficient banks | 27 | 30 | 26 | 26 | 27 | 27 | 29 | 24 | 26 | 26 | 10 |

Table 22 shows that, out of 60 commercial banks covered in this study, there are 10 fully efficient banks. The technical efficiency remain slightly stable over the period 1998-2003, then slightly improved to reach the highest level (92%) during the 2004, while the period 2005-2007 witnessed volatility of the efficiency score. The year 2005 exhibits a fallen technical efficiency across banks under study (77%). This may reflect the response to the economic and financial activity to the political instability aroused from conflict aggravation in the Gulf crisis.

## Technical efficiency trend

The technical efficiency literature provides no consensus on how efficiency in banking varies with the passage of time in response to market forces (Berger *et al.*, 1993). But, since the study period is relatively long and turbulent time (it includes the second gulf crisis in 2003), it is expected that the gulf crisis will dominate the market force, hence it is not an easy task to investigate bank response to market force. A simple plot of the technical efficiency score is presented in Figure 21.

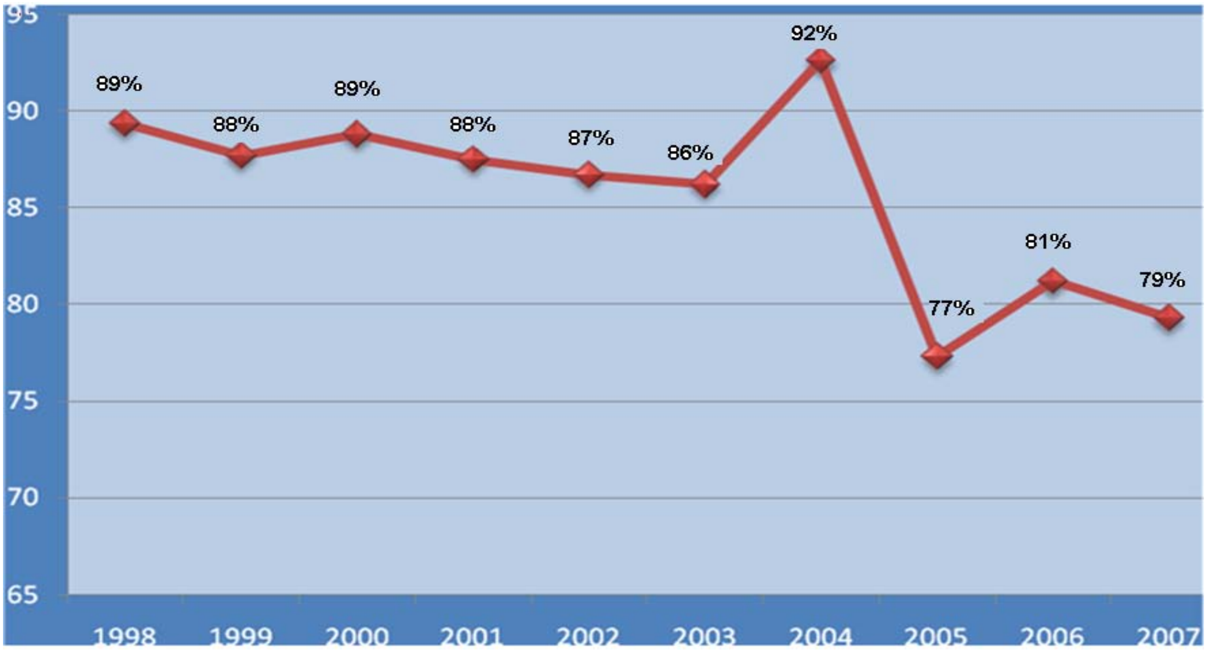



Figure 21: Technical efficiency of GCC banks over the study period

The overall results show relatively low average efficiency scores; nevertheless, it is possible to detect a slight improvement in the efficiency levels between the average efficiency score of the year 1998 and 2004 (+2.2%). In general, Figure 21 shows that bank efficiency mostly stable over the period between 1998 and 2003 (86%-89%). It is slightly improved in 2004 to reach it is highest level (92%), and then fluctuated to reach 79.3% at the end of the period. It seems that, over time, banks are wasting higher resources on average relative to the industry's best practice technical frontiers.

Although, GCC banking sector experienced substantial growth in the early 1990s, the poorest performance over the study period could be attributed to the second gulf crisis. To find out whether the efficiency scores show a particular trend during the period 1998–2007, we ask whether the mean efficiency score has increased since 1998. Figure 19 shows that the mean efficiency scores moves in the same direction over period 1998-2003, then it is raised to the highest level in 2004, whereas it is reached it is it is lowest efficiency level in 2005. Although, 2004 seems to be atypical year, it is important to note that the performance of GCC commercial banks is varying over the study period as it will explain later. Another appropriate way to study the trend is by looking at mean and the standard deviation of technical efficiency. If GCC's banking markets have become more alike over our 10 year period under consideration, we expect an increase in mean technical efficiency and a decrease in the spread of technical efficiency.

Table 23 shows the on average technical efficiency is slightly stable for the period 1998-2003, and then reached its highest level in the 2004. The lowest efficiency score exhibited during the year 2005, which is two years later to second Gulf crisis, then fluctuated below the average for the last two years. The standard deviation slightly stable for the period 1998-2003, and then reached it is lowest level in the 2004. The highest standard deviation reveals in 2005, then fluctuated over the mean for the last two years. The standard deviation tends to be low when average technical efficiency is high, and vice versa. This result strongly support the view that traditional efficiency techniques based on pooled frontier efficiency scores tend to estimate the actual efficiency levels of each banks. Additionally, the lowest values of Skewness and Kurtosis are strong evidence of a convergence trend.

Table 23: Statistical descriptive of the average overall technical efficiency

| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 89.4 | 87.7 | 88.8 | 87.5 | 86.7 | 86.2 | 91.6 | 77.3 | 81.2 | 79.3 | 85.6 |
| Std Dev | 12.4 | 14.6 | 12.2 | 14.5 | 16.5 | 16.5 | 11.4 | 25.4 | 23.3 | 24.6 | 11.6 |
| Skewness | -0.9 | -0.7 | -0.7 | -0.8 | -1.1 | -0.9 | -1.3 | -0.9 | -1.2 | -0.8 | -0.3 |
| Kurtosis | -0.4 | -0.9 | -0.9 | -0.6 | 0.3 | -0.3 | 0.4 | -0.4 | 0.6 | -0.6 | -1.2 |

The negative Skewness which is the degree of asymmetry of a distribution around its mean, indicates that the distribution of the technical efficiency with an asymmetric tail extending towards more negative values. While the negative kurtosis which is the relative peakedness or flatness of a distribution compared to the normal distribution indicates a relatively flat distribution

Technical efficiency cross GCC countries

To measure GCC commercial bank technical efficiency, Model 19 is computed, with four inputs and three outputs. The following table summarize the results for each country.

Table 24: GCC commercial bank technical efficiency

| Country | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bahrain | 89.5 | 83.7 | 86.5 | 86.2 | 79.3 | 81.6 | 90.7 | 82.9 | 85.2 | 85.1 | 85.1 |
| UAE | 89.6 | 89.6 | 89.5 | 88.0 | 89.5 | 90.4 | 93.4 | 77.4 | 79.8 | 76.4 | 86.3 |
| Kuwait | 93.9 | 93.5 | 94.5 | 95.6 | 95.7 | 93.1 | 95.0 | 54.1 | 55.9 | 58.0 | 82.9 |
| Oman | 87.3 | 82.7 | 87.5 | 83.6 | 81.7 | 81.0 | 89.9 | 81.1 | 88.4 | 93.8 | 85.7 |
| Qatar | 80.5 | 79.3 | 79.7 | 76.7 | 77.3 | 71.8 | 86.9 | 84.2 | 91.4 | 85.4 | 81.3 |
| Saudi Arabia | 91.3 | 91.2 | 91.5 | 89.6 | 89.4 | 88.0 | 89.2 | 86.9 | 93.7 | 87.6 | 89.8 |
| Average | 89.4 | 87.7 | 88.8 | 87.5 | 86.7 | 86.2 | 91.6 | 77.3 | 81.2 | 79.3 | 85.6 |

Table 24 shows that the overall technical efficiency for all GCC commercial banks. Although, the average efficiency score for all GCC commercial banks reached it is highest level in 2004, it is varying according to their geographical location. Take for example banks operating in Qatar and Saudi Arabia their highest efficiency score occurred in 2006, while banks operating in Oman their highest efficiency score occur in 2007. However, the reason could be due to the fact that the government of countries such as UAE, Kuwait and Bahrain injected more money in the financial market (banks) after the gulf crisis (2003-2004) to avoid their banking sector failure or bankruptcy. As a result, the banking sector performs well, when the government stopped such injection in 2005 the performance is decline to reach it is lowest level over the study period.

Saudi Arabia banks appear to be ahead of the GCC countries with average efficiency score, around 89.8%, followed by United Arab Emirates banks with efficiency score 86.3%. It seems to be a tight competition between Omani and Bahraini commercial banks with average efficiency score 85.7% and 85.1% respectively. Banks operating in Qatar are the lowest efficient banks, around 81.3%. Although, these efficiency scores are incomparable with the other studies results (as the frontier is not same), the GCC commercial banks efficiency score on average is less than their counterpart in other countries such as; Singapore (95%), Japan (87%), Germany (92%), and Peru (98%). Nevertheless, the results relatively is similar to what Al Shammari (2003) found for the same countries using SFA were he found that the average efficiency for GCC commercial banks is 88% over the period 1995-1999. Also, this is within the average of efficiency for the banks in some Industrialized countries like France 84.3%, US 83% and UK 83.9% Spain (82-84%) or developed countries like, Lebanon (84%) and China (85%). However it requires more effort from GCC bankers and decision makers to improve their banks efficiency.

The aforementioned results suggest that, even though it is possible to detect a slight improvement in the overall efficiency scores, there are marked differences in bank efficiency levels across GCC countries. This means that country-specific characteristics still play an important part in the explanation of bank efficiency levels. Perhaps the more interesting point is the comparisons of bank efficiencies, which are really much more dissimilar from each other. Therefore, next section examines the efficiency score based on the country level.

### Bahraini commercial banks' Technical efficiency

To measure the performance of Bahraini commercial banks, the average efficiency score is reported in Table 25.

Table 25: Technical efficiency of Bahraini commercial banks[7]

| Bank Code | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BCB01 | 66 | 77 | 91 | 89 | 89 | 88 | 95 | 63 | 80 | 79 | 82 |
| BCB03 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 74 | 90 | 100 | 96 |
| BCB04 | 89 | 78 | 78 | 73 | 71 | 68 | 71 | 78 | 78 | 56 | 74 |
| BCB05 | 100 | 56 | 85 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 94 |
| BCB06 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| BCB07 | 71 | 76 | 82 | 66 | 52 | 100 | 100 | 100 | 100 | 100 | 85 |
| BCB08 | 80 | 70 | 79 | 73 | 75 | 72 | 93 | 70 | 67 | 61 | 74 |
| BIB01 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| BIB02 | 100 | 100 | 100 | 100 | 37 | 38 | 67 | 56 | 55 | 41 | 69 |
| BIB03 | 79 | 100 | 66 | 82 | 76 | 63 | 100 | 100 | 93 | 99 | 86 |
| BIB04 | 100 | 63 | 69 | 66 | 72 | 69 | 71 | 69 | 74 | 100 | 75 |
| Average | 89 | 84 | 86 | 86 | 79 | 82 | 91 | 83 | 85 | 85 | 85 |

[7]) Note that in Bank Codes' the first letter stand for the country (Bahrain in this case) and the second letter represents the operating style (C for conventional banks and I for Islamic Banks), Banks cod and names are illustrated in appendix A-4

| Bank Code | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Std. Dev. | 13.3 | 16.9 | 12.6 | 14.7 | 21.3 | 21.1 | 13.6 | 17.3 | 15.5 | 22.2 | 11.2 |

Table 25 shows that there are 11 commercial banks operating in Bahrain; 7 Conventional and 4 Islamic banks. The average overall technical efficiency score of Bahraini commercial banks is 85.1%, which means that by adopting best practices, banks can produce 14.9% extra output from the same level of input. This efficiency is fluctuated over the time, it is 89% at the beginning of the period slightly decline to 84% at the second year then raised to reach it is highest level 1% in 2004, then it is fluctuated again to reach 85% at the end of the period. The fluctuated standard deviation over the study period 1998-2004 is suggesting that Bahraini banks vary in their efficiency. The high standard deviation suggests a higher differentiation across banks in terms of efficiency.

Out of the 11 banks operating in Bahrain there are only two fully efficient banks; BCB06, which is Conventional bank and BIB01 which is an Islamic bank. It is of interest to note that few banks appear to be fully efficient during the study period; i.e. BIB02, which is Islamic bank, is fully efficient over the period 1998-2001, then dropped down to 36.68% in 2002, slightly improved during the year 2004, then slightly rising to 67% in 2004, after that fluctuated to reach 41% at the end on the period. Also, BCB03 is fully efficient over the period 1998-2004, then dropped to 75% in the 2005, slightly improved to reach 90% in 2006 and to become fully efficient again at the end of the period. Take for example bank BIB02, the efficiency score is 100% for 2001 and 37% for 2002, to investigation of the source of this deviation Table 26 shows the analysis result for the two years.

Table 26: Bank (BIB02) technical efficiency for the year 2001-2002

| Year | Inputs | | | Outputs | | | |
|---|---|---|---|---|---|---|---|
| | Fixed Assets | Non Earning Assets | Deposits | Investment | Loans | OBS | Profit |
| 2001 | 0.08 | 3.64 | 13.42 | 1.52 | 12.94 | 6.12 | 0.19 |
| 2002 | 0.42 | 3.77 | 14.54 | 1.38 | 12.98 | 4.90 | 0.23 |
| Ratio | 5.4 | 1.04 | 1.08 | 0.91 | 1.0 | 0.80 | 1.19 |

As Table 26 shows that although, the input and output values are mostly close up, but the fixed asset during the year 2002 is 5.4 times of its value of 2001, thus the efficiency score become 37%. It is worth mentioning that bank BIB02 to be fully efficient during 2002; Table 26 must be used together with the derived lambdas (not presented here). However, since ECB07, ECB13 and OCB06 define the feasible improvement target for all BIB02s outputs, the feasible target for BIB02 from the given inputs can be calculated using the following expression:

$$\hat{Y}_{rj} = \sum \lambda_j^* Y_j$$

The feasible target output for BIB02 can be calculated as:

$$\hat{Y}_{BIB02}\begin{bmatrix} Investment \\ Loan \\ OBS\ Items \\ Profit \end{bmatrix} = 0.02\begin{bmatrix} 124.96 \\ 312.11 \\ 106.56 \\ 10.02 \end{bmatrix} + 0.01\begin{bmatrix} 214.75 \\ 407.55 \\ 821.21 \\ 10.87 \end{bmatrix} + 0.97\begin{bmatrix} 0.00 \\ 25.45 \\ 0.00 \\ 1.11 \end{bmatrix} = \begin{bmatrix} 4.65 \\ 35.00 \\ 10.34 \\ 1.38 \end{bmatrix}$$

Where 0.02; 0.01 and 0.97 are the $\lambda$-values for ECB07, ECB13 and OCB06 respectively; it is important to note that none of the peers of BIB02 are from Bahrain and all of them are conventional banks, whereas BIB02 is an Islamic bank. The feasible target inputs for BIB02 can be calculated as

$$\hat{Y}_{BIB02}\begin{bmatrix} \text{Fixed Assets} \\ \text{Non Earning Assets} \\ \text{Deposits} \end{bmatrix} = 0.02\begin{bmatrix} 3.68 \\ 7.73 \\ 310.66 \end{bmatrix} + 0.01\begin{bmatrix} 6.14 \\ 13.27 \\ 560.56 \end{bmatrix} + 0.97\begin{bmatrix} 0.17 \\ 0.14 \\ 1.74 \end{bmatrix} = \begin{bmatrix} 0.30 \\ 0.42 \\ 13.51 \end{bmatrix}$$

Table 27 summarize the target and observed (actual) inputs-output variable of bank BIB02

Table 27: Bank (BIB02) target and observed inputs-outputs

| Year | Inputs | | | Outputs | | | |
|---|---|---|---|---|---|---|---|
| | Fixed Assets | Non Earning Assets | Deposits | Investment | Loans | OBS | Profit |
| Observed | 0.42 | 3.77 | 14.54 | 1.38 | 12.98 | 4.90 | 0.23 |
| Target | 0.30 | 0.42 | 13.51 | 4.65 | 35.00 | 10.34 | 1.38 |
| Improvement | - 29% | -89% | -7% | +237% | +170% | +111% | +500% |

Table 27 shows that bank BIB02 to be fully efficient they should reduce their inputs as well as improve their output. Their fixed assets, non earning assets and deposits should be reduced by 29%, 89% and 7% respectively, whereas their investments, loans, OBS items and profits should be increase by 237%, 170%, 111% and 500% respectively.

## Omani commercial banks' Technical efficiency

To measure the performance of Omani commercial banks, the average efficiency score is reported in Table 28

Table 28: technical efficiency of Omani commercial banks

| Bank | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| OCB01 | 58 | 67 | 67 | 67 | 63 | 73 | 79 | 72 | 90 | 100 | 74 |
| OCB02 | 100 | 100 | 92 | 96 | 97 | 90 | 94 | 80 | 82 | 86 | 92 |
| OCB03 | 89 | 69 | 90 | 82 | 75 | 62 | 76 | 53 | 70 | 83 | 75 |
| OCB04 | 89 | 77 | 89 | 73 | 73 | 80 | 100 | 100 | 100 | 100 | 88 |
| OCB06 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Average | 87.3 | 82.7 | 87.5 | 83.6 | 81.7 | 81.0 | 89.9 | 81.1 | 88.4 | 93.8 | 85.7 |
| Std Dev | 17.2 | 16.3 | 12.2 | 14.3 | 16.0 | 14.6 | 11.5 | 19.9 | 12.7 | 8.6 | 11.3 |

Table 28 shows that there are 5 banks operating in Oman, all of them are Conventional banks, out of the 5 banks there is one fully efficient bank. The overall average technical efficiency is 85.7%, this means that by adopting best practices banks can produce 14.3% extra outputs than they actually produced from the same level of inputs. This efficiency is slightly fluctuated around the mean over the study period. It is 87.3% at the beginning of the period declining to reach 81% in 2003, then fluctuated again to reach it is highest score (93.8%) at the end of the period. Few banks appear to be fully efficient for one or more years during the study period; bank OCB04 is fully efficient over the period 2004-2007 and OCB02 is fully efficient over the period 1998-1999. However, OCB02 to be fully efficient during the year 2000, within the same level of input they should produce the following amount of outputs;

$$\hat{Y}_{OCB02} = 0.34\begin{bmatrix}191.85\\448.64\\416.97\\16.21\end{bmatrix} + 0.04\begin{bmatrix}180.51\\294.45\\179.69\\14.34\end{bmatrix} + 0.37\begin{bmatrix}27.55\\270.41\\59.01\\3.12\end{bmatrix} + 0.26\begin{bmatrix}0.25\\40.94\\0.00\\0.33\end{bmatrix} = \begin{bmatrix}82.71\\275.01\\170.79\\7.33\end{bmatrix}$$

This means that bank OCB02 to be fully efficient, they should improve their investment and loans by 11%, OBS items by 106% and profit by 152% more than they actually achieved.

## Kuwaiti commercial banks' Technical efficiency

To measure the performance of Kuwaiti commercial banks, the average efficiency score is reported in Table 29

Table 29: technical efficiency of Kuwaiti commercial banks

| Bank | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| KCB01 | 86 | 88 | 86 | 84 | 82 | 77 | 97 | 31 | 39 | 40 | 71 |
| KCB02 | 92 | 80 | 87 | 95 | 100 | 89 | 82 | 17 | 18 | 21 | 68 |
| KCB03 | 83 | 80 | 84 | 87 | 84 | 81 | 88 | 20 | 25 | 24 | 66 |
| KCB04 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 39 | 57 | 63 | 86 |
| KCB05 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| KCB06 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 40 | 32 | 33 | 80 |
| KCB07 | 90 | 100 | 100 | 99 | 100 | 100 | 100 | 100 | 100 | 100 | 99 |
| KCB08 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 38 | 39 | 42 | 82 |
| KIB01 | 95 | 94 | 94 | 96 | 95 | 91 | 88 | 100 | 93 | 100 | 95 |
| Average | 93.9 | 93.5 | 94.5 | 95.6 | 95.7 | 93.1 | 95.0 | 54.1 | 55.9 | 58.0 | 82.9 |
| Std. Dev | 6.6 | 8.8 | 7.1 | 6.2 | 7.3 | 9.2 | 7.1 | 35.4 | 33.3 | 33.7 | 13.1 |

Table 29 shows that there are 9 commercial banks operating in Kuwait; out of them one Islamic bank. Out of the 9 banks there is only one fully efficient bank, whereas, there are few banks appear to be fully efficient during the study period; such as KCB04, KCB06 and KCB08 those banks are fully efficient over the period 1998-2004, then their efficiency score is dramatically slump down, which is the results of second Gulf crisis. The overall average technical efficiency is 82.9%, which means that by adopting best practices banks can produce 17.1% extra outputs than they actually produced from the same level of inputs. The efficiency score is slightly stable during the period 1998-2004, then significantly dropped down to reach 54.1% in 2005, which is two years later to the second gulf crisis. The average efficiency score is then slightly improved to reach 58% at the end of the period. Although, the standard deviation is slightly low over the period 1998-2004, but it is consistently higher over the period 2005-2007, suggesting that this period contains both fully efficient and extremely inefficient banks.

### Qatar commercial banks' Technical efficiency

To measure the performance of Qatar commercial banks, the average efficiency score is reported in Table 30

Table 30: technical efficiency of Qatar commercial banks

| Bank | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| QCB01 | 71 | 71 | 64 | 54 | 63 | 58 | 79 | 85 | 83 | 62 | 69 |
| QCB02 | 64 | 59 | 71 | 64 | 78 | 86 | 93 | 49 | 65 | 71 | 70 |
| QCB03 | 90 | 100 | 91 | 84 | 100 | 65 | 82 | 100 | 100 | 83 | 89 |
| QCB04 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| QIB01 | 87 | 82 | 75 | 77 | 61 | 58 | 76 | 89 | 100 | 100 | 81 |
| QIB02 | 71 | 64 | 78 | 81 | 63 | 64 | 91 | 81 | 100 | 97 | 79 |
| Average | 80.5 | 79.3 | 79.7 | 76.7 | 77.3 | 71.8 | 86.9 | 84.2 | 91.4 | 85.1 | 81.3 |
| Std. Dev | 13.9 | 17.9 | 13.3 | 16.2 | 18.6 | 17.3 | 9.4 | 18.7 | 14.4 | 16.4 | 11.9 |

Table 30 shows that there are 6 commercial banks operating in Qatar, out of them two are Islamic. One bank is fully efficient over the study period. The overall average technical efficiency is 81.3%, which means that by adopting best practices banks can produce 19.7% extra outputs than they actually produced from the same level of inputs. This efficiency is fluctuated over the time, it is 80.5% at the beginning of the period decline to reach 71.8% in 2003, then it is improved to reach 91.4% which is the highest score in 2006, in 2007 it is slightly fallen down to reach 85.1%. The highest standard deviation suggests a higher differentiation across banks in terms of efficiency

### Saudi commercial banks' Technical efficiency

To measure the performance of Saudi commercial banks, the average efficiency score is reported in Table 31

Table 31: technical efficiency of Saudi commercial banks

| Bank | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| SCB01 | 92 | 100 | 90 | 89 | 89 | 87 | 88 | 83 | 91 | 87 | 90 |
| SCB02 | 62 | 59 | 66 | 54 | 54 | 58 | 64 | 62 | 100 | 45 | 62 |
| SCB03 | 100 | 100 | 100 | 100 | 97 | 92 | 99 | 87 | 100 | 100 | 97 |
| SCB04 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| SCB05 | 100 | 100 | 100 | 100 | 100 | 98 | 96 | 83 | 82 | 85 | 95 |
| SCB06 | 94 | 93 | 92 | 94 | 92 | 98 | 91 | 100 | 100 | 100 | 95 |
| SCB07 | 84 | 79 | 83 | 85 | 84 | 78 | 81 | 67 | 70 | 71 | 78 |
| SCB08 | 89 | 90 | 93 | 84 | 89 | 80 | 84 | 100 | 100 | 100 | 91 |
| SIB01 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Average | 91.3 | 91.2 | 91.5 | 89.6 | 89.4 | 88.0 | 89.2 | 86.9 | 93.7 | 87.6 | 89.8 |
| Std. Dev | 12.3 | 14.0 | 11.3 | 14.8 | 14.5 | 13.9 | 11.9 | 14.8 | 10.8 | 18.9 | 12.3 |

Table 31 shows that there are 9 commercial banks operating in Saudi Arabia, out of them only one Islamic bank. Out of the 9 banks there are two fully efficient banks SCB04, which is Conventional bank and SIB01, which is Islamic bank. Few banks appear to be fully efficient during the study period; SCB03 is fully efficient over the period 1998-2001, SCB05 is fully efficient during the period 1998-2002, whereas SCB06 and SCB08 are fully efficient over the period 2005-2007.

The overall average technical efficiency is 89.8%, which means that by adopting best practices banks can produce 10.2% extra outputs than they actually produced from the same level of inputs. This efficiency is relatively stable over the period 1998-2004, it is 91.3% at the beginning of the period declining to reach 88% in 2003, then fluctuated to reach it is highest level 93.7% in 2006, then slightly decline to reach 87.6% at the end of the period. The highest standard deviation suggests a higher differentiation across banks in terms of efficiency.

It is noticeable that in most cases the efficiency score has declined after 2003, which is reflect of the second Gulf crisis, while other cases the efficiency score is declined in 2005 which two years later to the Gulf crisis.

### UAE commercial banks' Technical efficiency

To measure the performance of Arab Emirates commercial banks, the average efficiency score is reported in Table 32

Table 32: technical efficiency of Emirates commercial banks

| Bank | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ECB01 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| ECB02 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 21 | 20 | 26 | 77 |
| ECB03 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| ECB04 | 74 | 100 | 100 | 100 | 74 | 87 | 100 | 100 | 100 | 68 | 90 |
| ECB05 | 68 | 72 | 71 | 61 | 77 | 67 | 62 | 53 | 51 | 57 | 64 |
| ECB06 | 82 | 89 | 87 | 88 | 95 | 87 | 90 | 39 | 50 | 55 | 76 |
| ECB07 | 95 | 100 | 100 | 100 | 100 | 100 | 100 | 32 | 100 | 92 | 92 |
| ECB08 | 73 | 62 | 71 | 68 | 88 | 100 | 100 | 43 | 60 | 57 | 72 |
| ECB09 | 100 | 60 | 65 | 82 | 100 | 100 | 100 | 90 | 100 | 100 | 90 |
| ECB10 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 82 | 63 | 71 | 92 |
| ECB11 | 100 | 87 | 89 | 89 | 95 | 88 | 96 | 100 | 89 | 100 | 93 |
| ECB12 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| ECB13 | 100 | 100 | 100 | 100 | 100 | 100 | 95 | 96 | 85 | 100 | 98 |
| ECB14 | 68 | 74 | 73 | 63 | 59 | 60 | 73 | 72 | 74 | 56 | 67 |
| ECB15 | 78 | 88 | 67 | 60 | 70 | 60 | 89 | 100 | 100 | 67 | 78 |
| ECB16 | 85 | 75 | 82 | 79 | 82 | 100 | 100 | 100 | 83 | 88 | 87 |
| EIB01 | 86 | 84 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 97 |
| EIB02 | 82 | 100 | 100 | 100 | 100 | 100 | 100 | 87 | 81 | 97 | 95 |
| EIB03 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 56 | 60 | 45 | 86 |
| EIB04 | 100 | 100 | 86 | 69 | 51 | 60 | 63 | 75 | 79 | 50 | 73 |
| Average | 89.6 | 89.6 | 89.5 | 88.0 | 89.5 | 90.4 | 93.4 | 77.4 | 79.8 | 76.4 | 86.3 |
| Std. Dev | 12.2 | 13.8 | 13.3 | 15.6 | 15.4 | 15.4 | 12.5 | 26.8 | 22.7 | 23.7 | 11.5 |

Table 32 shows that, out of the 20 commercial banks operating in UAE, there are only 4 Islamic banks. Three banks appear to be fully efficient over the study period, also few banks appear to be fully efficient during the study period such as; ECB02, ECB10 and EIB03 are fully efficient over the period 1998-2004, also, ECB07 and EIB02 are fully efficient over the period 1999-2004.

Also, Table 32 shows that the overall technical efficiency score between is 86.3%. It is mostly stable over the period 1998-2003, raised to it is highest level during the year 2004 to reach 93.4% then sharply decline to reach it is lowest level (76.4%) at the end of the period. This worst performance of UAE banks could be due to the influence of second gulf crisis, which means that the crisis took two years to start it is influence on banking system in UAE. Although, the standard deviation is slightly low over the period 1998-2004, but it is consistently higher over the period 2005-2007, suggesting that this period contains both fully efficient and extremely inefficient banks. Nevertheless, the highest standard deviation suggests a higher differentiation across banks in terms of efficiency.

## Peer groups

SORM identifies for each inefficient bank a set of excellent banks, which includes those banks that are efficient if evaluated with the optimal system of weights of an inefficient bank, this set called peer group. The peer group, made up of banks which are characterized by operating methods similar to the inefficient one being examined, is a realistic term of comparison which the bank should aim to imitate in order to improve its performance. In our case, Table 33 shows, out of the 60 GCC commercial banks (600 observations over the study period 1998-2007), 44 banks appeared to be fully efficient since their efficiency score equal to 100%. These banks together define the best practice frontier and thus, form the reference set.

Table 33: technical efficiency of Emirates commercial banks

| Bank Code | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| OCB06 | 20 | 16 | 22 | 21 | 18 | 21 | 13 | 14 | 17 | 12 | 174 |
| KCB06 | 29 | 20 | 22 | 27 | 21 | 20 | 18 | | | | 157 |
| BCB06 | 19 | 15 | 12 | 15 | 11 | 12 | 20 | 12 | 10 | 1 | 127 |
| ECB07 | 0 | 2 | 18 | 10 | 16 | 16 | 24 | | 21 | | 107 |
| ECB01 | 15 | 17 | 23 | 15 | 8 | 1 | 3 | 4 | 1 | 9 | 96 |
| ECB12 | 1 | 1 | 10 | 15 | 16 | 14 | 13 | 8 | 11 | 6 | 95 |
| SCB08 | | | | | | | | 37 | 31 | 26 | 94 |

| Bank Code | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| KCB04 | 2 | 2 | 8 | 11 | 13 | 27 | 12 | | | | 75 |
| BIB01 | 4 | 1 | 4 | 2 | 9 | 3 | 3 | 2 | 11 | 28 | 67 |
| QCB04 | 15 | 8 | 3 | 5 | 3 | 7 | 2 | 2 | 5 | 6 | 56 |
| EIB02 | | 23 | 6 | 10 | 6 | 5 | 5 | | | | 55 |
| SIB01 | 3 | 2 | 1 | 1 | 7 | 5 | 3 | 13 | 8 | 12 | 55 |
| EIB01 | | | 4 | 2 | 4 | 4 | 3 | 21 | 8 | 6 | 52 |
| BCB03 | 1 | 5 | 5 | 10 | 1 | 4 | 11 | | | 2 | 39 |
| ECB13 | 5 | 4 | 5 | 2 | 3 | 1 | | | | 19 | 39 |
| ECB04 | 0 | 2 | 1 | 1 | | | 6 | 18 | 9 | | 37 |
| KCB08 | 3 | 9 | 3 | 5 | 8 | 6 | 3 | | | | 37 |
| EIB03 | 4 | 6 | 7 | 3 | 6 | 7 | 3 | | | | 36 |
| KCB05 | 1 | 2 | 1 | 1 | 4 | 1 | 5 | 1 | 7 | 13 | 36 |
| SCB04 | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 4 | 5 | 7 | 31 |
| ECB10 | 9 | 2 | 3 | 6 | 3 | 1 | 5 | | | | 29 |
| BCB05 | 1 | | | 3 | 2 | 6 | 7 | 1 | 2 | 3 | 25 |
| KCB07 | | 4 | 3 | | 2 | 3 | 4 | 4 | 3 | 1 | 24 |
| ECB03 | 3 | 4 | 1 | 1 | 1 | 3 | 1 | 4 | 1 | 2 | 21 |
| QCB03 | | 6 | | | 2 | | | 9 | 2 | | 19 |
| SCB03 | 3 | 9 | 1 | 2 | | | | | 2 | 2 | 19 |
| ECB02 | 4 | 1 | 2 | 4 | 3 | 1 | 1 | | | | 16 |
| SCB05 | 3 | 3 | 4 | 4 | 2 | | | | | | 16 |
| ECB09 | 1 | | | | 1 | 1 | 2 | | 4 | 3 | 12 |
| OCB02 | 8 | 3 | | | | | | | | | 11 |
| QIB01 | | | | | | | | | 4 | 6 | 10 |
| ECB11 | 3 | | | | | | | 5 | | 1 | 9 |
| BCB07 | | | | | | 1 | 2 | 1 | 3 | 1 | 8 |
| BIB03 | | 2 | | | | | 4 | 2 | | | 8 |
| SCB06 | | | | | | | | 3 | 4 | 1 | 8 |
| EIB04 | 3 | 4 | | | | | | | | | 7 |
| OCB04 | | | | | | | 1 | 3 | 1 | 2 | 7 |
| BIB02 | 1 | 1 | 2 | 1 | | | | | | | 5 |
| BIB04 | 1 | | | | | | | | | 4 | 5 |
| ECB15 | | | | | | | | 2 | 2 | | 4 |
| ECB16 | | | | | | 1 | 1 | 1 | | | 3 |
| KIB01 | | | | | | | | 1 | | 2 | 3 |
| ECB08 | | | | | | 1 | 1 | | | | 2 |
| KCB02 | | | | | 2 | | | | | | 2 |
| **Number/ year** | **29** | **29** | **26** | **26** | **27** | **27** | **29** | **24** | **24** | **25** | **27** |

In DEA terminology, these banks are called peers and set as an example of good operating practices for the inefficient banks to emulate. At this point it is worth mentioning that a bank, which appears to be most times in the efficient frontier for the less efficient banks, is considered to be the Global leader. By counting how many times each bank appears to be in the reference set, we notice that bank OCB06,which is a Conventional bank located in Oman is the most efficient bank (Table 32). This bank appears 174 times to be part of the reference set during the time period considered. This means that its performance is greater on average in all dimensions of efficiencies as they are described in our Model compared to the other efficient sample banks. On the other hand, comparing the number of peers over the study period shows that the number is mostly stable over the study period; it is between 24 banks for the year 2005 and 2007 to 29 banks in the year 1998, 1999 and 2004. This means that there is no reason to believe that one year is atypical year regarding to bank performance.

## Slacks and targets

Once inefficiencies have been identified, appropriate measures may be taken to improve the performance of inefficient banks. SORM results not only help managers to evaluate their performance and identify best practice in banking sector, but also point to the direction and magnitude that inefficient banks can improve.

Since, the most efficient bank has operated in an environment similar to the others thus the inefficient banks could improve their performance by choosing the same policies and managerial structure of their respective peer banks. The output target for inefficient bank is the amount of investment, loan, OBS items and profit that will enable the bank to have the same ratio output to input incurred by the most efficient bank.

One can reach to the following expression from SORM Model 19 or 22;

$$\boxed{\begin{aligned}
&\sum_j \lambda_j Y_{rj} + s_r^{+} \geq hY_{rj_0} && ;\forall r \in R\\
&\sum_j \lambda_j {Y^1}_{kj} + s_k^{+} \geq h{Y^1}_{kj_0} && ;\forall r \in K\\
&\sum_j \lambda_j {Y^2}_{kj} + s_k^{-} \leq h{Y^2}_{kj_0} && ;\forall r \in K
\end{aligned}}$$

Where;

R is an output variable which takes positive value for all DMUs and

K is an output variable which takes positive values for some DMUs and negative for others

As it can be seen from the above mathematical formulation, the feasible target for the improvement of every output is achieved by summing up the products of the weights $\lambda_j$ and the respective outputs($y$ ). For inefficient banks, the target for the positive output is more than actual output, whereas it is less than actual output for the negative ones. Table 34 (also, Table A-2 in the appendix) show the actual outputs of the inefficient banks and the feasible target for improving. However, since there is no difference between the actual outputs and the feasible targets for the fully efficient banks, therefore they are excluded from the table, only we present the target for all banks whose efficiency is less than 100%. Over the year 2007 there are 26 banks that are fully efficient, and the others are inefficient.

Table 34: Observed and target level for some of inefficient banks for year 2007

| **Bank Code** | | **Outputs** | | | |
|---|---|---|---|---|---|
| | | **Investment** | **Loans** | **OBS** | **Profit** |
| BCB01 | Observed | 219.2 | 277.3 | 35.9 | 8.2 |
| | Target | 276.8 | 507.8 | 209.2 | 16.6 |
| ECB02 | Observed | 24.0 | 25.0 | 49.3 | 2.0 |
| | Target | 189.4 | 129.1 | 189.3 | 71.7 |
| ECB04 | Observed | 7.4 | 33.3 | 35.4 | 2.5 |
| | Target | 41.5 | 49.4 | 52.5 | 34.2 |
| ECB08 | Observed | 9.5 | 44.4 | 31.2 | 2.0 |
| | Target | 22.8 | 78.2 | 54.9 | 9.7 |
| ECB10 | Observed | 4.4 | 28.0 | 21.1 | 1.8 |
| | Target | 17.9 | 39.5 | 29.7 | 14.2 |
| SCB07 | Observed | 111.3 | 169.5 | 122.0 | 2.7 |
| | Target | 156.8 | 263.8 | 201.9 | 8.9 |

Table 34 shows the improvement level for each bank. Take for example bank SCB07 which the SORM Model found to be running inefficiently. Bank's SCB07 efficiency is 71%, the reference set for this bank are: banks; BCB03, BIB01, ECB13, KCB05 and SCB08, can be emulated to enhance the technical efficiency of bank SCB07. In particular and of the reference banks, KCB13 (which is Conventional bank and located in Kuwait) features the highest weight ($\lambda$ ) and is therefore the most similar to SCB07 in terms of their input-output structures and should be the most appropriate benchmarking target. Comparison of bank SCB07 with the reference set reveals how bank SCB07's input-output levels should be restructured, and results from analysis of the difference between bank SCB07's actual figures and improvement target figures projected on the efficient frontier. To be considered as efficient one, bank SCB07 needs to close the gap between the actual value and the target value. From the given inputs bank SCB07 target outputs are calculated as follow; $Y_j = \lambda \mathrm{Y}_{\mathrm{BCB03}} + \lambda \mathrm{Y}_{\mathrm{BIB01}} + \lambda \mathrm{Y}_{\mathrm{ECB13}} + \lambda \mathrm{Y}_{\mathrm{KCB05}} + \lambda \mathrm{Y}_{\mathrm{SCB08}}$

$$Y_j = 0.08\begin{bmatrix}436.3\\284.1\\189.5\\002.9\end{bmatrix} + 0.14\begin{bmatrix}59.2\\49.6\\00.0\\08.1\end{bmatrix} + 0.11\begin{bmatrix}085.0\\405.9\\077.2\\010.\end{bmatrix} + 0.51\begin{bmatrix}133.9\\279.1\\240.1\\011.0\end{bmatrix} + 0.16\begin{bmatrix}229.4\\142.3\\313.9\\005.1\end{bmatrix} + \begin{bmatrix}S_1^+\\S_2^+\\S_3^+\\S_4^+\end{bmatrix} = \begin{bmatrix}156.8\\263.8\\201.9\\008.9\end{bmatrix}$$

It is important to note that SCB07 and all of it is peers are Conventional banks except BIB01 which Islamic, also, all of it is peers are located outside Saudi Arabia except SCB08. The same scenario can be used for other inefficient banks, which means that those banks to be considered as fully efficient banks, they should produce more output from the given inputs. Compare for example bank ECB02, which is Conventional bank located in UAE with SCB08 (which is Conventional bank too but located in Saudi Arabia) (table 33); bank ECB02 used relatively the same level of SCB08 fixed assets, 0.7 of non earning assets and 1.62 of their deposit whereas they produce 0.1 of SCB08 investment, 0.18 loan, 0.16 OBS items and 0.39 of SCB08 profits. This is why their efficiency score become 26% for ECB02 and 100% for SCB08. To gain efficiency, Bank ECB02 should follow the policies of Bank BIB01, ECB09, SCB08 and Bank SIB01. Hence, one way for bank ECB02 to improve its efficiency is therefore by increasing their investment to US$ 189.4 Million, loans to US$ 129.1 Million, OBS items to US$ 189.3 Million and profits to US$ 71.7 Million.

## Target levels

In order to further illustrate the possibility of improved performance, the target level is computed for each inefficient bank as a ratio of the difference between target and observed output to the target output level, ($\frac{\text{Target}-\text{Observed}}{\text{Observed}}$). Figure 22 confirms the previous part results, that the GCC commercial banks managers in order to improve their performance they need to give high priority to profits and investments, at the same time increase banks loans and OBS items. Unlike the efficient banks, the inefficient banks' managers mostly rely on the less risky decisions (Loan and OBS items) to generate profits, rather than risky decisions (investments). This means that the inefficient banks' managers are less efficient in generating profit, which makes it necessary to improve their investment decisions through increasing their skills and knowledge to become more effective.  Also the policy makers should aim to create a favourable environment for investment and innovation and ensure a predictable legal and regulatory environment for market growth.

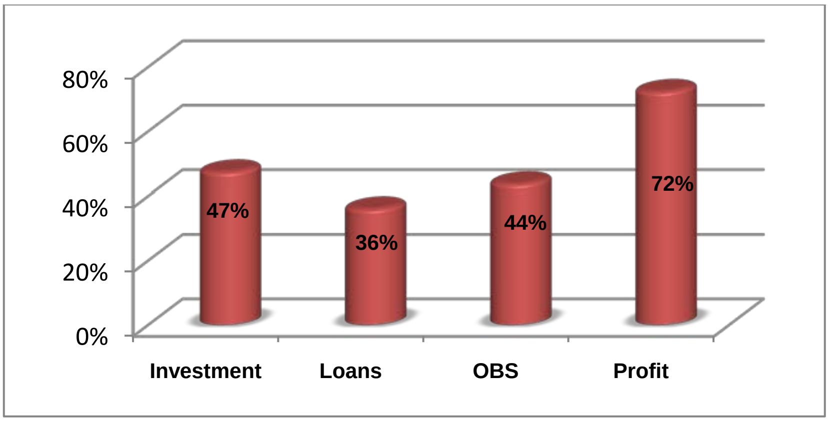



Figure 22: Average target level of the output variables

Comparing the Islamic with Conventional banks; Figure 23 shows that bank (Islamic and Conventional) managers are more oriented toward generating loans and OBS items and less oriented toward optimizing investment and profit. Although both banks are less profitable, Conventional banks are more profitable with less investment and Islamic banks are more investment maker with less profit. This could be due to the fact that the relation between bank and clients is different in the two cases; it is based on profit/ loss sharing in Islamic banks, while it is based on fixed rate (interest rate) in Conventional banks, which make Conventional banks make more profit with less investments compared with Islamic banks which make more investment with less profit. The fixed interest rate policy that used by Conventional banks is working well in economic growth stage, but it will worse in case of financial crises. This is why the Islamic banks are not affected by the current global financial crisis (2008) compared to the Conventional banks. Turning to the loans and OBS items, it seems to be that the Islamic bankers are relatively more effective in generating loans and OBS items than the Conventional ones. This means that Conventional bankers are advised to be more oriented toward generating more OBS items.

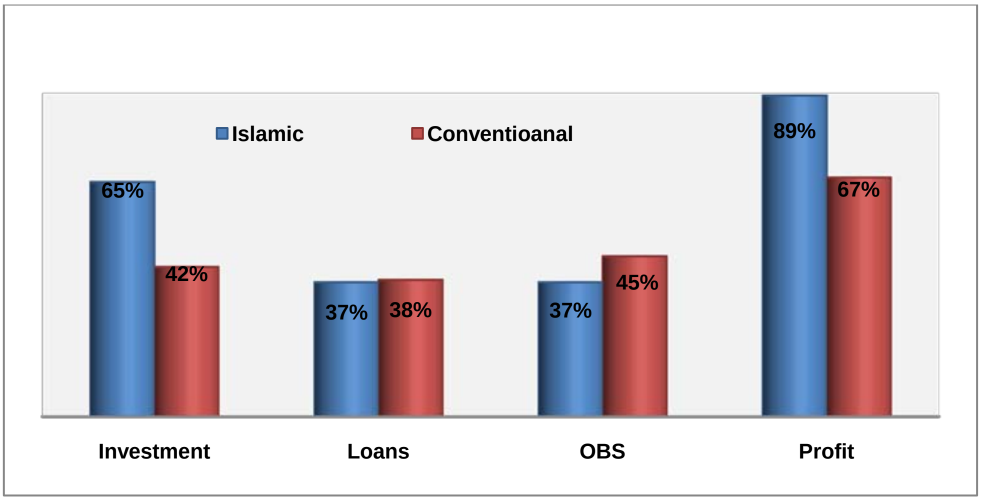



Figure 23: Average improvement level of Islamic and Conventional banks

To analyze the outputs improvement for inefficient banks at country level, Figure 24 shows that most GCC inefficient banks are oriented toward generating more loans and more OBS items with less profit and investments. Excluding the affected countries by Gulf crises (Kuwait, Bahrain and Saudi Arabia) it is clear that UAE inefficient banks are the worst performing banks, followed by Qatar commercial banks. Omani Inefficient banks seem to be the best compare to their inefficient counterpart in other GCC countries. However, inefficient banks to be considered as efficient ones, they need to give more priority to improve their investment and profit.

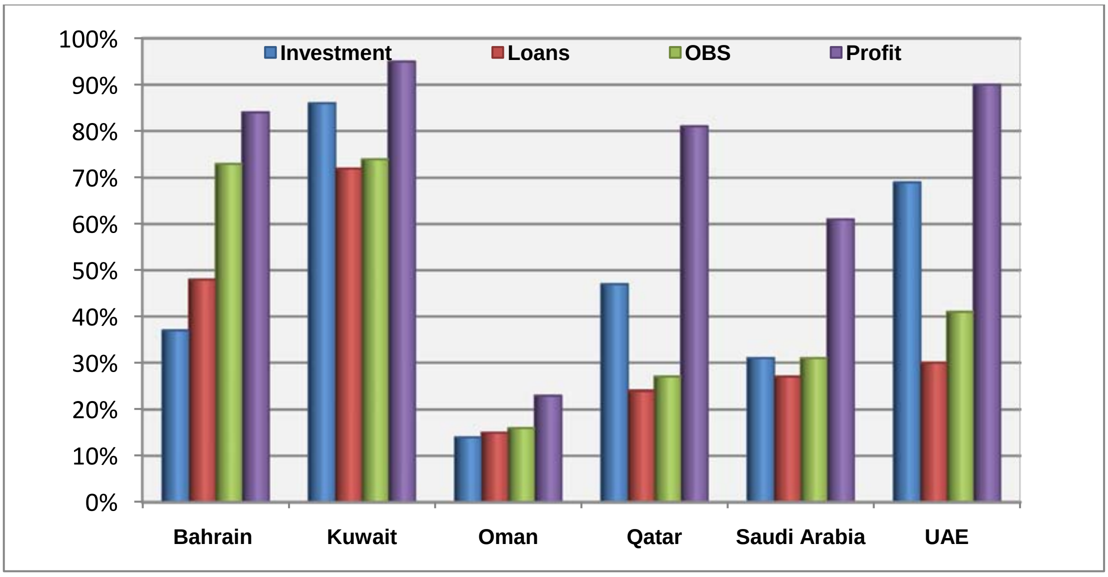



Figure 24: County-wise analysis for the average improvement level

At the sector (operating style) level; Figure 25 shows that all Kuwaiti and Saudi Arabia Islamic banks are fully efficient while some of the Bahrain, Qatar and

UAE Islamic banks are inefficient. Islamic bankers in the latter countries have poor managerial skill in producing more profits and investment compare to their skills in generating loan and OBS items. Bahraini Islamic banks are the worst performing banks then UAE and Qatar banks.

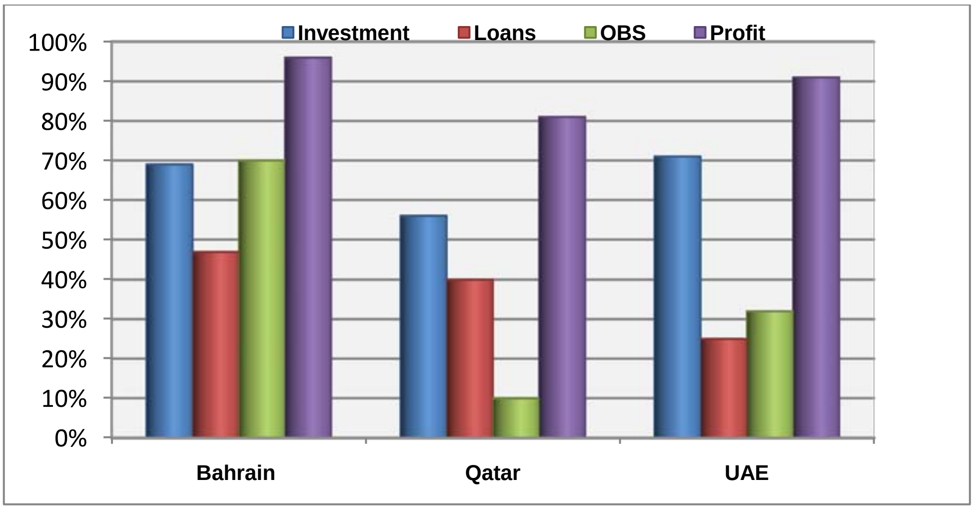



Figure 25: The average improvement level of Islamic banks

The same trend is for Conventional banks as Figure 26 shows; banks are more oriented toward generating more loans and OBS items and less profit and investments. Kuwait, UEA and Qatar conventional inefficient banks are the worst performing banks; while Omani inefficient banks seem to be the best performing banks

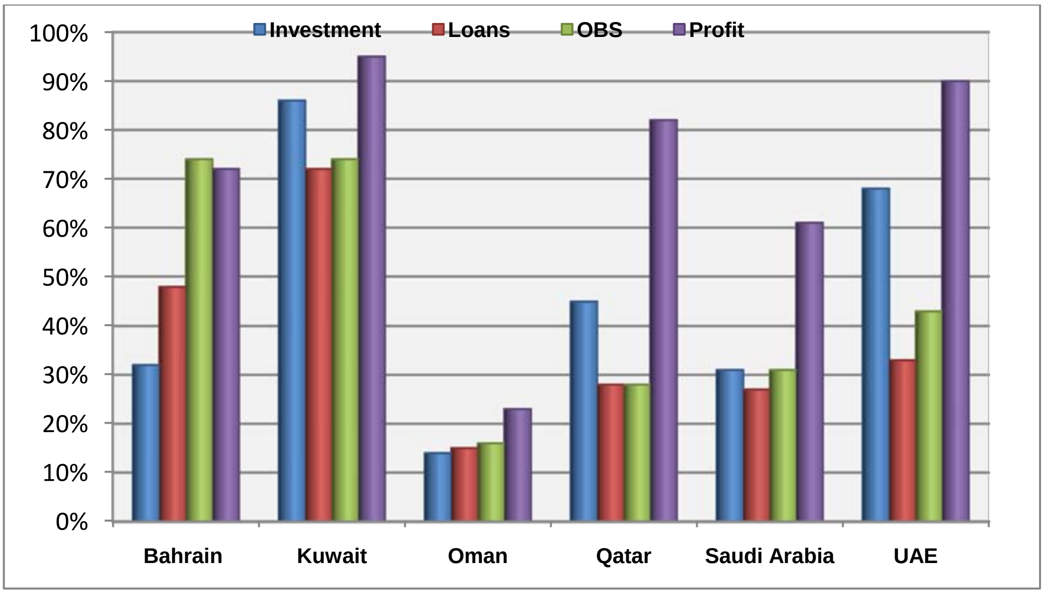



Figure 26: The average improvement level of Conventional banks

## Improvement

After knowing the efficiency of GCC commercial banks it is of interest to know the improvement targets for inefficient banks. Inefficient banks need to find out the most feasible way to catch up. It is crucial that the process of efficiency improvement should be made in a short time period. Also, it is always good to learn from the efficient peers with the same or similar input–output mix. The reference set offers inefficient banks a feasible means to emulate their efficient peers, learning from their practices (Yao *et al*, 2008).

In order to better evaluate the inefficient banks, we derive the improvement figures for each bank. The improvement figures are derived as the ratio of observed to target for the outputs and the ratio of target to observed for the inputs. The efficiency measures obtained converted to percentages appears in Table 35 and Table A-3 (in the appendix) with the actual, target, improvements and benchmarking target for each inefficient bank.

It is important to note that the negative values for the improvements mean that these variables should be reduced, whereas the positive values mean that these outputs should be increased. For example, Bank BCB01 has 79.2% technical efficiency. The results indicate that Bank BCB01 has over employed inputs as well as low produced outputs. Bank ECB13, SCB08, SCB04 and Bank KIB01 are peers for Bank BCB01 with peer weights of 0.28, 0.38, 0.29 and 0.06.

Table 35: Improvement level for some of the inefficient banks

| Bank | Input/ Output | | Actual | Target | Improvement | Benchmarking |
|---|---|---|---|---|---|---|
| BCB01 (79.18%) | Inputs | Fixed Assets | 6.74 | 6.74 | 0% | ECB13 (0.28), SCB08 (0.38), SCB04 (0.29), KIB01 (0.06) |
| | | NEA | 20.96 | 3.69 | -82% | |
| | | Deposits | 409.45 | 409. | 0% | |
| | Outputs | Investment | 219.15 | 276. | 26% | |
| | | Loans | 277.31 | 507. | 83% | |
| | | OBS | 35.93 | 209. | 482% | |
| | | Profit | 8.24 | 16.6 | 101% | |
| SCB07 (71.0%) | Inputs | Fixed Assets | 2.0 | 2.0 | 0% | BCB03 (0.08), BIB01 (0.14), ECB13 (0.11), KCB05 (0.51), SCB08 (0.16) |
| | | NEA | 4.9 | 4.9 | 0% | |
| | | Deposits | 269.2 | 269.2 | 0% | |
| | Outputs | Investment | 111.3 | 156.8 | 41% | |
| | | Loans | 169.5 | 263.8 | 56% | |
| | | OBS | 122.0 | 201.9 | 66% | |

| Bank | Input/ Output | | Actual | Target | Improvement | Benchmarking |
|---|---|---|---|---|---|---|
| | | Profit | 2.7 | 8.9 | 230% | |

Furthermore, taking CSB07 as another example, BCB03, BIB01, ECB13, KCB05 and SCB08 are identified as its efficient peers in the reference set as their corresponding $\lambda$= 0.08, $\lambda$= 0.14, $\lambda$= 0.11, $\lambda$= 0.51 and $\lambda$ = 0.16 are the only positive values at the optimal solution to the envelopment model. Compared with SCB07, KCB05 has fewer fixed assets and a lower non-earning assets but more deposits, which is an input, and more investment, loans, OBS items and profit. Although KCB05 has 12.4% more deposit than SCB07, the former earns 3.08 % more profit than the latter.

If we scale up BCB03, BIB01, ECB13, KCB05 and SCB08 by 0.08, 0.14, 0.11, 0.51 and 0.16 respectively, the combination of scaled-up output levels of BCB03, BIB01, ECB13, KCB05 and SCB08 offers the same output level as SCB07 could deliver but it uses only 71% of the inputs used by SCB07. This underlies the efficiency rating of SCB07 at 0.71. BCB03, BIB01, ECB13, KCB05 and SCB08 are thus regarded as the efficient benchmarks for SCB07 in 2007; same scenario can be used for other inefficient banks. This calls for inefficient banks managers' to study their efficient peers' practices and set up targets in relation to the combination of input and output levels of their efficient benchmarks.

## Efficiency rankings

In order to further analyze the results this section turns to efficiency rankings, in particular, the stability of efficiency rankings over the study period. In other words we are interested in the question of how long an inefficient bank has remained inefficient. To address this question, the temporal relationship of the cross sectional rankings of efficiency is examined. Table 36 reports the Spearman rank correlations of the efficiency estimates between 1998 and subsequent periods.

Table 36: Rank-order correlation coefficients

| Year | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|---|---|---|---|---|
| **1998** | 1.00 | | | | | | | | | |
| **1999** | 0.62 | 1.00 | | | | | | | | |
| **2000** | 0.68 | 0.79 | 1.00 | | | | | | | |
| **2001** | 0.72 | 0.72 | 0.90 | 1.00 | | | | | | |
| **2002** | 0.58 | 0.47 | 0.62 | 0.74 | 1.00 | | | | | |
| **2003** | 0.46 | 0.37 | 0.61 | 0.66 | 0.83 | 1.00 | | | | |

| Year | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|---|---|---|---|---|
| **2004** | 0.35 | 0.38 | 0.52 | 0.62 | 0.69 | 0.82 | 1.00 | | | |
| **2005** | 0.16 | 0.18 | 0.11 | 0.10 | 0.07 | 0.13 | 0.22 | 1.00 | | |
| **2006** | 0.03 | 0.07 | 0.04 | 0.02 | 0.01 | 0.08 | 0.17 | 0.87 | 1.00 | |
| **2007** | 0.19 | 0.10 | 0.16 | 0.21 | 0.24 | 0.30 | 0.34 | 0.80 | 0.85 | 1.00 |

For the full sample, the rank of efficiency is found to be correlated significantly over time. While the Spearman rank correlation was significant up to 2007, the correlation coefficient is declining over time and fell below 0.5 over the period 2005-2007. Thus, the evidence suggests that efficiency ratings at bank level are fair persistent, over time. As the above table shows the correlation is relatively high between banks' performance at the beginning of the period (1998-2003) then it is reduced from the year 2004. Its lowest relationship is in the year 2006-2007.

For further analysis, to determine the stability of the efficiency score estimates over time Bauer *et al.* (1998) adapted Spearman rank-order correlations. Based on adopted test, firstly we computed the Spearman rank-order correlations of efficiencies in 1998 with 1999, 1999 with 2000 to 2006 with 2007, and then take the average of those 9 correlations, which are referred to as the correlation of 1-year-apart efficiency. Likewise, the correlation of 2-years-apart efficiency is equal to the mean of the Spearman correlations of efficiencies in 1998 with 2000, 1999 with 2001 and, 2000 with 2002, an average of 8 correlations in all. In general, the t-years-apart figures are means of the (10-t) correlations between pair wise efficiencies that are t years away from each other. By conducting averages of rank-order correlation coefficients, the effect of random noise on DEA efficiency estimates is mostly mitigated. The Spearman rank-order correlation coefficients of t-years-apart efficiencies are summarized in Table 37.

Table 37: Rank-order correlation coefficients of t-year-apart efficiencies

| k-year | Technical efficiency |
|---|---|
| 1-Year-apart | 0.74 |
| 2-Years-apart | 0.56 |
| 3-Years-apart | 0.42 |
| 4-Years-apart | 0.31 |
| 5-Years-apart | 0.24 |
| 6-Years-apart | 0.19 |
| 7-Years-apart | 0.13 |
| 8-Years-apart | 0.07 |

| | |
|---|---|
| 9-Years-apart | 0.19 |

Table 37 shows that, for the given data, there are at most 9 such rank-order correlations to be computed. It can be seen that most of the correlation coefficients decline, as anticipated, with the number of years apart and they are statistically significant. These figures reveal that the sample banks change their rankings gradually over time. It is interesting to note that, Huang and Wang (2002) and Wang and Huang (2007) obtained similar results for bank efficiency over time.

So far the analysis has only focused on technical efficiency, but it is of interest to see whether efficiency is directly related to profitability. Spong *et al.* (1995), note that it is important to combine both efficiency scores with a profitability test so as to evaluate financial bank efficiency. This is because one needs to evaluate banks' ability to use resources effectively in producing products and services (technical efficiency), and their skill at generating income from these services (profitability). Next section investigates this relationship in GCC commercial banks

### b. Consistency of the SORM efficiency scores

Bauer *et al.* (1998) suggested that the efficiency scores to be useful, the estimated scores should be positively correlated with the traditional measures of performance. Therefore, to investigate the relationship between efficiency scores with profitability ratio, the sample of banks is partitioned according to their technical efficiency into two categories; the most, and least efficient. The most/ least efficient banks are those that rank in the upper/ lower quartile according to the estimated efficiency score, and in the upper/ lower half in terms of return on assets (ROA) and return on equity (ROE).

Table 38 shows the number of banks and their efficiency and profitability characteristics according to the aforementioned partitioning.

Table 38: Cross Tabulation of efficiency scores and other profitability Measures (1998–2007)*

| Year | Banks | No of banks | Technical eff. (averages) (%) | ROA (averages) (%) | ROE (averages) (%) |
|---|---|---|---|---|---|
| 1998 | Least efficient | 16 | 71.69 | -0.20 | 3.53 |
| | Most efficient | 27 | 100.0 | 3.55 | 21.83 |
| 1999 | Least efficient | 15 | 66.47 | -0.07 | 1.87 |
| | Most efficient | 30 | 100.0 | 3.59 | 20.34 |

| Year | Banks | No of banks | Technical eff. (averages) (%) | ROA (averages) (%) | ROE (averages) (%) |
|---|---|---|---|---|---|
| 2000 | Least efficient | 15 | 71.38 | 0.60 | 6.25 |
| | Most efficient | 26 | 100.0 | 3.67 | 21.56 |
| 2001 | Least efficient | 15 | 65.87 | 0.79 | 5.07 |
| | Most efficient | 26 | 100.0 | 3.19 | 22.28 |
| 2002 | Least efficient | 16 | 63.31 | 0.01 | 2.88 |
| | Most efficient | 27 | 100.0 | 3.26 | 24.18 |
| 2003 | Least efficient | 15 | 61.47 | 0.50 | 6.22 |
| | Most efficient | 27 | 100.0 | 3.38 | 25.58 |
| 2004 | Least efficient | 15 | 74.0 | 1.25 | 7.52 |
| | Most efficient | 29 | 100.0 | 3.77 | 29.08 |
| 2005 | Least efficient | 15 | 40.56 | 1.15 | 7.15 |
| | Most efficient | 24 | 100.0 | 5.51 | 32.56 |
| 2006 | Least efficient | 15 | 46.73 | 1.13 | 8.40 |
| | Most efficient | 26 | 100.0 | 5.15 | 29.32 |
| 2007 | Least efficient | 15 | 43.20 | 1.24 | 7.63 |
| | Most efficient | 26 | 100.0 | 4.58 | 25.07 |

Notes:
* The two groups, comprising the most efficient and least efficient banks, were partitioned in the following way:
- Most efficient group: banks that rank in the upper quartile of GCC commercial banks on the technical efficiency estimates and rank in the upper half in term of ROA and ROE; and
- Least efficient group: banks that rank in the bottom quartile on the cost efficiency estimates and rank in the bottom half in terms of ROA and ROE.

For the ten years under study, an average of 27 banks satisfy the selection criteria for the most efficient group and 15 banks are classified in the least efficient group. The mean bank in the least efficient group has a technical efficiency of only 60.5% (average over the study period), which indicates that by adopting best practices banks can produce 39.5% extra outputs than they actually produced from the same level of inputs. In contrast, the average technical efficiency level for the most efficient banks is approximately 100%, thus indicating less disparity with the 'best' bank in the sample. Moreover, as an average for the ten years the ROA for the most efficient banks is equal to 3.97% compared with 0.64% for the poorest performers. In contrast, on average for the ten years, the ROE for the most efficient banks is equal to 25.18% compared with 5.65% for the poorest performers.

For further investigation of this relationship, Table 39 presents the Spearman Rank correlations between the efficiency score of the banking industry in GCC countries generated by SORM and ROA and ROE. It is expected to have a positive correlation between these two measures with the frontier based efficiency scores.

Table 39: Correlation test analysis

| | Technical efficiency | ROA | ROE |
|---|---|---|---|
| Technical efficiency | 1.0 | 0.42 | 0.10 |
| ROA | | 1.0 | 0.37 |
| ROE | | | 1.0 |

The results in Table 39 suggest that the average rank order correlation between SORM results, ROA and ROE are statically significant at $\propto \leq 5\%$. The low magnitude is in line with those reported by Bauer *et al*. (1998) and Koetter (2006) and confirms that efficiency measures contain additional information compared to traditional performance ratios; ROE and ROA are simple ratios of one variable relative to another whereas, DEA is a multi-input multi-output method taking many variables into account simultaneously. Further, DEA gives a relative measure while ROA and ROE are absolute measures. However, we are not expecting that each method will give the same rank, since each of them has different meaning, but a positive rank-order correlation with these measures would give assurance that the frontier measures are not simply artificial products of the assumptions made regarding the underlying optimization concept (Bauer *et al*., 1998).

The above analysis estimates the efficiency of each bank over the study period, but this is not enough for the managers, regulators or investors. We would like to be able to say what bankers can do to increase their efficiency? A simple way to find out what bankers should do to raise efficiency could be to go to their reference set banks and see what they are doing differently. But, this is discussed before, thus in next part we would like to investigate the characteristics of benchmark performers in order to provide useful information for the decision makers in less efficient banks. The analysis will include the performance in year 2007, the reason behind this selection is the advice we received from the managers of some of these banks in the 3$^{ed}$ international Islamic banks conference (Jakarta, Feb, 2008). They said it is enough to know how to improve bank performance based on the last year results rather than the average performance.

### c. Characteristics of benchmark banks

This section tries to find out the characteristics of extreme performer banks, through comparing the efficiency of different groups' results. This means that we are less interested into identifying single winners or losers. Rather, we focus on groups of best and worst performers. We investigate how bank operating style, size and geographical location affect the composition of the highest and lowest performing banks and subsequently characterize extreme performers.

## Efficiency across bank operating style

A Mann Whitney rank sum test is applied to compare mean scores of efficiency across different bank operating styles; Islamic and Conventional. For this test efficiency score is considered as group variable and bank operating style is considered as test variable.

Mann-Whitney test, which is an alternative to the independent group t-test, is non-parametric (distribution-free) test for testing whether the number of times scores from one sample are ranked significantly higher than score from another unrelated sample. Like many non-parametric tests, it uses the ranks of the data rather than their raw values to calculate the statistic. Table 40 shows the result of this test.

Table 40: Mann-Whitney test concerning 2007 results

| Bank Type | Sample Size | Mean Rank | Mann-Whitney U | Wilcoxon W | Z- value |
|---|---|---|---|---|---|
| Islamic | 12 | 29.6 | 245.5 | 1421.5 | -0.82 |
| Conventional | 48 | 34.04 | | | |

The results of the Mann-Whitney test reveal that there is no significance difference in bank efficiency performance due to the differences in their operating style means that the Islamic and Conventional banks more or less have the same performance. Hence, Mann-Whitney test under the null hypothesis that two efficiency scores have the same value of median is rejected at the 5% level of significance.

## Efficiency across bank size

To investigate the efficiency scores of GCC commercial banks across different bank size we used Kruskal-Wallis test. The Kruskal-Wallis test is a non-parametric approach with no requirement on the normal distribution of the variables within the clusters. Rather than examining the means of the data, this method relies on the ranks of the scored values and the means of those ranks. We adopted Kruskal-Wallis rank test (Sueyoshi and Aoki, 2001) to examine whether scores vary according to bank size or not? The samples are categorized according to their total assets into three groups; small banks (with total assets less than US $5,000 Million); medium size (total assets US $5,000-15,000 Million) and large size (total assets more than US $15,000 Million); Table 41 presents the test results.

Table 41: Kruskal-Wallis results concerning 2007 efficiency scores

| Bank size | N | Mean Rank | $\chi^2$ | d.f. | Asymp. Sig. |
|---|---|---|---|---|---|
| Small | 24 | 28.56 | 7.604 | 2 | 0.022 |
| Medium | 16 | 23.50 | | | |
| Large | 20 | 38.42 | | | |

The Kruskal Wallis test reveals that there is statistical significant difference in banks efficiency due to their size.

## Efficiency across bank geographical location

To investigate the efficiency score of GCC commercial banks across different regional locations we adopted the Kruskal-Wallis rank test (Sueyoshi and Aoki, 2001) to examine whether scores vary among countries or not. Table 42 shows the test results.

Table 42: Kruskal-Wallis results concerning 2007 efficiency scores

| Bank Location | N | Mean Rank | $\chi^2$ | d.f. | Asymp. Sig. |
|---|---|---|---|---|---|
| Bahrain | 11 | 34.32 | 6.952 | 5 | 0.224 |
| Kuwait | 9 | 19.94 | | | |
| Oman | 5 | 39.20 | | | |
| Qatar | 6 | 32.00 | | | |
| Saudi Arabia | 9 | 36.00 | | | |
| UAE | 20 | 28.05 | | | |

The Kruskal Wallis $\chi^2$ statistics are 6.952, means that Kruskal Wallis test reveals that there is no statistically significant relationship between bank geographical location and its efficiency concerning 2007 results. This means that there is no reason to believe that bank performance differs in their ratings from a statistical perspective according to their locations. The above result is far away from those results obtained by Al Shammari (2003) and Limam (1998) where according to

Al Shammari results; Saudi Arabia and United Arab Emirates had the largest efficiency score 92% and 90% respectively while Qatar and Bahrain the poorest efficiency score 83% and 84% respectively. Limam results; Bahrain and Saudi Arabia commercial banks had the highest efficiency score 94.5% and 94.3% respectively, while Oman and Qatar commercial banks had the lowest score 89.3% and 82.9% respectively. The difference could be due to the differences in input-output variables used in the model, time period captured in the analysis and to different model that employed.

Pervious sections give information about the performance of GCC commercial banks and suggest different ways to improve their efficiency. Furthermore, they provide some information about the characteristics of the extreme performer banks. To provide in depth analysis and furthermore, explore the characteristics of efficient banks, the next section sets in the form of ‘rules’ the characteristics for the efficient and inefficient banks.

## 4. Second stage: Re-sampling

As stated early using C&R need huge number of data, since our sample is limited by 60 banks, so we randomly selected 60 units (by replacement) and we repeated this sampling 61 times to get 3660 banks, this will ensure us to get a better accuracy on the predicted C&R tree. The 3660 banks are divided into two datasets: train set and validation set by the ratio of 7:3.

## 5. Third stage: C&R tree analysis

The first stage results show the differences in inefficiency among banks in the six countries. To incorporate for more environmental factors (internal and external) that would have affect on bank efficiency, we proposed C&R tree to investigate there influences. SORM results from stage one are categorized into two groups; efficient group (score=100) and inefficient group (score<100). These groups are used as the target variable in the C&R tree, while factors presented in Table 43 are used as predictor. Sensitivity analysis is used to determine the appropriate factors to be included in C&R analysis. Correlation tests show high correlation between a numbers of factors, for example; number of branches and number of employees are highly correlated hence we included only a number of branches to reflect the size of banks. Also, Price/ Book value and Price Earnings ratio are highly correlated hence we included only a Price/ Book value factors to reflect the size of stock market price for each banks. In the third stage analysis, we consider the following factors in the C&R algorithm.

Table 43: Statistical Description of the Environmental Factors

| | Descriptive Statistics | | | | |
|---|---|---|---|---|---|
| | Variable type | Minimum | Maximum | Mean | Std. Deviation |
| Age (Establish Date) | Categorical | 1 | 5 | | |
| Country (geographical Location) | Categorical | 1.00 | 6.00 | | |
| GDP Growth | Numerical | 1.90 | 8.40 | 6.34 | 1.98 |
| Inflation | Numerical | 3.60 | 14.00 | 8.61 | 4.71 |
| Population Density | Categorical | 0.70 | 23.60 | | |
| Operating Style | Categorical | 1.00 | 2.00 | | |
| Internal Growth | Numerical | 0.27 | 45.15 | 14.93 | 8.74 |
| Bank Size | Categorical | 1 | 3 | | |
| Return on Assets (ROA) | Numerical | - 2.53 | 8.28 | 2.76 | 1.53 |
| Return on Equity (ROE) | Numerical | - 34.18 | 33.37 | 17.79 | 8.86 |
| Financial Strength | Numerical | 1.00 | 13.00 | 7.90 | 4.36 |
| Support Rating | Categorical | 1.00 | 4.00 | | |
| Price / Book value | Categorical | 1.19 | 17.23 | | |
| Loan to Deposit Ratio | Numerical | 28.50 | 1,904.35 | 138.76 | 263.59 |
| Number of Branches | Numerical | 5.00 | 585.00 | 62.00 | 89.00 |
| Beta | Numerical | -0.09 | 1.83 | 0.82 | 0.25 |
| Market Share | Numerical | 0.00 | 8.44 | 1.67 | 1.80 |
| Asset Structure | Numerical | 0.02 | 3,534.00 | 209.70 | 518.82 |

### a. C&R factor definitions [8]

Age (Established date): Banks are grouped according to their established date into 5 groups to capture the age affect: group 1 banks established before 1960; group 2 (1960-1970); group 3 (1970-1980); group 4 (1980-1990) and group 5 (1990-2000).

Country: it is expected to have a variation in efficiency score according to their geographical location.

GDP growth: is used to reflect the general income level. A higher income level is more likely to be associated with a more developed banking sector, and hence bank efficiency.

[8]) Some definitions are presented in chapter 4, so we are going to use the same definitions in this part.

Inflation: is an indicator of macroeconomic stability, and is directly related to the interest rate levels and, thus, interest expense and revenue.

Population density: is measured as a ratio of country population to the GCC countries total populations. It is believed that banks in heavily populated countries are more likely to operate closer to their optimal size than banks in less populated country. Hence it is easier for bank management to sustain higher efficiency levels in heavily populated areas than in less populated.

Operating style: to capture the efficiency of Islamic rule and regulations.

Internal growth rate: is calculated as the percentage of retained profits of the year on the equity at the beginning of the year.

Bank size: is measured by the bank total assets, which classified into three groups hence, the larger banks (with total assets more than US $15,000 Million), medium size (with total assets between US $5,000 – 15,000 Million) and small size (total assets less than US $5,000 Million).

Profitability ratios: we measure this variable using return on assets (ROA) and return on equity (ROE).

Financial strength rating: it provides an opinion of a bank's intrinsic safety, soundness and risk profile (Arab banking and finance, 2007). It takes a scale from AAA (extremely strong finance and highly attractive operating environment) to D (extremely weak financial condition and untenable position).

Support rating: it assesses the possibility that the bank will receive enough financial assistance from the government or private owners in the event of difficulties to enable them to meet their financial obligations. It takes a scale from 1 (very likely) to 5 (very unlikely) (Arab banking and finance, 2007).

Price /book value: It is expected to have a positive relationship between price/book value and the likelihood that a bank will be efficient.

Beta: is a relative measure of the systematic return of the stock to the overall market.

Market Share: is the ratio of total deposit of each bank to total deposit of all banks.

Loan/ Deposit: loan-to-deposit ratio is a measure of the efficiency of banks in terms of the extent to which they are able to transform deposits into loans. It is mainly used to measure the loan and deposit fund utilization of banks.

Asset structure: is the ratio of tangible assets to the total assets.

## b. Results and discussion

We built different C&R trees with a different selection of input factors for C&R with the efficiency score as target. First we included all factors as inputs and efficiency classification as output. Figure 27 shows the importance of variables.

| Variable | Score |
|---|---|
| ASSET_STRUCTURE | 100.00 |
| FIN_STRENGTH | 91.74 |
| ROA | 91.16 |
| INT_GROWTH | 69.04 |
| MARKET_SHARE | 65.85 |
| GDP_GROWTH | 60.33 |
| ESTABLISH_DATE | 45.97 |
| LOAN_DEPOSIT | 40.09 |
| ROE | 37.92 |
| COUNTRY | 28.10 |
| INFLATION | 26.14 |
| OP_STYLE | 23.06 |
| TOTAL_POP | 20.64 |
| SIZE | 12.89 |
| SUPP_RATING | 4.62 |

Figure 27: Factor importance in predicting fully efficient banks

Figure 27 shows the out of the 18 environmental factors, 15 are considered to be important in predicating the fully efficient banks; only 7 of them are considered as primary splitters for the decision tree. Assets structure is the most important factor (100%), followed by financial strength (92%) and ROA (91%), whereas, operating style, population density, size and support rating have low importance. This suggests that banks should give more importance to their assets structures as it is one of the important factors for banks to be efficient. Figure 28 shows the predicated accuracy of the generated tree.

| Actual Class | Total Cases | Percent Correct | 1 N=1586 | 0 N=2074 |
|---|---|---|---|---|
| 1 | 1,586 | 100.00 | 100.00 | 0.00 |
| 0 | 2,074 | 100.00 | 0.00 | 100.00 |
| Total: | 3,660.00 | | | |
| | Average: | 100.00 | | |
| | Overall % Correct: | 100.00 | | |

Figure 28: Predicated accuracy of the tree

Out of 3,660 cases, 1586 cases are predicted to be efficient and 2074 cases are predicted to be inefficient, hence the accuracy in predicting the efficient and inefficient banks is 100.00%, which represents a high level of confidence.

Figure 29 illustrates the rules for efficient and in efficient banks that can be extracted as follow:

Rules for efficient banks

Banks are efficient (total of 1586 cases) if:

Rule one: Financial strength is greater than or equal 4.0, ROA is greater than or equal to 2.59 and country is less than 4 (122 cases).

Rule two: Financial strength is greater than or equal 4.0, ROA is greater than or equal to 2.59, country is greater than or equal to 4 and internal growth is greater than or equal to 4 (61 cases).

Rule three: Financial strength is greater than or equal to 4.0, ROA is less than 2.59, internal growth is greater than or equal to 5.66 and established date is greater than or equal 4 (100 cases).

Rule four: Financial strength is less than 4.0 and ROA is less than 2.86 (549 cases).

Rule five: Financial strength is less than 4.0, ROA is greater than or equal 2.86, country is less than 5, market share is less than 0.40, assets structure is less than 101.37 and established date is greater than or equal to 4 (122 cases).

Rule six: Financial strength is less than 4.0, ROA is greater than or equal 2.86, country is less than or equal 5 and market share is greater than or equal to 0.40 (122 cases).

Rule seven: Financial strength is less than 4.0, ROA is greater than or equal 1.45, country is greater than or equal 5, assets structure is less than 134.87 and established date is less than 4 (61 cases).

Rule eight: Financial strength is less than 4.0, ROA is greater than or equal 1.45 but less than 2.86, country is greater than or equal 5 and assets structure is greater than or equal to 134.87 (488 cases).

Rules for inefficient banks

The banks are inefficient (total of 2074 cases) if:

Rule one: Financial strength is greater than or equal 4.0, ROA is greater than or equal to 2.59, country is greater than or equal to 4 and the internal growth is less than 4.44 (122 cases).

Rule two: Financial strength is greater than or equal 4.0, ROA is less than 2.59 and internal growth is less than 5.66 (854 cases).

Rule three: Financial strength is greater than or equal 4, ROA is less than 2.59, internal growth is greater than or equal to 5.66 and established date is less than 4 (61 cases).

Rule four: Financial strength is less than 4, ROA is greater than or equal 2.86, country is less than 5, market share is less than 0.40, assets structure is less than 101.37 and established date is less than 4 (61 cases).

Rule five: Financial strength is less than 4, ROA is greater than or equal 2.86, country is less than 5, market share is less than 0.40 and assets structure is greater than or equal to 101.37 (671 cases).

Rule six: Financial strength is less than 4, ROA is greater than or equal to 2.86, country is greater than or equal to 5 and assets structure is greater than or equal 134.87 (183 cases).

Rule seven: Financial strength is less than 4, ROA is less than or equal to 1.45, country is greater than or equal to 5, assets structure is greater than or equal to 134.87 and established date is greater than or equal to 4 (122 cases).

With limitation of the number of banks and because of the large number of input factors included in the C&R tree it can be seen that only assets structure, ROA, financial strength, established date, market share, country and internal growth are sufficient to extract the rules. To investigate the impact of other factors that are not included in the above decision tree, two more C&R trees are drawn the first one by including the internal factors as input for the C&R tree and the second by only including the external factors. The following results are obtained from the two analyses.

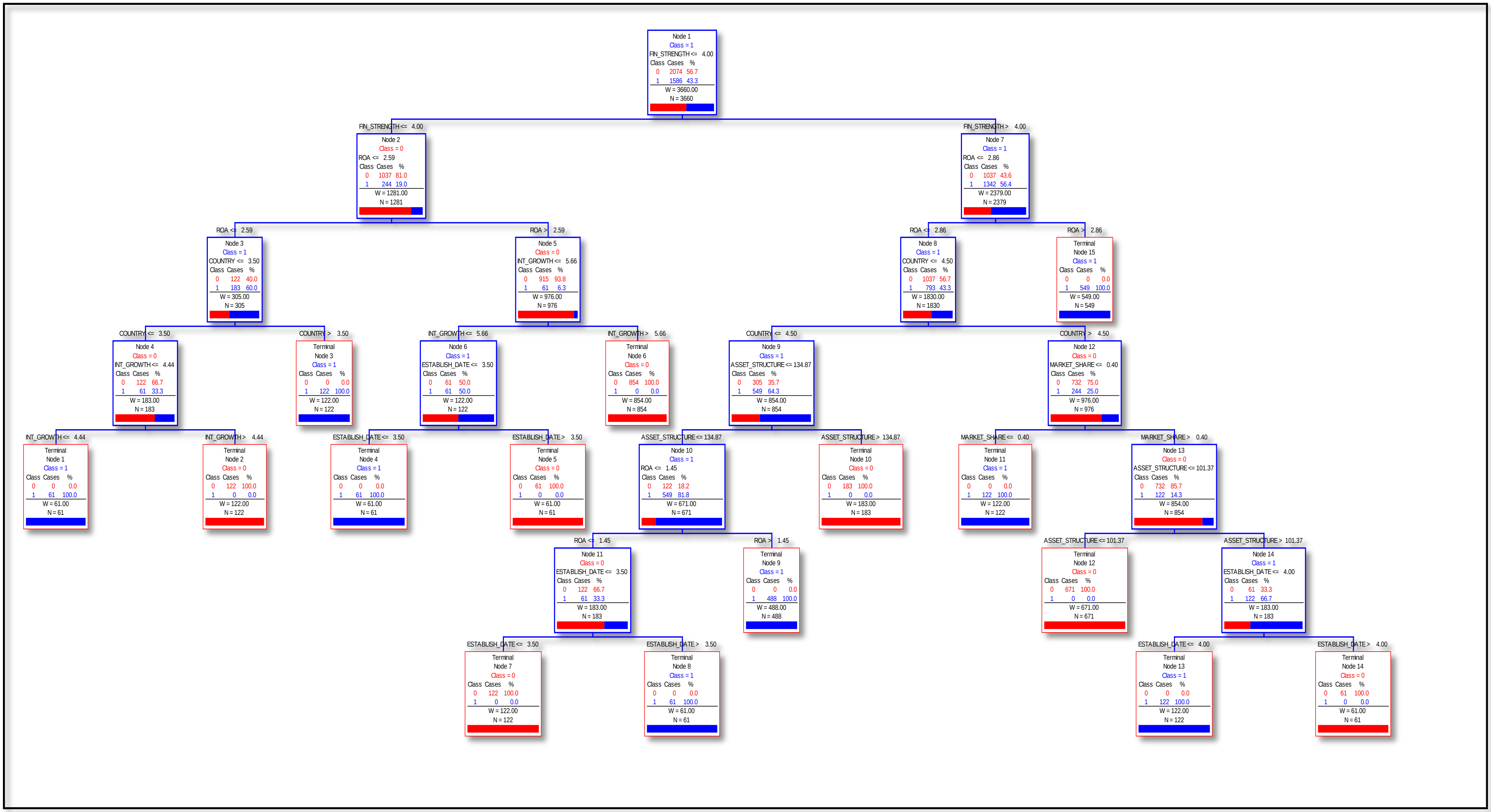


Figure 29: C&R tree

### c. The internal factors as input for C&R tree results

Figure 30 shows the importance of variables when we investigate the impact of the internal factors as input for the C&R tree and the efficiency as a target

| Variable | Score |
|---|---|
| MARKET_SHARE | 100.00 |
| ROA | 85.22 |
| FIN_STRENGTH | 80.10 |
| ROE | 70.29 |
| ASSET_STRUCTURE | 58.63 |
| LOAN_DEPOSIT | 49.99 |
| INT_GROWTH | 42.10 |
| SIZE | 30.36 |

Figure 30: Internal factor importance in predicting fully efficient banks

Figure 30 shows the out of the 11 internal environmental factors; 8 are considered to be important in setting rules for the fully efficient banks. Market share and ROA are the most important factors followed by financial strength (80.10%). ROE, assets structure and loan to deposit ratio have medium importance whereas bank size has the lowest importance in setting rules for the efficient banks.

Figure 31 shows the predictive accuracy of the generated tree. Out of 3,660 cases, 1586 cases are predicted to be efficient with an accuracy of 100%, and 2074 cases are predicted to be inefficient, hence the accuracy in predicting the efficient and inefficient banks is 100%, which represents a high level of confidence.

| Actual Class | Total Cases | Percent Correct | 0 N=2074 | 1 N=1586 |
|---|---|---|---|---|
| 0 | 2,074 | 100.00 | 2,074 | 0 |
| 1 | 1,586 | 100.00 | 0 | 1,586 |
| Total: | 3,660.00 | | | |
| | Average: | 100.00 | | |
| | Overall % Correct: | 100.00 | | |

Figure 31: Predicated accuracy of the tree

Figure 32 illustrates the rules for efficient and inefficient banks that can be extracted as follow:

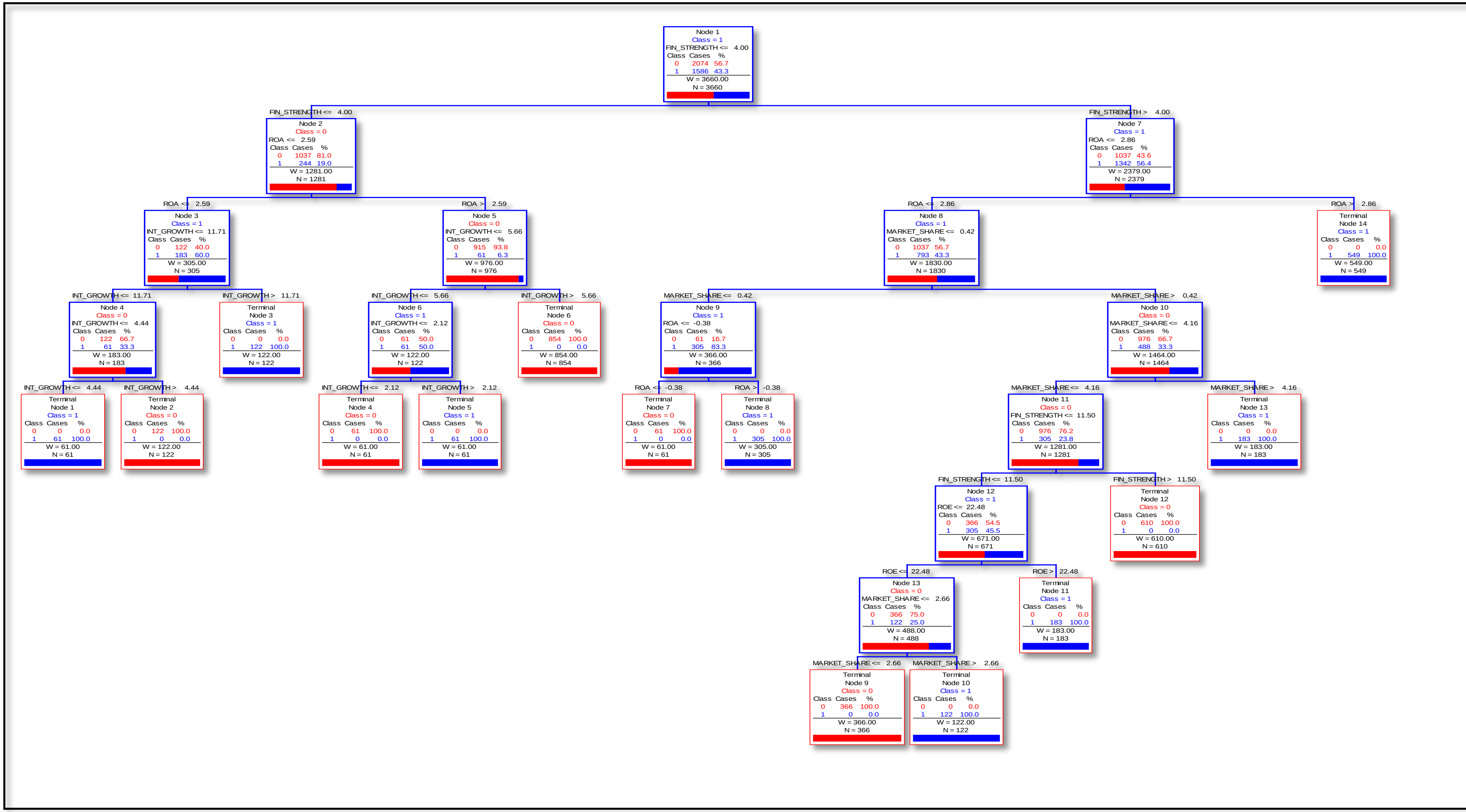


Figure 32: C&R Tree Rules for efficient banks

Banks are efficient (total of 1586 cases) if:

Rule one: Financial strength is greater than or equal 2.5 but less than or equal to 4.0, bank size is greater than or equal 5.5, loan to deposit ratio less than 81.7% and ROE is greater than or equal to 17.5 (122 cases).

Rule two: Financial strength is greater than or equal 4.0 and bank size is less than 5.5 (122 cases).

Rule three: Financial strength is less than 4.0 and ROA is less than 2.9 (549 cases).

Rule four: Financial strength is less than 4.0, ROA is greater than or equal to -0.38 but less than or equal 2.9, country is greater than or equal 5, assets structure is greater than or equal 134.9 and market share is greater than or equal to 0.42 (305 cases).

Rule five: Financial strength is less than 4.0, ROA is greater than or equal 2.9 and market share is less than 4.2 (183 cases).

Rule six: Financial strength is less than 4.0, ROA is greater than or equal 2.9, market share is greater than or equal 4.16 and ROE is less than 22.5 (183 cases).

Rule seven: Financial strength is less than 4.0, ROA is greater than or equal 2.9, market share is less than 2.7 and ROE is less than 22.5 (122 cases)

Rules for inefficient banks

The banks are inefficient (total of 2074 cases) if:

Rule one: Financial strength is greater than or equal 2.5 but less than or equal to 4.0, bank size is greater than or equal 5.5 (732 cases).

Rule two: Financial strength is greater than or equal 2.5 but less than or equal to 4.0, bank size is greater than or equal 5.5 and loan to deposit ratio is less than 81.7 (244 cases).

Rule three: Financial strength is greater than or equal 2.5 but less than or equal to 4, bank size is less than 5.5, loan to deposit ratio is less than 81.7 and ROE is less than 17.54 (61 cases).

Rule four: Financial strength is less than 4, ROA is less than 2.9 but greater than or equal -0.38 and market share is greater than or equal to 0.42 (61 cases).

Rule five: Financial strength is less than 4, ROA is greater than or equal 2.9, market share is greater than 0.42 but less than or equal to 4.16 (610 cases).

Rule six: Financial strength is less than 4, ROA is greater than or equal to 2.9, market share is less than or equal to 4.16 but greater than or equal 0.42 and ROE greater than or equal to 22.48 (366 cases).

### d. The external factors as input for C&R tree results

Figure 33 shows the importance of variables when we investigate the impact of the external factors as input for the C&R tree and the efficiency as a target.

Figure 33: External factor importance in predicting fully efficient banks

| Variable | Score |
|---|---|
| OP_STYLE | 100.00 |
| ESTABLISH_DATE | 99.98 |
| INFLATION | 89.14 |
| SUPP_RATING | 61.74 |
| GDP_GROWTH | 60.80 |
| COUNTRY | 24.83 |
| TOTAL_POP | 15.79 |

Figure 33 shows that out of the 7 external environmental factors all are considered to be important in setting rules for the fully efficient banks. Operating style and established date are the most important factor in setting rules for the fully efficient banks, followed by inflation (89.14%). Support rating and GDP growth seems to have medium importance whereas country and total population density have low importance in setting rules for the efficient banks. Figure 34 shows the predictive accuracy of the generated tree. Out of 3,660 cases, 1,525 cases are predicted to be efficient with an accuracy of 96%, and 1,830 cases are predicted to be inefficient with an accuracy of 88%, hence the accuracy in predicting the efficient and inefficient banks is 92%, which represents a high level of confidence.

| Actual Class | Total Cases | Percent Correct | 0 N=1891 | 1 N=1769 |
|---|---|---|---|---|
| 0 | 2,074 | 88.24 | 1,830 | 244 |
| 1 | 1,586 | 96.15 | 61 | 1,525 |
| Total: | **3,660.00** | | | |
| | Average: | 92.19 | | |
| | Overall % Correct: | 91.67 | | |

Figure 34: Predicated accuracy of the tree

Figure 35 shows the predictive accuracy of the generated tree for the test dataset. Out of 3,660 cases, 1,525 cases are predicted to be efficient with an accuracy of 96%, and 1,952 cases are predicted to be inefficient with an accuracy of 94%, hence the accuracy in predicting the efficient and inefficient banks is 95%, which represents a high level of accuracy.

| Actual Class | Total Cases | Percent Correct | 0 N=2013 | 1 N=1647 |
|---|---|---|---|---|
| 0 | 2,074 | 94.12 | 1,952 | 122 |
| 1 | 1,586 | 96.15 | 61 | 1,525 |
| Total: | **3,660.00** | | | |
| | Average: | 95.14 | | |
| | Overall % Correct: | 95.00 | | |

Figure 35: Predicated accuracy of the tree

Figure 36 illustrates the rules for efficient and inefficient banks that can be extracted as follow:

Rules for efficient banks:

Banks are efficient (total of 1586 cases) if:

Rule one: established date is greater than or equal to 5, GDP growth is less than 7.95%, inflation is less than 5.72, country less than or equal to 4, support rating is greater than or equal to 2.5 but less than or equal to 3.5 and operating style is 1 (61 cases).

Rule two: established date is greater than or equal to 5, GDP growth is less than 7.95%, inflation is less than 5.72, country less than or equal to 4, support rating is greater than or equal to 2.5 but less than or equal to 3.5 and operating style is 2 (61 cases that represent 16.7%).

Rule three: established date is greater than or equal to 5, GDP growth is less than 7.95%, inflation is less than 5.72, country less than or equal to 4, support rating is greater than or equal to 2.5 but less than or equal to 3.5 and operating style is 2 (183 cases).

Rule four: establish date is greater than or equal to 5 and GDP growth is less than 7.95% (305 cases).

Rule five: established date is greater than or equal to 2, but less than or equal to 5, GDP growth is greater than or equal to 7.95%, inflation is greater than 4.8 but less than or equal to 5.72 and support rate is greater than or equal to 2.5 (244 cases).

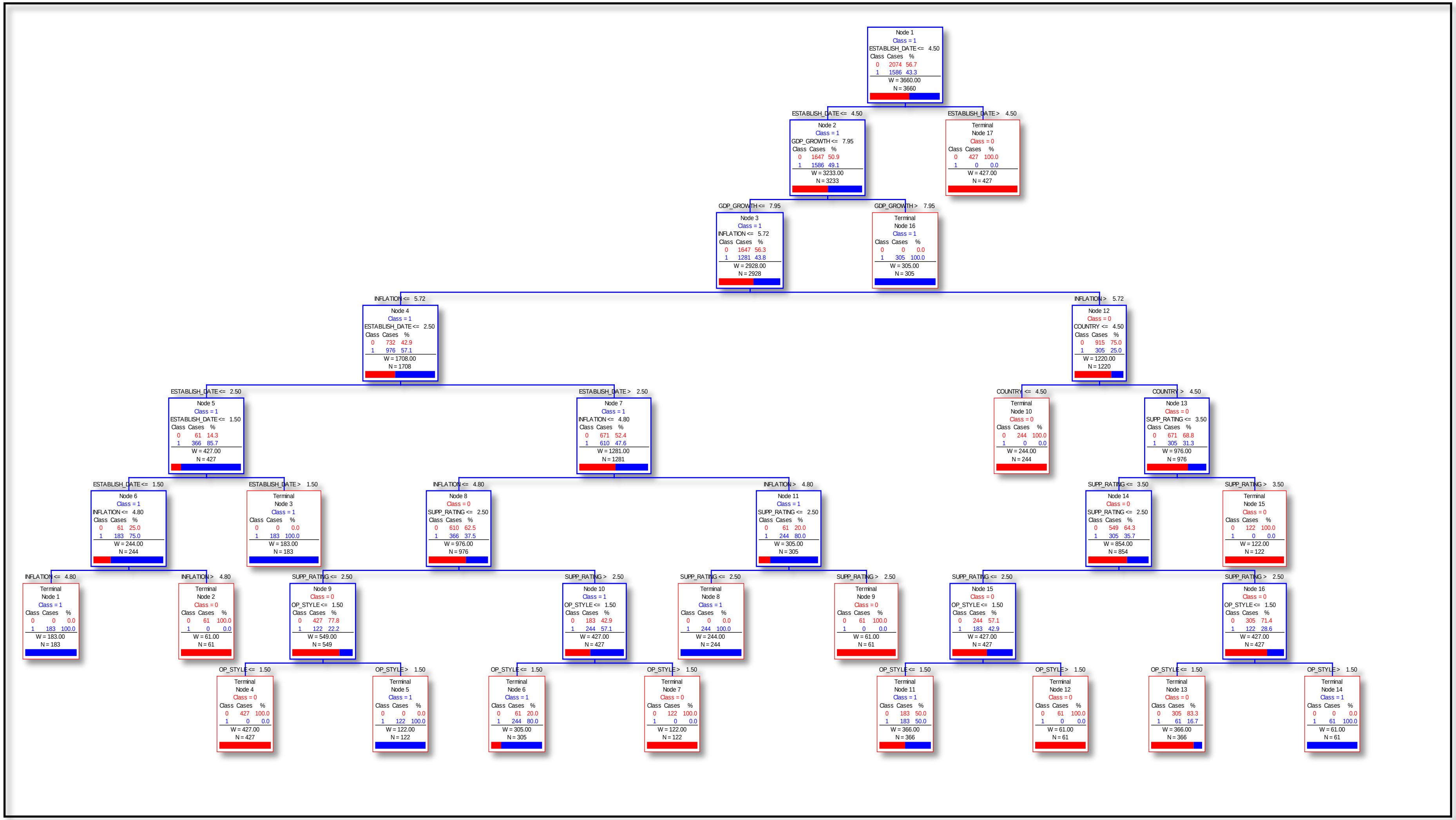


Figure 36: C&R Tree

Rule six: established date is greater than or equal to 3 but less than or equal to 5, GDP growth is greater than or equal to 7.95%, inflation is greater than or equal to 4.5 but less than or equal to 5.72, support rating is less than 2.5 and operating style is 2 (244 cases that represent 80%).

Rule seven: established date is greater than 2 but less than 5, GDP growth is greater than or equal to 7.95%, inflation is greater than or equal 4.5 and less than or equal to 5.72, support rating is less than 2.5 and operating style is 1 (122 cases)

Rule eight: established date is greater than or equal to 2 but less than 5, GDP growth is greater than or equal to 7.95%, inflation is greater than or equal 5.72 (183 cases)

Rule nine: established date is greater than or equal to 2 but less than 5, GDP growth is greater than or equal to 7.95% and inflation is greater than or equal 4.8 but less than or equal to 5.72 (183 cases).

Rules for inefficient banks:

The banks are inefficient (total of 2074 cases) if:

Rule one: The established date is less than 4 (427 cases).

Rule two: Country is greater than or equal to 5, the inflation is less than 5.72 and GDP growth is greater than or equal to 7.95% (122 cases).

Rule three: Country is greater than or equal to 5, inflation is less than 5.71, GDP growth is greater than or equal to 7.95 and established date is greater than or equal to 5 (244 cases).

Rule four: established date greater than or equal to 5, GDP growth is less than 7.95%, inflation is less than 5.72, country is less than 5, support rating is greater than or equal to 2.5 and the operation style is 2 (183 cases).

Rule five: the established date is greater than or equal to 4, GDP growth is less than 7.95, inflation is less than 5.72, country is less than or equal 4, support rating is greater than or equal to 3.5 and the operation style is equal to 1 (61 cases).

Rule six: established date is greater than or equal to 4¸GDP growth is less than 7.95, inflation is less than 5.72, country is less than 5, support rating is greater than or equal to 2.5 and operating style is equal to 2 (305 cases).

Rule seven: established date is greater than or equal to 5, GDP growth is less than 7.95, inflation rate is greater than or equal to 4.8 but less than or equal to 5.72 and support rating is less than 2.5 (61 cases).

Rule eight: established date is greater than or equal to 3 but less than or equal to 5, GDP growth is less than 7.95, inflation is greater than or equal to 4.5 but less than or equal to 5.72, support rating is less than 2.5 and operating style is 1 (122 cases).

Rule nine: established date is greater than or equal to 3, but less than or equal to 5, GDP growth is less than 7.95%, inflation rate is greater than or equal to 4.5% but less than or equal to 5.72%, support rating is less than or equal to 2 and operating style is 2 (61 cases).

Rule ten: established date is greater than or equal to 3 but less than or equal to 5, GDP growth is less than 7.95%, inflation rate is greater than or equal to 4.5% but less than or equal to 5.72, support rating is greater than or equal to 2.5 and operating style is 2 (427 cases).

Rule eleven: established date is greater than or equal to 2, but less than or equal to 5, GDP growth is greater than or equal to 7.95% and inflation rate is greater than or equal to 4.8 but less than or equal to 5.72 (61 cases).

## 6. Conclusion

This chapter evaluates the efficiency of GCC commercial banks during the period 1998-2007 using SORM model and investigates the influence of environmental factors (internal and external) on the efficiency score using Classification and Regression tree. The overall technical efficiency for all GCC commercial banks, are relatively stable over the time, with average of 85.6%. Saudi Arabia commercial banks appears to be ahead of the GCC countries with average efficiency score, around 89.8%, followed by United Arab Emirates banks with efficiency score 86.3%. Banks operating in Qatar are the lowest efficient banks, around 81.3%. The improvement analysis shows that inefficient banks managers' are oriented toward generating more loans and more OBS items with less profit and investments.

Banks of GCC countries can be equally competitive when it comes to technical efficiency; Islamic and conventional banks ranks more or less are same, and there is no relationship between bank geographical location and it is efficiency. This means that there is no reason to believe that bank performance differs in their ratings from a statistical perspective according to their locations or operating style. However, the results confirm that he large banks and small size GCC commercial banks are more efficient than the medium size.

Out of the 18 environmental factors; 15 are considered to be important in predicating the fully efficient banks and only 7 of them are considered as primary splitters for the decision tree. Assets structure is the most important factor followed by financial strength and ROA. The operating style, population density, size and support rating have low importance. Testing only for the internal environmental factors; 8 are considered to be important in setting rules for the fully efficient banks; market share and ROA. Bank size has the lowest importance in setting rules for the efficient banks. Once we considered only the external environmental factors; operating style and established date are the most important factor, whereas country and total population density have low importance.

# CHAPTER 7 : CONCLUSIONS AND RECOMMENDATIONS

## 1. Introduction

The previous chapters introduce the performance measurement approaches and Models, compare them and select the most appropriate one. Although, DEA seems to be the most popular method among researchers, it has some drawbacks, especially in dealing with negative data. Therefore, in this study we proposed a new DEA based Model to deal with negativity issue in DEA. Furthermore, the study reviewed the most published literature in banking performance and it is clear that there are still some difficulties facing researchers in measuring banking performance such as the way to deal with uncontrollable (environmental) factors. Hence we proposed C&R Tree as an integrated method with DEA results to deal with such factors. The proposed SORM Model and C&R are used to evaluate the performance of GCC commercial banks and to compare the performance of Islamic and Conventional banks. We believe that this is the first study that integrated C&R tree as an exploratory technique with DEA method as an efficiency evaluation method to measure bank efficiency. This chapter draws some conclusions, recommendations and the stimulated future research.

The following sections are organized as follow; section two summarizes the findings of the theoretical and empirical chapters. Section three provides some managerial and policy implications, followed by the study limitations, where as section five presents some recommendations and future research.

## 2. Theoretical findings

The comparative results between OLS Models, SFA and DEA show mixed results; each method has advantages and limitations. OLS and SFA mostly have the same characteristics while DEA is completely different. Both SFA and OLS are regression based analysis, accounting for noise, easy to test the hypothesis about causal relationships holding in the production context being modelled, allowing for environmental differences and have the ability to provide a Model for predicting.

Meanwhile, they cannot identify the sources of inefficiency; have low flexibility; need to specify the form of production function and need more specific assumptions about the distribution of efficiencies. On the other hand DEA as a nonparametric approach does not required the specification of a functional form of the production frontier and has the ability to handle multi-input and multi-output variables. Also, it provides the sources and the amount of inefficiency as well as it is more fixable and does not require many assumptions.

The related literature gives a mixed result too; therefore, the best selection of the employed approach would be depended on the situation and the main question of interest. But since, banks are using multi-input to produce multi-output, and the number of observation (sample size) in most of the reviewed studies is relatively small; therefore, we believe that DEA would be more suitable for measuring banks performance. Furthermore, banking managers are in need to know the source and the amount of their inefficiency and to improve their performance. DEA could easily handle these requirements.

The in depth analysis for the 204 published studies in this field representing 62 countries and six continents shows that DEA is the most popular nonparametric method and SFA is the most popular parametric method. However DEA seems to be the most applicable method between researchers (53%) whereas, SFA is the second one (33%). About half of the reviewed studies that used the standard DEA Models are based on VRS assumption (55%) compared to (45%) based on CRS assumption. Based on the CRS assumption around half of the studies have used output-oriented Model, while based on the VRS assumption more than half of the studies have used an output-oriented Model. Regarding the SFA method, it seems that the Translog form is the most popular function (58%), followed by Fourier Flexible (33%), whereas the Cobb–Douglas form is the least popular one (8%).

In bank behaviour term, the result shows that the Intermediation approach is the most favoured approach between researchers (63%) of the total applications, followed by the production approach with 10%. Also, the surveyed literatures show that the financial statement mainly is the major source for input and output variables. It is clear that there is there is a good level of agreement between researchers over the input and output variables to evaluate bank efficiency. Although, deposits seem to be the problematic variable, the majority of the researchers (76%) used it as an input against only (24%), which means that there is an agreement between researchers to use it as an input rather than output variable. Hence, one can safely conclude that, regardless to the bank approach, the input variables categories are: fixed assets, deposits and expenses. Likewise, the output variables broad categories are: liquid assets, loan and income or profit.

## 3. Empirical findings

### a. First Stage results

The data used in this study are a cross-country bank-level data, compiled from income statements and balance sheets of 60 banks each year in the 1998-2007 periods in all GCC countries. The intermediate banking approach is employed to measure the performance of GCC commercial banks with 3 inputs and 4 outputs. The input variables include; fixed assets, non-earning assets, and deposits, while the outputs are; loans, investments, net profit and off-balance sheet. These variables are varying over the study period; however, given the long time period being analyzed, it is expected that we will find such variation. The SORM Model was used to measure the technical efficiency for all GCC commercial banks. The technical efficiency measure from the SORM Model is tested with five consistency checks over the study period. These were: efficiency levels; rankings; identification the best and worst efficient banks; the stability of efficiency scores over the study period and their relation with non-frontier measures of performance.

The results show that the average overall technical efficiency for all GCC commercial banks based on the selected input-output is 85.6%, out of the 60 commercial banks covered in this study; only 10 are fully efficient. To find out whether the efficiency scores show a particular trend during the period 1998–2007, the result shows the mean is relatively stable for the period 1998-2003; then it reaches its highest level in 2004. The lowest efficiency score is found during 2005, which is two years after the second Gulf crisis. Finally the mean dropped below the average for 2006-2007. The standard deviation tends to be low when average technical efficiency is high, and vice versa. It should be noted that the foregoing efficiencies are comparable as a pooled frontier over 1998-2007 was used.

It is clear, that the average efficiency score of GCC commercial banks is slightly lowest than their counterpart in other countries. However, Saudi Arabia appears to be ahead of the GCC countries with average efficiency score, around 90%, followed by United Arab Emirates banks with efficiency score 86%. Although, it seems to be a tight competition from Omani and Bahraini commercial banks with average efficiency score 85.7% and 85.1% respectively, banks operating in Qatar and Kuwait seem to be the lowest bank performances, around 81% and 83% respectively, which requires more effort from GCC bankers and decision makers to improve their banks' efficiency. This seems to be in accordance with the assumption that country-specific characteristics still play an important part in the explanation of bank efficiency levels. Perhaps the more interesting point is the comparison of bank efficiencies, which are really much more dissimilar to each other.

Kruskal-Wallis test shows, that there is no statistically significant relationship between bank geographical location and its efficiency concerning 2007 results. This means that there is no reason to believe that bank performance differs in their ratings from a statistical perspective according to their geographical location. However, the same test shows that there is statistically significant relationship between bank size and their efficiency; the large bank size is the most efficient whereas the medium bank size is the less efficient ones. Mann-Whitney test shows that there is no significance difference in bank efficiency performance due to the differences in their operating style. These results suggest that banks of GCC countries can be equally competitive when it comes to technical efficiency.

The stability of efficiency rankings over the study period, or how long an inefficient bank remained inefficient, is addressed through computing Spearman rank-order correlations and the adapted Spearman rank-order correlations (t-year-apart efficiency). The result shows that banks change their rankings gradually during the study period, which means that banks' performances are found to be moderately persistent. To study the consistency of the SORM results with other performance measurement tools, we computed the Spearman Rank correlations between the efficiency score generated by SORM and the two non-frontier based measures (ROA and ROE). The correlation is low but positive. However, we are not expecting that each method will give the same rank to a bank, since each method has different meaning. Nevertheless, a positive rank-order correlation with these measures would give assurance that the frontier measures are not simply artificial products of the assumptions made regarding the underlying optimization concept. Furthermore, the low correlations are in line with those reported by Bauer *et al*. (1998) and Koetter (2006) and confirm that efficiency measures contain additional information compared to traditional performance ratios.

### b. Second Stage results

This section provides recommendations for the managers and regulators to improve the performance of their banks and strengthen the banking sector. The result shows that out of the 18 environmental factors, 15 are considered to be important in predicting the fully efficient banks; only 7 of them are considered as primary splitters for the decision tree. Assets structure is the most important factor, followed by financial strength and ROA. Internal growth, market share and GDP growth are middle importance, whereas, operating style, population density, size and support rating have low importance. This suggests that banks should give more importance to their assets structures as it is one of the important factors for banks to be efficient.

Once we split the 18 environmental factors according to their sources into: internal (bank) and external (country) specification factors, to investigate the impact of each one on efficiency scores. In term of internal factors, it is found that market share is the most important factor in setting rules for the fully efficient banks, followed by ROA, financial strength and ROE. Assets structure seems to have medium importance whereas loan to deposit ratio, internal growth and bank size have low importance in setting rules for the efficient banks. On the other hand, the impact of external factors shows that the operating style; country and support rating are the most important factors in setting rules for the efficient banks.

## 4. Recommendations

Although, the first stage results show differences in inefficiency among banks in the six countries, the second stage analysis results conclude that the rule for efficient banks could be helpful to specify the characteristics of efficient banks. This section provides recommendations for the managers and regulators to improve the performance of their banks and strengthen the banking sector.

### a. Managerial Recommendations

The main message from the previous chapter is that managers should not spend additional resources in trying to improve their outputs, since in our case; more resources do not contribute to a rise in outputs. Results obtained by SORM for potential outputs improvements should encourage managers to explore better ways of operating a bank. Observing how outputs are generated from inputs in the reference set of the inefficient banks can provide valuable insights and aid managerial decision making, to benchmark the best practice banks.

When we presented SORM results to banks manager[9], mostly, they agree with the results, some of them, who are challenged by SORM results to increase outputs, argued that the Model is deficient because a certain key output variable is omitted (social responsibility). Although, it is difficult to include such variable as it is unpublished data and it is not easy to measure, we believe there is no other logical output variable to include. Although, the managers of inefficient banks may work hard there simply may not be enough potential outputs in their marketplace to justify the current bank inputs. This means that no matter how hard the manager works, their bank may never be efficient if it has insufficient potential outputs.

To account for the environmental differences several test were carried out. Although, Islamic banks seem to be little bit more efficient, they face a stiff competition from conventional banks. Therefore, Islamic and Conventional banks managers are advised to see how they become more efficient and improve their investment decisions and profitability.

---

[9] ) The results presented to banks managers from Bahrain, Qatar, Saudi Arabia and UAE commercial banks at the 3[ed] International Islamic banks conference, Jakarta, Feb,2010

The medium size bank managers are advised to explore the option of merger either with small banks or large banks to be more efficient. At this point it is worth to note that all the medium size banks are Conventional banks[10]. Therefore, medium size Conventional bank managers are advised to explore the option of merger with Islamic banks with the same group or with other groups.

Qatar, UEA and Kuwaiti bank managers are advised to work hard to improve their efficiency; otherwise they will face a tight competition from their counterparts in other GCC countries.

As Dubai (in UAE), Qatar and Saudi Arabia are fighting to be an international financial hub in this area, bank managers of these countries are advised to work hard to improve their efficiency. This should be through more training courses that enrich bank managers' financial skills specially in generating more profits and investments. Top management of these banks in this three countries in particular and in other GCC countries in general, are advised to monitor their bank's relative efficiency using the suggested method (on quarter; half annual; annual bases or over number of years); this provides an insight into the performance of that bank compared to its peers. Also, it provides a strategic tool for top management to measure the impact of any change over the time.

## b. Policy Recommendations

Regulators are advised to monitor bank efficiency using the suggested method on annual bases over time; those banks that steadily lose efficiency are likely to become candidates for closure or downsizing, therefore urgent corrective action should be taken. Also, it is possible for regulators to generate a national index (e.g. average of all efficiencies of measured banks) that can be used to track periodically the impact of changes made by regulators in term of polices and processes to improve the banks' efficiency.

To be an international financial hub; UAE, Saudi Arabia and Qatar policy makers, in particular and other GCC countries in general are advised to introduce more regulation that encourage the banking sector to achieve high efficiency score. Also,

[10] ) Islamic banks are include; 8 small size and 3 large size banks

policy makers are advised to learn from other international hub such as Japan, Singapore, UK or USA through using the suggested method and compare their banking sector efficiency score with their counterpart in one country or all of these countries.

Based on C&R tree results, it is possible to recognize the most critical banks in GCC countries, in this way such banks can be submitted to a constant monitoring action with the aim of improving the efficiency. Therefore, the policy makers are advised to provide these banks with enough technical support and closely monitor these banks decisions to improve their performance over time.

Also, the C&R tree shows that inflation is one the most important environmental factors that influence bank performance, hence policy makers are suggested to control the inflation rate up to some level that motivate banks to be efficient. The GDP growth results suggest that the policy makers should maintain high economic growth rate to sustain high efficiency rate for their banking sector.

Finally, as some banks are given large efficiency improvement challenges, dysfunctional behaviour may result if the banks are not also supported with appropriate policy changes. For example, challenging a bank to make large investments without providing enough incentives for such investment may lead to extra expenses and less profit. Therefore policy makers are advised to work side by side with the suggested improvement results to strengthen their banking sector.

## 5. Study Limitations

Although, the method used here to evaluate banking performance is valid for any future application, the results from the application are specific to the data used. Including different dataset (input variables and/ or output variables and/or banks and/or time span) could produce different results (efficiency scores). Therefore, like other DEA based Models, the availability of the dataset is one of the limitations to generalize the results of this study. However, the results could give an indication of the efficient and inefficient banks, as well as the important factors that could be use to identify efficient banks.

## 6. Future Research

There are quite a number of theoretical and empirical issues still open to discussion and closer examination. Theoretical issues include SORM WHICH IS DEA BASED MODEL and C&R tree methods. Although, SORM is a new Model to deal with negative data, proposed to measure the efficiency of DMUs, it could be extended to measure the productivity too which future research can address. In the C&R tree method, there are a number of additional topics which need further research and investigation. These includes: the choice of independent factors for banking sector; when to stop decision tree; the use of different splitting rules and accuracy measures as well as improving re-sampling technique, researchers are encourage to study these issues .

This study compares the performance of Islamic and Conventional banks in GCC countries; the result shows that the operating style is not an important factor to predict the efficient banks but other studies have results contrary to this. Hence, we believe that Islamic banking is in need for more studies to highlight its importance and relationship with bank performance, especially the recently published papers in the global financial crisis of 2008 showed that the Islamic banks were less affected than the Conventional ones.

In the light of the ongoing international financial crisis, and the generated large costs for both national and international financial systems, the need for a new warning system becomes an important issue. This study success to identify efficient banks could guide bankers and regulators to avoid financial risk or bank failure; therefore, future research can build on the suggested methodology and include more environmental factors to propose an early warning system.

# REFERENCES

Afrait, S.C. (1972), Efficiency Estimation of Production Functions, *International Economic Review*, **13** (3): 568-598.

Ahmed, A. (1995), The Evolution of Islamic banking*, Encyclopaedia of Islamic Banking, London*: Institute of Islamic Banking and Insurance. pp. 15 – 30

Aigner, D.J., Lovell, C.A.K., Schmidt, P (1977), Formulation and estimation of stochastic frontier production function Models, *Journal of Econometrics*, **6**(1): 21-37.

Aigner, D.J., and Chu, S.F. (1968), On Estimating the Industry Production Function, *The American Economic Review*, **58**(4): 826-839.

Akhavein, Jalal, Humphrey, David and Eminent, Smith (1997), The Effects Of Megamergers On Efficiency And Prices: Evidence From A Bank Profit Function, *Review of Industrial Organization*, **12** (1): 95-139.

Akhigbe, Aigbe and McNulty, James (2003), The profit efficiency of small US commercial banks, *Journal of Banking & Finance*, **27** (2): 307-325.

Al Shamsi, Fatima, Aly, Hassan and El-Bassiouni, Mohamed (2009), Measuring and explaining the efficiencies of the United Arab Emirates banking system, *Applied Economics*, **41**(27): 3505-3519.

Alam, Mohammed (2003), Micro Credit Through 'Bai-Muajjal' Mode of Islamic Banking Financing System, Paper to present at the First Annual Conference of SANABEL, *Islamic Microfinance in the Arab World: Shapint the Industries Future*, Amman-Jordan, December 15-17, 2003.

Ali, A. and Seiford, L. (1990), Translation Invariance in Data Envelopment Analysis, *Operations Research Letters*, **9**(6): 403-405.

Al-Jarrah, Idries and Molyneux, Philip (2003), Cost efficiency, scale elasticity and scale economics in Arabian banking, *paper presented at the International conference on Financial development in Arab countries*, United Arab Emirates University- Abu Dhabi, 31 March-2 April, 2003.

Allen, Linda and Rai, Anoop (1996), Operational efficiency in banking: An international comparison, *Journal of Banking & Finance*, **20**(4): 655-672.

Al-Sharkas, A.A., Hassan, M.K. and Lawrence, S. (2008), The Impact of Mergers and Acquisitions on the Efficiency of the US Banking Industry: Further Evidence. *Journal of Business Finance and Accounting*, **35**(1): 50-70.

Al-Tamimi, Hussein and Lootah, Ahmad (2007), Evaluating the operational and profitability efficiency of a UAE-based commercial bank, *Journal of Financial Services Marketing*, **11**(4): 333-348.

Altunbas, Y., Liu, M-H, Molyneux, P. and Seth, R. (2000), Efficiency and risk in Japanese banking, *Journal of Banking & Finance*, **24**(10): 1605-1628.

Ariss, Rima (2008), Financial liberalization and bank efficiency: evidence from post-war Lebanon, *Applied Financial Economics*, **18**(11): 931-946.

Asaftei, Gabriel (2008), The contribution of product mix versus efficiency and technical change in US banking, *Journal of Banking & Finance*, **32**(11): 2336-2345.

Ashton, J.K. (2001), Cost Efficiency Characteristics of British Retail Banks, *The Service Industries Journal*, **21**(2): 159-174.

Ataullah, Ali and Le, Hang (2006), Economic reforms and bank efficiency in developing countries: the case of the Indian banking industry, *Applied Financial Economics*, **16**(9): 653 – 663.

Ataullah, Ali, Cockerill, Tony and Le, Hang (2004), Financial liberalization and bank efficiency: a comparative analysis of India and Pakistan, *Applied Economics*, 36(17): 1915-1924.

Avkiran N.K., (1999), The evidence on efficiency gains: The role of mergers and the benefits to the public, *Journal of Banking & Finance*, **23**(7): 991-1013.

Avkiran, Necmi (2009), Removing the impact of environment with units-invariant efficient frontier analysis: An illustrative case study with intertemporal panel data, *OMEGA*, **37**(3): 535-544.

Banker, R.D., Charnes, A., and Cooper, W.W. (1984), Some Models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, **30**(9):1078-1092.

Batchelor, Valli and Wadud, Mokhtarul (2004), Technical and scale efficiency of Islamic banking operations in Malaysia: an empirical investigation with a longitudinal perspective, *Labuan Bulletin of International Business & Finance,* **2**(1): 2004, 51-69.

Battese, George, Hjalmarsson, Lennart and Heshmati, Almas (2000), Efficiency of labour use in the Swedish banking industry: a stochastic frontier approach, *Empirical Economics*, **25**(4): 623-640.

Bauer, Pad, Berger, Allen, Ferrier, Gary and David Humphrey (1998), Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Methods, *Journal of Economics and Business*, **50** (2): 85-114.

Beccalli, E., B. Casu, and Claudia Girardone (2006), Efficiency and Stock Performance in European Banking, *The Journal of Business, Finance and Accounting*, **33**(2): 218–235.

Benamraoui, Abdelhafid (2008), Islamic banking: the case of Algeria, *International Journal of Islamic and Middle Eastern Finance and Management*, **1** (2): 113-131.

Berg, S., Forsund, F. and Jansen, E. (1991), Technical efficiency of Norwegian banks: a nonparametric approach to efficiency measurement, *Journal of Productivity Analysis*, **2**(2): 127–142.

Berger A.N., (2007), International Comparisons of Banking Efficiency, Financial Markets, *Institutions & Instruments*, **16**(3): 119- 144.

Berger, A.N. and Humphrey D.B. (1992), Measurement and efficiency issues in commercial banking, pp. 245-79, in Zvi Griliches, (Edit), Output measurement in the service sectors, *National Bureau of Economic Research Studies in Income and Wealth*, Chicago: University of Chicago Press.

Berger, A.N. Humphrey, D.B. (1991), The Dominance of Inefficiencies over Scale and Product Mix Economies in Banking, *Journal of Monetary Economics*, **28**(1): 117-148.

Berger, A.N., (1993), Distribution-free estimates of efficiency in the U.S. banking system and tests of the standard distributional assumptions, *Journal of Productivity Analysis*, **4**(3): 261–292.

Berger, A.N., and DeYoung, Robert (1997), Problem loans and cost efficiency in commercial banks, *Journal of Banking & Finance*, **21** (6): 849-870.

Berger, A.N., and Hannan, Timothy (1998), The Efficiency Cost Of Market Power In The Banking Industry: A Test Of The "Quiet Life" And Related Hypotheses, *The Review of Economics and Statistics*, **80**(3): 454-465.

Berger, A.N., and Mester, Loretta (2003), Explaining the dramatic changes in performance of US banks: technological change, deregulation, and dynamic changes in competition, *Journal of Financial Intermediation*, **12**(1): 57-95.

Berger, A.N., Humphrey, D.B. (1997), Efficiency of financial institutions: international survey and directions for future research, *European Journal of Operations Research*, **98**(2): 175-212.

Bos, J.W.B. and Kolari, James (2005), Large Bank Efficiency in Europe and the United States: Are There Economic Motivations for Geographic Expansion in Financial Services?, *Journal of Business*, **78** (4): 1555-1592.

Bos, J.W.B. and Schmiedel, H. (2007), Is there a single frontier in a single European banking market? *Journal of Banking & Finance*, **31**(7): 2081-2012.

Bos, J.W.B., Koetter, M. Kolari, J.W. and Kool, C.J.M. (2009), Effects of heterogeneity on bank efficiency scores, *European Journal of Operational Research*, **195**(1): 251-261.

Bowlin, W. (1998), Measuring performance: An introduction to Data Envelopment Analysis (DEA), *Journal of Cost Analysis*, **3**(3): 3–27.

Breiman, L., Friedman, J., Olshen, R. and Stone, C. (1984), C*lassification and regression trees*, Pacific Grove, Wadsworth-Monterey, USA.

Burki, Abid and Niazi, G.S. (2009), Impact of financial reforms on efficiency of state-owned, private and foreign banks in Pakistan, *Applied Economics*, 1-14 URL: http://dx.doi.org/10.1080/00036840802112315.

Butler, T.W and Li, Ling (2005), The utility of return to scale in DEA programming: an analysis of Michigan hospitals, *European Journal of Operational Research*, **161** (2): 469–477.

Carbo, S., Gardener, E. and Williams, J. (2002), Efficiency in Banking: Empirical Evidence from the Savings Banks Sector, *The Manchester School*, **70** (2): 204-228.

Casu, B. and C. Girardone (2002), A Comparative Study of the Cost Efficiency of Italian Bank Conglomerates, *Managerial Finance*, **28**(9): 3–23.

Casu, Barbara and Molyneux, Philip (2003), A comparative study of efficiency in European banking, *Applied Economics*, **35**(17): 1865-1876.

Caudill, S.B. (2002), SFA, TFA and a new thick frontier: graphical and analytical comparisons, *Applied Financial Economics*, **12**(5): 309 – 317.

Cazals, Catherine, Dudley, Paul, Florens, Jea-Pierre, Patel, Shital and Rodrigouz, Frank (2008), Delivery Offices Cost Frontier: A Robust Non Parametric Approach with Exogenous Variables, *Review of Network Economics*, **7** (2): 294-308.

Chambers, R, Chung, Y. and Fare, R (1998), Profit, directional distance functions, and Nerlovian efficiency, *Journal of Optimization Theory and Applications,* **98** (2): 351–364.

Chambers, R. Chung, Y. and Fare, R (1996), Benefit and distance functions, *Journal of Economic Theory,* **70**(2): 407–419.

Charnes, A., Clark, T., Cooper, W.W. and Golany, B. (1985), A developmental study of Data Envelopment Analysis in measuring the efficiency of maintenance units in US Air Forces, in R. Thompson & R. M. Thrall (Edit.), *Annals of Operational Research*, **2**: 95-112.

Charnes, A., Cooper, W.W, and Rhodes, E. (1978), Measuring the efficiency of decision making units, *European Journal of Operational Research*, **2**(6): 429-444.

Charnes, A., Cooper, W.W., Lewin, A., and Seiford, L.M (2001), *Data Envelopment Analysis: Theory, Methodology and Applications* (Edit), Kluwer Academic Publisher, Boston, USA, Sixth Edition.

Chen, Tser-Yieth (1998), A study of bank efficiency and ownership in Taiwan, *Applied Economics Letters*, **5**(10): 613-616.

Chen, Tser-Yieth and Yeh, Tser-Lien (2000), A Measurement of Bank Efficiency, Ownership and Productivity Changes in Taiwan, *The Service Industries Journal*, **20**(1): 95-109.

Chen, Yao, Gregoriou Greg N. and Rouah Fabrice (2009), Efficiency persistence of bank and thrift CEOs using data envelopment analysis, *Computer & Operations Research*, **36**(5):1554-1561.

Chiu, Yung-Ho, Jan, Chyanlong, Shen, Da-Bai and Wang, Pen-Chun (2008), Efficiency and capital adequacy in Taiwan banking: BCC and super-DEA estimation, *The Service Industries Journal*, **28**(4): 479-496.

Chiu, Yung-Ho, Ma, Chun-Mei and Sun, Ming-Yuan (2009), Efficiency and credit rating in Taiwan banking: data envelopment analysis estimation, *Applied Economics (iFirst)*, URL: http://dx.doi.org/10.1080/00036840801964443

Čihák, Martin and Hesse, Heiko (2008), Islamic Banks and Financial Stability: An Empirical Analysis, *IMF working paper, WP/08/16:* (1-29).

Clark, L. and Pregibon D. (1992), *Tree-based Model*, in Hastie, T.J. Statistical Models in S. Pacific Grove, California, Wadsworth & Brooks / Cole Advanced Boorks & Software: 377-419.

Coelli, T.J, Rao, D.S, O'Donnell, C.J. and G.E. Battese (2005), *An Introduction to Efficiency and Productivity Analysis* (2ed Edit), Springer, New York.

Coelli, T.J., Perelman, S., (1996), Efficiency measurement, multiple-output technologies and distance functions: With application to European railways, *CREPP Working Paper 96/05*, University of Liege.

Cooper W.W., Seiford, L and Tone, K. (2000), *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, Kluwer Academic Publishers.

Cooper, W.W., L.M. Seiford and K. Tone, (2000), *Data Envelopment Analysis: A comprehensive text with Models, applications references and DEA*, Kluwer Academic publishers, Boston, USA.

Cooper, W.W., Seiford, L.M., Zhu, J. (2004), *Handbook on Data Envelopment Analysis*, Kluwer Academic Publishers, Norwall, MA.

Cubbin, J. and Tzanidakis, G. (1998), Regression versus Data Envelopment Analysis for Efficiency Measurement: An Application to the England and Wales Regulated Water Industry, *Utilities Policy*, **7**(2): 75-85.

De Borger B., Ferrier G. and Kerstens K. (1998), The choice of a technical efficiency measure on the Free Disposal Hull reference technology: a comparison using US banking data, *European Journal of Operational Research*, **105**(3): 427-446.

Debnath, Mitra and Shankar, Ravi (2008), Measuring performance of Indian banks: an application Data Envelopment Analysis, *International Journal of Business Performance Management*, **10**(1): 57–85.

Debreu, G. (1951), The Coefficient of Resource Utilization, *Econometrica*, **19** (3): 273–292.

Delis, Manthos D, and Papanikolaou, Nikolaos (2009), Determinants of Bank Efficiency: Evidence from a Semi- parametric Methodology, *Managerial Finance*, **35**(3): 260-275.

DeYoung, Robert (1997), A diagnostic test for the distribution-free efficiency estimator: An example using U.S. commercial bank data, *European Journal of Operational Research*, **98**(2): 243-249.

Didar, Erdinç (2004), Bank Performance and Credit Availability in the Bulgarian Banking Sector, 1997-2001, *Journal of East-West Business*, **9**(3): 137-161.

Drake, L. and Hall, MJB (2003), Efficiency in Japanese banking: an empirical analysis, *Journal of Banking & Finance*, **27**(3): 891-917.

Edelstein, H. (1996) Data mining: exploiting the hidden trends in your data, DB2 Online Magazine, URL: http://wwww.db2mag.com/db_area/archives/19 97/q1/9701edel.html

El-Gamal, M.A. (2001), An Economic Explanation of the Prohibition of Gharar in Classical Islamic Jurisprudence, in Iqbal, M. (Edit) *Islamic Banking and Finance: Current Developments in Theory and Practice,* Leicester: Islamic Foundation.

Elyasiani, Elyas and Mehdian, Seyed (1990a), Efficiency in the Commercial Banking Industry, a Production Frontier Approach, *Applied Economics*, **22**(4): 539-551.

Elyasiani, Elyas and Mehdian, Seyed (1995), The comparative efficiency performance of small and large US commercial banks in the pre- and post-deregulation eras, *Applied Economics*, **27**(11): 1069-1080.

Elyasiani, Elyas, Mehdian, Seyed, Rezvanian, Rasoul (1994), An empirical test of association between production and financial performance: The case of the commercial banking industry, *Applied Financial Economics*, **4**(1): 55-59.

Emrouznejad, A. and Anouze, AL. (in press), Data envelopment analysis with classification and regression tree: a case of banking efficiency, *Expert Systems with Applications.*

Emrouznejad, A., Anouze, AL. and Thanassoulis, E. (2010), A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA, *European Journal of Operational Research*, **200**(1): 297-304.

Emrouznejad, A., Amin, G., Thanassoulis, E. and Anouze, AL. (2010), On the boundedness of the SORM DEA models with negative data, *European Journal of Operational Research*, **206**(1): 265-268.

Emrouznejad, A and Thanassoulis, E. (2005), *Performance Improvement Management Software*, www.DEAsoftware.co.uk

Emrouznejad, A., Parker, B. and Tavares G. (2008), Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA, *Journal of Socio-Economics Planning Science*, **42**(3): 151-157.

Färe, Rolf, Grosskopf, Shawna and Weber, William (2004), The effect of risk-based capital requirements on profit efficiency in banking, *Applied Economics*, **36**(15): 1731-1743.

Farrell, M.J. (1957), The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society, Series A*, **120**(3): 253-290.

Favero, C.A. and Papi, L. (1995), Technical efficiency and scale efficiency in the Italian banking sector, *Applied Economics*, **27**(4): 385-395.

Ferrier, G.D., and Lovell, C.A.K. (1990), Measuring cost efficiency in banking: econometric and linear programming evidence, *Journal of Econometrics*, **46**(1): 229-245.

Fethi, Meryem Duygun and Pasiouras, Fotios (2010), Assessing Bank Performance with Operational Research and Artificial Intelligence Techniques: A Survey, *European Journal of Operational Research*, **204**(2): 189-198.

Field, Kamal (1990), Production efficiency of British building societies, *Applied Economics*, **22**(3): 415 - 426

Figueira, Catarina and Nellis, Joseph (2009), Bank merger and acquisitions activity in the EU: much ado about nothing? *The Service Industries Journal*, **29**(7): 875-886.

Figueira, Catarina, Nellis, Joseph and Parker, David (2009), The effects of ownership on bank efficiency in Latin America, *Applied Economics*, **41**(18): 2353-2368.

Fiorentino, Elisabetta, Karmann, Alexander and Koetter, Michael (2006), *The Cost Efficiency of German Banks: A Comparison of SFA and DEA*, Deutsche Bundesbank working paper No 10/2006 Available at SSRN: http://ssrn.com/abstract=947340

Fitzpatrick, Trevor and McQuinn, Kieran (2007), Measuring bank profit efficiency, *Applied Financial Economics*, **18**(1): 1-8.

Forster, Jeremy and Shaffer, Sherrill (2005), Bank efficiency ratios in Latin America, *Applied Economics Letters*, **12**(9): 529-532.

Fried, C.K. Lovell and S. Schemidt (1993), *The measurement of productive efficiency: Techniques and applications*, Oxford University Press, New York. Pp (1-5).

Fukuyama, H. (1993), Technical and scale efficiency of Japanese commercial banks: A non-parametric approach, *Applied Economics*, **25**(8): 1101-1112.

Fukuyama, H., Guerra, R. and Weber, W.L. (1999), Efficiency and ownership: evidence from Japanese credit cooperatives, *Journal of Economics and Business*, **51** (6): 473-487.

Girardone, C., Molyneux, P. and Gardener, E. (2004), Analysing the determinants of bank efficiency: the case of Italian banks, *Applied Economics*, **36**(3): 215-227.

Giuffrida, A., and Gravelle, H. (2001), Measuring performance in primary care: Econometric analysis and DEA, *Applied Economics*. **33**(2):163-175.

Gong B.H., Sickles R.C. (1989), Finite sample evidence on the performance of stochastic frontiers and data envelopment analysis using panel data, *Journal of Productivity Analysis*, **1**(3): 229-261.

Gong B.H., Sickles R.C. (1992), Finite sample evidence on the performance of stochastic frontiers and data envelopment analysis using panel data, *Journal of Econometrics*, **51**(2): 259-284.

Gonza'lez, Francisgo (2009), Determinants of Bank-Market Structure: Efficiency and Political Economy Variables, *Journal of Money, Credit and Banking*, **41**(4): 735-754.

Greene, W.H. (2003), *Econometric Analysis*, New Jersey: Pearson Education, Inc.

Greene, W.H. (2008) The Econometric Approach to Efficiency Analysis, in: H. Fried, C.A.K. Lovell, S. Schmidt (Edit) *The Measurement of Productive Efficiency and Productivity Growth*, Oxford University Press, Oxford.

Grifell-Tatje, E, Lovell, C.A.K. (1997), The sources of productivity change in Spanish banking, *European Journal of Operational Research*, **98**(2): 364-380.

Hahn, Franz (2007), Environmental determinants of banking efficiency in Austria, *Empirica*, **34**(3): 231–245.

Hall, M. and C. Winsten (1959), The ambiguous notion of efficiency, *The Economic Journal*, **69**(273): 71-86.

Han, J and Kamber, M. (2001), *Data Mining Concepts and Techniques*, San Francisco: Morgan Kaufmann Publishers.

Hermes, Niels and Nhung, Thi Hong (2008), The impact of financial liberalization on bank efficiency: evidence from Latin America and Asia, Applied Economics, URL:http://dx.doi.org/10.1080/00036840802112448

Hjalmarsson L, Kumbhakar SC, Heshmati A. (1996), DEA, DFA, and SFA: a comparison. *Journal of Productivity Analysis*, **7**(3):303–327.

Ho, Chien-Ta (2006), Measuring bank operations performance: an approach based on Grey Relation Analysis, *Journal of the Operational Research Society*, **57**(4): 337-349.

Hoff, Ayoe (2007), Second stage DEA: Comparison of approaches for Modelling the DEA score, *European Journal of Operational Research*, **181**(1): 425-435.

Holger Scheel (1998), Negative data and undesirable outputs in DEA, *Paper presented at the Euro Summer Institute*, 1998 - Data envelopment Analysis - 20 years on.

Huang, Tai-Hsin, Liao, Ying-Ting and Chiang, Li-Chih (2010), An examination on the cost efficiency of the banking industry under multiple output prices' uncertainty, *Applied Economics*, **42**(9): 1169 – 1182.

Huang, T-H and Chen, Ying-Hsiu (2009), A study on long-run inefficiency levels of a panel dynamic cost frontier under the framework of forward-looking rational expectations, *Journal of Banking & Finance*, **33** (5): 842-849.

Huang, T-H and Wang, M-H (2002), Comparison of economic efficiency estimation methods: parametric and non-parametric techniques, *The Manchester School*, **70**(5): 682-709.

Hunter, William C., and Stephen G. Timme (1995), Core Deposits and Physical Capitol: A Reexamination of Bank Scale Economies and Efficiency with Quasi-Fixed Inputs, *Journal of Money, Credit and Banking*, **27**(1): 165-185.

Hussein, Khaled (2004), Banking Efficiency in Bahrain: Islamic vs Conventional Banks, *Islamic Development Bank research paper number*

Ila, M. Semenick, Alam (2001), A Nonparametric Approach for Assessing Productivity Dynamics of Large U.S. Banks, *Journal of Money, Credit and Banking*, **33** (1): 121-139.

Ismail Ahmad, Davidson, Ian and Frank, Regina (2009), Operating performance of European bank mergers, *The Service Industries Journal*, **29**(3): 345-366.

James, Christopher (1984), An Analysis of the Effect of State Acquisition Laws on Managerial Efficiency: The Case of the Bank Holding Company Acquisitions, *Journal of Law and Economics*, **27**(1): 211-226.

Kalish, Lionel and Gilbert, Alton (1973), The influence of bank regulation on the operating efficiency of commercial banks, *The Journal of Finance*, **28**(5): 1287-1301.

Kao, Chiang and Liu, Shiang-Tai (2004), Predicting bank performance with financial forecasts: A case of Taiwan commercial banks, *Journal of Banking & Finance*, **28** (10): 2353-2368.

Kao, Chiang and Liu, Shiang-Tai (2009), Stochastic data envelopment analysis in measuring the efficiency of Taiwan commercial banks, *European Journal of Operational Research*, **196**(1): 312-322.

Kaparakis, Emmanuel, Miller, Stephen, Noulas, Athanasios (1994), Short-run cost inefficiency of commercial banks: A flexible stochastic frontier approach, *Journal of Money, Credit, and Banking*, **26**(4): 875-893.

Kim, H. and G. J. Koehler (1995), Theory and Practice of Decision Tree Induction, *OMEGA*, **23(**6): 637-652.

Koetter, Michael (2008), The stability of bank efficiency rankings when risk preferences and objectives are different, *The European Journal of Finance*, **14**(2): 115-135.

Koopmans TC (1951), Analysis of production as an efficient combination of activities, In: Koopmans TC (Edit) *Activity analysis of production and allocation*. Wiley, New York London, pp 33-97.

Kraft, Evan, Hofler, Richard and Payne, James (2006), Privatization, foreign bank entry and bank efficiency in Croatia: a Fourier flexible function stochastic cost frontier analysis, *Applied Economics*, **38**(17): 2075-2088.

Kumbhakar, Subal C. and Lovell, C.V Knox (2000), *Stochastic Frontier Analysis*, Cambridge University Press, UK, Pp (6-7).

Lang, Günter and Welzel, Peter (1999), Mergers among German Cooperative Banks: A Panel-based Stochastic Frontier Analysis, *Small Business Economics*, **13**(4): 273–286.

Lensink, Robert Meesters, Aljar and Naaborg Ilko (2008), Bank efficiency and foreign ownership: Do good institutions matter? *Journal of Banking & Finance*, **32**(5): 834-844.

Lin, Ping-wen (2005), An Empirical Analysis of Bank Mergers and Cost Efficiency in Taiwan, *Small Business Economics,* **25**(2): 197-206

Lin, Yi-Hsing, Hsu J. Y. and Hsiao, Ching-Kai (2007), Measuring efficiency of domestic banks in Taiwan: application of data envelopment analysis and Malmquist index, *Applied Economics Letters*, **14**(11): 821-827.

Lovell, C.A.K. (1994), Linear programming approaches to the measurement and analysis of productive efficiency, *TOP*, **2**(2): 175-248.

Lovell, C.A.K. (1995), Measuring the macroeconomic performance of the Taiwanese economy, *International Journal of Production Economics*, **39**(2):165-178.

Lovell, C.A.K. and Pastor, J.T. (1995), Units invariant and translation invariant DEA Models, *Operations Research Letters*, **18**(3):147-151.

Mahesh, H.P. and Rajeev, Meenakshi (2008), Producing financial services: an efficiency analysis of Indian commercial banks, *Journal of Services Research*, **8**(2): 7-29.

McAllister, P.H. and McManus, D. (1993), Resolving the scale efficiency puzzle in banking, *Journal of Banking & Finance*, **17**(2): 389-405.

McCarty, T. and Yaisawarng, S. (1993), *Technical efficiency in New Jersey school districts, The Measurement of Productive Efficiency*, H. O. Fried, C.A.K. Lovell and S. S. Schmidt (Edit), New York, Oxford University Press: 271-287.

McDonald, John (2009), Using least squares and Tobit in second stage DEA efficiency analyses, *European Journal of Operational Research*, **197**(2): 792-798

Meeusen W, van den Broeck J (1977), Efficiency estimation from Cobb-Douglas production functions

Mester, Loretta (1994), How efficient are third district banks? *Business Review*: 3-18 http://www.phil.frb.org/research-and-data/publications/business-review/1994/brjf94lm.pdf

Mester, Loretta (1997), Measuring efficiency at U.S. banks: Accounting for heterogeneity is important, *European Journal of Operational Research*, **98**(2): 230-242.

Metwally, M. (1997), Economic Consequences of Applying Islamic Principles in Muslim Societies, *International Journal of Social Economics*, **24**(7): 941 – 957.

Mlima, Ponary and Hjalmarsson, Lennart (2002), Measurement of inputs and outputs in the banking industry, *Tanzanet Journal*, **3**(1): 12-22

Mokhtar, Hamim, Ahmad, Naziruddin Abdullah, and Syed Al-Habshi (2006), Efficiency of Islamic Banking in Malaysia: A Stochastic Frontier Approach, *Journal of Economic Cooperation*, **27**(2): 37-70.

Nikiel, Ewa and Opiela, Timothy (2002), Customer type and bank efficiency in Poland: implications for emerging market banking, *Contemporary Economic Policy*, **20**(3): 255-271.

Noman A. (2003), Imperatives of financial innovation for Islamic banks, *International Journal of Islamic Financial Services*, **4** (3)

Noulas, A., (1997), Productivity growth in the Hellenic banking industry: state versus private banks, *Applied Financial Economics*, **7**(3): 223-228.

Okeahalam, Charles (2008), Internationalisation and firm performance: Evidence from estimates of efficiency in banking in Namibia and Tanzania, *Journal of International Development*, **20**(7): 942-964.

Olgu, Ozlem and Weyman-Jones, Thomas (2008), Parametric and nonparametric Malmquist productivity decomposition: a case study of European commercial banks International, *Journal of Business Performance Management*, **10**(4): 344-365.

Ozkan-Gunay, E and Tektas, Arzu (2006), Efficiency analysis of the Turkish banking sector in precrisis and crisis period: A DEA approach Contemporary, *Economic Policy*, **24**(3): 418-431.

Pastor, J.T. (1994), *How to discount environmental effects in DEA: an application to bank branches,* Working paper N. 011/94, Depto, De Estadistica e Investigacion Operativa, Universidad de Alicante, Spain

Pastor, J.T. (1996), Translation invariance in data envelopment analysis: A generalization, *Annals of Operations Research*, **66**(2): 93-102.

Pastor, Jose Manuel and Tortosa- Ausina, Emili (2008), Social Capital and bank performance: an international comparison for OECD countries, *The Manchester School*, **76**(2): 223-265.

Portela, Maria and Thanassoulis, Emmanuel (2010), Malmquist-type indices in the presence of negative data: An application to bank branches, *Journal of Banking & Finance*, **34**(7): 1472-1483.

Portela Silva, Thanassoulis, Emmanuel and Simpson, Gary (2004), A Directional distance approach to deal with negative data in DEA: an application to bank branches, *Journal of Operational Research Society*, **55**(10): 1111-1121.

Ray, S.C. (1988), Data envelopment analysis, nondiscretionary inputs and efficiency: an alternative interpretation, *Socio-Economic Planning Science*, **22**(4): 167-176.

Ray, S.C. (1991), Resource-use efficiency in public schools: a study of Connecticut data, *Management Science*, **37**(12): 1620-1628.

Read, L, and Thanassoulis, Emmanuel. (1995), A comparison of data envelopment analysis and stochastic frontiers under variation of fit, Business School, *Working Paper 234*, University of Warwick

Resti, A. (1997), Evaluating the Cost Efficiency of the Italian Banking System: What can be learned from the Joint Application of Parametric and Nonparametric Techniques, *Journal of Banking & Finance*, **21**(2): 221–250.

Richmond, J. (1974), Estimating the Efficiency of Production, *International Economic Review*,**15** (2): 515-521.

Ripley, B.D. (1996), *Pattern recognition and neural networks*, Cambridge University Press, Cambridge

Ruggiero J. (1998), A new approach for technical efficiency estimation in multiple output production, *European Journal of Operational Research*, **111**(3): 369-380.

Sahoo, Biresh and Tone, Kaoru (2009), Decomposing capacity utilization in data envelopment analysis: An application to banks in India, *European Journal of Operational Research*, **195**(2): 575.

Saal, David, Parker, David and Weyman-Jones, Tom (2007), Determining the contribution of technical change, efficiency change and scale change to productivity growth in the privatized English and Welsh water and sewerage industry: 1985–2000, *Journal of Productivity Analysis*, **28**(1) :127–139

Scheel, H. (2001), Undesirable outputs in efficiency valuations, *European Journal of Operational Research*, **132**(2): 400–410.

Schmidt, Peter (1976),On the Statistical Estimation of Parametric Frontier Production Functions, *The Review of Economics and Statistics*, **58** (2): 238-239.

Schure, Paul, Wagenvoort, Rien and O'Brien, Dermot (2004), The efficiency and the conduct of European banks: Developments after 1992, *Review of Financial Economics*, **13**(4): 371-396.

Seiford, L. and Zhu, J. (2002), Modeling undesirable factors in efficiency evaluation, *European Journal of Operational Research*, **142**(1): 16-20.

Sensarma, Rudra (2006), Are foreign banks always the best? Comparison of state-owned, private and foreign banks in India, *Economic Modelling*, **23**(4): 717-735.

Shams, Khalid (2003), The economics of GCC banking efficiency, *unpublished PhD thesis*, School of Business and Regional development, University of Wales, Bangor. Pp (1-2).

Shams, Khalid and Molyneux, Philip (2003), Are GCC banks efficient?, *paper presented at the International conference on Financial development in Arab countries*, United Arab Emirates University- Abu Dhabi, 31 March-2 April, 2003.

Sharma, K.R., Leung, P., Zaleski, H.M., (1997), Productive efficiency of the swine industry in Hawaii: stochastic frontier vs data envelopment analysis, *Journal of Productivity Analysis,* **8**(4): 447–459.

Sharp, J., Liu, W. and Meng, W. (2006), A modified slacks-based measure Model for data envelopment analysis with ‘natural’ negative outputs and inputs, *Journal of Operational Research Society*, **57**(11): 1–6.

Shen, Chung-Hua (2005), Cost efficiency and banking performances in a partial universal banking system: application of the panel smooth threshold Model, *Applied Economics*, **37**(9): 993-1009

Shephard, R.W*. (1953), Cost and Production Functions,* Princeton: The University Press

Sherman, David and Gold, Franklin (1985), Bank branch operating efficiency: evaluation with Data Envelopment Analysis, *Journal of Banking & Finance*, **9**(2): 297-315.

Sherrill, Shaffer (1993), Can megamergers improve bank efficiency?, *Journal of Banking & Finance*, **17**(3): 423-436.

Spong, K. Sullivan, R. J. and DeYoung, R. (1995), What Makes a Bank Efficient? A Look at Financial Characteristics and Bank Management and Ownership Structure, *Financial Industry Perspective,* Federal Reserve Bank of Kansas City

Sufian, Fadzlan (2009a), The determinants of efficiency of publicly listed Chinese banks: evidence from two-stage banking Models, *Macroeconomics and Finance in Emerging Market Economies*, **2**(1): 93-133.

Sufian, Fadzlan (2009b), The impact of the Asian financial crisis on bank efficiency: The 1997 experience of Malaysia and Thailand, *Journal of International Development*, DOI: 10.1002/jid.1589.

Sufian, Fadzlan and Abdul Majid, Muhd-Zulkhibri (2007), Banks' Efficiency and Stock Prices in Emerging Markets: Evidence from Malaysia, *Journal of Asia-Pacific Business*, **7**(4): 35-53

Suhaimi, Rosita (2008), Profit Efficiency and K-Economy of Commercial Banks in Malaysia, *The Business Review*, **11**(2): 206-213.

Swamy, P.A., Tavlas, George and Lutton, Thomas (2003), An Analysis of Differences in Earnings Between Small and Large Commercial Banks, *Journal of Productivity Analysis*, **20**(1): 97–114.

Thanassoulis, Emmanuel (1993), A Comparison of Regression Analysis and Data Envelopment Analysis as Alternative Methods for Performance Assessments, *Journal of the Operational Research Society*, 44(11): 1129–1144.

Thanassoulis, Emmanuel (2001), *Introduction to the Theory and application of data envelopment analysis: a foundation text with integrated software*, Kluwer Academic Publisher, Massachusetts, USA.

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

Torgo, L. (1997), Functional Models for regression tree leaves, *Proceedings of the Fourteenth International Conference on Machine Learning (ICML 1997)*, Nashville, Tennessee, USA, July 8-12, 1997.

Vassiloglou, M. and Giokas, D. (1990), A Study of the Relative Efficiency of Bank Branches: An Application of Data Envelopment Analysis, *The Journal of the Operational Research Society*, **41**(7): 591-597

Wadud A. and White B. (2000) Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics*, **32**(13):1665–1673.

Wang, Mei-Hui and Huang, Tai-Hsin (2007), A study on the persistence of Farrell's efficiency measure under a dynamic framework, *European Journal of Operational Research*, **180**(3): 1302-1316.

Weber, William and Devaney, Michael (1999), Bank Efficiency, Risk-Based Capital, and Real Estate Exposure: The Credit Crunch Revisited, *Real Estate Economics*, **27**(1): 1-25.

Weill, L. (2004), Measuring cost efficiency in European banking: A comparison of frontier techniques, *Journal of Productivity Analysis*, **21** (2): 133–152.

Wheelock, D., Wilson, C. and Paul, W. (1995), Evaluating the efficiency of commercial banks: Does our view of what banks do matter? *Review - Federal Reserve Bank of St*, **77**(4): 39-51.

Wheelock, D.C., Whilson, P.W. (1999), Technical Progress, Inefficiency, and Productivity Change in U.S. Banking, 1984-1993, *Journal of Money, Credit, and Banking*, **31** (2): 212-234.

Worthington, Andrew (2001), Efficiency in Pre-Merger and Post-Merger Non-Bank Financial Institutions, *Managerial and Decision Economics*, **23**(8): 439-452.

Yao, Shujie, Han, Zhongwei and Feng, Genfu (2008), Ownership Reform, Foreign Competition and Efficiency of Chinese Commercial Banks: A Non-parametric Approach, *The World Economy*, **31**(10): 1310-1326.

Zaim, Osman (1995) The effect of financial liberalization on the efficiency of Turkish commercial banks, *Applied Financial Economics*, **5**(4): 257-264.

Zhou, Z. and Jiang, Y. (2003), Medical Diagnosis with C4.5 Rule Preceded by artificial Neural network ensemble, *IEEE Transactions on information Technology in Biomedicine*, **7**(1): 37-42

# APPENDIX

**Table (A-1): Summary of banks technical efficiency**

| Bank Code | Efficiency score | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
| BCB01 | 66 | 77 | 91 | 89 | 89 | 88 | 95 | 63 | 80 | 79 | 82 |
| BCB03 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 74 | 90 | 100 | 96 |
| BCB04 | 89 | 78 | 78 | 73 | 71 | 68 | 71 | 78 | 78 | 56 | 74 |
| BCB05 | 100 | 56 | 85 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 94 |
| BCB06 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| BCB07 | 71 | 76 | 82 | 66 | 52 | 100 | 100 | 100 | 100 | 100 | 85 |
| BCB08 | 80 | 70 | 79 | 73 | 75 | 72 | 93 | 70 | 67 | 61 | 74 |
| BIB01 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| BIB02 | 100 | 100 | 100 | 100 | 37 | 38 | 67 | 56 | 55 | 41 | 69 |
| BIB03 | 79 | 100 | 66 | 82 | 76 | 63 | 100 | 100 | 93 | 99 | 86 |
| BIB04 | 100 | 63 | 69 | 66 | 72 | 69 | 71 | 69 | 74 | 100 | 75 |
| ECB01 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| ECB02 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 21 | 20 | 26 | 77 |
| ECB03 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| ECB04 | 74 | 100 | 100 | 100 | 74 | 87 | 100 | 100 | 100 | 68 | 90 |
| ECB05 | 68 | 72 | 71 | 61 | 77 | 67 | 62 | 53 | 51 | 57 | 64 |
| ECB06 | 82 | 89 | 87 | 88 | 95 | 87 | 90 | 39 | 50 | 55 | 76 |
| ECB07 | 95 | 100 | 100 | 100 | 100 | 100 | 100 | 32 | 100 | 92 | 92 |
| ECB08 | 73 | 62 | 71 | 68 | 88 | 100 | 100 | 43 | 60 | 57 | 72 |
| ECB09 | 100 | 60 | 65 | 82 | 100 | 100 | 100 | 90 | 100 | 100 | 90 |
| ECB10 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 82 | 63 | 71 | 92 |
| ECB11 | 100 | 87 | 89 | 89 | 95 | 88 | 96 | 100 | 89 | 100 | 93 |
| ECB12 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| ECB13 | 100 | 100 | 100 | 100 | 100 | 100 | 95 | 96 | 85 | 100 | 98 |
| ECB14 | 68 | 74 | 73 | 63 | 59 | 60 | 73 | 72 | 74 | 56 | 67 |
| ECB15 | 78 | 88 | 67 | 60 | 70 | 60 | 89 | 100 | 100 | 67 | 78 |
| ECB16 | 85 | 75 | 82 | 79 | 82 | 100 | 100 | 100 | 83 | 88 | 87 |
| EIB01 | 86 | 84 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 97 |
| EIB02 | 82 | 100 | 100 | 100 | 100 | 100 | 100 | 87 | 81 | 97 | 95 |
| EIB03 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 56 | 60 | 45 | 86 |
| EIB04 | 100 | 100 | 86 | 69 | 51 | 60 | 63 | 75 | 79 | 50 | 73 |
| KCB01 | 86 | 88 | 86 | 84 | 82 | 77 | 97 | 31 | 39 | 40 | 71 |
| KCB02 | 92 | 80 | 87 | 95 | 100 | 89 | 82 | 17 | 18 | 21 | 68 |

**Table (A-1): Summary of banks technical efficiency**

| Bank Code | Efficiency score | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
| KCB03 | 83 | 80 | 84 | 87 | 84 | 81 | 88 | 20 | 25 | 24 | 66 |
| KCB04 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 39 | 57 | 63 | 86 |
| KCB05 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| KCB06 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 40 | 32 | 33 | 80 |
| KCB07 | 90 | 100 | 100 | 99 | 100 | 100 | 100 | 100 | 100 | 100 | 99 |
| KCB08 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 38 | 39 | 42 | 82 |
| KIB01 | 95 | 94 | 94 | 96 | 95 | 91 | 88 | 100 | 93 | 100 | 95 |
| OCB01 | 58 | 67 | 67 | 67 | 63 | 73 | 79 | 72 | 90 | 100 | 74 |
| OCB02 | 100 | 100 | 92 | 96 | 97 | 90 | 94 | 80 | 82 | 86 | 92 |
| OCB03 | 89 | 69 | 90 | 82 | 75 | 62 | 76 | 53 | 70 | 83 | 75 |
| OCB04 | 89 | 77 | 89 | 73 | 73 | 80 | 100 | 100 | 100 | 100 | 88 |
| OCB06 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| QCB01 | 71 | 71 | 64 | 54 | 63 | 58 | 79 | 85 | 83 | 62 | 69 |
| QCB02 | 64 | 59 | 71 | 64 | 78 | 86 | 93 | 49 | 65 | 71 | 70 |
| QCB03 | 90 | 100 | 91 | 84 | 100 | 65 | 82 | 100 | 100 | 83 | 89 |
| QCB04 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| QIB01 | 87 | 82 | 75 | 77 | 61 | 58 | 76 | 89 | 100 | 100 | 81 |
| QIB02 | 71 | 64 | 78 | 81 | 63 | 64 | 91 | 81 | 100 | 97 | 79 |
| SCB01 | 92 | 100 | 90 | 89 | 89 | 87 | 88 | 83 | 91 | 87 | 90 |
| SCB02 | 62 | 59 | 66 | 54 | 54 | 58 | 64 | 62 | 100 | 45 | 62 |
| SCB03 | 100 | 100 | 100 | 100 | 97 | 92 | 99 | 87 | 100 | 100 | 97 |
| SCB04 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| SCB05 | 100 | 100 | 100 | 100 | 100 | 98 | 96 | 83 | 82 | 85 | 95 |
| SCB06 | 94 | 93 | 92 | 94 | 92 | 98 | 91 | 100 | 100 | 100 | 95 |
| SCB07 | 84 | 79 | 83 | 85 | 84 | 78 | 81 | 67 | 70 | 71 | 78 |
| SCB08 | 89 | 90 | 93 | 84 | 89 | 80 | 84 | 100 | 100 | 100 | 91 |
| SIB01 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Average | 89 | 88 | 89 | 88 | 87 | 86 | 92 | 77 | 81 | 79 | 85.6 |

**Table (A-2): Observed and target level for inefficient banks (year 2007)**

| Bank Code | | Outputs | | | |
|---|---|---|---|---|---|
| | | Investment | Loans | OBS | Profit |
| BCB01 | Observed | 219.2 | 277.3 | 35.9 | 8.2 |
| | Target | 276.8 | 507.8 | 209.2 | 16.6 |
| BCB04 | Observed | 52.0 | 58.0 | 24.2 | 2.4 |
| | Target | 104.9 | 159.5 | 91.3 | 8.6 |
| BCB08 | Observed | 39.4 | 69.1 | 36.8 | 1.7 |
| | Target | 76.0 | 113.9 | 65.7 | 19.0 |
| BIB02 | Observed | 10.3 | 41.8 | 6.3 | 0.3 |
| | Target | 58.4 | 102.4 | 22.1 | 40.6 |
| BIB03 | Observed | 11.7 | 26.9 | 0.9 | 1.5 |
| | Target | 11.8 | 27.4 | 2.0 | 2.4 |
| ECB02 | Observed | 24.0 | 25.0 | 49.3 | 2.0 |
| | Target | 189.4 | 129.1 | 189.3 | 71.7 |
| ECB04 | Observed | 7.4 | 33.3 | 35.4 | 2.5 |
| | Target | 41.5 | 49.4 | 52.5 | 34.2 |
| ECB05 | Observed | 3.7 | 49.9 | 31.3 | 1.9 |
| | Target | 30.2 | 86.9 | 55.4 | 28.1 |
| ECB06 | Observed | 15.7 | 130.4 | 60.5 | 5.8 |
| | Target | 97.5 | 235.0 | 109.1 | 79.7 |
| ECB07 | Observed | 112.2 | 371.6 | 73.9 | 12.6 |
| | Target | 122.0 | 460.5 | 136.7 | 13.8 |
| ECB08 | Observed | 9.5 | 44.4 | 31.2 | 2.0 |
| | Target | 22.8 | 78.2 | 54.9 | 9.7 |
| ECB10 | Observed | 4.4 | 28.0 | 21.1 | 1.8 |
| | Target | 17.9 | 39.5 | 29.7 | 14.2 |
| ECB14 | Observed | 5.9 | 51.3 | 20.8 | 2.5 |
| | Target | 71.4 | 92.0 | 40.6 | 68.7 |
| ECB15 | Observed | 2.9 | 31.1 | 42.2 | 2.1 |
| | Target | 43.2 | 46.6 | 63.2 | 42.0 |
| ECB16 | Observed | 38.4 | 235.1 | 157.6 | 7.3 |
| | Target | 66.8 | 268.2 | 180.0 | 31.5 |
| EIB02 | Observed | 60.1 | 408.9 | 113.0 | 14.9 |
| | Target | 161.9 | 442.8 | 138.5 | 115.4 |
| EIB03 | Observed | 21.3 | 74.4 | 17.7 | 1.4 |
| | Target | 73.8 | 165.2 | 44.6 | 34.9 |
| EIB04 | Observed | 6.3 | 49.7 | 10.1 | 1.7 |
| | Target | 63.2 | 99.1 | 24.2 | 58.3 |
| KCB01 | Observed | 10.6 | 43.0 | 39.0 | 1.8 |
| | Target | 67.6 | 107.6 | 98.7 | 46.8 |
| KCB02 | Observed | 9.6 | 28.7 | 5.0 | 1.3 |
| | Target | 154.3 | 291.2 | 178.9 | 115.1 |
| KCB03 | Observed | 12.5 | 32.7 | 16.8 | 1.8 |
| | Target | 121.8 | 189.1 | 121.7 | 76.5 |
| KCB04 | Observed | 10.3 | 54.5 | 41.4 | 5.9 |

**Table (A-2): Observed and target level for inefficient banks (year 2007)**

| Bank Code | | Outputs | | | |
|---|---|---|---|---|---|
| | | Investment | Loans | OBS | Profit |
| BCB01 | Observed | 219.2 | 277.3 | 35.9 | 8.2 |
| | Target | 276.8 | 507.8 | 209.2 | 16.6 |
| BCB04 | Observed | 52.0 | 58.0 | 24.2 | 2.4 |
| | Target | 104.9 | 159.5 | 91.3 | 8.6 |
| BCB08 | Observed | 39.4 | 69.1 | 36.8 | 1.7 |
| | Target | 76.0 | 113.9 | 65.7 | 19.0 |
| BIB02 | Observed | 10.3 | 41.8 | 6.3 | 0.3 |
| | Target | 58.4 | 102.4 | 22.1 | 40.6 |
| BIB03 | Observed | 11.7 | 26.9 | 0.9 | 1.5 |
| | Target | 11.8 | 27.4 | 2.0 | 2.4 |
| ECB02 | Observed | 24.0 | 25.0 | 49.3 | 2.0 |
| | Target | 189.4 | 129.1 | 189.3 | 71.7 |
| ECB04 | Observed | 7.4 | 33.3 | 35.4 | 2.5 |
| | Target | 41.5 | 49.4 | 52.5 | 34.2 |
| ECB05 | Observed | 3.7 | 49.9 | 31.3 | 1.9 |
| | Target | 103.7 | 107.8 | 66.0 | 75.9 |
| KCB0706 | Observed | 5.1 | 6.7 | 0.9 | 0.6 |
| | Target | 18.5 | 20.4 | 3.6 | 5.6 |
| KCB08 | Observed | 35.0 | 135.9 | 72.8 | 6.6 |
| | Target | 146.0 | 370.7 | 220.5 | 78.5 |
| OCB02 | Observed | 48.3 | 161.0 | 60.9 | 5.0 |
| | Target | 56.0 | 186.9 | 71.5 | 6.7 |
| OCB03 | Observed | 11.3 | 57.9 | 27.3 | 2.7 |
| | Target | 13.7 | 69.9 | 33.1 | 3.3 |
| QCB01 | Observed | 28.2 | 64.1 | 35.8 | 1.9 |
| | Target | 65.0 | 103.4 | 61.1 | 25.9 |
| QCB02 | Observed | 98.9 | 162.9 | 146.2 | 8.8 |
| | Target | 148.4 | 238.9 | 206.8 | 12.5 |
| QCB03 | Observed | 43.2 | 130.8 | 94.9 | 5.9 |
| | Target | 97.0 | 158.1 | 114.8 | 51.9 |
| QIB02 | Observed | 26.6 | 92.9 | 9.1 | 7.9 |
| | Target | 60.7 | 96.3 | 10.1 | 41.5 |
| SCB01 | Observed | 135.1 | 376.0 | 125.8 | 15.1 |
| | Target | 203.1 | 439.9 | 152.7 | 65.4 |
| SCB02 | Observed | 52.8 | 60.8 | 13.6 | 5.0 |
| | Target | 130.1 | 216.6 | 98.9 | 10.9 |
| SCB05 | Observed | 194.4 | 414.3 | 284.5 | 18.5 |
| | Target | 228.0 | 485.8 | 333.6 | 21.7 |
| SCB07 | Observed | 111.3 | 169.5 | 122.0 | 2.7 |
| | Target | 156.8 | 263.8 | 201.9 | 8.9 |

**Table (A-3): Improvement level for the inefficient banks**

| Bank | Input/ Output | | Actual | Target | Improvement (%) | Benchmarking Target |
|---|---|---|---|---|---|---|
| BCB01 (79.18%) | Inputs | Fixed Assets | 6.74 | 6.74 | 0% | ECB13 (0.28), SCB08 (0.38), SCB04 (0.29), KIB01 (0.06) |
| | | NEA | 20.9 | 3.69 | -82% | |
| | | Deposits | 409. | 409.45 | 0% | |
| | Outputs | Investment | 219. | 276.78 | 26% | |
| | | Loans | 277. | 507.84 | 83% | |
| | | OBS | 35.9 | 209.17 | 482% | |
| | | Profit | 8.24 | 16.61 | 101% | |
| BCB04 (56.4%) | Inputs | Fixed Assets | 4.0 | 2.5 | -162% | BIB01 (0.66), KCB05 (0.25), SCB08 (0.08) |
| | | NEA | 1.6 | 1.6 | 0% | |
| | | Deposits | 43.8 | 43.8 | 0% | |
| | Outputs | Investment | 6.3 | 63.2 | 904% | |
| | | Loans | 49.7 | 99.1 | 100% | |
| | | OBS | 10.1 | 24.2 | 141% | |
| | | Profit | 1.7 | 58.3 | 3232% | |
| BCB08 (60.68%) | Inputs | Fixed Assets | 1.2 | 0.6 | -52% | BIB01 (0.64), EIB01 (0.13), KCB05 (0.18), SCB08 (0.05) |
| | | NEA | 1.2 | 1.2 | 0% | |
| | | Deposits | 90.2 | 90.2 | 0% | |
| | Outputs | Investment | 39.4 | 76.0 | 93% | |
| | | Loans | 69.1 | 113.9 | 65% | |
| | | OBS | 36.8 | 65.7 | 78% | |
| | | Profit | 1.7 | 19.0 | 991% | |
| BIB02 (40.8%) | Inputs | Fixed Assets | 1.52 | 0.74 | -51% | BIB01 (0.74), EIB01 (0.17), ECB13 (0.07), SCB08 (0.02) |
| | | NEA | 1.52 | 1.52 | 0% | |
| | | Deposits | 48.9 | 48.95 | 0% | |
| | Outputs | Investment | 10.2 | 10.27 | 0% | |
| | | Loans | 41.8 | 102.40 | 145% | |
| | | OBS | 6.32 | 22.10 | 250% | |
| | | Profit | 0.32 | 40.64 | 12784% | |
| BIB03 (99.24%) | Inputs | Fixed Assets | 0.2 | 0.2 | 0% | BIB01 (0.14), BIB04 (0.04), OCB06 (0.49), QIB01 (0.33) |
| | | NEA | 0.5 | 0.5 | 0% | |
| | | Deposits | 28.4 | 6.1 | -78% | |
| | Outputs | Investment | 11.7 | 11.8 | 1% | |
| | | Loans | 26.9 | 27.4 | 2% | |
| | | OBS | 0.9 | 2.0 | 123% | |
| | | Profit | 1.5 | 2.4 | 61% | |
| | Inputs | Fixed Assets | 2.7 | 2.1 | -21% | BIB01 (0.37), |

**Table (A-3): Improvement level for the inefficient banks**

| Bank | Input/ Output | | Actual | Target | Improvement (%) | Benchmarking Target |
|---|---|---|---|---|---|---|
| ECB02 (26.05%) | | NEA | 4.7 | 4.7 | 0% | ECB09 (0.01), |
| | | Deposits | 44.5 | 44.5 | 0% | SCB08 (0.58), |
| | Outputs | Investment | 24.0 | 189.4 | 690% | SIB01 (0.04) |
| | | Loans | 25.0 | 129.1 | 417% | |
| | | OBS | 49.3 | 189.3 | 284% | |
| | | Profit | 2.0 | 71.7 | 3568% | |
| ECB04 (67.53%) | Inputs | Fixed Assets | 0.5 | 0.5 | -1% | |
| | | NEA | 4.3 | 0.4 | -108% | BCB05 (0.18), |
| | | Deposits | 41.9 | 41.8 | 0% | BIB01 (0.17), |
| | Outputs | Investment | 7.4 | 41.5 | 462% | ECB12 (0.05), |
| | | Loans | 33.3 | 49.4 | 48% | OCB06 (0.54), |
| | | OBS | 35.4 | 52.5 | 48% | SCB08 (0.07) |
| | | Profit | 2.5 | 34.2 | 1279% | |
| ECB05 (57.46%) | Inputs | Fixed Assets | 0.6 | 0.6 | 0.% | |
| | | NEA | 5.8 | 3.1 | -47% | BIB01 (0.28), |
| | | Deposits | 56.5 | 56.5 | 0% | ECB01 (0.14), |
| | Outputs | Investment | 3.7 | 30.2 | 706% | OCB06 (0.57), |
| | | Loans | 49.9 | 86.9 | 74% | SCB08 (0.02) |
| | | OBS | 31.3 | 55.4 | 77% | |
| | | Profit | 1.9 | 28.1 | 1343% | |
| ECB06 (55.47%) | Inputs | Fixed Assets | 2.6 | 2.6 | 0% | BIB01 (0.14), |
| | | NEA | 6.4 | 6.4 | 0% | ECB01 (0.04), |
| | | Deposits | 153. | 153.2 | 0% | ECB13 (0.28), |
| | Outputs | Investment | 15.7 | 97.5 | 522% | QCB04 (0.04), |
| | | Loans | 130. | 235.0 | 80% | SCB08 (0.17), |
| | | OBS | 60.5 | 109.1 | 80% | SIB01 (0.070 |
| | | Profit | 5.8 | 79.7 | 1267% | |
| ECB07 (91.95%) | Inputs | Fixed Assets | 4.8 | 4.0 | -17% | |
| | | NEA | 10.0 | 10.0 | 0% | ECB13 (0.64), |
| | | Deposits | 313. | 313.0 | 0% | QCB04 (0.07), |
| | Outputs | Investment | 112. | 122.0 | 9% | SCB04 (0.04), |
| | | Loans | 371. | 460.5 | 24% | SCB08 (0.13), |
| | | OBS | 73.9 | 136.7 | 85% | SIB01 (0.11) |
| | | Profit | 12.6 | 13.8 | 9% | |
| ECB08 (56.84%) | Inputs | Fixed Assets | 0.6 | 0.6 | 0% | BIB01 (0.17), |
| | | NEA | 4.4 | 3.2 | -28% | ECB01 (0.10), |
| | | Deposits | 61.8 | 61.7 | 0% | |

**Table (A-3): Improvement level for the inefficient banks**

| Bank | Input/Output | | Actual | Target | Improvement (%) | Benchmarking Target |
|---|---|---|---|---|---|---|
| | Outputs | Investment | 9.5 | 22.8 | 141% | ECB12 (0.03), OCB06 (0.69), SCB08 (0.01) |
| | | Loans | 44.4 | 78.2 | 76% | |
| | | OBS | 31.2 | 54.9 | 76% | |
| | | Profit | 2.0 | 9.7 | 380% | |
| ECB10 (70.88%) | Inputs | Fixed Assets | 0.3 | 0.3 | 0% | BCB05 (0.05), BIB01 (0.13), BIB04 (0.04), ECB12 (0.05), OCB06 (0.73) |
| | | NEA | 2.3 | 0.4 | -82% | |
| | | Deposits | 38.3 | 38.3 | 0% | |
| | Outputs | Investment | 4.4 | 17.9 | 308% | |
| | | Loans | 28.0 | 39.5 | 41% | |
| | | OBS | 21.1 | 29.7 | 41% | |
| | | Profit | 1.8 | 14.2 | 685% | |
| ECB14 (55.76%) | Inputs | Fixed Assets | 0.7 | 0.7 | 0% | BIB01 (0.75), ECB13 (0.07), KCB05 (0.06), OCB06 (0.06), SCB0808 (0.05) |
| | | NEA | 1.4 | 1.4 | 0% | |
| | | Deposits | 46.9 | 46.9 | 0% | |
| | Outputs | Investment | 5.9 | 71.4 | 1111% | |
| | | Loans | 51.3 | 92.0 | 79% | |
| | | OBS | 20.8 | 40.6 | 95% | |
| | | Profit | 2.5 | 68.7 | 2627% | |
| ECB15 (66.81%) | Inputs | Fixed Assets | 0.6 | 0.7 | 0% | BIB01 (0.19), ECB03 (0.09), KCB05 (0.03), OCB04 (0.43), OCB06 (0.15), SCB08 (0.11) |
| | | NEA | 1.2 | 1.2 | 0% | |
| | | Deposits | 30.7 | 30.7 | 0% | |
| | Outputs | Investment | 2.9 | 43.2 | 1378% | |
| | | Loans | 31.1 | 46.6 | 50% | |
| | | OBS | 42.2 | 63.2 | 50% | |
| | | Profit | 2.1 | 42.0 | 1905% | |
| ECB16 (87.65%) | Inputs | Fixed Assets | 1.8 | 1.8 | 0% | ECB01 (0.29), ECB13 (0.10), KCB05 (0.30), OCB06 (0.17), QIB01 (0.14) |
| | | NEA | 10.3 | 10.3 | 0% | |
| | | Deposits | 255. | 255.2 | 0% | |
| | Outputs | Investment | 38.4 | 66.8 | 74% | |
| | | Loans | 235. | 268.2 | 14% | |
| | | OBS | 157. | 180.0 | 14% | |
| | | Profit | 7.3 | 31.5 | 330% | |
| EIB02 (97.22%) | Inputs | Fixed Assets | 4.0 | 4.0 | 0% | BIB01 (0.06), ECB01 (0.16), ECB13 (0.59), SCB04 (0.18), |
| | | NEA | 14.2 | 14.2 | 0% | |
| | | Deposits | 407. | 407.9 | 0% | |
| | Outputs | Investment | 60.1 | 161.9 | 169% | |
| | | Loans | 408. | 442.8 | 8% | |

**Table (A-3): Improvement level for the inefficient banks**

| Bank | Input/ Output | | Actual | Target | Improvement (%) | Benchmarking Target |
|---|---|---|---|---|---|---|
| | | OBS | 113.0 | 138.5 | 23% | SIB01 (0.01) |
| | | Profit | 14.9 | 115.4 | 674% | |
| EIB03 (45.05%) | Inputs | Fixed | 1.74 | 0.51 | -71% | BIB01 (0.61), EIB01 (0.04), ECB13 (0.29), SCB08 (0.05) |
| | | NEA | 3.37 | 3.37 | 0% | |
| | | Deposits | 87.27 | 87.27 | 0% | |
| | Outputs | Investment | 21.25 | 73.76 | 247% | |
| | | Loans | 74.43 | 165.24 | 122% | |
| | | OBS | 17.74 | 44.59 | 151% | |
| | | Profit | 1.40 | 34.90 | 2394% | |
| EIB04 (50.12%) | Inputs | Fixed | 1.2 | 1.2 | 0% | BIB01 (0.76), ECB13 (0.08), EIB01 (0.12), SCB08 (0.04) |
| | | NEA | 18.0 | | -100% | |
| | | Deposits | 84.0 | 84.0 | 0% | |
| | Outputs | Investment | 10.3 | 103.7 | 907% | |
| | | Loans | 54.5 | 107.8 | 98% | |
| | | OBS | 41.4 | 66.0 | 59% | |
| | | Profit | 5.9 | 75.9 | 1186% | |
| KCB01 (40%) | Inputs | Fixed | 1.00 | 1.00 | 0% | BIB01 (0.37), ECB01 (0.13), OCB06 (0.34), SCB01 (0.16) |
| | | NEA | 11.74 | | -100% | |
| | | Deposits | 59.12 | 59.12 | 0% | |
| | Outputs | Investment | 10.59 | 67.57 | 538% | |
| | | Loans | 43.04 | 107.60 | 150% | |
| | | OBS | 39.03 | 98.69 | 153% | |
| | | Profit | 1.84 | 46.81 | 2441% | |
| KCB02 (21.0%) | Inputs | Fixed | 1.80 | 1.80 | 0% | BIB01 (0.35), ECB13 (0.10), SCB08 (0.54) |
| | | NEA | 6.66 | 2.79 | -58% | |
| | | Deposits | 43.51 | 43.51 | 0% | |
| | Outputs | Investment | 9.64 | 154.31 | 1501% | |
| | | Loans | 28.71 | 291.17 | 914% | |
| | | OBS | 5.03 | 178.91 | 3453% | |
| | | Profit | 1.31 | 115.09 | 8665% | |
| KCB03 (23.69%) | Inputs | Fixed Assets | 1.63 | 1.63 | 0% | BIB01 (0.50), ECB13 (0.14), SCB08 (0.35), SIB01 (0.01) |
| | | NEA | 17.92 | | -100% | |
| | | Deposits | 54.85 | 54.85 | 0% | |
| | Outputs | Investment | 12.53 | 121.80 | 872% | |
| | | Loans | 32.74 | 189.08 | 478% | |
| | | OBS | 16.78 | 121.70 | 625% | |
| | | Profit | 1.81 | 76.55 | 4123% | |

**Table (A-3): Improvement level for the inefficient banks**

| Bank | Input/Output | | Actual | Target | Improvement (%) | Benchmarking Target |
|---|---|---|---|---|---|---|
| KCB04 (62.6%) | Inputs | Fixed Assets | 1.18 | 1.18 | 0% | BIB01 (0.78), SCB03 (0.14), SCB08 (0.06), SIB01 (0.01) |
| | | NEA | 17.98 | | -100% | |
| | | Deposits | 83.99 | 83.98 | 0% | |
| | Outputs | Investment | 10.34 | 103.67 | 903% | |
| | | Loans | 54.54 | 107.80 | 98% | |
| | | OBS | 41.36 | 66.04 | 60% | |
| | | Profit | 5.94 | 75.93 | 1177% | |
| KCB06 (33.04%) | Inputs | Fixed Assets | 0.42 | | -100% | BIB01 (0.26), SCB08 (0.01), OCB06 (0.73) |
| | | NEA | 4.68 | | -100% | |
| | | Deposits | 1.98 | 1.98 | 0% | |
| | Outputs | Investment | 5.07 | 18.47 | 264% | |
| | | Loans | 6.75 | 20.43 | 203% | |
| | | OBS | 0.91 | 3.59 | 293% | |
| | | Profit | 0.55 | 5.63 | 915% | |
| KCB08 (41.99%) | Inputs | Fixed Assets | 11.09 | 3.01 | -73% | ECB13 (0.05), SCB08 (0.61), SIB01 (0.33) |
| | | NEA | 66.32 | | -100% | |
| | | Deposits | 221.64 | 221.64 | 0% | |
| | Outputs | Investment | 34.98 | 146.00 | 317% | |
| | | Loans | 135.86 | 370.71 | 173% | |
| | | OBS | 72.78 | 220.47 | 203% | |
| | | Profit | 6.62 | 78.45 | 1085% | |
| OCB02 (86.2%) | Inputs | Fixed Assets | 1.1 | 1.1 | 0% | BIB01 (0.05), ECB13 (0.26), KCB05 (0.20), QIB01 (0.49) |
| | | NEA | 13.1 | | -100% | |
| | | Deposits | 179.8 | 150.7 | -16% | |
| | Outputs | Investment | 48.3 | 56.0 | 16% | |
| | | Loans | 161.0 | 186.9 | 16% | |
| | | OBS | 60.9 | 71.5 | 17% | |
| | | Profit | 5.0 | 6.7 | 33% | |
| OCB03 (82.74%) | Inputs | Fixed Assets | 0.4 | 0.4 | 0% | BIB04 (0.46), ECB01 (0.06), ECB12 (0.01), KCB05 (0.01), QIB01 (0.45) |
| | | NEA | 4.2 | 3.2 | -24% | |
| | | Deposits | 69.8 | 69.8 | 0% | |
| | Outputs | Investment | 11.3 | 13.7 | 21% | |
| | | Loans | 57.9 | 69.9 | 21% | |
| | | OBS | 27.3 | 33.1 | 21% | |
| | | Profit | 2.7 | 3.3 | 25% | |
| QCB01 (62%) | Inputs | Fixed Assets | 0.79 | 0.79 | 0% | BIB01 (0.45), |
| | | NEA | 1.47 | 1.47 | 0% | |

**Table (A-3): Improvement level for the inefficient banks**

| Bank | Input/ Output | | Actual | Target | Improvement (%) | Benchmarking Target |
|---|---|---|---|---|---|---|
| | | Deposits | 78.86 | 78.85 | 0% | KCB05 (0.15) ECB13 (0.07), SCB08 (0.05), OCB06 (0.28) |
| | Outputs | Investment | 28.22 | 65.00 | 130% | |
| | | Loans | 64.08 | 1043 | 61% | |
| | | OBS | 35.80 | 61.12 | 71% | |
| | | Profit | 1.92 | 25.89 | 1252% | |
| QCB02 (70.68%) | Inputs | Fixed Assets | 4.6 | 4.6 | 0% | BIB01 (0.27), ECB09 (0.05), KCB05 (0.01), QCB04 (0.13), SCB08 (0.40), SIB01 (0.15) |
| | | NEA | 6.6 | 6.6 | 0% | |
| | | Deposits | 187.1 | 187.1 | 0% | |
| | Outputs | Investment | 98.9 | 148.4 | 50% | |
| | | Loans | 162.9 | 238.9 | 47% | |
| | | OBS | 146.2 | 206.8 | 41% | |
| | | Profit | 8.8 | 12.5 | 41% | |
| QCB03 (82.7%) | Inputs | Fixed Assets | 1.9 | 0.9 | -52% | BIB01 (0.34), ECB13 (0.01), EIB01 (0.25), KCB05 (0.22), SCB08 (0.18) |
| | | NEA | 2.5 | 2.5 | 0% | |
| | | Deposits | 129.6 | 129.6 | 0% | |
| | Outputs | Investment | 43.2 | 97.0 | 125% | |
| | | Loans | 130.8 | 158.1 | 21% | |
| | | OBS | 94.9 | 114.8 | 21% | |
| | | Profit | 5.9 | 51.9 | 785% | |
| QIB02 (97.2%) | Inputs | Fixed Assets | 0.6 | 0.6 | -1% | BIB01 (0.84), ECB13 (0.13), QIB01 (0.04) |
| | | NEA | 4.6 | | -100% | |
| | | Deposits | 77.2 | 2.0 | -97% | |
| | Outputs | Investment | 26.6 | 60.7 | 128% | |
| | | Loans | 92.9 | 96.3 | 4% | |
| | | OBS | 9.1 | 10.1 | 11% | |
| | | Profit | 7.9 | 41.5 | 423% | |
| SCB01 (87.1%) | Inputs | Fixed Assets | 4.76 | 4.76 | 0% | ECB13 (0.55), KCB06 (0.10), QCB04 (0.09), SCB04 (0.22), SIB01 (0.03) |
| | | NEA | 11.23 | 11.23 | 0% | |
| | | Deposits | 480.72 | 480.72 | 0% | |
| | Outputs | Investment | 135.10 | 203.13 | 50% | |
| | | Loans | 376.03 | 439.95 | 17% | |
| | | OBS | 125.85 | 152.69 | 21% | |
| | | Profit | 15.14 | 65.40 | 332% | |
| SCB02 (45.2%) | Inputs | Fixed Assets | 2.8 | 2.8 | 0% | BIB01 (0.60), SCB04 (0.03), SCB08 (0.27), |
| | | NEA | 6.8 | 1.7 | -74% | |
| | | Deposits | 100.7 | 100.7 | 0% | |
| | Outputs | Investment | 52.8 | 130.1 | 146% | |

| Table (A-3): Improvement level for the inefficient banks | | | | | | |
|---|---|---|---|---|---|---|
| Bank | Input/ Output | | Actual | Target | Improvement (%) | Benchmarking Target |
| | | Loans | 60.8 | 216.6 | 256% | SIB01 (0.10) |
| | | OBS | 13.6 | 98.9 | 626% | |
| | | Profit | 5.0 | 10.9 | 121% | |
| SCB05 (85.3%) | Inputs | Fixed Assets | 9.1 | 3.9 | -57% | ECB01 (0.15), ECB12 (0.06), QCB04 (0.49), SCB04 (0.20), SIB01 (0.10) |
| | | NEA | 24.9 | 6.9 | -72% | |
| | | Deposits | 628.3 | 628.3 | 0% | |
| | Outputs | Investment | 194.4 | 228.0 | 17% | |
| | | Loans | 414.3 | 485.8 | 17% | |
| | | OBS | 284.5 | 333.6 | 17% | |
| | | Profit | 18.5 | 21.7 | 17% | |
| SCB07 (71.0%) | Inputs | Fixed Assets | 2.0 | 2.0 | 0% | BCB03 (0.08), BIB01 (0.14), ECB13 (0.11), KCB05 (0.51), SCB08 (0.16) |
| | | NEA | 4.9 | 4.9 | 0% | |
| | | Deposits | 269.2 | 269.2 | 0% | |
| | Outputs | Investment | 111.3 | 156.8 | 41% | |
| | | Loans | 169.5 | 263.8 | 56% | |
| | | OBS | 122.0 | 201.9 | 66% | |
| | | Profit | 2.7 | 8.9 | 230% | |

**Table (A-4): Banks code, name, geographical location and operating style**

| Bank Code | Bank Name | Location | Operating Style |
|---|---|---|---|
| BCB01 | Ahli United Bank | Bahrain | Conventional |
| BCB03 | Arab Banking Corporation | Bahrain | Conventional |
| BCB04 | National Bank of Bahrain | Bahrain | Conventional |
| BCB05 | United Gulf Bank | Bahrain | Conventional |
| BCB06 | Gulf International Bank | Bahrain | Conventional |
| BCB07 | Bahrain Saudi Bank | Bahrain | Conventional |
| BCB08 | Bank of Bahrain and Kuwait | Bahrain | Conventional |
| BIB01 | Arcapita Bank (First Islamic Investment Bank) | Bahrain | Islamic |
| BIB02 | Al Baraka Islamic Bank | Bahrain | Islamic |
| BIB03 | Bahrain Islamic Bank | Bahrain | Islamic |
| BIB04 | Shamil Bank of Bahrain | Bahrain | Islamic |
| ECB01 | Abu Dhabi Commercial Bank | UAE | Conventional |
| ECB02 | Arab Bank for Investment & Foreign Trade-ARBIFT | UAE | Conventional |
| ECB03 | United Arab Bank | UAE | Conventional |
| ECB04 | Bank of Sharjah | UAE | Conventional |
| ECB05 | Commercial Bank International | UAE | Conventional |
| ECB06 | Commercial Bank of Dubai | UAE | Conventional |
| ECB07 | Emirates Bank International | UAE | Conventional |
| ECB08 | National Bank of Fujairah | UAE | Conventional |
| ECB09 | First Gulf Bank | UAE | Conventional |
| ECB10 | Investment Bank | UAE | Conventional |
| ECB11 | Mashreq Bank | UAE | Conventional |
| ECB12 | National Bank of Abu Dhabi | UAE | Conventional |
| ECB13 | National Bank of Dubai | UAE | Conventional |
| ECB14 | National Bank of Ras Al-Khaimah | UAE | Conventional |
| ECB15 | National Bank of Umm Al-Qaiwain | UAE | Conventional |
| ECB16 | Union National bank | UAE | Conventional |
| EIB01 | Abu Dhabi Islamic Bank | UAE | Islamic |
| EIB02 | Dubai Islamic Bank | UAE | Islamic |
| EIB03 | Emirates Islamic Bank | UAE | Islamic |
| EIB04 | Sharjah Islamic Bank | UAE | Islamic |
| KCB01 | Alahli Bank of Kuwait | Kuwait | Conventional |
| KCB02 | Bank of Kuwait & The Middle East | Kuwait | Conventional |
| KCB03 | Burgan Bank | Kuwait | Conventional |
| KCB04 | Commercial Bank of Kuwait | Kuwait | Conventional |
| KCB05 | Gulf Bank | Kuwait | Conventional |
| KCB06 | Industrial Bank of Kuwait | Kuwait | Conventional |
| KCB07 | Kuwait Real Estate Bank | Kuwait | Conventional |
| KCB08 | National Bank of Kuwait | Kuwait | Conventional |
| KIB01 | Kuwait Finance House | Kuwait | Islamic |
| OCB01 | Bank Dhofar | Oman | Conventional |
| OCB02 | Bank Muscat | Oman | Conventional |
| OCB03 | National Bank of Oman | Oman | Conventional |
| OCB04 | Oman Arab Bank | Oman | Conventional |
| OCB06 | Oman Housing Bank | Oman | Conventional |
| QCB01 | Al Ahli Bank (Al Ahli Bank of Qatar) | Qatar | Conventional |
| QCB02 | Commercial Bank of Qatar | Qatar | Conventional |
| QCB03 | Doha Bank | Qatar | Conventional |

| | | | |
|---|---|---|---|
| QCB04 | Qatar National Bank | Qatar | Conventional |
| QIB01 | Qatar International Islaimc Bank | Qatar | Islamic |
| QIB02 | Qatar Islamic Bank | Qatar | Islamic |
| SCB01 | Arab National Bank | Saudi Arabia | Conventional |
| SCB02 | Bank Al Jazira | Saudi Arabia | Conventional |
| SCB03 | Banque Saudi Fransi (Al Bank Al Saudi Al Faransi) | Saudi Arabia | Conventional |
| SCB04 | National Commercial Bank | Saudi Arabia | Conventional |
| SCB05 | Riyad Bank | Saudi Arabia | Conventional |
| SCB06 | Saudi British Bank | Saudi Arabia | Conventional |
| SCB07 | Saudi Hollandi Bank | Saudi Arabia | Conventional |
| SCB08 | Saudi Investment Bank | Saudi Arabia | Conventional |
| SIB01 | Al Rajhi Banking & Investment Corporation | Saudi Arabia | Islamic |