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FINANCIAL PERFORMANCE ANALYSIS OF STOCK EXCHANGE LISTED MONGOLIAN COMPANIES

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The aim of this dissertation is to obtain a doctoral (Ph.D.) degree in the scientific field of "Management and Business"

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DECLARATION

I undersigned (name: Batchimeg Bayaraa, date of birth: 05/06/1988) declare under penalty of perjury and certify with my signature that the dissertation I submitted to obtain doctoral (Ph.D.) degree is entirely my own work.

Furthermore, I declare the following:

- I examined the Code of the Károly Ihrig Doctoral School of Management and Business Administration, and I acknowledge the points laid down in the code as mandatory.
- I handled the technical literature sources used in my dissertation fairly, and I conformed to the provisions and stipulations related to the dissertation.
- I indicated the original source of other authors' unpublished thoughts and data in the references section in a complete and correct way in consideration of the prevailing copyright protection rules.
- No dissertation which is fully or partly identical to the present dissertation was submitted to any other university or doctoral school for the purpose of obtaining a Ph.D. degree.

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Table of contents

INTRODUCTION

Performance evaluation plays an essential role in every type of business; used for revealing their deficiencies and comparing current business activities with that of their peers. However, the importance of performance measurement is underestimated in Mongolia.

As for business entities, one of the most crucial goals is producing and selling their goods and services, which are assured for customers' satisfaction with their quality and design. Every manager and investor aim to work efficiently to raise the company's value. However, every business and sector have uncertainty, which is needed to be determined and managed. It is important to evaluate the financial performance to protect a business, with that of their peer companies, as well as to be able to take corrective steps. The systematic comparison of the performance of one entity against other entities (benchmarking) helps to detect disadvantages the company investigated and helps to find out the way to improve its performance. Performance evaluation ratios can be an action guide on what should be done (Tehrani et al., 2012).

Producing goods and services without any waste is important for companies to survive economically, which is called efficiency, which had been achieved by a company for a specific period. Although efficiency is determined in many ways, yet there is not perfect and exact determination. The most widely used efficiency approach is Farrel efficiency, which seeks the possibility to reduce input without changing output or increase output without increasing input. Another important efficiency measurement tool is allocative efficiency. "Allocative efficiency (AE) is related to the choice of the least costly resource mix; in terms of output, it relates to the choosing a revenue-maximizing product mix" (Bogetoft & Otto, 2011). Allocative efficiency seeks the optimal products, and services must be produced without waste and by the minimal costs to maximize the profit.

Efficiency measurement methods can be divided into three main categories: ratio indicators, parametric, and non-parametric methods (Vincová, 2005). Efficiency measurement usually applies one of the following analyses: DEA (Data Envelopment Analysis) or SFA (Stochastic Frontier Analysis). However, it is not common to use and compare both models in one study. It is important to mention that there is not any research concerning performance measurement, which used Mongolian companies' financial data. Therefore, financial ratios were used as variables to execute parametric and non-parametric methods in the case of Mongolia.

Mongolian companies are divided into public companies (listed companies) and private companies (unlisted companies). As stated in the Mongolian law of auditing, listed companies' financial statements must be audited before stockholders' general meetings. This regulation increases the reliability of data compared with unlisted companies' financial statements. Because of data availability and reliability, listed companies' financial statements can be used to analyze the Mongolian economy since they cover the main sectors of the Mongolian economy. The thesis analyzes the financial performance of 100 Mongolian companies - listed on the Mongolian Stock Exchange (MSE) from 2012 to 2018.

Researchers aimed to examine financial performance determinants for a long time (for instance, Elliot (1972); Capon et al. (1990); Kipesha and James (2014), etc.) However, industrial characteristics are one of the most important aspects to consider when it comes to analyzing performance. In other words, every sector differs considering its operations and characters; therefore, different sectors can have different determinants. If we compare financial ratios of companies in different sectors, the financial analysis would be inadequate due to the different sector characteristics. The thesis applied panel regression (fixed and random effect model) to identify the financial performance determinants of each sector.

Agriculture and mining are the predominant sectors in the Mongolian economy, followed by construction and industrial sectors. Businesspeople and investors have often criticized Mongolian economic sectors due to their inefficiency. Based on the importance of industrial characteristics, companies are divided into three different sectors in financial analysis: heavy industry, manufacturing, and service. Each sector was analyzed separately and compared by their efficiencies.

The importance of the thesis is twofold. Firstly, the thesis compares the Mongolian economy with three other Asian countries' economies, studies Mongolian current economic situation, and determines economic growth factors. Secondly, it evaluates the financial performance of Mongolian companies in different sectors and with corporate sizes. Accordingly, output variables and their determinants are diagnosed by panel regression. Also, the thesis uses frontier efficiency techniques across parametric and non-parametric approaches to estimate corporate efficiency. Frontier efficiency estimations applied were the following: output-oriented DEA, input-oriented DEA, DEA combined with Principal Component Analysis (PCA), DEA with k-medoids clustering, and SFA.

Research justification

Businesspeople and investors often debate Mongolian economic sectors due to their inefficiency. Therefore, the financial performance of Mongolian three main sectors (heavy industry, manufacturing, and service) and different sizes (SMEs and big corporates), are examined and compared to recommend appropriate suggestions to improve their efficiency.

In the thesis, financial performance is measured by DEA and SFA using secondary data published by Mongolian Stock Exchange from 2012 to 2018.

Research hypotheses

Hypothesis 1 (H1): The heavy industry is the most efficient sector in the Mongolian economy like other selected Asian countries.

Hypothesis 2 (H2): Big corporates are more efficient than SMEs.

Hypothesis 3 (H3): The k-medoids clustering improves the performance measurement of the Mongolian companies investigated.

Hypothesis 4 (H4). Efficiency results by SFA are compatible with that of DEA and PCA-DEA in the case of Mongolian listed companies.

Hypothesis 5 (H5). IC has a significant positive impact on financial performance.

1 BUSINESS ANALYSIS AND PERFORMANCE MEASUREMENT

1.1 Business strategy analysis

This chapter introduces business analysis with its components, as well as performance measurement. Short- and long-term goals of organizations are defined through the management, and analytical processes and performance are measured and managed against these goals (Masri, 2013). Business analysis is defined in many ways. For example, Brennan (2009) defined business analysis as a set of tasks and techniques used to work as a liaison among stockholders to understand the structures, policies, and operations, and provide a guide that enables the organization to attain its targets. Woolfs (2015) characterizes business analysis as "an analysis of the entity's strategic position, making strategic choices and putting the chosen strategies into an action". Palepu et al. (2000) noted that business analysis is a practice to enable change in an organizational context, by defining needs and recommending solutions that deliver value to stakeholders. For simplicity's sake, business analysis is the evaluation of a company's prospects and risks to make business decisions. According to Subramanyam (2014), "business analysis aids in making informed decisions by helping structure the decision task through an evaluation of a company's business environment, strategies," financial positions, and performances.

According to Palepu et al. (2000), there are four key steps to outline the framework of business analysis using financial statements: business strategy analysis, accounting analysis, financial analysis, and prospective analysis (Figure 1.1). Among the four types of analysis, financial analysis is the prime focus of this thesis. Although beyond the scope, business strategy analysis, accounting analysis, and prospective analysis would be briefly discussed in this chapter.

Strategy analysis is a good basis for financial statement analysis, which helps to analyze the company at the qualitative level. The purpose of business strategy analysis is to identify key profit drivers as well as business risks and to assess the company's profit potential (Palepu et al., 2000). Analysis of business strategy seeks to identify and assess a company's competitive strengths and weaknesses along with its opportunities and threats (SWOT analysis) (Palepu et al., 2000). A firm's profit potential is determined by its strategic choices, which are shown in Table 1.1.

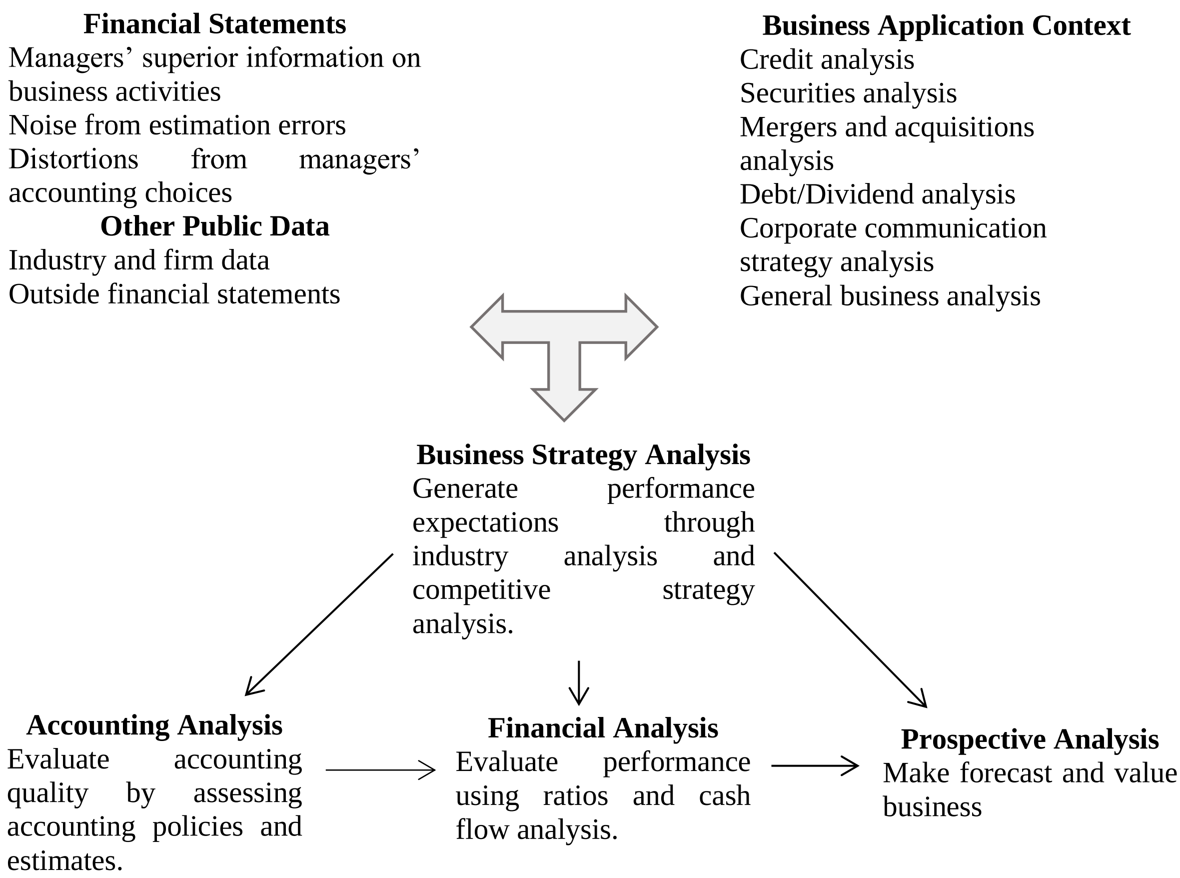


Figure 1.1 Business Analysis Using Financial Statements

Source: Palepu et al., 2000

Table 1.1 Strategic choices

Industry structure	Strategies for Creating Competitive Advantage	Corporate Strategy Analysis
• Rivalry among existing firms, • Thread of new entrants, • The availability of a substitute product • Bargaining power of the buyers, • Bargaining power of suppliers. • Thread of substitute products or services	• Cost leadership: offering the same product or service that other firms offer at a lower cost. • Differentiation: satisfying a customer need better than the competition, at an incremental cost that is less than the price premium that customers are willing to pay.	• Examining whether a company can create value by being in multiple businesses at the same time.

Source: Palepu et al., 2000

1.1.1 Accounting Analysis

The reliability of financial analysis' results depends on the accuracy of financial statements, which requires accounting analysis. Accounting analysis evaluates the company's accounting system, which reflects its economic position. Accounting analysis is done by studying a company's transactions and events, assessing the effects of its accounting policies on financial statements (Subramanyam, 2014). Especially when one makes a comparative analysis of the companies, it is important to analyze each company's accounting principles.

According to Subramanyam (2014), there are two problems in the analysis which affect the usefulness of financial statements: comparability problems and accounting distortions. As for comparative financial analysis, companies must use the same principles for the same transactions.

<u>The accounting principles which can affect analysis results are:</u>

- Revenue recognition principle: Even though there are certain criteria in IAS 18 (International Accounting Standard) for revenue recognition, the revenue recognition process can still be different for the companies.
- Cost formula of inventories: FIFO (first-in-first-out) and weighted average cost.
- Methods of depreciation: straight-line, double declining balance, units of production, the sum of years' digits. Although the compared companies use the same method for depreciation calculation, the salvage value and useful life should be considered, which makes a difference.
- Interest rate during the construction: Some companies capitalize on the interest rate during the construction, while some companies recognize as an interest rate in the income statement.

Comparability problems can occur either horizontal (comparative analysis among the companies in the same sector) or vertical analysis (comparative analysis of a company over a period). Although companies are required to adopt one accounting principle consistently, there can be some occasions that we have to change the accounting principle. For example, the companies used LIFO (last-in-first-out) cost accounting, were forced to change this procedure when IFRS (International Financial Reporting Standards) banned LIFO. It causes a comparability problem in a vertical analysis.

The second problem is connected to discretion and imprecision in accounting. "Accounting distortions are deviations of accounting information from the underlying economy" (Subramanyam, 2014). Companies have a variety of interests in distorting their financial statements. For instance,

- Inflate current revenues or deflate expenses to higher the stock price or to attract investors.
- Reduce profit to pay less tax.
- Change its capital structure to show better solvency.

There are three potential distortions in accounting data:

1. Errors or omissions related to estimation error.
2. Managers might use also introduce noise and bias into accounting data through their own accounting decisions to manipulate or window-dress financial statements (earnings management) (Palepu et al., 2000).
3. Accounting policy choice according to accounting standards: The degree of distortion introduced by accounting standards depends on how well uniform accounting standards capture the nature of a firm's transactions (Subramanyam, 2014).

Accounting distortion in the financial statement can change financial users' decisions, which are called accounting risk. Restatement and reclassification of financial statements are usually required to reduce accounting risk and to improve its economic content and comparability (Subramanyam, 2014).

<u>Accounting analysis has six key steps:</u>

- Identifying the key accounting policies and estimates (key risks and crucial business factors)
- Evaluating accounting flexibility. If managers have accounting freedom to choose their accounting principle and methods, financial statements are highly likely distorted according to the managerial purpose.
- Evaluating accounting strategy. By comparing the company with its competitors who applied the same accounting principle and methods, we can analyze the similarities and dissimilarities. In the case of dissimilarities, it is advised to check whether the company changed its accounting policy lately. How did the changes affect their accounting?
- Assessing the firm's disclosures. By checking whether the key accounting policies and principles explained or not.

- Identifying red flags (accounting distortion). By examining unexplained or unexpected transactions, determining the gap between profit and net operating cash flow, etc. Companies with poor performance are highly advised to be checked their accounting policy changed, which could result in a higher profit.
- Undoing any accounting distortion-restating accounting numbers to remove any noise and bias caused by the accounting rules and management decisions (Palepu et al., 2000). Financial statements, cash-flow statements, and tax's footnotes are used to restate accounting.

1.1.2 Prospective Analysis

Financial analysis is the preceding research stage of a prospective analysis. Nevertheless, this subchapter discusses prospective analysis before dealing with financial analysis. Because the main scope of this thesis is financial analysis, which is examined in detail, while prospective analysis is discussed briefly in this subchapter as it is beyond the scope of the thesis.

The prospective analysis focuses on forecasting a firm's future, is the final step in the business analysis. Managers need forecasts for planning and to provide performance targets; analysts need forecasts to help communicate their views of the firm's prospects to investors; bankers and debt market participants need forecasts to assess the likelihood of loan repayment. Two commonly used techniques in the prospective analysis are financial statement forecasting and valuation. As Palepu et al. (2000) stated, forecasting represents the first step of prospective analysis and serves to summarize the forward-looking view that originates from business strategy analysis, accounting analysis, and financial analysis. On the contrary, the previous ones, valuation is the process by which forecasts of performance are converted into estimates of the price (Palepu et al., 2000).

Instead of forecasting income statement alone only, it is better to forecast the complete financial statements. Financial ratios derived from the pro forma financial statements need to check by feasibility against historical results. These comparisons must be made to historical ratios and must recognize adjustments for factors expected to affect them (Subramanyam, 2014).

Steps of forecasted financial statements based on Figure 1.2 are:

<u>Step 1: Identify the key variables affecting the future financial performance</u>

External and internal variables affect future financial performance. External variables usually related to government policies and economic conditions, such as tax rates, interest rates for borrowings, inflation rate, etc. Internal variables cover the policies and agreements of the businesses (for example, capital expenditure commitments, financing agreements, inventory holding policies, credit period allowed for customers, etc.) (Atrill, 2009).

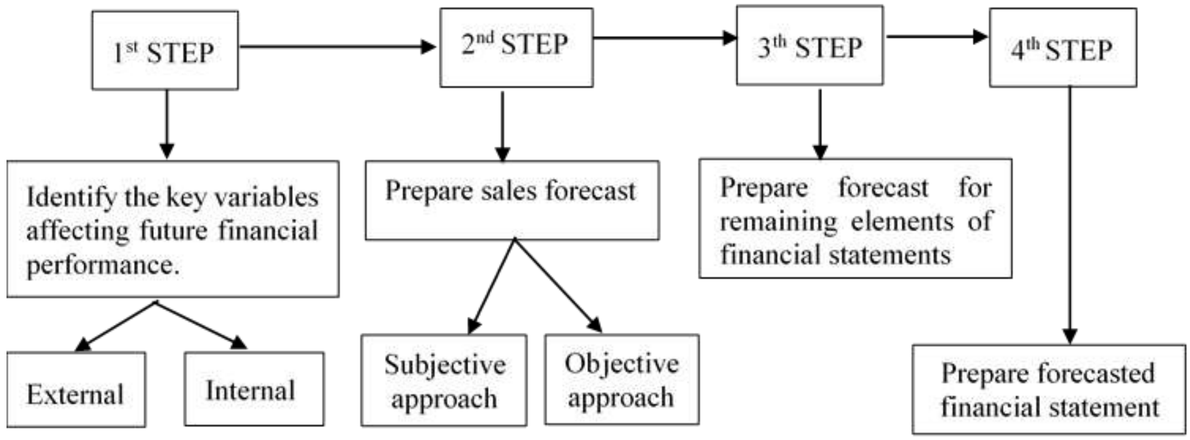


Figure 1.2 Steps of forecasted financial statements

Source: Atrill, 2009

<u>Step 2: Forecast the sales for the period</u>

Forecasting usually starts with the sales prediction. Although forecast drivers can differ depending on the industry, the sales forecast is the most important driver for the forecast, followed by profit margin (Palepu et al., 2000). Making a reliable sales forecast is crucial since it affects many other accounts such as Cost of Goods Sold (COGS), overheads, inventories, receivables, etc. Therefore, if the sales forecast is not correct, other forecasts will be inaccurate as well. Producing a reliable sales forecast requires an understanding of general economic conditions, industry conditions, and the threat posed by major competitors (Atrill, 2009).

There are two main approaches for sales forecasts: the subjective and the objective approach. The subjective approach usually relies on the views of the sales force or sales managers. It is a 'bottom-up' approach that involves aggregating forecasts from those with special knowledge of particular products, services, or market segments (Atrill, 2009). On the contrary, the objective approach uses statistical techniques or econometric models for sales forecasting.

<u>Step 3: Forecast remaining elements of financial statements</u>

All other items appearing in the projected financial statements can be forecasted, having forecast the level of sales. Expenses must be classified as variable and fixed to prepare a forecasted income statement. Fixed costs are predicted as the same amount as usual, while variable costs are predicted based on the predicted sales volume. Semi-variable costs, such as electricity expenses must be divided into fixed and variable parts. When the forecasted income statement is ready, information for the cash flow statement forecast will be available. Benchmark is used not only for performance measurement but also to prove whether the forecasted amounts are close to the financial statements' elements (Palepu et al., 2000).

Step 4: Prepare the projected financial statements

The forecasted statement of financial position reveals the end-of-period balances for assets, liabilities, and equity, and it is the last statement to be prepared (Atrill, 2009). An alternative approach to preparing a projected income statement and balance sheet is the percent-of-sales method, which assumes that most items appearing in the income statement and balance sheet vary with the level of sales. These statements can be prepared by expressing most items as a percentage of the sales for the forecast period. During the percent-of-sales method, the forecast increase in assets may exceed the forecast increase in equity, which results in the so-called financing gap. How a business decides to fill the financing gap is referred to as a plug. There are various forms of financing that might be used as a plug, including borrowings and share capital (Atrill, 2009).

For some purposes, including short-term planning and security analysis, forecasts for quarterly periods are desirable. One crucial feature of quarterly data is seasonality, which can occur in the sales and earnings data of nearly every industry (Palepu et al., 2000).

There are three possible methods to help managers to deal with any uncertainty surrounding the reliability. Sensitivity analysis is a useful technique to employ when evaluating the contents of projected financial statements. Sensitivity analysis examines a chosen variable's effect (e.g., the volume of sales) on changes in the likely performance and position of the business. Another approach is scenario analysis, which changes several variables simultaneously to portray a possible state. The third approach, simulation, create a distribution of possible values to key variables in the projected financial statements, and a probability of occurrence is attached to each value (Atrill, 2009).

1.2 Financial Analysis

Financial analysis is the scope of the thesis; therefore, it would be considered in detail rather than three other analysis (business strategy analysis, accounting analysis, and prospective analysis) under the umbrella of business analysis. Financial analysis is the process of evaluating business activity and performance of entities typically based on their financial statements. In other words, it "is the application of analytical tools and techniques to derive estimates and inferences useful in business analysis" (Subramanyam, 2014). The main goal of the financial analysis is providing its users with efficient, reliable, and useful information that helps them to make correct decisions.

<u>Financial analysis users can be grouped as follows:</u>

- Current and potential investors are interested mainly in profitability analysis as they want to secure their investment.
- Managers may wish to know if their business is successful or not by using financial analysis. Also, financial analysis helps them to make their financial decisions and reassure the accuracy of past decisions.
- Employees: For their job security and the possibility of the pay rise.
- Stockholders are interested in profitability and solvency analysis. Based on the financial analysis, they can decide whether to buy more stock or to sell the stocks they own.
- The government organizes government policies based on the companies' performance. Moreover, tax authorities use financial statements to analyze with the purpose of tax control.
- Suppliers use financial analysis to assure to get paid for their goods and services.
- Creditors usually interested more in liquidity and solvency. Financial analysis helps them to make their decision about whether to lend money or not. For the short-term loan creditors, liquidity analysis is more important, while long-term loan creditors pay more attention to the firm's solvency.

The most important skill in financial analysis is systematic and efficient. Additionally, the analysis should allow the analyst to use financial data to explore business issues (Palepu et al., 2000).

The role of financial analysis includes, but not limited to:

- To evaluate entities' financial performance and results

- To evaluate the efficiency of resources' usage (financial, raw materials, and workforce)
- To reveal the unused capacity
- To examine the accuracy of managerial decisions
- Improve the justification of business plan and standards
- To evaluate the implementation of the project and plan.

Table 1.2 Steps of Financial Statement Analysis

№	Steps	Output
1	Establish objectives	A list of specific questions to be answered according to the purpose. Timetable and budgeted resources.
2	Collect data	Financial data table
3	Process the data	Common-size financial statements
4	Conduct analysis	Analytical results
5	Make recommendations	Analytical report answering questions. Recommendation regarding the purpose of the analysis
6	Follow up	Updated reports and recommendations.

Source: Robinson, van Greuning, Elaine, & Broihahn, 2009

As mentioned before, financial analysis is used by a variety of users for a variety of purposes. Also, financial analysis can be classified into internal and external by its users. The difference between internal and external analysis are illustrated in Table 1.3.

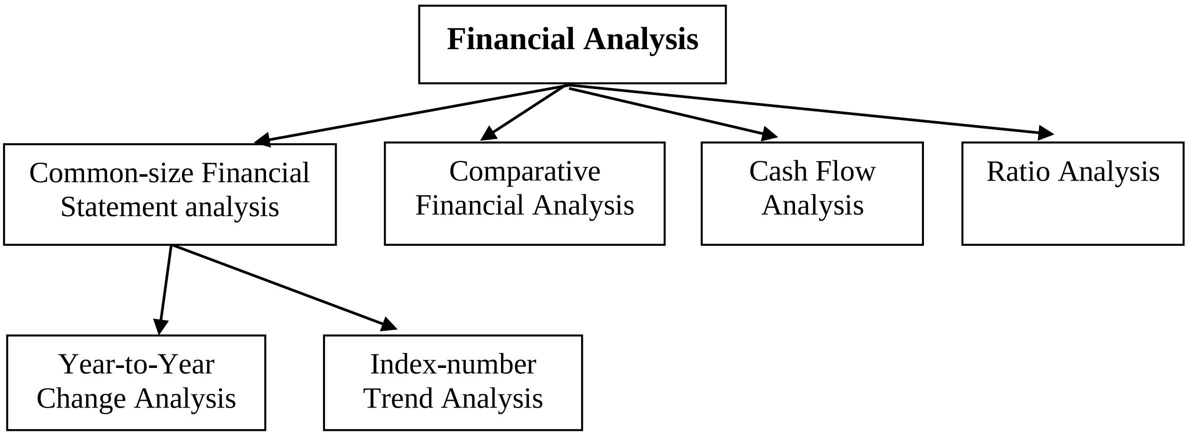
Table 1.3 The difference between internal and external analysis

Characteristics	Internal Analysis	External Analysis
User	Managers and employers	Has a wide variety of users
Aim	Used as internal purposes, i.e., plan	Variety of purpose
Data	Uses financial reports, internal records, policies, and plans	Do not have any internal access to the internal records, based on financial statements only.
The openness of the results	Results are open to internal users	Results are open for public purposes
Consideration	Usually considers revenue, expenses and, use of resources	Usually considers broader issues such as liquidity, solvency, and profitability

Source: Robinson, van Greuning, Elaine, & Broihahn, 2009

Based on the techniques to use, financial statements can be classified as Figure 1.3 Financial Analysis Technique. All the financial analysis techniques are mentioned in this chapter; although, ratio analysis is the main focus of this thesis.

Figure 1.3 Financial Analysis Technique



Source: Subramanyam, 2014

1.2.1 Analysis of Financial Statements

Vertical analysis of financial statements is a proportional analysis that shows the proportion of assets, liabilities, and equity, each item listed as a percentage. By vertical analysis, we can observe how the proportions of financial statements have been changed and whether the proportion is appropriate. Balance sheet items are expressed as a percentage of total assets, while income statement items are expressed as a percentage of sales. This analysis is also called as yield common-size financial statements since the sum of individual accounts within groups is 100%. “A company’s common-size statements are useful in revealing any proportionate changes in accounts within groups of assets, liabilities, expenses, and other categories” (Subramanyam, 2014).

The vertical analysis allows analyzing companies of different sizes and reduces the inflation effect on the balance sheet items, which makes this analysis more beneficial.

Individuals make a comparative financial statement analysis by reviewing consecutive balance sheets, income statements, or statements of cash flows from period to period (Subramanyam, 2014). The horizontal analysis presents changes in the balance sheet and income statement items in absolute monetary value as well as in percentages.

As for horizontal analysis, it is recommended to consider if the inflation had affected revenue and profit or if there was a steep decline or increase in balance or income statement items. “A comparison of statements over several periods can reveal the direction, speed, and extent of a trend Two techniques of comparative analysis are especially popular: year-to-year change analysis” (2- or 3-years period) and index-number trend analysis (3 or more years) (Subramanyam, 2014).

Index-number trend analysis requires choosing a base period, for all items, with a pre-selected index number usually set to 100. Because the base period is a frame of reference for all comparisons, it is best to choose an average year concerning business conditions (Subramanyam, 2014). It is possible to choose either constant base (using the first given year as a base) or variable base (using the previous year as a base). A constant base is appropriate to analyze the general trend, while the variable base is appropriate to analyze average changes.

1.2.2 Cash Flow Analysis

The cash flow statement contains useful information about a company’s liquidity, solvency, and future perspective. The cash flow statement divides cash inflows and outflows into three sources: operating, investing, and financing activities. Cash flow statement analysis is used by creditors, investors, and other users for different types of evaluations. Companies can prepare their cash flow statements either by a direct or an indirect method. Although both methods give the same results, the way to prepare operating cash flow is different. The direct method shows operating cash flow by its’ sources, such as cash received from customers, cash paid for the merchandise, cash paid for employees, and cash paid for interests, and so on. In Mongolia, companies are required to prepare cash flow statements by the direct method. Cash flow analysis provides perceptions about how a company gains its financing resources. “It is used in cash flow forecasting and as part of liquidity analysis” (Subramanyam, 2014).

Cash flow analysis gives the opportunity to

- Determine cash inflow and outflow in the accounting period.
- Evaluate the cash management of the company.
- Predict the possible amount of money that can be generated by a company in the next accounting period.
- Investors and creditors can see how the company spends its investments.
- Reveal the difference between net cash flow and net income.

- Measure the financial ratios of a company's profitability, performance, and financial strength.

The following steps are required to analyze the cash flow statement:

Step 1: Determining the major sources of cash flow statement

The major cash sources are different regarding their stage of growth. In the long run, large mature businesses must generate sufficient cash to cover interest and dividends for finance providers. Small mature businesses must generate sufficient cash to cover interest and scheduled debt repayment; medium mature businesses generate cash to cover interest, scheduled debt repayment, and dividends (Jury, 2012). Generally, it is desirable to have the primary source of cash by operating activities (Robinson et al., 2009). In case a company has a negative net operating cash flow, the company must borrow money or issue new shares. However, a company can finance its operation by debt or shares, and it is not a long-term solution.

As noted by Robinson et al. (2009), the following questions must be answered:

- What are the major sources of cash inflows and uses of cash outflows?
- Is operating cash flow enough to cover capital expenditures?

Step 2: Analyzing the operating cash flow

It is crucial to compare operating cash flow with net income. Since net income includes non-cash expenses, such as depreciation and amortization, the operating cash flow should exceed net income (Robinson et al., 2009). Cash flow components usually show the stability of the sources. For example, increases in operating cash flows that result from the securitization of accounts receivables or the reduction in inventories are not usually a reliable source of cash since these assets are limited itself (Subramanyam, 2014). The relationship between net income and operating cash flow is also an indicator of earnings quality. If a company has a large net income but poor operating cash flow, it may be a sign of poor earnings quality (Robinson et al., 2009).

Step 3: Analyzing investing cash flow

Investing cash flow shows how much cash was invested in properties, plants, and equipment, and how much was spent on investments, such as stocks and bonds. If the company is making major capital investments, one should consider where the cash is coming from to cover these investments (Robinson et al., 2009).

Step 4: Analyzing the financing cash flow

Financing cash flow indicates whether the company raised capital or repaid the capital and the nature of its capital sources are.

The common-size statement analysis is an essential part of the cash flow statement analysis. There are two approaches to prepare the common-size cash flow analysis, to express each cash inflow (outflow) by

- the percentage of the total cash inflow (outflow)
- the percentage of net revenue.

The common-size format is easier to understand, and useful in forecasting future cash flows because individual items in the common-size statement (e.g., depreciation, fixed capital expenditures, debt borrowing, and repayment) are expressed as a percentage of net revenue (Robinson et al., 2009). Thus, once the analyst has forecast revenue, the common-size statement provides a basis for forecasting cash flows.

1.3 Ratio Analysis

Ratio analysis is the most popular tool of financial analysis, which expresses a mathematical relation between two quantities. Ratio analysis focuses on evaluating a firm’s performance and financial policies. The computed ratio is not the “answer”, but it is an indicator of some aspect of a company’s performance, telling what happened, but not why it happened (Robinson et al., 2009). As for ratio analysis, we must be aware that a single ratio cannot evaluate a company. That is why ratios are used as a group to achieve a meaningful conclusion about the company. Moreover, we must consider:

- Comparing financial statements by the horizontal analysis must be in the same accounting period.
- Comparing financial statements must be prepared under the same accounting principles and methods.
- Inflation effects on the financial statements.

The computed ratio itself is not important, but the meaning of the ratio is important. Ratios are compared either with other companies or with the results of the previous period to get a meaningful conclusion and recommendation. In other words, ratio analysis can be interpreted by the following comparisons:

- Cross-sectional comparison (comparison to a subset of companies in the same industry to reveal the flaws in the company's activity).
- Time-series comparison (to reveal the prospect of the company).
- Company's goals and strategies. Actual ratios can be compared with the company's objectives to determine whether objectives are being attained and whether the results are consistent with the company's strategies (Robinson et al., 2009).
- Comparison of ratios to the absolute benchmark.

For cyclical companies, financial ratios tend to improve when the economy is strong and weaken during recessions. Therefore, financial ratios should be examined in light of the current phase of the business cycle (Robinson et al., 2009). In a time-series comparison, the analyst can hold firm-specific factors on a constant value and examine the effectiveness of a firm's strategy over time. Cross-sectional comparison facilitates examining the relative performance of a firm within its industry, holding industry-level factors constant (Palepu et al., 2000). Although ratios reduce the effect of size, which enhances comparisons among the companies in the industry, it is still possible to face some challenges. The limitations of the ratio analysis are:

- The results of ratios heavily depend on industry features. However, numerous companies operate their business more than one industry, particularly big corporations. In that case, it is even more challenging to determine the absolute benchmark for the company. However, it can be beneficial to make time-series comparisons or interpret each branch's ratios individually.
- Differences in accounting methods and principles affect the results of ratios.
- Financial statements in one accounting period cannot describe the company and its whole performance in an adequate way. Thus, it is essential to analyze in the longer term.
- Correlation among the ratios. Some financial ratios can be replaced by other ratios, which means it is more important to select the relevant ratios, not all the ratios.

Ratio analysis does not end with computation, while the interpretation of the result is the most important (Robinson et al., 2009). Economic and finance theories suggest a positive association between a firm's efficiency and financial strength. Fabozzi and Anderson (2003) state that financial ratios can be used to evaluate five aspects of operating performance and financial condition:

1. Return on investment,
2. Liquidity,
3. Profitability,
4. Activity,
5. Financial leverage.

Some ratios can also represent more than one aspect of the groups mentioned above. This section reviews the literature on financial ratios that express profitability (combined with return on investment), activity, and financial strength (liquidity and solvency).

1.3.1 Profitability analysis

The meaning of profit and profitability is different. Profit is the difference between revenue and expenses, while profitability measures how effective and efficient the business is. More precisely, profitability indicates how effectively a firm generates profits from sales, total assets, and stockholders' investments. "Therefore, anyone whose economic interests are tied to the long-run survival of a firm will be interested in profitability analysis" (Moyer et al., 2008). Based on the income statement information, we can analyze the common-size analysis of the income statement and profitability ratios. Profitability ratios can be classified as

Figure 1.4.

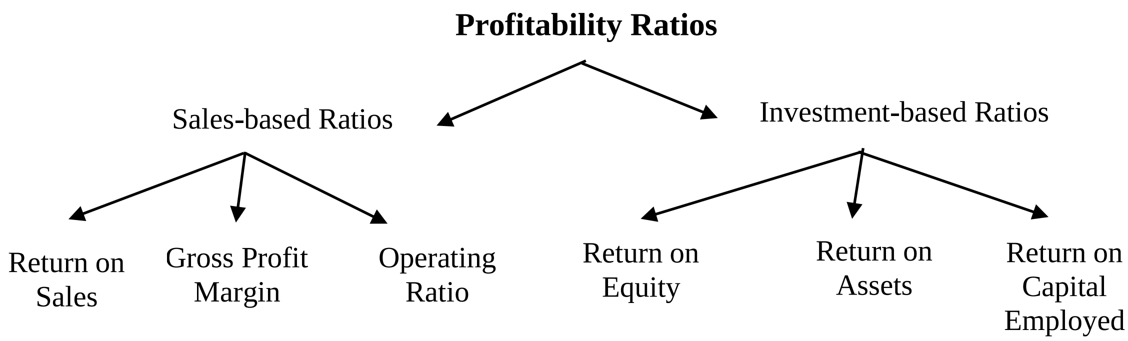


Figure 1.4 Profitability Ratios

Source: Author's compilation

Friedlob and Lydia (2003) stated that its success in operating and financing activities could measure the profit achievement of a company and its investing efficiency. In other words, we can define success by ROE, which is decomposed as (Figure 1.5):

- Return on sales (ROS) - Determines the operating success of a company.

- Asset turnover (ATO) - Determines the investing success of a company.
- Assets to equity ratio - Determines the financing success of a company (Friedlob & Lydia, 2003).

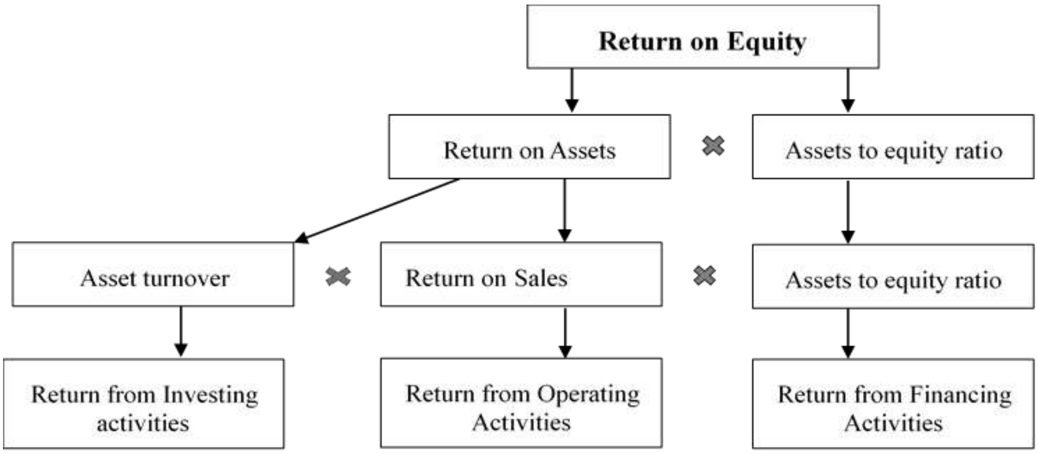


Figure 1.5 Decomposition of Return of Equity

Source: Penman, 2013

Return on Equity (ROE) is one of the most common profitability ratios, which is calculated:

$$ROE=\frac{Net\ profit}{Owners'\ equity}*100 \qquad 1.1$$

Palepu et al. (2000) noted that "ROE is a comprehensive indicator of a firm's performance because it indicates how well managers are employing the funds invested by the firm's shareholders to generate returns". In other words, ROE shows how many cents can be earned from each dollar of the owner's investment. If we convert ROE into percent format, it means what percent can be earned on the stockholders' investment in the given accounting year. ROE is used when we want to compare the company with other companies in the same industry. A comparison of ROE shows not only which company is more profitable but also considers the path of future profitability.

ROE decomposed into two ratios (ROA and Assets to Equity Ratio) too:

$$ROE=ROA*\ Assets\ to\ Equity\ Ratio \qquad 1.2$$

ROE, by two factors, indicates how efficiently companies employ their assets for generating earnings (ROA) and how much can the companies multiply their equities in their assets (Equity multiplier ratio). Equity multiplication occurs only if the company has debt; otherwise, the equity multiplier is equal to 1. On the other hand, Assets to Equity Ratio indicates how many dollars of assets the firm can generate for each dollar invested by its shareholders (Palepu et al., 2000).

$$\textit{Assets to Equity Ratio} = \frac{Assets}{Owners' equity} \qquad 1.3$$

ROA indicates how many cents can be earned from each dollar of assets invested:

$$ROA = \frac{Net\ profit}{Assets} \qquad 1.4$$

If we convert ROA into a percent format, that means how many percent the company earns from the assets invested. In the ROA formula, the denominator includes the assets covered by all capital providers of the firm, but the numerator only the earnings available to equity holders. The assets of the above formula include both operating and financial assets (Palepu et al., 2000). To eliminate non-operating items, we can use Operating ROA, as shown in equation 1.9, which is adequate.

$$\textit{Operating ROA} = \frac{Operating\ profit}{Operating\ assets} \qquad 1.5$$

Operating profit can be replaced by EBIT (Earnings Before Interests and Taxes) (Palepu et al., 2000).

ROE decomposed into three ratios:

$$\textit{ROE=Return on Sales * Asset turnover * Assets to equity ratio} \qquad 1.6$$

Return on Sales (ROS) ratio shows that a firm increases value by growing sales, earning high income per dollar of sales, and keeping its net operating assets that generate the sales as low as possible (Penman, 2013). Return on Sales (ROS) ratio indicates how much profit can be earned from each dollar of sales, so it illustrates the operating efficiency of the company.

$$ROS = \frac{Net\ profit}{Sales} \qquad 1.7$$

In other words, ROS shows how efficiently a company generates profits from sales. If we convert the formula into a percent format, that means what percent of the sales remain to the company as profit.

The Asset turnover (ATO) ratio indicates the efficiency of a company using its assets to generate revenue.

$$ATO=\frac{Sales}{Assets} \tag{1.8}$$

Asset turnover indicates how efficiently the company uses its assets to generate revenue, which means how much revenue is incurred using a one-unit asset.

ROE can be replaced by ROCE (Return on Capital Employed) for a more complete and precise evaluation of financial performance. ROCE is useful for comparing the profitability across the companies. Both ROE and ROCE are used to evaluate the operational efficiency and future growth. Unlike ROE, ROCE considers not only owners' equity but also long-term debt.

$$ROCE=\frac{Earnings\ before\ other\ income,interest,tax,depreciation\ and\ amortisation}{Capital\ employed} \tag{1.9}$$

Preferred shareholders receive a fixed amount of return. On the contrary, common shareholders' return varies depending on the residual earnings after paying all the debts and preferred shareholders' dividends. Therefore, we can adjust ROE for the common shareholders:

$$Return\ on\ common\ equity=\frac{Net\ profit-Prefferred\ dividends}{Owners'\ equity-Preferred\ equity} \tag{1.10}$$

Similar to the profitability ratios mentioned above, the Gross Profit Margin (GPM) is also widely used for profitability analysis.

$$Gross\ Profit\ Margin=\frac{Sales-COGS}{Sales} \tag{1.11}$$

GPM indicates how much of the sales are the gross profit. Practically, companies produce more than one product, which has different prices, quantities, and costs. In that case, it is advisable to determine GPM for every product, which can help to decide what products should be produced more.

According to the formula 1.11, those can affect GPM directly:

- Changes in sales (quantity),
- Changes in price,
- Changes in COGS (Cost of Goods Sold).

To maintain reasonable COGS amount, these are important:

- To explore the potential substitute materials if the price of core raw materials increases
- To upgrade the technique and technology
- To produce within the economic production quantity

- To avoid losing its market share.

It is also possible to evaluate a firm's operating performance by calculating Operating Profit Margin (OPM):

$$OPM = \frac{Sales - COGS - Operating\ expenses}{Sales} = \frac{EBIT}{Sales} \qquad 1.12$$

OPM is affected by the same factors as GPM, plus the operating expenses, such as expenses related to sales (Fabozzi & Anderson, 2003). Although GPM and OPM describe operating performance, none of them shows its financial sources. Profitability ratios provide very little and uncertain information about future profitability, and it does not explain the reasons for current profitability. Therefore, we need to conduct an activity analysis to predict future profitability. The activity ratios measure how efficiently assets are being used (Fabozzi & Anderson, 2003).

1.3.2 Activity analysis

In economics, growth can be classified as intensive and extensive. Intensive growth is the increase caused by more efficient use of inputs, while extensive growth is the increase of output quantity caused by the enlargement of the inputs used. Therefore, intensive growth is preferable than extensive growth. Since the input quantity is limited, firms aim for maintaining intensive growth, such as improvements in technology, reduction of waste during the production, improvement of employees' skills, reducing idle time of equipment, etc.

Activity analysis aims for

- Determining the firm's current situation
- Revealing unused capacity
- Identifying the contributing factors of growth and evaluating its effects
- Making suggestions for corrective actions.

Activity analysis involves many factors that are correlated with each other. Mostly turnover ratios are used to evaluate the benefits produced by the firm's assets (Fabozzi & Anderson, 2003). In this section of the thesis, I concern the most common turnover ratios, such as assets turnover.

As noted by Penman (2013), a detailed analysis of asset turnover (five components) allows the analyst to evaluate the effectiveness of a firm's investment management. From those five components, receivables turnover, inventory turnover, and payables turnover allow the analyst to examine how efficiently three principal components of working capital management are used (Sneidere, 2013).

Turnover ratios are calculated either by times or by days. Turnovers by times answer to the question of how many times, while turnovers by days answer to how many days does it take to…?

$$\textit{Accounts receivable turnover (times)} = \frac{Sales\ on\ credit}{Average\ accounts\ receivable} \qquad 1.13$$

Receivables turnover (times) indicates the number of times that accounts receivable are collected within a year. Since sales in cash do not generate receivables, we use sales on credit to compute receivables turnover. The limitation of this ratio is that we are not able to distinguish sales on credit from net sales based on the income statement. If most of the sales are credit sales and cash sales are insignificant compared to credit sales, we can use net sales to calculate this ratio. Based on receivables turnover (times), we can calculate the average days needed to collect receivables. This ratio expresses how often accounts receivable are converted to cash during a year (Keown et al., 2014).

$$\textit{Accounts receivable turnover (days)} = \frac{365}{Accounts\ receivable\ turnover\ (times)} \qquad 1.14$$

The following conditions can cause a higher account receivable turnover (days):

- Poor collection efforts,
- Delays in customer payments,
- Customers in financial distress.

Inventory turnover (times) shows how many times inventories are sold or used in a year:

$$\textit{Inventory turnover (times)} = \frac{COGS}{Average\ inventory} \qquad 1.15$$

Based on inventory turnover (times), we can calculate the average days to sell the products or use raw materials. We can compare the current results with the past results of the company when we analyze inventory turnover. Inventory management can be used to keep the inventory levels lower by ordering and receiving raw materials and/or inventories only when it is needed to produce, not before.

$$\textit{Inventory turnover (days)} = \frac{365}{Inventory\ turnover\ (times)} \qquad 1.16$$

Accounts payable turnover (times) indicates how many times the company pays its payables in a year.

$$\textit{Accounts payable turnover (times)} = \frac{COGS}{Average\ accounts\ payable} \qquad 1.17$$

Based on payables turnover (times), we can calculate average days to pay off the payables, which means how many outstanding days to pay back the liabilities.

$$\textit{Accounts payable days outstanding} = \frac{365}{Accounts\ payable\ turnover\ (times)} \qquad 1.18$$

The turnover ratios show conversions from one account to another. Receivables turnovers show the conversion from account receivables into cash, and inventory turnovers show the conversion from inventories into account receivables, etc. Using these ratios, we can determine the operating cycle.

$$\textit{Operating cycle = Account receivable (days) + Inventory turnover(days)} \qquad 1.19$$

The operating cycle is the duration from the day, cash is invested in goods and services, until the day, when investment produces cash (Fabozzi & Anderson, 2003); therefore, the less operating cycle is more efficient. Fabozzi and Anderson (2003) described that an operating cycle comprises four phases:

1. Purchase of raw materials may be made in cash or on credit.
2. Sale of the inventories in cash or on credit.
3. Collecting the account receivables.
4. Repayment of debts.

Like an operating cycle, we can determine the net operating cycle using the payables turnover ratio (in days) additionally. The operating cycle shows the number of days from investing money on raw materials until the cash comes back from the sales. The payables turnover ratio expresses how long it takes to pay its debt on purchases made to create the products. Therefore, the difference between the operating cycle and payables turnover ratio (in days) is the net operating cycle (cash cycle):

$$\textit{Net operating cycle = Operating cycle - Account payable turnover(days)} \qquad 1.20$$

The net operating cycle shows how long it takes for the firm to get back their cash from the investments in inventories and accounts receivables, considering that the purchases may be made on credit (Fabozzi & Anderson, 2003). The net operating cycle assumes the ability of the intervention in the financial market. To clarify, if the ratio has a negative value, it shows the capability to use the money from receivables until the payables' due date. A positive value of the ratio indicates the duration of financial discomfort.

1.3.3 Liquidity

To measure a company's financial health, one must analyze profitability, risk (liquidity and solvency), and efficiency. "Risk analysis is the evaluation of a company's ability to meet its commitments. Risk analysis involves assessing the solvency and liquidity of a company, along with its earnings variability" (Subramanyam, 2014). Liquidity reflects the ability of a firm to meet its short-term obligations using those assets that are most readily converted into cash (Fabozzi & Anderson, 2003). Based on the liquidity definition, we can assume that liquid assets are easily converted into cash in a short period. Liquidity is defined as the ability of a company to meet its current liabilities, while solvency refers to the ability of an enterprise to meet its long-term financial obligations. As debts must be paid before dividends, both shareholders and creditors are interested in liquidity analysis. Liquidity analysis indicates an ability to repay the debts in time, which is measured by liquidity ratios. If liquidity ratios have an inappropriate value, the company has a higher level of risk. To measure financial health in the short-term, we analyze liquidity, which shows the ability to pay its debts in time. In the long-term, we analyze solvency to determine a company's long-term survival. Liquidity shows the ability to meet financial obligations as the due date comes. To have sufficient money to pay all the debts, a company must organize its money management.

"Both long- and short-term creditors are concerned with the amount of leverage a company employs. Because it indicates the company's risk exposure in meeting debt service charges, i.e., interest and principal repayment. A company heavily financed by debt gives creditors less protection in the event of bankruptcy" (Moyer et al., 2005). Companies can be classified by their financial state as a solvent, a distressed but solvent, and an insolvent.

The Net Working Capital (NWC) shows how long-term debts or equities finance a part of the current assets. Since NWC is measured by value, it is difficult to determine a benchmark or to compare it with the values of other companies. Nevertheless, NWC can be compared with past performance.

$$Net\ Working\ Capital = Current\ assets - Current\ liabilities \qquad 1.21$$

In the case of comparison with the other companies in the same industry, it is advisable to use the NWC turnover ratio:

$$NWC\ turnover\ ratio = \frac{Net\ sales}{NWC} \qquad 1.22$$

This ratio shows the effectiveness of Working Capital (WC) usage for supporting sales. The higher ratio indicates the effective usage of WC. On the contrary, a low ratio indicates the company has too much cash, account receivables, inventories to support sales.

$$Current\ ratio = \frac{Current\ assets}{Current\ liabilities} \qquad 1.23$$

An important liquidity ratio is a current ratio, which indicates how many times the company can pay its current liabilities using its current assets. Although the current ratio of 2 is usually preferred, the benchmark value depends on the company's size, maturity, industry, etc. It is preferable to use industry norms or changes in past years' ratios to reach reasonable conclusions. The higher the ratio, the greater the liquidity; however, the higher ratio can also indicate that the company does not use its currents assets efficiently. For example, a high value of receivables shows there is no guarantee that the money will be paid. Receivables are the amount of money used by another company, and not the company owns the receivables. Like receivables, a high amount of inventories is also a red flag that can mean the company struggles to make sales or accumulated excess raw materials, although it depends on its industry. The current ratio considers all current assets; however, not all of the current assets can be converted into cash in a short period. Therefore, we use slightly other ratios, such as the quick ratio and cash ratio alternatively.

$$Quick\ ratio = \frac{Cash + Account\ Receivable + Short-term\ investments}{Current\ liabilities} \qquad 1.24$$

Quick and Current ratios are some of the most frequently used liquidity ratios (Brigham & Ehrhardt, 2011). Quick ratio (is also called Acid-test ratio) is a more stringent version of the current ratio. This ratio shows how much of the current liabilities can be paid in a short period. The quick ratio does not contain inventories since we cannot guarantee the exact time when the inventory will be sold; the amount of inventory cannot be quickly converted into cash to pay the liabilities immediately. Inventories are the least liquid assets compared with other items of current assets. The higher ratio indicates that the company is more financially secure. Although its value is highly dependent on the industry, the quick ratio of 1 is a good benchmark. The Quick and Current ratio can be too high when tying too much money up in inventories or receivables that may prevent a company from investing in assets that will generate more profits. In other words, there is usually a balance between having more liquidity and generating profits (Keown, Martin, & Petty, 2014). The most stringent version of liquidity ratios is the cash ratio.

$$Cash\ ratio = \frac{Cash+Cash\ Equivalents}{Current\ liabilities} \qquad 1.25$$

The Cash ratio differs from the Quick ratio by excluding account receivables. Although the customer company is obliged to pay back the debt, there is not any guarantee that money will be paid. It depends on the financial possibility of the obligor.

The Operating cash flow ratio shows how much of the current liabilities can be covered by operating cash flow. “Since liabilities are paid in cash, that is why a comparison of operating cash flow to current liabilities is important” (Subramanyam, 2014).

$$Operating\ cash\ flow\ ratio = \frac{Cash\ Flow\ from\ operations}{Current\ liabilities} \qquad 1.26$$

One of “the important qualitative considerations bearing on short-term liquidity” depends “on the financial flexibility of the company. Financial flexibility is the ability of a company to take steps to counter unexpected interruptions in the flow of funds. It can mean the ability to borrow from various sources, to raise equity capital, to sell and redeploy assets, or to adjust the level and direction of operations to meet changing circumstances” (Subramanyam, 2014).

1.3.4 Solvency and financial leverage

To measure a company’s financial health, one must analyze profitability, liquidity, solvency, and efficiency. Liquidity is defined as the ability of a company to meet its current liabilities, while solvency refers to the ability to meet its long-term financial obligations. Solvency refers to a company’s long-run financial viability and its ability to cover long-term obligations (Subramanyam, 2014).

Solvency analysis involves capital structure analysis, which refers to the sources of financing and, earnings power which is an ability to generate cash from operations (Subramanyam, 2014). Capital structure is an important part of the solvency which determines the performance of a firm, and it refers to the ratios of debt and equity financing, and other economic attributes (Mirza & Javed, 2013). A firm can finance its assets either by debt or by equity. If the company is financed by debt, the company is obliged to pay its principal and interest. Nevertheless, if the company issues stocks, the company pays its dividends at the discretion of the board of directors. “An appropriate capital structure can generate a maximum profit for the organization. Too less equity financing decreases the control of the owners to a large extent” (Abu-Rub, 2012). If the company has more debts, it will have more financial risks. Financial risk is related to a firm’s ability to pay its debts as due comes. Financial leverage ratios are used to assess how much financial risk the firm has taken on (Fabozzi & Anderson, 2003). For example, Burca and Batrinca (2014) argued that “the financial leverage, company size, growth of gross written premiums, underwriting risk, risk retention ratio, and solvency margin” are determinants of Romanian insurance companies' performance. We can measure those solvency ratios, which indicate capital structure.

Financing can range from relatively permanent equity capital to more risky or temporary short-term financing sources (Subramanyam, 2014). Based on the debt to equity ratio, we can see creditors and owners’ investment ratio. A ratio of 1 shows that the amount of equity is equal to the amounts of debts. If the ratio is high, there is a higher risk for creditors. The higher the risk means, the higher the interest rate.

$$\textit{Debt to Equity ratio (Financial leverage)} = \frac{Total\ liabilities}{Owners'\ equity} \qquad 1.27$$

One of the most important solvency ratios is the shareholder’s equity ratio, which is called the Proprietary ratio. The Proprietary ratio indicates how much of the total assets are invested by owners’ equity. Some of the financial ratios are highly correlated with each other. For example, the Proprietary ratio can be replaced by the Debt to equity ratio.

$$\textit{Shareholders' equity Ratio} = \frac{Owners' equity}{Total\ assets} \qquad 1.28$$

The Debt ratio indicates the percentage of the total assets, which is financed by liabilities. Higher the ratio higher the financial risk.

$$\textit{Debt ratio} = \frac{Total\ liabilities}{Total\ assets} \qquad 1.29$$

Long-term debt to total assets ratio is also an important ratio of solvency, which is similar to the Debt ratio. The difference is that short-term liabilities are not included in Long-term debt to total assets ratio. The differences between long-term and short-term debts are that long-term debts have a higher interest rate and lower risk than short-term debts.

$$\textit{Long-term debt to total assets ratio} = \frac{Long-term\ debt}{Total\ assets} \qquad 1.30$$

The Interest coverage ratio shows the ability to pay the interest rate. If the ratio is higher, the company is more solvent. The benchmark of the ratio is 5.

$$Interest\ coverage\ ratio = \frac{EBIT}{Interest\ expenses} \tag{1.31}$$

There are some other costs that do not arise from debt. Nevertheless, those costs must be considered in the same way we consider the cost of debt in a firm's financial obligations (Fabozzi & Anderson, 2003). An example of that kind of expense can be leasing' expenses. We are obliged to pay leasing expenses for using the property. The firm's ability to satisfy its fixed financial costs is referred to as the Fixed charge coverage ratio (Fabozzi & Anderson, 2003).

$$Fixed\text{-}charge\ coverage\ ratio = \frac{EBIT+Lease\ expense}{Interest+Lease\ expense} \tag{1.32}$$

The ratio indicates the ability to cover its fixed costs by its operating profit. Since lease expense is deducted from EBIT, we should add lease expense back to the numerator. The Fixed charge coverage ratio can be expanded to accommodate the sinking funds and preferred stock dividends as fixed charges (Fabozzi & Anderson, 2003). If someone is more interested in the firm's ability to meet obligations, it is preferable to use the cash flows from operations.

$$Cash\ flow\ interest\ coverage\ ratio = \frac{CF\ from\ operations+Interest+Taxes}{Interest} \tag{1.33}$$

To arrive at the cash flow before interest and tax payment, we have to add the interests and taxes back to cash flow from operations. The main difference between using cash flow from operations and EBIT is noncash items, such as depreciation and gain or loss from property's sale.

All activities, i.e., operating, investing, and financing, affect solvency. A company can increase risks (and potential returns) of shareholders by increasing leverage. There are two types of leverage: operating leverage to increase ROA and financial leverage to increase ROE (Subramanyam, 2014).

Operating leverage is the result of fixed and variable cost combination. Companies with higher fixed costs and lower variable costs have higher operating leverage. Fixed costs do not change along with the product quantity. Therefore, relatively small changes affect bigger changes in net operating income. The Degree of Operating Leverage (DOL) ratio measures how much EBIT will change in response to one-unit changes in sales.

$$Degree\ of\ Operating\ Leverage = \frac{\%\ change\ in\ EBIT}{\%\ change\ in\ Sales} \quad 1.34$$

The Degree of Financial Leverage (DFL) ratio measures the percentage change in Earnings Per Share (EPS) in response to the one-unit change in EBIT.

$$Degree\ of\ Financial\ Leverage = \frac{\%\ change\ in\ EPS}{\%\ change\ in\ EBIT} \quad 1.35$$

DOL measures risk at the top of the income statement, from revenue to operating profit, while DFL measures risk at the bottom of the income statement, from operating profit to net profit. Total risk is measured by the Degree of Combined Leverage ratio, which is the product of DOL and DFL ratios.

Long-term debt and owners' equity are both long-term financing sources. Thus, the Capitalization ratio shows how many percent of long-term finance is debt. A lower ratio indicates a lower risk.

$$Capitalization\ ratio = \frac{Long-term\ debt}{Long-term\ debt + Owners'\ equity} \quad 1.36$$

DEA and SFA are explained in detail in Data and Methodology 2.5-2.7 sections.

1.4 Performance measurement

We begin the performance measurement with the concepts of what is performance and how to measure it. As it is explained in the business dictionary, performance is the fulfilment of the obligation or the accomplishment of a given task measured against pre-set accuracy, completeness, cost, and speed. "Company performance is the measurement of what had been achieved by a company which shows good conditions for a certain period. The purpose of measuring the achievement is to obtain useful information related to the flow of funds, the use of funds, effectiveness, and efficiency. Besides, the performance information can also motivate the managers to make the best decision" (Almajali et al., 2012).

Corporate performance measurement is an assessment of how well a firm accomplishes on its most important parameters. It is easy to rank firms based on the evaluation of some variables and call it a performance measurement. However, not all indicators are performance indicators; only managerial variables that can be influenced by the decision-making/action process (Tonchia & Quagini, 2015).

According to Kaydos (2000), there are five main reasons to measure performance:

- Improved control: The feedback provided by performance measures gives managers better control over their responsibility areas, whether it is a department or a division.
- Clear responsibilities and objectives: good performance measures clarify who is responsible for specific results or problems.
- Strategic alignment of objectives: performance measures are essential for assessing the effectiveness of a strategy.
- Understanding business processes: Performance measurement is the first step that leads to control and eventually to improvement.
- Determining process capability: insufficient capability can be evaluated and corrected.

Performance measurement helps to learn from the past, to examine where you are today, to plan where we want to go, and manage this pathway (Tonchia & Quagini, 2015). Performance measurement is needed for the companies to reveal their failures and to improve their competitiveness by comparing with their competitors. The best performance can be discovered by benchmarking - a comparison of one DMU’s (Decision Making Unit) performance metrics to the best practices from other companies - as for a company or a sector.

Performance is divided into two parts: efficiency and effectiveness (Azadeh et al., (2007)), which are often confused. Terms of efficiency and effectiveness are used differently. Neely et al. (1995) noted effectiveness refers to the extent to which “customers’ requirements are met, while efficiency is a measure of how economically the firm’s resources are utilized when providing a given level of customer satisfaction.” Cooper et al. (2006)., determined that effectiveness refers to goal achievement and effects its evaluations without reference to the resources used. Effectiveness is an ability to state goals and to achieve goals. Efficiency is ‘to do things right’ or perform current activities as well as possible, whereas effectiveness is ‘to do the right thing’ or choose the proper activities (Munisamy-Doraisamy, 2004). Compared with efficiency, effectiveness is vague and harder to measure, which depends on a firm’s strategic plan. The thesis focuses only on efficiency analysis.

Productivity and efficiency are also two different terms. Productivity is a ratio between output and input, while efficiency is the ratio between productivity and a standard (Tonchia & Quagini, 2015). To put it in a simpler term, it is a difference between quantity and quality. Productivity defines as the ratio of an index of outputs over an index of inputs consumed to produce it (Munisamy-Doraisamy, 2004). In terms of productivity, quality should also take into consideration. If efforts are made in the wrong direction, it implies zero productivity.

$$Productivity = \frac{Actual\ output}{Actual\ input} \quad 1.37$$

Furthermore, efficiency should not be confused with efficacy. Efficacy is the ratio between actual output (or performance) and the desired output (or performance). Therefore efficacy measures the ability to achieve goals, regardless of the input (resources) used (Tonchia & Quagini, 2015).

$$Efficacy = \frac{Actual\ output}{Desired\ output} \quad 1.38$$

Efficiency is determined by comparing the observed and optimal values of inputs and outputs. By producing goods and services successfully without any waste is important for companies to survive economically, which is called efficiency that had been achieved during a specific period. Although efficiency is defined in many ways, yet there is not a perfect and exact definition.

The main goal of measuring efficiency is to reveal the weak areas so that appropriate efforts can be made to improve performance. Efficiency is an indicator calculated by input resources and output outcomes to evaluate whether the input resources utilized are effectively employed to or not (Azadeh et al., 2007; Ueasin et al., 2015). “The smaller the inefficiency is, the better the performance” (Bogetoft & Otto, 2011). For every company, monitoring efficiency is one of the key activities.

Efficiency (cost efficiency or overall efficiency) has two components: technical efficiency (the ability to avoid waste by producing as much as output as input usage allows), allocative efficiency (combining inputs and outputs in an optimal proportion based on the price) (Munisamy-Doraisamy, 2004). The most widely used technical efficiency approach is Farrel efficiency (1957a), which seeks the possibility to reduce input without changing output or increasing output without increasing input. “Since higher quality can be attained by reducing productivity and increasing costs, technical efficiencies can be gained by sacrificing quality” (Sudit, 1996). The allocative efficiency (AE) is related to the choice of the least costly resource mix; it is related to the choosing a revenue-maximizing product mix that has a relation to the output (Bogetoft & Otto, 2011). Allocative efficiency seeks the optimal production and service must be produced without waste by minimal costs to maximize the profit.

Technical efficiency signifies a level of performance that describes a process that uses the lowest amount of inputs to create the greatest amount of outputs. In the simplest case where a process or unit has a single input and a single output, technical efficiency is defined as:

$$Efficiency = \frac{Output}{Input} \tag{1.39}$$

It is more typical that processes and organizational units have multiple disproportionate inputs and outputs (Boussofiane et al., 1991). This complexity can be built in an efficiency measure by defining technical efficiency:

$$Efficiency = \frac{Weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ inputs} \tag{1.40}$$

Efficient companies take a score of 1, so the efficiency score, which is closer to 1, shows better performance. After calculating the efficiency score, we can easily determine the inefficiency score by subtracting the efficiency score from 1.

Technical efficiency only requires input and output data, but economic efficiency (allocative efficiency) requires price data as well (Vincová, 2005). Allocative efficiency refers to the ability to combine inputs and outputs in optimal proportions considering prevailing prices. Allocative efficiency is the use of cost-minimizing input combination and a revenue-maximizing output mix. Therefore, overall efficiency (cost efficiency) is the ability to reduce inputs or augment outputs proportionately to minimize costs.

$$Overall\ efficiency = \frac{Minimal\ cost}{Actual\ cost} \tag{1.41}$$

"Overall efficiency (cost efficiency) means the firm must be able to choose the right mix of inputs and use them in a technically efficient manner" (Bogetoft & Otto, 2011). The high cost of the firm, i.e., the vertical distance between the actual cost level of the firm and the minimal necessary costs, is an absolute measure of the inefficiency. The relative inefficiency could, therefore, be measured by

$$Inefficiency = \frac{Actual\ cost - Minimal\ cost}{Actual\ cost} \tag{1.42}$$

The relationship between allocative and technical efficiency can derive as equation 1.44.

$$CE = AE * TE \tag{1.43}$$

The firm must use the right resources in the right way to be cost-efficient (Bogetoft & Otto, 2011). The efficiency measurement mentioned above is illustrated in Figure 1.6.

Minimum input bundles are required to produce various outputs or maximum output bundles producible with various inputs in a given technology. It is called the production frontier. As Farrell (1957b) noted, an efficient production function (production frontier) is the output that a perfectly efficient firm can obtain from any combination of inputs. Producers operating on the production frontier are labelled technically efficient, while producers operating below the frontier are labelled technically inefficient (Kumbhakar & Lovell, 2000). If a company uses inputs expressed by *P* to produce outputs, the technical efficiency would be:

$$\frac{OQ}{OP} \Rightarrow 1 - \frac{QP}{OP} \qquad 1.44$$

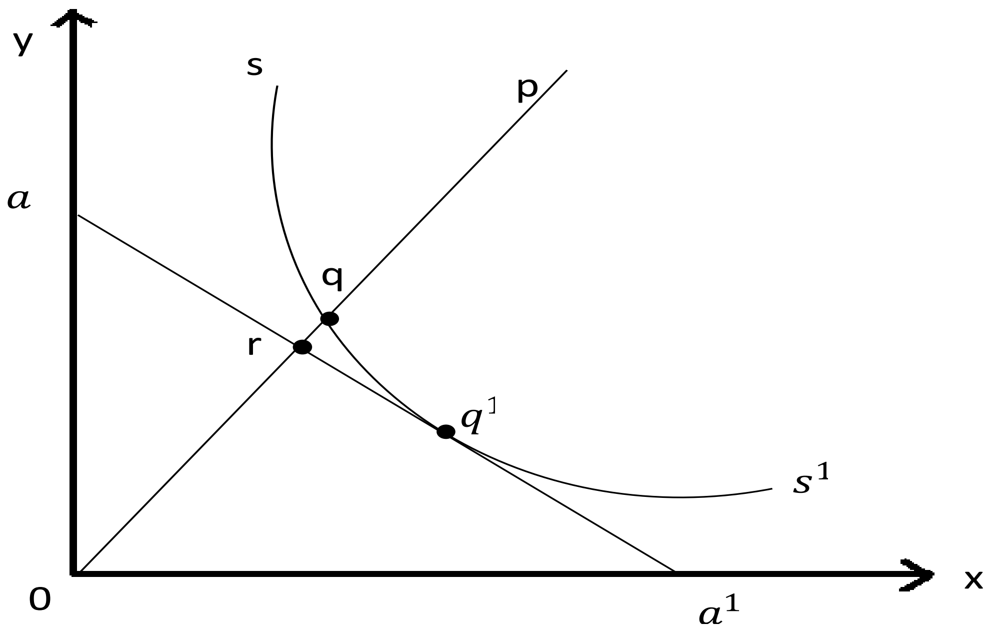


Figure 1.6 Measuring efficiency

Source: Farrell, 1957b

AA^1 – iso-cost line

SS^1 – production frontier

If the price information is given, cost efficiency can be determined. To be cost-efficient, using minimum inputs is insufficient, but also companies are required to allocate their inputs cost-effectively. Moreover, cost-efficient companies may fail in allocating their outputs in a revenue-maximizing manner (revenue efficiency) in given output prices, which leads to profit-maximizing (profit efficiency) failure. Therefore, being profit efficient is not easy. When the price information is available, cost efficiency would be:

$$\frac{OR}{OP} \quad (1.45)$$

Allocative efficiency would be like:

$$\frac{OR}{OQ} \quad (1.46)$$

The thesis concern only about technical efficiency as data are only available for that calculation.

1.5 Intellectual Capital and Firm's Financial Performance

Performance evaluation is an important way to reveal companies' deficiencies by comparing their current business situation with that of their competitors. In performance measurement, tangible assets are mostly used as variables, because researches rely mostly on the balance sheet. Lev (2018) argues that the private industries invest increasingly in intangible assets than tangible assets, and the percentage of investment in intangible assets grew, which is almost doubled from 1977 to 2017. The intangible assets are a crucial integral part of the assets to create output. However, some of the intangible assets are not recorded in the financial statements, which often referred to as Intellectual Capital (IC). The definition "Intellectual capital" can be explained from different perspectives. From a managerial perspective, IC is defined as the knowledge, applied experience, organizational technology, relationships, and professional skills that provide for a competitive edge in the market (Chatzkel, 2002). From another perspective, IC is the ability to transform knowledge and intangible assets into wealth-creating resources. IC can be either knowledge, information, experience owned by employees of the company.

As noted in Edvinsson's research (1997), IC is the quantum of Human Capital (HC) and Structural Capital (SC). SC is the database, structure, and mechanism of the company to enable HC to perform. SC can be owned, while HC can only be rented, which makes it more volatile. Edvinsson (1997) determined the HC as the hidden value in the company, which must be considered as goodwill. Unfortunately, the value of HC is not recorded in the balance sheet and studied less compared with material assets.

IC is commonly classified into three dimensions depending on the perspective, including HC based on human resources, SC relying on organizations and Relational Capital (RC) based on coordinating the relationship between the organization and the surrounding environment (Abdullah and Sofian, 2012; Kalkan et al., 2014; Gogan et al., 2016; Hashim et al., 2015).

HC refers to the sum of all employees` capabilities. Joshi et al. (2013) described HC as the skills and knowledge of employees, which can be further enhanced by training. In the VAIC (Value Added Intellectual Coefficient) model, HC is defined as salaries and salary-related expenses. Employees with greater skills are supposed to contribute more to the Value Added (VA), which means relatively lower salary and higher VA represents the company is using their HC efficiently (Human Capital Efficiency - HCE).

$$HCE = \frac{Value\ Added}{Human\ Capital} \tag{1.47}$$

RC consists of all of the market channels, and customer and supplier relationships, as well as an understanding of government and industry association impacts (Chatzkel, 2002). Instead of working efficiently individually, the company can reach its goals far more efficiently by cooperating and sharing the knowledge from its customers and suppliers. Customers and suppliers can give feedbacks and give suggestions and work on a new product together.

$$RCE = \frac{Relational\ Capital}{Value\ Added} \tag{1.48}$$

SC refers to the company's supportive structures, processes, and databases to enable human capital to function. Joshi et al. (2013) referred to structural capital as the capability which enhances employee capability but is not related to employees at the individual level. Examples of structural capital are patents, strategies, concepts, etc.

$$SCE = \frac{Structural\ Capital}{Value\ Added} \tag{1.49}$$

Structural capital efficiency (SCE) is calculated by dividing the structural capital by VA. SCE is, therefore, the dollar of SC within the firm, for every dollar of value-added, and as HCE increases, SCE increases.

$$VAIC = HCE + RCE + SCE \tag{1.50}$$

Although VAIC is a simple and common model, there are some flaws in it. For example, the VAIC model uses financial statements that are from the past, while it might not be appropriate to evaluate future ability to create value. Xu and Wang (2018) argue that the model cannot consider the combined effects of tangible and intangible assets. Also, the required information is unavailable to those outside the firm, and the information is often qualitative. Therefore, the information cannot be translated into quantitative dollar values (Clarke et al., 2011).

1.6 Performance Measurement System

The Performance Measurement System (PMS) is used by an organization not just to determine whether its objectives have been met but also as a means of comparing the performance with that of other DMUs (Masri, 2013). DMUs can be firms, organizations, divisions, industries, projects, or individuals. PMS may be considered as one of the most interesting managerial innovations over recent years because they pose as the important organizational-informative link between strategic planning and operational control (Tonchia & Quagini, 2015). Understanding performance measurement will give managers insight into what makes a good measurement system. Performance measurement has been challenging, since what can be evaluated and what is wanted to be evaluated differs. If we want to manage performance, we have to be able to measure it: you can manage what you can measure (Tonchia & Quagini, 2015). In other words, we can only measure how the firm performed in the past, which does not always have to be the same in the future. Measuring performance solely based on the financial metrics would be like driving a car by looking in the rear-view mirror since financial metrics show only the performance of the past. Therefore, Robert Kaplan and David Norton introduced the Balanced Scorecard (BSC), which is one of the most popular PMS models. BSC uses financial and non-financial information in four different area so-called legs, as can be seen from Figure 1.7. Firms may fail regardless of their sizes, often due to incapacity to execute on a balanced strategy. BSC is also designed to ensure that performance metrics and strategic goals are balanced with financial and nonfinancial, operational and financial, leading and lagging indicators (Nair, 2004).

DMUs usually overanalyse financial perspective; however, they tend to forget the link between the company's strategy and financial goals. From the financial perspective, we should remember that financial ratios are lagging indicators as they are recorded based on past activities. Customer Perspective measures how satisfied our customers are based on the service and products delivered. Internal Business Processes Perspective measures how the company educate their employee and use the knowledge to maintain its competitiveness in the market. Organizational Capacity Perspective: measures the critical-to-customer process requirements and measures. If one of these perspectives is not measured, analyzed, and improved, and operating business would be like sitting on the chair with a broken leg and ends with failure. A PMS should be integrated with at least three other types of systems (Tonchia & Quagini, 2015), as shown in Figure 1.7.

- The Accounting or Management Control System (including internal and external accounting such as cost performance data)
- The Production Management System (material requirements, production capacity, integration to all corporate areas provides mostly non-cost data, i.e., performance targets)
- The Strategic Planning System

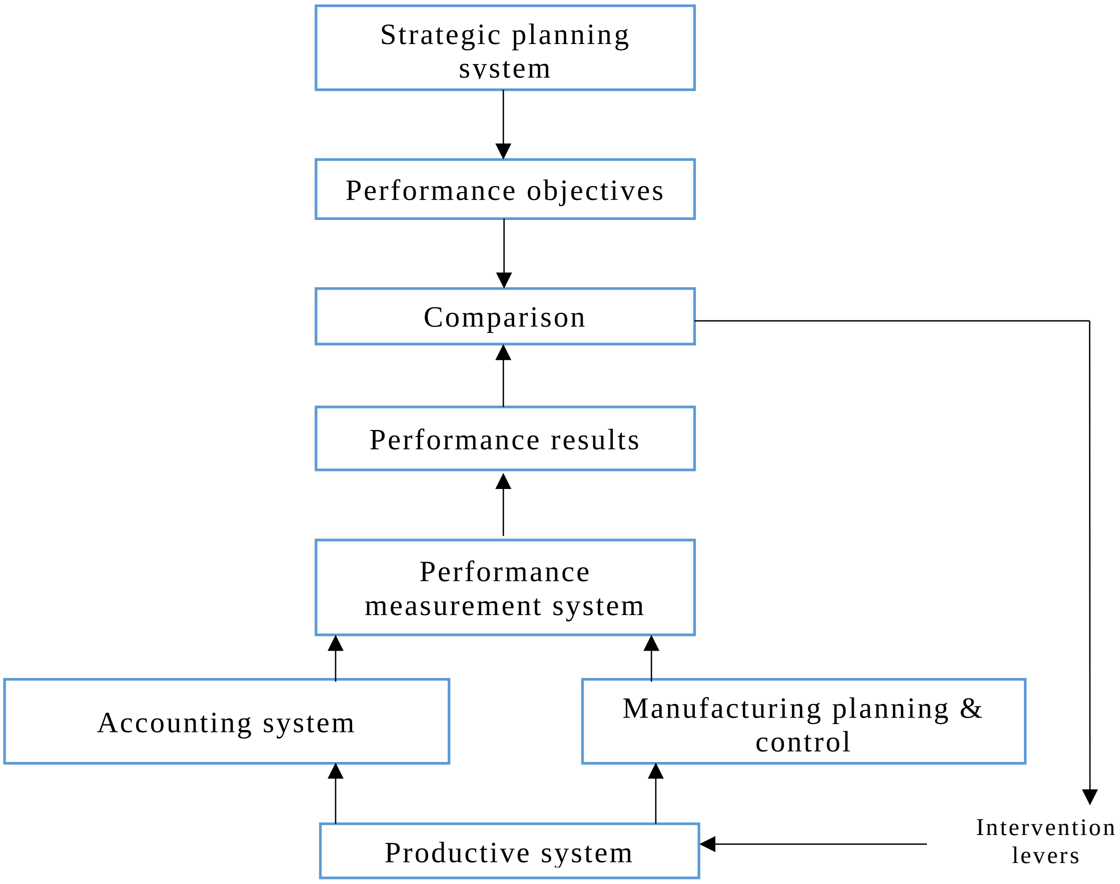


Figure 1.7 Integration between PMS and other firm's systems

Source: Tonchia & Quagini, 2015

"Efficiency measurement methods can be divided into three main categories: ratios, parametric, and nonparametric methods" (Vincová, 2005). A main difference between the parametric and the non-parametric approaches is the estimation method. Data Envelopment Analysis (DEA) is a non-parametric approach to weigh the inputs/outputs and measure the relative efficiency of DMUs (Ablanedo-Rosas et al., 2010). “Stochastic Frontier Analysis (SFA) is a parametric approach and is suited to measure efficiencies of the industry using input/output information” (Lin and Tseng 2005). “Whereas the DEA methods rely on the idea of minimal extrapolation, the parametric approaches use classical statistical principles, most notably the *maximum likelihood principle”* (Bogetoft and Otto, 2011).

2 DATA AND METHODOLOGY

2.1 Data

This chapter explains performance measurement methodologies employed in the thesis, along with its data. The thesis utilizes two sets of secondary data. The first data set is financial reports which are collected from the Mongolian Stock Exchange's (MSE) website. The second's data set is statistical information, which is provided by the National Statistics Office of Mongolia, Statistics of the Central Bank of Mongolia, Central Intelligence Agency, and the World Bank's statistics.

Mongolian economic growth was compared with some Asian countries' economic growth (i.e., Kazakhstan, Kyrgyzstan, and Indonesia) to reveal the characteristics of the Mongolian economy. The macroeconomic variables, which cover 26 years from 1991 to 2017, are obtained from the World Bank website. The criteria to choose the countries are to be dependent on mining export economically and to be classified as lower-middle-income countries like Mongolia. Kazakhstan is an exception since it is classified as an upper-middle-income country. Nevertheless, Kazakhstan is located in a similar geographical area and possesses oil reserves and minerals.

Mongolian companies are organized in either of two ways: public and non-public companies. According to statistics from the Mongolian General Department of Taxation (2018), 334 public companies are registered as taxpayers by the end of June 2018, while the number of registered non-public companies is enormously high, which is 135,850. As stated by the Mongolian law of auditing, public companies' financial statements must be audited before stockholders' general meetings, which increases the reliability of the data compared with non-public companies' financial statements (Law of Auditing, 2015). In 2018, 85.9% of the companies reported their financial statements to the Departments of Taxation. From the companies mentioned above, 50.6% of the financial statements were declared their loss, while 40% of the companies stayed dormant. As for 2019, 100,909 companies reported their corporate income tax. From that above, 42,549 companies (42.1%) declared X statements – stayed dormant. It shows that performance measurement is needed for those companies to reveal their failures and to improve their competitiveness. Competitiveness is determined by effectiveness and efficiency (Csath, 2007). The "competitiveness of the corporation and its performance is judged by comparison with its peers and against the best practice" (Manzoni, 2007).

A researcher cannot cover all the companies' financial statements within the constraints of time and resources. Therefore, I chose public companies' financial reports as my secondary data. Since the public companies' financial reports are required to be audited, their data are more reliable than that of the non-public companies, and they are publicly available from the MSE website. Moreover, public companies cover the main sectors and different sizes so they can provide a good representation of the population.

MSE was established in connection with the transition period from a centrally planned economy to a market economy in Mongolia on 18 January 1991. Mongol Shiltgeen company became a public company by issuing 10 million shares, and 1 million shares of them offered to the public. It registered at Mongolian Stock Exchange on 25 May 2005, which was the first IPO launched in Mongolia ("Mongolian Stock Exchange - History," 2015). From 2009, MSE started uploading downloadable financial statements, which included only nine companies' financial statements at that time. In 2010, the number of publicly available financial statements rose dramatically from 9 to 100. However, the form of financial statements was changed in 2012, which made it difficult to compare the financial statements before and after 2012. Although there are 334 registered public companies, I could not use the statements of all the companies in my analysis. Some companies' financial reports were deducted from research due to bankruptcy; others had no annual reports, or their reports contained zero values in their financial data. Out of 334 companies, only 137 companies reported their financial statements of 2017 publicly. After excluding the companies with non-adequate financial statements, the actual unbalanced sample for the 100 public companies remained as a database (this number includes 3 companies went bankrupt in 2016 and 1 in 2017). The financial statements of 100 public companies were available for the period 2012-2018, which met the requirements of consistency and accuracy. The data of the unbalanced panel is divided into three main sectors: heavy industry 33, manufacturing 31, and service companies 36 (Table 2.1).

The methods applied in the research were: panel regression, DEA, SFA, Principal Component Analysis (PCA), k-medoids clustering, and Unconditional Quantile Regression (UQR). Since the database contained cross-sectional and time-series data, the panel data analysis was employed. Panel models with fixed or random effects were used, and the choice was based on the results of the Hausman specification test in the thesis. One of the main methods of the thesis were DEA and SFA, which have been widely applied to evaluate efficiency in different countries and different sectors, but not yet in Mongolian case.

Table 2.1 Financial statements by sectors and years

Industry	2012	2013	2014	2015	2016	2017	2018	Total
Heavy Industry (total):	33	33	33	33	32	32	32	228
- *Thermal Power Station*	10	10	10	10	10	10	10	70
- *Construction*	9	9	9	9	8	8	8	60
- *Heavy manufacturing*	3	3	3	3	3	3	3	21
- *Mining*	11	11	11	11	11	11	11	77
Manufacturing (total):	31	31	31	31	30	29	29	212
- *Food industry*	13	13	13	13	13	13	13	91
- *Light industry*	8	8	8	8	7	6	6	51
- *Agriculture*	10	10	10	10	10	10	10	70
Service (total):	36	36	36	36	35	35	35	249
- *Transportation*	5	5	5	5	5	5	5	35
- *Trade*	6	6	6	6	6	6	6	42
- *Other services*	25	25	25	25	24	24	24	172
Total number of financial statements	100	100	100	100	97	96	96	689

Source: Author's computation

Both DEA and SFA require input and output data; therefore, measuring the input and output attributes is fundamental. However, it is hard to acquire these data for outsiders. Moreover, companies use different inputs and produce different outputs. Therefore, inputs and outputs are generally replaced by financial ratios. Also, when data contains companies of different sizes, financial parameters expressed in monetary values should be avoided. Considering above mentioned problems, I used financial ratios as variables, which can be an output of each three sectors. Three ratios were used as dependent variables (ROE, ROA, and ROS) separately and were determined the financial performance impacts for each of the three sectors.

Multidimensional scaling was applied to determine the differences in comparable countries to Mongolia's economy. Stepwise regression was used to select the variables for further analyses. Pearson correlation was applied to examine the correlation between variables. MANOVA and one-way ANOVA were used to determine statistically significant differences among the sectors' efficiency results. R-Excel and SPSS software were used for the calculations throughout the thesis.

Table 2.2 Variables used in the estimation

Variables		Measured by
Dependent variables:		
Y1	Return on assets (ROA)	Net profit divided by total assets
Y2	Return on equity (ROE)	Net profit divided by equity
Y3	Return on sales (ROS)	Net profit divided by sales
Independent variables:		
X1	Cost to revenue ratio	Cost divided by revenue
X2	Gross profit margin	Gross profit divided by revenue
X3	Return on costs	Net profit divided by costs
X4	Asset turnover ratio	Revenue divided by total asset
X5	Assets to equity ratio	Assets divided by equity
X6	Debts to total asset	Debts divided by total asset
X7	WC turnover ratio	Sales divided by working capital
X8	Current assets/Total assets	Current assets divided by total assets
X9	Operating cash flow ratio	Operating cash flow divided by revenue
X10	Quick ratio	Liquid assets divided by short-term debt
X11	Current ratio	Current assets divided by short-term debt
X12	Cash ratio	Cash divided by short-term debt
X13	Operating cycle	Inventory turnover plus receivables turnover
X14	Net operating cycle	Operating cycle subtracted by payables turnover
X15	Receivable turnover (days)	365 divided by receivables turnover (times)
X16	Inventory turnover (days)	365 divided by inventory turnover (times)
X17	Payable turnover (days)	365 divided by payables turnover (times)
X18	Assets growth	Assets (current year) divided by assets (previous year)
X19	Sales growth	Sales (current year) divided by sales (previous year)

Source: Author's compilation

2.2 Basic statistical analysis

Numerical values can be described by

- Central tendency: mean, median, mode
- Spread: range, quartiles
- Variability: variance

Central tendency is commonly measured by mean, median, and mode. Central tendency does not give any information about the range of the data. Common measures of the scatter of the data are the total range, the quartiles, the interquartile range, the mean absolute deviation, the variance, the standard deviation, and the coefficient of variant, which are all based on deviations from the arithmetic mean. The total range is the poorest and simplest measure of the scatter of data, which is the difference between the highest and the lowest value in the sample. The outliers affect the total range significantly; therefore, the inter-quartile range is often used, which is the difference between lower (Q1) and upper (Q3) quartiles. Quartiles are the values that divide the dataset into quarters (Dalgleish et al., 2007). The mean absolute deviation is the average of the absolute values of the deviations from the mean. Unlike the total range, the mean absolute deviation uses all the variables in the dataset, which makes it more valuable. The mean absolute deviation is less sensitive for the outliers than the variance and standard deviation (Lind, Marchal, & Wathen, 2006).

The variance shows the average squared deviations of the numbers from the mean. The analysts use the standard deviation (σ) more frequently, which is the square root of variance (σ^2).

$$\text{Variance } (\sigma^2) = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \qquad 2.1$$

where

$(x_i - \mu)^2$ - *the squared deviations*

n - *the number of elements in the example*

Another characteristic of a dataset is the shape. There are four shapes commonly observed: symmetric, positively skewed, negatively skewed, and bimodal. In a symmetric set of observations, the mean and median are equal, and the data values are evenly spread around these values. A set of values is skewed to the right or positively skewed if there is a single peak, and the values extend much further to the right of the peak than to the left of the peak. In this case, the mean is larger than the median. In a negatively skewed distribution, the mean is smaller than the median. Positively skewed distributions are more common (Lind et al., 2006).

If two variables are measured, the data are called bivariate data. Data analysts frequently want to understand the relationship between two variables (Lind et al., 2006) by widely using correlation and regression.

Correlation shows how closely the data points locate to the line of best fit, while regression shows the characteristics of that line. First, the equation of the line that best fits the data is determined, then the error of the estimate is determined, and finally, confidence and prediction intervals for the estimate are established (Lind et al., 2006).

$$y' = a + bx + \varepsilon \qquad 2.2$$

where

y - dependent variable
x - independent variable
b - slope coefficient
ε – residuum, the error of the estimate.

The standard error of the estimate is a measure that describes how precise the prediction of Y variable based on the X variable or, conversely, how inaccurate the estimate is. The standard error of the estimate is a measure of the scatter of the observed values around the regression line (Lind et al., 2006). The standard error of the estimate can express by the following equation:

$$\sigma_\varepsilon = \sqrt{\frac{\sum(y-y\prime)^2}{n}} \qquad 2.3$$

The standard error of the estimate is based on squared deviations between the observed y values and its predicted values, y'. The regression line represents all the values of y'. If σ_ε is small, this means that the data are close to the regression line and the regression equation can be used to predict y with little error. If σ_ε is large, this means that the data are widely scattered around the regression line, and the regression equation will not provide a precise estimate on Y (Lind et al., 2006).

2.3 Panel regression

Panel data analysis is appropriate when the database contains both cross-sectional and time-series data. In principle, panel data can be seen as a *data cube* with three dimensions: units $i=1,\dots, n$, time points $t=1,\dots, T$, and variables $v=1,\dots, V$. To analyze panel data with statistical computer software, we need to rearrange the three-dimensional data cube into a two-dimensional *working dataset* (Andreß et al., 2013). Panel data models provide information about a two-dimensional sample: across individuals N (cross-sectional dimensions) and over time T (time-series dimensions). Panel data is called balanced when each unit is observed in each wave $(T = T_i)$, while in unbalanced panel data, the number of observations per unit differs ($T \neq T_i$) (Andreß et al., 2013).

Panel data types:

- Short panel: many individuals within a short period, e.g., 1000 individuals and two years.
- Long panel: few individuals within a long-time period, e.g., 500 time period and three individuals.
- Both: many individuals within a long period.

Researchers must be careful when conducting short or long panel analysis. Data used in the thesis contains 100 companies, from 2012 to 2018 (4 companies went bankrupt during this period); therefore, the unbalanced short panel is executed.

Regressors (Independent variables)

- Varying regressors: changes within the period and individuals (salary).
- Time-invariant regressors: constant within time vary within individuals (gender, race). They are variables that are the same for a given cross-sectional unit through time, but that vary across cross-sectional units (ability, sex, and socioeconomic-background variable) (Hsiao, 2004).
- Individual-invariant regressors: constant within individuals vary within time (economic trend).

Variation for the dependent variable and regressors:

- Overall variation: variation over time and individuals
- Between variation: variation between individuals
- Within variation: variation within individuals (over time).

Time-invariant regressors (e.g., gender, race) have 0 within variation. Individual-invariant regressors (time, economy trends) have 0 between variation (Katchova, 2013).

There are three types of panel data models:

- Pooled model: it specifies constant coefficients, the usual assumptions for cross-sectional analysis
- Random effects model (RE): In the RE model, the individual-specific effect is a random variable that is uncorrelated with the explanatory variables (Schmidheiny, 2015).
- Fixed effects model (FE): In this model, the individual-specific effect is correlated with the explanatory variables.

Pooled model:

Like cross-sectional analysis, parameter homogeneity, when $\beta_{it} = \beta$ for all i, t.

$$y_{it} = a + \beta x_{it} + u_{it} \tag{2.4}$$

y denotes a dependent variable, and *x* denotes an independent variable. The i subscript denotes the individuals, whereas *t* denotes time. a is scalar, constant coefficient; u_{it} is a composite error.

$$u_{it} = \mu_i + v_{it} \tag{2.5}$$

μ_i denotes the *unobservable* individual-specific effect, and v_{it} denotes the remainder disturbance (idiosyncratic disturbance). Note that μ_i is time-invariant, and it accounts for any individual-specific effect that is not included in the regression, during the remainder disturbance v_{it} varies with individuals and time and can be thought of as the usual disturbance in the regression (Baltagi, 2005). The pooled model is the most restrictive and not often used in the literature.

The error term has two separate components, one of which is specific to the individual and does not change over time (μ_i) (Croissant & Millo, 2008), which is called individual-specific effects models and divided into random and fixed effects models. If the individual-specific effects are correlated with the regressors x, we use the FE model. If not, we use the RE model.

FE model:

In the FE model, individual-specific effects (μ_i) can be correlated with the explanatory variables *($x_{it}^{\cdot}$)*.

$$y_{it} = a + \beta x_{it}^{\cdot} + \mu_i + v_{it} \tag{2.6}$$

where

μ_i*- intercepts (individual-specific effects) differ by individuals.*
β *- slope parameter*

If μ_i can be arbitrarily correlated with each element of $x_{it}^{\cdot}$, there is no way to distinguish the effects of time-constant observables from the time-constant unobservable μ_i (Wooldridge, 1960). Also, this fixed effect estimator cannot estimate the effect of any time-invariant variable like sex, race, religion, schooling, or union participation (Baltagi, 2005). The fact that $x_{it}^{\cdot}$ cannot include time-constant explanatory variables, which is a drawback in certain applications, but when the interest is only on time-varying explanatory variables, it is convenient without worrying about modeling time-constant factors that are not of direct interest (Wooldridge, 1960).

If many dummies may aggravate the problem of multicollinearity among the regressors; the μ_i are assumed to be fixed parameters to be estimated and the remainder disturbances stochastic with v_{it} independent. The $x_{it}^{\cdot}$ are assumed independent of the v_{it} for all *i* and *t*. The "fixed-effects model is an appropriate specification if we are focusing on a specific set of *N* firms" (Baltagi, 2005).

RE model:

In the RE model, μ_i is a random variable that is independent on regressors and included in the error term (u_{it}). $u_{it} = \mu_i + v_{it}$

$$y_{it} = \beta x_{it}^{\cdot} + u_{it} \qquad 2.7$$

the variances and covariances of the elements of u_{it}: $var(u_{it}) = \sigma_{\mu}^2 + \sigma_v^2$;

$p_u = cor(u_{it}, u_{is}) = \sigma_{\mu}^2/(\sigma_{\mu}^2 + \sigma_v^2)$

This correlation is also the ratio of the variance of μ_i to the variance of the composite error, and it is useful as a measure of the relative importance of the unobserved effect μ_i (Wooldridge, 1960). The interclass correlation of the error (p_u) is the fraction of the variance in the error due to μ_i. It approaches to 1 if the μ_i dominate the idiosyncratic error (Katchova, 2013).

The advantages of random effects are:

1. The number of parameters stays constant when the sample size increases.
2. It allows the derivation of efficient estimators that make use of both within and between variation.
3. It allows the estimation of the impact of time-invariant variables (Hsiao & Yanan, 2006).

If there are too many parameters in the FE model, and the loss of degrees of freedom can be avoided if the μ_i can be assumed random. The μ_i are independent of the v_{it}. Also, the $x_{it}^{\cdot}$ are independent of the μ_i and v_{it}, for all *i* and *t*.

When the type of effects (group versus time) and property of effects (fixed versus random) combined, there are several specific models: fixed group effect model (one-way), fixed time effect model (one-way), fixed group and time effect model (two-way), random group effect model (one-way), random time effect (one-way), and random group and time effect model (two-way) (H. M. Park, 2010). To choose the appropriate model, we can use the Breusch Pagan Lagrange multiplier test, F test, and Hausman test.

Table 2.3 Determination of model

FE **(F test or Wald test)**	RE **(Breusch-Pagan LM test)**	Model to choose
H_0 is not rejected (no FE)	H_0 is not rejected (no RE)	Pooled OLS
H_0 is rejected (FE)	H_0 is not rejected (no RE)	FE model
H_0 is not rejected (no FE)	H_0 is rejected (RE)	RE model
H_0 is rejected (FE)	H_0 is rejected (RE)	Choose the model depending on the result of the Hausman test.

Source: Park, 2010

Breusch Pagan Lagrange multiplier test is for the RE model based on OLS residual. If the LM test is significant, we use random effects instead of the OLS model (Katchova, 2013).

The FE "model is an appropriate specification if we are focusing on a specific set of *N* firms and our inference is restricted to the behaviour of these sets of firms, while the RE model is an appropriate specification if we are drawing *N* individuals randomly from a large population" (Baltagi, 2005). The Hausman specification test was applied in this thesis to decide whether the FE or RE model is more appropriate. The null hypothesis for the Hausman test is "RE model is better than the FE model" and "RE model is consistent". If the null hypothesis is rejected, the FE model is more appropriate; otherwise, the RE model (Park, 2010).

2.4 Cluster analysis (k-medoids algorithm)

The basis of all types of analysis is data. We face various data in our everyday life, with or without any prior knowledge. But precise analysis cannot be made without knowing the pattern and the characteristics of data. Therefore, data classification or grouping (cluster) can be one of the primary analysis. The clusters can be determined in many ways, but there is no single determination that is globally accepted. Cluster analysis can be used for understanding (finding meaningful groups of objects that share common characteristics) and utility (to abstract the representative objects from individual objects in the same clusters) (Wu, 2012).

Clustering plays an essential role in supporting analysts to analyze, describe, and utilize the valuable information hidden in the groups (Wu, 2012). Clustering techniques can be divided into the partitional clustering and hierarchical clustering. Partitional clustering directly divides data points into some prespecified number of clusters without any hierarchical structure, while hierarchical clustering groups data with a sequence of nested partitions, either from singleton clusters to a cluster, including all individuals or vice versa (Xu & Wunsch, 2008). Partitioning methods relocate the instances by moving them from one cluster to another, starting from an initial partitioning (Rokach & Maimon, 2010).

Based on the way to approach the centre, cluster analysis is classified: hard (crisp) clustering and soft (fuzzy) clustering (Ho-Kieu et al., 2018). The most common and well-known hard clustering is the k-means clustering. The k-means clustering is simple and fast. Also, a k-means algorithm has a good ability to handle a huge number of data. This algorithm applies a standard distance measure formula to calculate the similarity of the data repetitively to obtain a high inter-cluster distance among clusters (Arbin et al., 2016). The k-means clustering iteratively finds the k centroids and assigns every object to the nearest centroid (Park & Jun, 2009). The centroids are updated by taking the average of all data. Therefore, if there are outliers, the centroids shift to the outliers. The extremely large value might substantially distort the distribution of data, which is the drawback of the k-means clustering.

In contrast to the k-means clustering, the k-medoids method uses the most centrally located object in a cluster instead of centre mass, which helps to overcome k-means' drawbacks. K-medoids algorithm is computationally harder than k-means due to computing the medoids using the frequency of occurrences. Clustering tendency, which shows whether the clustering is appropriate for the data, must be assessed, before employing a clustering algorithm. Afterwards, the number of clusters and the algorithm must be determined. Finally, cluster validation (goodness of clustering results) should be done.

According to Kassambara (2017), the most common realization of *k*-medoids clustering is the Partitioning Around Medoids (PAM) algorithm, which is as follows:

- Initialization: randomly select k of the n data points as the medoids. Like k-means, k-medoids also require a pre-set number of clusters (k). There is not an ultimate approach to determine the number of clusters, but to set an inappropriate number of clusters can lead to meaningless clusters. A useful approach to determine the optimal number of clusters is the silhouette method (Kassambara, 2017).

- Calculation of the dissimilarity matrix. A standard way of expressing similarity is the determination through a set of distances between pairs of objects (Hartigan, 1989). Data within the group (intra-cluster) are similar, while data between the groups (inter-cluster) are different based on the specific criteria.
- Assign every object to the closest medoid. The closest medoid can be defined using any valid distance metric, most commonly use Euclidean distance (the root-sum-of-squares of differences), Manhattan distance (the sum of absolute distances), or Minkowski distance. Manhattan is more robust than Euclidean distances when data contains outliers.
- If any of the objects of the cluster decreases the average dissimilarity coefficient, select the entity that reduces this coefficient the most as the medoid for this cluster.

Each clustering algorithm creates a different cluster for the same data, which makes cluster validation important to evaluate whether the clusters are meaningful or just artefacts of the clustering algorithm.

There are three categories of validation:

- External: it can be used to select the suitable clustering algorithm
- Internal: it measures the compactness (within-cluster variation), the connectedness, and the separation (how well-separated) of the cluster partitions.
- Relative criteria (Kassambara, 2017).

2.5 Data envelopment analysis

DEA is a linear programming based technique for measuring the relative performance of organizational units where the presence of multiple inputs and outputs makes comparison difficult (Boussofiane et al., 1991). The idea of DEA was first introduced by Farrell (1957b), and it was developed by Charnes et al. (1978). DEA is a data-oriented approach for evaluating the performance of a set of peer entities that convert multiple inputs into multiple outputs (Seiford, Zhu 2011). In the DEA method, both input and output efficiency take a score 1 for the efficient companies, which means one-unit marginal input results in the one-unit marginal output. Once the efficient frontier is determined, the inefficient DMUs can improve their performance to reach the efficient frontier either by increasing their current output levels or decreasing their current input levels (Färe & Grosskopf 2004).

2.5.1 Efficiency technologies and concepts

The basic idea in benchmarking is that the firms compared have the same technology (Bogetoft & Otto, 2011), which is called production possibility set T (technology set). The technology set is the set of outputs that can be produced by using available inputs. The technology set takes a positive number or zero as input and output variables. Based on the technology set, the efficient frontier is determined. Frontier touches at least one point, and all points are, therefore, on or below this line (Cooper et al., 2006). The DMUs operate along the efficient frontier are determined as efficient entities, while the other DMUs out of the frontier are inefficient.

The DEA methods differ by orientations, models, and formulations. One of the assumptions related to DEA is free disposability. Free disposability assumes that we can freely discard either unwanted outputs or unnecessary inputs. Free disposability can be classified as free disposability of inputs and free disposability of output. The free disposability of input means that if we can produce a certain quantity of outputs (y) with a given quantity of input (x), then we can also produce the same quantity of outputs with more inputs (x') (Bogetoft & Otto, 2011). Free disposability of input:

$$(x, y) \in T, x' \geq x \Rightarrow (x', y) \epsilon = T \qquad 2.8$$

Likewise, free disposability of output means it is possible to produce less output with the same amount of input. Free disposability of output:

$$(x, y) \in T, y' \leq y \Rightarrow (x, y') \epsilon = T \qquad 2.9$$

Another class of assumption in DEA is convexity, which means any weighted average of feasible production plans is also feasible. In benchmarking, convexity enlarges the technology since it allows us to interpolate from observed firms to firms with input-output profiles between the observations. Moreover, convexity also creates technologies that are better able to distinguish between average performance and best practices (Bogetoft & Otto, 2011). Convexity:

$$(x, y) \in T, (x', y') \in T, \alpha \in [0, 1] \Rightarrow \alpha[x, y] + (1 - \alpha)(x', y') \epsilon = T \qquad 2.10$$

Most benchmarking methods presume free disposability and convexity.

2.5.2 DEA orientations and technologies

DEA models produce explicit peers which are the firms with positive weights in the evaluation of a given firm (Bogetoft & Otto, 2011).

DEA determines two orientations: output efficiency and input efficiency.

- Input orientation: A DMU is not efficient if it is possible to decrease any input without augmenting any other input and without decreasing any output.
- Output orientation: Decision Making Unit (DMU) is not efficient if it is possible to augment any output without increasing any input and without decreasing any other output (Charnes et al., 1978).

Input efficiency is appropriate when somebody is interested in minimizing input, while if we are interested in maximizing output, output efficiency is used. The "single most widely used approach measuring the degree of efficiency in a general multi-input and the multi-output setting is the strategy suggested by Debreu and Farrell, usually referred to simply as Farrell efficiency" (input efficiency/technical efficiency - E) (Bogetoft & Otto, 2011). Input efficiency:

$$E^0 = E((x^0, y^0); T^* = min\,\{E \ \in R_+ | (Ex^0, y^0) \in= T^*\} \qquad 2.11$$

where *x* is the input vector, *y* is the output vector, and *(x, y)* means the feasibility of the vector. Input efficiency takes the value between 0-1.0; for example, a value of 0.6 obtained by the input-oriented method means that we could still produce the same output if we decreased the inputs by 40%.

Like input efficiency, output efficiency *(F)* means the given enterprise, compared with effective firms, uses much more input to produce the particular output (Bogetoft & Otto, 2011).

$$F^0 = F((x^0, y^0); T^* = max\,\{F \ \in R_+ | (x^0, Fy^0) \in= T^*\} \qquad 2.12$$

For example, a value of 1.4 obtained by the output-oriented model means that the given company, compared to effective firms, could increase its output by 40% without involving any additional input source.

Being technically efficient means to minimize inputs at a given level of outputs or maximize outputs at a given level of inputs (Vincová, 2005). Both input efficiency and output efficiency take the value 1.0 for efficient companies.

DEA encompasses two main models: Variable Return to Scale (VRS) and Constant Return to Scale (CRS). The assumption is that if there is any possible production combination can arbitrarily be scaled up or down. VRS consists of increasing (IRS) and decreasing return to scale (DRS) (Fenyves et al., 2015). The VRS and CRS models are treated in input-oriented forms, while the multiplicative model is treated in the output-oriented form (Banker et al., 2004).

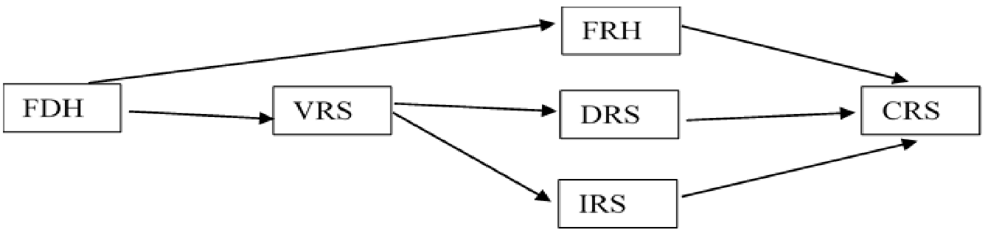


Figure 2.1 Technology sets of DEA

Source: Bogetoft & Otto, 2011

FDH (Free Disposability Hull) is the smallest technology set, while FRH (Free Replicability Hull) is a modified version of FDH. VRS consists of IRS (Increasing Return to Scale) and DRS (Decreasing Return to Scale) models. Choosing between DRS and the IRS depends on the firm's production function. If the variation of inputs is the same as output variation, the production has constant returns to scale. Marginal productivity remains constant when the production scale changes. If the variation of inputs is smaller than the output variation, the production is called as increasing returns to scale (the marginal productivity is greater than one). If the variation of inputs is larger than the outputs, the production is called decreasing returns to scale (the marginal productivity is less than one) (Benicio & De Mello, 2015).

DRS means that the output will tend to increase less than the input, so it will be possible to scale down but not up. The reason to choose DRS is a firm can run a process at reduced speed, reduced capacity utilization, or reduced the amount of time that the process takes (Bogetoft & Otto, 2011). Decreasing Return to Scale:

$$(x, y) \in T, 0 \leq \lambda \leq 1 \Rightarrow \lambda(x, y) \epsilon = T \quad 2.13$$

IRS means that the output will tend to grow faster than the input. One reason for this is that a larger scale implies more experience, more efficient processes, and a better ability to utilize specialization possibilities (Bogetoft & Otto, 2011). Increasing Returns to Scale:

$$(x, y) \in T, \lambda \leq 1 \Rightarrow \lambda(x, y) \epsilon = T \qquad 2.14$$

The largest technology, CRS, is the extreme assumption, which means any possible production combination can arbitrarily be scaled up or down. Constant Returns to Scale:

$$(x, y) \in T, 0 \leq \lambda \Rightarrow \lambda(x, y) \epsilon = T \qquad 2.15$$

CRS is determined as allowing full rescaling and convexity (Bogetoft & Otto, 2011).

2.5.3 Scale and allocative efficiencies

At the most productive scale size is the constant return to scale, where the average output is maximal, and in a single-input cost model, the average costs are minimal. The loss from not operating at optimal scale size is called Scale Efficiency *(SE).* SE is determined in the case of the input efficiency CRS model and, to some extent, the DRS and IRS models, not for the VRS model (Bogetoft & Otto, 2011). Scale Efficiency:

$$SE(x^0, y^0) = \frac{E(x^0, y^0; crs)}{E(x^0, y^0; vrs)} \qquad 2.16$$

SE is never higher than one, and it is precisely one when the VRS and CRS technologies coincide when a firm is operating at an optimal scale size. The smaller the value of SE, the more is lost from not having the high average product. SE can be rewritten as:

$$E(x^0, y^0; crs) = E(x^0, y^0; vrs) * SE(x^0, y^0) \qquad 2.17$$

The efficiency expressed by a CRS technology can be divided into two components: 1) pure (technical) efficiency, measuring the ability to use best practices in the VRS technology, and 2) SE, measuring the ability to operate where the average output bundle per input bundle is maximal. The reason for SE less than one can be due to the firm's being too small or too large.

The firm is below the optimal scale size, if

$$E(x^0, y^0; drs) = E(x^0, y^0; crs) \qquad 2.18$$

The firm is above the optimal scale size, if

$$E(x^0, y^0; drs) = E(x^0, y^0; vrs) \quad 2.19$$

In a firm, this can shape the strategic planning process and can help firms decide whether to choose an expansive or constrictive strategy. SE does not work if the market is not competitive, or the companies are unable to change their scale of operation.

2.5.4 Additional topics (Super efficiency, Slack consideration)

Both input and output efficiencies take a score one for efficient DMUs; however, in the case of several firms are ranked as fully efficient, we can rank efficient firms via Super-Efficiency (E^{SUP}). Super-efficiency measures are constructed by avoiding that the evaluated firm can help span the technology. The efficiency of (x^k, y^k) relative to $T^*(\mathbb{N}|\text{-}k)$ is called super-efficiency:

$$E^{SUP\ k}=E((x^k, y^k); T^*(\mathbb{N}|\text{-}k)) \quad 2.20$$

The super-efficiency measures on the input and output sides are not restricted to either below or above one when we are interested in differentiating among the firms with traditional efficiency scores of one (Bogetoft & Otto, 2011).

"One of the drawbacks of the traditional Farrell approach is that a firm can have an efficiency score of one and still be Koopmans inefficient in the sense that some inputs could be reduced, or some outputs could be expanded without affecting the need for other inputs or the production of other outputs" (Bogetoft & Otto, 2011). The slack problem is quite common in DEA models due to the vertical and horizontal segments of the frontier.

2.6 Stochastic frontier analysis

There are two main approaches to modern benchmarking, a non-parametric (deterministic), which is DEA, and a parametric, which is SFA. DEA is widely used and flexible approach (Zohdi et al., 2012; Hollingsworth and Smith 2003; Halkos & Tzeremes 2012; Daraio & Simar 2007; Amin et al., 2011, etc..). DEA does not allow any noise in the data and considers all deviations as inefficiency. In other words, deterministic frontier models have the drawbacks of not allowing random noise in the data generating process and, as a result, being very sensitive to outliers (Zelenyuk & Simar, 2008).

"In terms of methods, the DEA approach has its roots in mathematical programming, whereas the SFA approach is much more directly linked to the econometric theory" (Bogetoft & Otto, 2011).

2.6.1 The production frontier model

Similar to the DEA method, the SFA method is also commonly used for measuring efficiency, for instance, Crisci et al., 2016; Erkoc 2012; Lensink and Meesters 2014; Price et al., 2017, etc. SFA is a parametric approach and is suited to measure efficiencies of the industry using input/output data (Lin & Tseng 2005). The differences between parametric and non-parametric approaches are the production possibility sets and the data generation process. A production function describes the maximum amount of outputs that can be produced in various inputs given. The production function *f(x)* is a line that can be drawn by connecting the plots of maximum possible outputs *(y)* in given inputs *(x).*

If *y* is the single output and *x* are inputs, the production function would be:

$$y = f(x_1, x_2 \dots x_n) = f(x) \qquad 2.21$$

A production plan is technically inefficient if a higher level of output is technically attainable for the given inputs (output-oriented measure), or that the observed output level can be produced using fewer inputs (input-oriented measure) (Kumbhakar et al., 2015).

The technologies use minimum input bundles to operate, or maximum output for a given input is referred to as the production frontier. There are four types of efficiencies using frontier: technical efficiency, cost efficiency, revenue efficiency, and profit efficiency. Companies operating on their frontier are labelled efficient, while companies below the frontier are inefficient.

The objective of producers might be: producing given outputs by the minimum inputs (technical efficiency) with a minimum cost (cost efficiency), or the utilization of the given inputs to maximize the revenue (revenue efficiency), or the allocation of inputs and outputs (allocative efficiency) to maximize profit (profit efficiency) (Kumbhakar & Lovell, 2000).

2.6.2 Parametric approaches

Two factors make companies work beneath the frontier: environmental effect (noise *v*), and failure to optimize (efficiency *u*) (Kumbhakar & Lovell, 2000). The parametric approach is divided into three main processes, depending on how to explain the variation from the optimal:

- Regression: To consider any deviation as noise corresponding to an ordinary regression model.
- Deterministic: To consider any deviation as an expression of inefficiency, the so-called deterministic frontier.
- Stochastic: Deviations are the results of both noise and inefficiency, which is the stochastic frontier approach (Bogetoft & Otto, 2011).

The regression approach interprets all deviations from the frontier as measurement noise. The simplest way to estimate is to assume that deviations are symmetric around zero and follow a normal distribution.

Deterministic frontier models suppose every variation from the production function is due to the inefficiency. Therefore, it is argued that the deterministic model has not flexible frontier like DEA, although it has the same drawback as DEA by not allowing noise.

Two common deterministic frontiers are the Corrected Ordinary Least Squares (COLS) and Thick Frontier Approach (TFA). One of the most common regression models which do not allow noise is COLS. Because COLS measures the frontier function as a shifted mean regression, it implies that the difference between the efficient frontier producer and the mean producer is only in the intercept but not in the slope coefficients, which is a strong assumption (Subhash et al., 2015). Therefore, deviations from the estimated frontier are entirely attributed to inefficiency, and there is no role for another randomness such as data errors, atypical events (Subhash et al., 2015).

Another distribution-free approach is TFA, which groups samples into four quartiles (or N quantiles) according to an observed efficiency indicator such as the average output or the average cost. The production function is first estimated using data of the last sample quartile (the efficient group) and then estimated using data of the first sample quartile (the inefficient group). Differences between the two estimated production functions (evaluated at their respective mean values) are due to either market factors or inefficiency (Subhash et al., 2015).

Compared to COLS, TFA allows the existence of random errors within the quartiles, although the between-quartile variations are assumed to be due entirely to market factors and inefficiency (Subhash et al., 2015). TFA will be problematic when multiple inputs used, or data is small. Moreover, the frontier function cannot be distinguished from the inefficiency effect of the model when using cross-sectional data (Kiplimo & Ngeno, 2016).

When $f(x_i;\beta)$ is the production function with unknown parameter β, a stochastic production frontier model with output-oriented technical inefficiency can be specified:

$$ln\, y_i = ln y_i^* - u_i, \quad u_i \geq 0, \qquad 2.22$$

where

y_i - a scalar of observed output,
$u_i \geq 0$ - the effect of production inefficiency.

The term u_i is the log difference between the maximum and actual output. Since u_i refers to the technical inefficiency index, closer to 0 shows better efficiency. While u_i refers to the inefficiency index, $\exp(-u_i)$ refers to the efficiency index.

$$\exp(-u_i) = \frac{y_i}{y_i^*} \qquad 2.23$$

The efficiency index takes a value between 0 (minimum efficiency) and 1 (fully efficient production). The production frontier in SFA would be:

$$ln\, y_i^* = f(x_i;\beta) + v_i - u_i, \qquad 2.24$$

where

x_i - a $k \times 1$ vector of input variables,
β - a $k \times 1$ vector of the corresponding coefficient vector (unknown parameter),
v_i - a zero-mean random error.

The *v* term takes care of the stochastic nature of the production process and possible measurement errors of the inputs and outputs, and *u* term is the possible inefficiency of the firm. We assume that the terms *v* and *u* are independent (Bogetoft & Otto, 2011).

The main interest of efficiency analysis is evaluating a particular firm's efficiency and an individual firm's efficiency, ε must be decomposed.

$$\varepsilon_i = v_i - u_i, \Rightarrow (composed\ error) \qquad 2.25$$

The variance of the compose error (σ^2) and the ratio of firm-specific variability to total variability (λ) are calculated as:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2; \qquad \lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}} \qquad 2.26$$

If λ = 0, the deviation is due to noise term, not because of inefficiency. A positive and significant λ implies that the firm-specific technical efficiency is important in explaining the total variability of output produced (Chen et al., 2016).

The percentage of total error variance due to inefficiency can be calculated from

$$\frac{\lambda^2}{\lambda^2 + 1} \qquad 2.27$$

For example, when the λ is 1.19; $\frac{\lambda^2}{\lambda^2+1} \Rightarrow \frac{1{,}19^2}{1{,}19^2+1} \Rightarrow 0.586$, it means 58.6% of the total variation stems from the inefficiency, and 40.4% from the random noise.

Table 2.4 Parametric approaches to noise $\boldsymbol{v}$ and inefficiency $\boldsymbol{u}$

Approach	Additive	Multiplicative
Regression	$f(x_i;\beta) + v_i,$	$f(x_i;\beta)\exp(v_i)$
Deterministic	$f(x_i;\beta) - u_i$	$f(x_i;\beta)\exp(-u_i)$
Stochastic	$f(x_i;\beta) + v_i - u_i,$	$f(x_i;\beta)\exp(v_i)\exp(-u_i)$

Source: Bogetoft & Otto, 2011

When we use cross-sectional data, we take a snapshot of the companies' performance of specific time. In contrast, panel data allows us to evaluate the performance of each company with its changes throughout the years. The stochastic frontier methodology has subsequently been extended in many directions using both cross-sectional and panel data. One advantage of using panel data is that it allows examining and model behaviour of technical efficiency over time (Simwaka, 2012).

The efficiency of the specific firm in both the additive and multiplicative models depends on u. In the multiplicative model, the efficiency depends only on u, and, in the additive model, the efficiency also depends on the maximal expected output, that is, the output determined from the estimated function (Bogetoft & Otto, 2011).

Efficiency of a particular firm in the additive case by output efficiency is

$$D_0(x^0, y^0) = \frac{Actual\ output}{Maximal\ expected\ output} = \frac{f(x^0; \beta) - u^0}{f(x^0; \beta)} \qquad 2.28$$

If we use a multiplicative formula, we retrieve similar results after a log transformation:

$$D_0(x^0, y^0) = \frac{f(x^0; \beta)\ \exp(-u^0)}{f(x^0; \beta)} = \exp(-u^0) \qquad 2.29$$

Like the DEA method, the SFA method also receives a score of 1 for efficient companies. However, it does not require any efficient company for every observation unless the possible inefficiency (u) is equal to zero.

2.6.3 Estimation principle

A significant difference between the parametric and the non-parametric approaches is the estimation principle. Whereas the DEA methods rely on minimal extrapolation, the parametric approaches use classical statistical principles, most notably the maximum likelihood principle (Bogetoft & Otto, 2011).

The minimal extrapolation principle states that the technology set should be the smallest set containing all data and fulfilling certain technological assumptions such as returns to scale.

SFA method does not fulfil the minimal extrapolation principle (Bogetoft & Otto, 2011); but it is based on the maximum likelihood estimation. The consequence can be seen as a drawback of the SFA method, but it can also be an advantage of the method, as it represents a way to handle uncertainty (Bogetoft & Otto, 2011).

For each set of observations, we have a likelihood function L(β)=φ(y; β), and for each parameter, we have a density function φ(y; β). The likelihood function can be interpreted as the likelihood or “probability” of the parameter β. In mathematical terms, we choose β by maximizing L(β). φ is the distribution function of the standard normal distribution with mean 0 and variance 1 when the parameter is 0, there is no effect from differences in the efficiency, and if it is very large, differences are almost only due to differences in the efficiency and not another kind of uncertainty (Bogetoft & Otto, 2011).

2.7 Principal Component Analysis (PCA)

The discrimination power of DEA declines (and possibly proves the majority of DMUs as efficient) when the number of inputs and outputs is relatively high. To overcome the ‘curse of dimensionality’ of DEA, it can be combined with the PCA. PCA is a multivariate technique capable of reducing the dimensionality of a multivariate dataset while accounting for much of the variation present in the original dataset.

PCA is a statistical method that converts several correlated p variables into several uncorrelated k variables providing a condition $p \geq k$ (Unsal & Orkcu, 2017). PCA is a multivariate technique for reducing the dimensionality of a multivariate dataset while accounting for as much as possible of the variation present in the original dataset. This is achieved by transforming to a new set of variables, the Principal Components (PC), which are uncorrelated, and sorted in that order that the first few include most of the variation in all the original variables (Gentlemen et al., 2011). The first PC consists of the highest variance of the sample data, the second for the second-highest variance, and so on (Alimohammad et al., 2011). New variables (PCs) can be used as the substitutes for the originally large number of variables, and they provide a more straightforward basis for representing or summarizing the data; and perhaps to perform additional multivariate analysis of the data (Gentleman et al., 2011).

The PCs are estimated as the projections on the eigenvectors of the covariance or correlation matrix of the dataset. The variance of a dataset indicates how scattered the data. The larger the deviation, the more information included (Hsin-Pin & Jia-Ruey 2013).

PCA has two main central conceptions. First, it is an effective data analyzing tool to identify and express patterns in the dataset. Second, it highlights the data’s similarities and differences (Omrani et al., 2015). The result of a PCA is a smaller number of “new variables” than it was in the original dataset.

PCA is useful when

- There are too many explanatory variables relative to the number of observations.
- The explanatory variables are highly correlated (Gentleman et al., 2011).

The most common procedures for deciding the number of principal components to retain are

- Retain just enough principal components to explain some specified, large percentage of the total variance of the original variables. Values between 70% and 90% are usually suggested.
- Exclude those PCs whose eigenvalues are less than 1.0 (Gentleman et al., 2011).

The main steps of the PCA are as follows:

- Standardization of the original data.
- Calculation of the correlation coefficient matrix of the standardized data.
- Calculation of the characteristic values of related coefficients and the eigenvalues of the corresponding feature vectors and the contributions of variance.
- Determination of the number of PCs.
- Tectonic comprehensive evaluation function (Li & Zhang, 2011).

The use of less than full information can result in the loss of some of the explanatory powers of the data but can improve the discriminatory power of the model. The only other possibility to reduce dimensionality is to drop specific variables. By doing so, all information drawn from those variables is automatically lost. However, if certain PCs are removed, entire variables are not lost unless the PC weight is placed entirely on that variable in the, PC dropped (with a zero weighting in all other PC combinations) (Adler & Golany, 2002). This is why some researchers use PC scores as input data, including Serrano-Cinca and Mar Molinero (2004); Zhu (1998); as well as Annapoorni and Prakash (2016). Similarly, Vargas and Bricker (2000) combined DEA with factor analysis. The PCA can reduce the dimensionality of the correlated evaluation indicators - through a linear transformation - while minimizing information loss (Chen et al., 2016).

The procedures for PCA-DEA are as follows:

PCA is applied to input and output variables separately, to calculate PC scores. The PC scores are obtained only at the end of the PCA calculation, which makes it is difficult to use them as direct inputs to the DEA. Therefore, the PC scores are extracted from the PCA results, and then, using the PC scores, the DEA was completed separately and sequentially using an R program.

$$X_i = PC_i + b > 0 \qquad\qquad i = 1, ..., p \leq m \qquad\qquad 2.30$$

where

X_i = new DEA inputs;
i = 1, ...; $p \leq m$ = eigenvalue greater-than-one rule; and
PC_i = the PCs of the input variables.

Calculation of the eigenvalues and the related eigenvectors: the eigenvalue greater-than-one rule and scree plot were applied to choose the number of PCs.

The data of the DEA model must be positive, but some of the PC scores can be negative. Therefore, negative scores must be converted into positive data (Tavakoli & Shirouyehzad, 2013). The most negative value has increased inputs and outputs PC data in the vector plus the absolute value of the minimum negative PC score (Adler & Yazhemsky 2010). The following is done to get rid of the negative values in the PC scores:

$$b = PC_i + abs(min(PC\ scores)) \qquad 2.31$$

The input-oriented VRS PCA-DEA model was applied. In the PCA-DEA model, the input and output variables of the conventional DEA are replaced by PC scores of the input and output variables.

The input-oriented conventional VRS DEA model was applied using (initially) the chosen seven inputs and four outputs.

The results of conventional DEA and PCA-DEA models were compared.

3 RESEARCH FINDINGS AND EVALUATION

This chapter includes empirical analysis and discussions about the results of the research. There are four subchapters in this section. At first, Mongolian economic growth is compared with that of some other Asian countries (i.e., Kazakhstan, Kyrgyzstan, and Indonesia). Secondly, the characteristics of Mongolian economic growth and crucial sectors of the Mongolian economy are investigated. Although the companies are in many different sectors, the thesis deals with three main sectors, which are manufacturing, heavy industry, and service sectors. The appropriate descriptive analyses preceded the empirical analyses. A fixed or a random-effects model, which was adequate based on a test used to find the variables. By k-medoids clustering, companies were classified by their size to measure their performance properly and to offer appropriate suggestions. The financial performance of Mongolian listed companies was determined in the case of sectors and the sizes using DEA, PCA-DEA, and SFA methods. The objectives and chosen analysis are summarized in Table 3.1.

Table 3.1 Empirical strategies

	Research objectives	Data analysis strategy
1	Comparing Mongolian economic growth with that of other Asian countries.	Stepwise regression Multidimensional scaling
2	Examining Mongolian economic growth and economic sectors, identifying Mongolian economic growth determinants	Descriptive analysis Regression analysis
3	Examining ratios which can determine the financial performance of three main sectors in the Mongolian economy.	Ratio analysis Panel regression
4	Analyzing the heterogeneity of data	k-medoids clustering
5	Performance measurement	DEA, SFA, PCA-DEA methods
6	Analyzing the Impact of Intellectual Capital on financial performance	ANOVA, MANOVA, UQR methods

Source: Author's compilation

As for DEA, input-oriented VRS and CRS models, as well as super efficiency, were implemented. Size and sector-related suggestions and recommendations were made. Results of the DEA, PCA-DEA, and SFA methods were compared, and the results' consistency was evaluated. Descriptive analysis and regression analysis were computed by SPSS, while k-medoids, DEA, PCA-DEA, and SFA methods were calculated by RExcel (an add-in for Microsoft Excel).

3.1 Comparison of some selected Asian countries' economic growth

The aim of the economic comparison of Mongolia with other Asian countries was to reveal the distinctiveness of the Mongolian economy. The financial performance of the selected countries was compared with that of Mongolian, and the best practices were formulated. Corresponding macroeconomic data - covers 26 years from 1991 to 2017 - are obtained from the World Bank database. There are many Asian countries like Pakistan, India, Uzbekistan, Vietnam, etc. However, I chose the countries, which are more dependent on Mining export and classified as lower-middle-income countries like Mongolia (Kazakhstan, Kyrgyzstan, and Indonesia). Kazakhstan is an exception because it is classified as an upper-middle-income country; still, Kazakhstan locates in a similar geographical area, and it possesses oil reserves and minerals. Kazakhstan is the world's largest landlocked country, followed by Mongolia. By crude oil output and price increase, Kazakhstan jumped from lower-middle-income economies to upper-middle-income economies just in two decades.

Economic growth is determined by two dependent variables and 20 independent variables. The ANOVA test is used for every variable to determine whether a significant difference exists among the countries (Table 3.2.).

Table 3.2 illustrates that there are significant differences among countries in the case of most of the independent variables, except the inflation rate and consumer price index. A line mark signs the insignificant differences among countries in their cases. Unlike the previous one, none of the dependent variables is significantly different among the countries. Since significant differences occurred most of the variables, stepwise regression was applied (Table 3.3).

Consumer price index and employment to population ratios are significantly important ratios for all the four countries' economic growth. Population density affects Kyrgyzstan negatively; the urban population positively affects Kazakhstan's economy, which is unique than the other countries (Table 3.3).

Table 3.2 Economic growth and variables

	Country	Year	Variables
y1	-		GDP growth (annual %)
y2	-		GDP per capita growth (annual %)
x1			Salaried workers (% of total employment)
x2		-	Employment to population ratio, total (%)
x3		-	Adjusted savings: consumption of fixed capital (% of GNI)
x4		-	Ores and metals exports (% of merchandise exports)
x5		-	Manufactures exports (% of merchandise exports)
x6		-	Agricultural raw materials exports (% of merchandise exports)
x7			School enrollment, tertiary (% gross)
x8		-	School enrollment, secondary (% net)
x9		-	Merchandise trade (% of GDP)
x10			Urban population (% of total)
x11		-	Urban population growth (annual %)
x12			Population growth (annual %)
x13			Life expectancy at birth, total (years)
x14			Central government debt, total (% of GDP)
x15	-		Inflation, consumer prices (annual %)
x16	-		Consumer price index
x17			Unemployment, total (% of the total labour force)
x18		-	Labour force, total
x19		-	Gross domestic savings (% of GDP)
x20		-	Population density (people per sq. km of land area)

Source: Author's compilation

Table 3.4 demonstrates which variables affect the GDP growth the most. Significantly important variables are given in the italic form. The consumer price index is significantly important for all four countries (at a 10% confidence level in the case of Kyrgyzstan). Moreover, the urban population significantly affects economic growth except for Kyrgyzstan. As for Kazakhstan, population growth weighs more than half of the given variables.

Table 3.3 Stepwise regression results of GDP growth by countries

Explanatory variables	Kazakhstan	Mongolia	Kyrgyzstan	Indonesia
Salaried workers (% of total employment)	-1.24		-0.99	
Employment to population ratio, total (%)	-2.34	3.65	-5.28	-6.58
Urban population (% of total)	47.31			
Urban population growth (annual %)	159.16	-2.68	-8.38	
Population growth (annual %)	-163.36	19.73		
Consumer price index	-0.23	-0.76	0.18	-1.06
Unemployment, (% of the total labor force)		1.99	-4.58	-3.16
Labor force, total		207.40	0.00005	3.65E-06
Population density (people per sq. km of land)			-5.18	

Source: Author's compilation

Table 3.4 Analysis of variance (by GDP growth)

(percentage)

Explanatory variables	Kazakhstan	Mongolia	Kyrgyzstan	Indonesia
Salaried workers (% of total employment)	*11.54*	0.80	8.14	7.49
Employment to population ratio total (%)	*7.80*	3.83	0.01	0.03
Urban population (% of total)	*6.32*	*33.42*	7.53	*43.96*
Urban population growth (annual %)	*14.71*	2.09	2.57	2.63
Population growth (annual %)	*50.42*	11.73	2.77	1.94
Consumer price index	*7.74*	*19.78*	*28.01*	*26.54*
Unemployment (% of total labor force)	0.04	0.80	12.94	2.95
Labor force, total	0.30	12.56	17.97	1.47
Population density	0.04	10.58	13.90	8.89
Residuals	1.08	4.40	6.15	4.11

Source: Author's compilation

The multidimensional scaling was applied to compare the selected Asian economies to the Mongolia economy, and multidimensional scaling is applied (Appendix 1). If all four countries are compared, the Indonesian economy is significantly different from other countries' economies. Kyrgyzstan's economy is the most similar to the Mongolian economy based on the variables given (Figure 3.1).

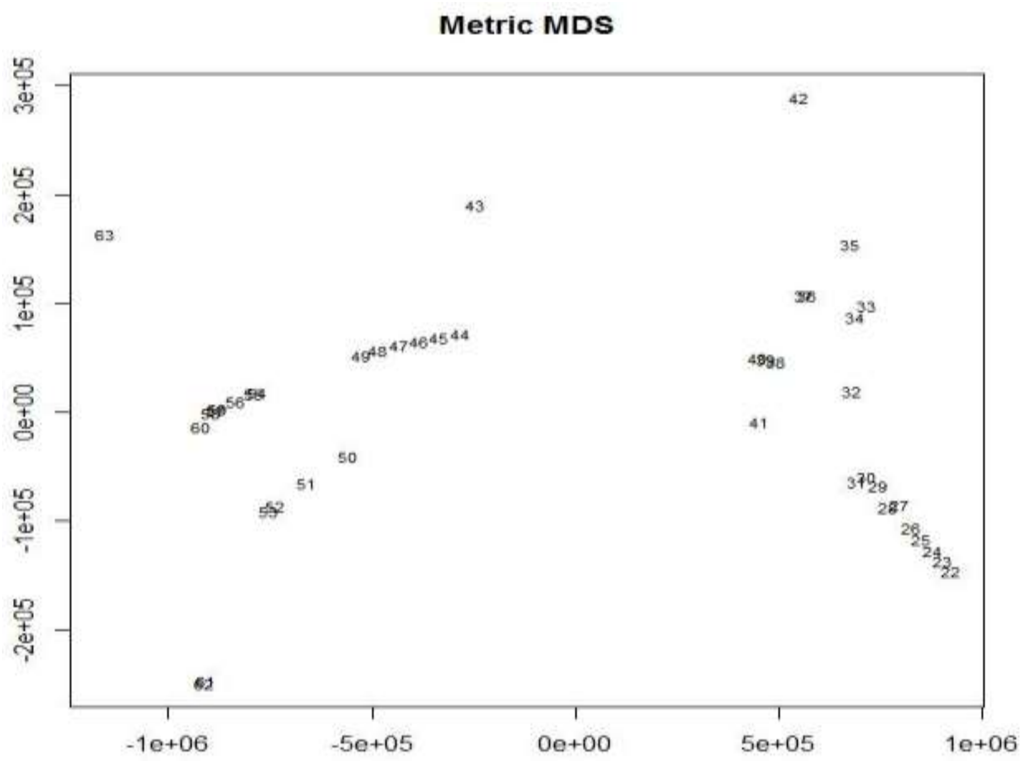


Figure 3.1 Multidimensional scaling (Mongolia 22:42 and Kyrgyzstan 43:63)

Although Kyrgyzstan's economy is the closest by similarity, Mongolian economic growth and Kyrgyzstan's economic growth are determined by different variables (Table 3.5). Linear regression is applied in the countries individually and determined significant independent variables for each country. It is noteworthy that different variables drive each country's economy.

Table 3.5 Linear regression results of GDP growth

Country	Explanatory Variables	Estimate	R-squared	Adjusted R-squared
Mongolia	Consumer price index	-0.78	0.664	0.389
Kazakhstan	Inflation (annual %)	180.3	0.893	0.805
	Consumer price index	-185.2		
Kyrgyzstan	Salaried workers (% of total employment)	-0.91	0.581	0.238
	Employment to population ratio, total (%)	-5.62		
	Unemployment, total (% of total labor force)	-4.81		
Indonesia	Consumer price index	-1.11	0.679	0.417

Source: Author's compilation

Consumer price index and inflation rate are commonly determined by economic growth except for Kyrgyzstan. Although the inflation rate and consumer price index together determine 80.5% of the economic growth, there is high multicollinearity among the macroeconomic variables. As for Mongolian and Kyrgyzstan economic growth, only 38.9% and 23.8% are explained by the given variables. Moreover, both countries' economic growth is explained by different variables. Therefore, it is assumed that the Mongolian economy is unique and inappropriate to be compared with other countries. In the thesis, only Mongolian companies' financial performance is determined, and Mongolian three main sectors' performance is compared to achieve reasonable conclusions.

3.2 Mongolian economy and economic growth

Before evaluating the financial performance of Mongolian companies, it is crucial to describe the Mongolian current economic climate and its features. The Mongolian business sectors and the indicators of Mongolian economic growth are presented in this chapter to illustrate the performance of the economy. Mongolia is a landlocked East Asian country that is bordered by the Russian Federation to the north and the People's Republic of China on the east, west, and south. Mongolia is the 18th largest country in the world by area, and second-largest landlocked country behind Kazakhstan, which has a land area of 1,566,600 square kilometres. However, some international resources misinformed as 1,564,116 square kilometres in 2016.

Mongolia is divided into 21 provinces (aimag). Ulaanbaatar is the capital city of Mongolia, with a population of 2,131,823 people (68.3%) by the end of 2016. Interestingly, the land area of Ulaanbaatar is only 4,704.4 square kilometres (0.3% of the total landscape), where more than half of the Mongolian population live.

The total population of Mongolia in 2016 was 3,119,935, particularly 1,533,983 males (49.1%) and 1,585,952 females (50.9%). The population was increased by 62,157 compared with 2015 (2.03%). According to the National Statistics Office of Mongolia (2016), 64.67% of the population is under the age of 35. Specifically, 30.5% of the total population is children aged 0-14, 34.61% is the people with the age of 15-34, 29.2% of the people are aged between 35-59, and only 6.13% is older than 60 years in 2016.

As for foreign trade, 85.1% of the total export went to China, followed by 11.6% to the United Kingdom, 4.8% to Switzerland, and 1.2% to the Russian Federation. Like export, the main importing countries were China, with 31.6% of the products and the Russian Federation with 26.2%. Afterwards, 9.3% of the products were imported from Japan, 5.8% from the Republic of Korea, 4.1% from the USA, and 3.5% from Germany, respectively.

In the thesis, public companies were divided into three main sectors, namely, heavy industry, manufacturing, and service companies. The most important sector in the Mongolian economy is the service sector, which constitutes 28.7% of the Mongolian GDP, followed by the mining sector, 20.7%, and the agriculture sector, 11.5%.

3.2.1 Economic sectors in Mongolia

The Mongolian mining sector is one of the most important sectors of the Mongolian economy, which constitutes 20.7% of the GDP in 2016. In 2016, 3.3% of the workforce, which is 38,203 people worked in the mining sector. The mining sector accounted for 69.2% of the country's gross industrial output in 2016, and 70.86% of its export revenue. The most exported mineral commodities are coal, crude oils, gold (unwrought or in semi-manufactured forms), copper concentrate, and molybdenum ores. According to the minerals law of Mongolia, mineral means naturally occurring utilizable mineral concentration that was formed on the surface or in the subsoil as the result of geological evolutionary processes (Legalinfo.mn, 2006).

Mongolian economy relies heavily on mineral extraction, particularly in 2016, copper, coal, and gold, which constitute 32.7%, 19.8%, and 15.4% of export, respectively. Mongolian economy faced with an economic recession with regards to its dependency on the mining sector, and from double-digit economic growth. Mongolian economic condition is considered to be affected by two factors. First, more than 90 percent of Mongolian exports consistently goes to China; and so, any slowing of Chinese growth affects the Mongolian economy. Second, economic policies designed to protect Mongolia’s sovereign interests and to respond to the expectations of the Mongolian public have discouraged FDI (Foreign Direct Investment) (Brown & Coleman, 2014).

From 1995 to 2016, the amount of total export was 5,774.3 million USD, and the mining product’s export was 4,791.4 million USD in 2014, which was the highest point in Figure 3.2. The highest growth in total export (68.63%) was in 2011, when the export amount of mining products increased by 82.6%. Between 1995 and 2003, the amount of export was stable; however, from 2004 the amount of export increased gradually. The export amount also boosted during 2007-2008, but export declined from 2,534.4 million USD to 1,885.3 million USD by 25.6% due to the economic recession in 2009. In 2010, the mining sector exports were 81.0 percent of total exports, and during 2011-2012 this figure rose to 89.2 percent.

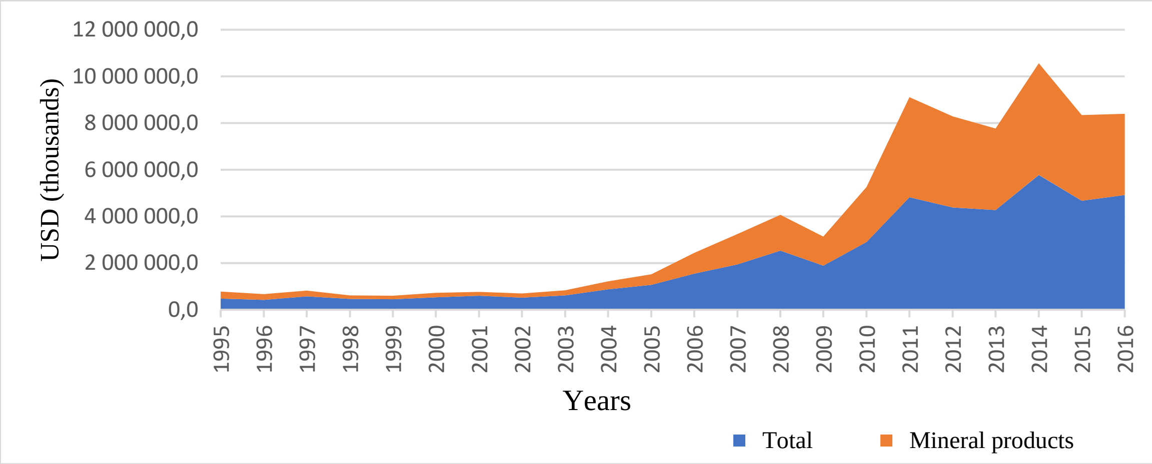


Figure 3.2 Comparison of Mongolian total export and mining export

Source: Mongolian Statistical Information Service's database and author's calculation

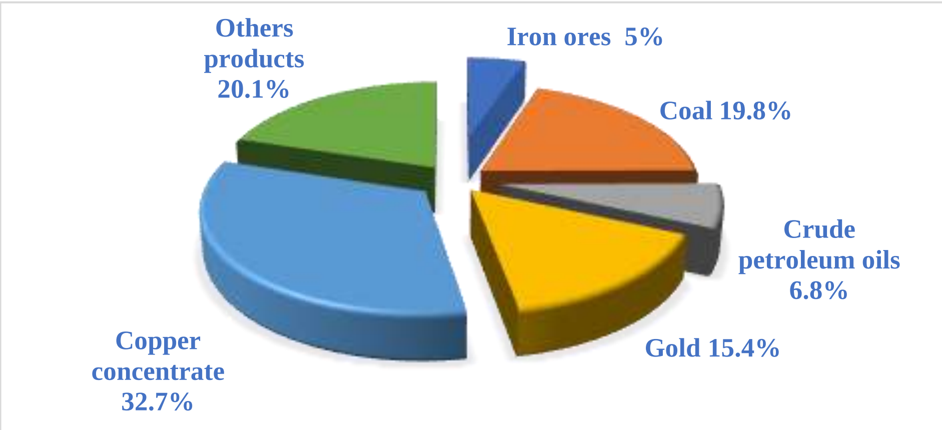


Figure 3.3 Composition of total Mongolian export in 2016

Source: Mongolian Statistical Information Service's database and author's calculation

Copper concentrate constitutes most of the total export, which is 32.7%, as shown in Figure 3.3. Coal, gold, and crude oils are also crucial for the Mongolian economy, which represent 19.8%, 15.4%, and 6.8% of the total export, respectively. However, the other products, such as food products, animal origin products, wooden and textile products together constitute only 20.1% of the total export.

The price of mineral exports, however, is largely anchored by international market prices. Export to China and the total Mongolian export is illustrated in

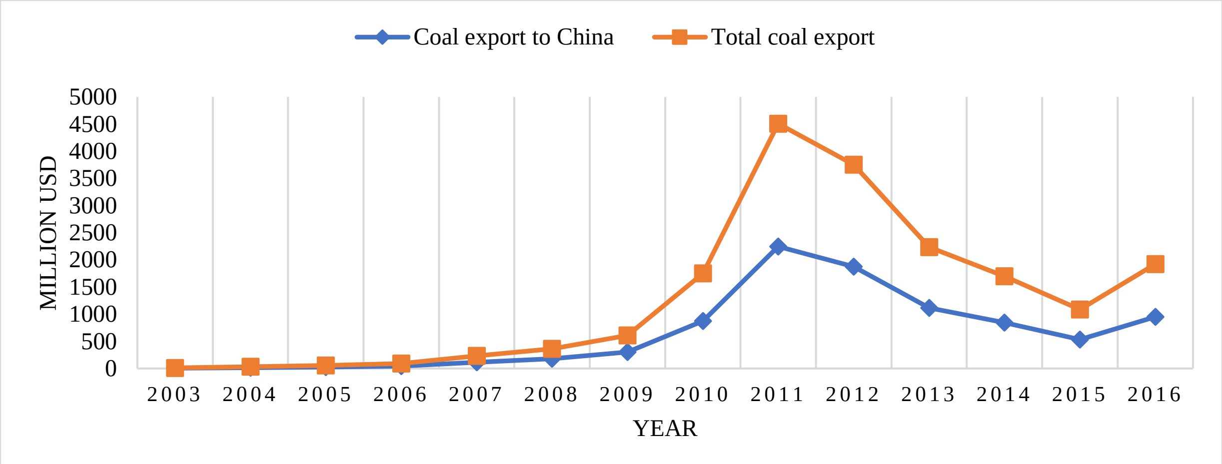


Figure 3.4.

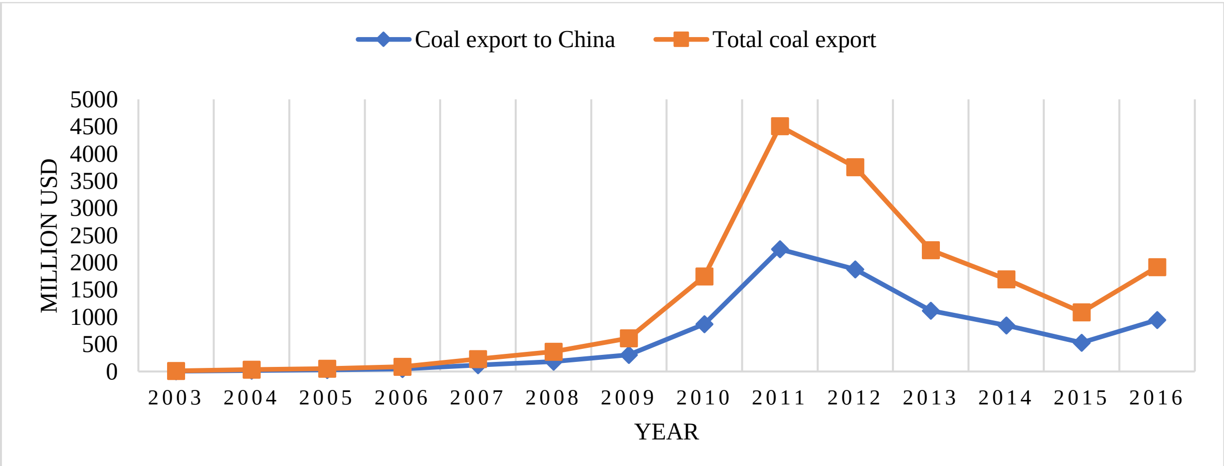


Figure 3.4 Comparison of total coal export and coal export to China

Source: Mongolian Statistical Information Service's database and author's calculation

The biggest client for Mongolian coal export is China (Mongolia's trade with China was about 97.6% in 2016). This lack of diversification has made the economy highly exposed to the ups and downs of China's commodity demand (Li et al., 2017).

The highest reduction was in 2011 (-20.5%), and the highest increase was in 2014 (38,4%) in the period examined in the productivity of the mining sector. The productivity is a measure of output of products and services per unit of input, which is measured by the value-added per 1000 tugrik and expenditures spent on production and services (National Accounts, n.d.).

The Mongolian agricultural sector plays an essential role in the Mongolian economy. It constitutes for 11.68% of the total GDP (2,796.1 million MNT[1]) and employed 30.36 percent

[1] Mongolian tugrik

of the workforce (348,487 people) in 2016. Mongolian economy is traditionally based on agriculture and mainly on animal husbandry. The number of livestock is about 19.72 times more than the population. The number of herdsmen is relatively high compared to the total agricultural workforce that means 311,373 herdsmen (89% of the agricultural workforce). The output of animal husbandry was 3.49 billion MNTs in 2016, which came to 14.6% of GDP, which was 23.9 billion MNTs.

Herdsmen's biggest disaster is a Zud, which occurs in a severe winter when a lot of animals perish with hunger or cold. In 1999-2002, and 2009-2010, Mongolia was hit by Zud, which caused 41.9% (within three years), and 31.5% loss in the livestock, respectively. By 2016, the number of livestock was 61,549,240 again, namely, 3,635,490 horses (5.9%), 4,080,940 cattle (6.6%), 27,856,600 sheeps (45.2%), 25,574,860 goats (41.5%), 401,350 camels (0.6%).

The annual decrease in agricultural productivity was the highest (-17.5%) in 2010. The productivity peaked at 29.3% in 2013, and since then continuously dropped until -1.5% in 2016.

The Mongolian construction sector made up 3.96 percent of the GDP in 2016 and produced 948.1 million MNTs. The highest increase in the construction sector (197.4%) appeared during 1992-1993, followed by 190.2% in 2010 and 107.9% in 2013. Growth in 2013 is tightly connected with a 120% rise in the residential segment from 2012 levels. The state's mortgage loan program can explain the increase in the residential segment with 8% interest, which gave citizens access to home financing at a heavily subsidized interest compared to the 13% of the earlier annual mortgage loan. Mongolian economy also faced the economic crisis between 2008 and 2009, and the construction sector was no exception which deteriorated by 29.3%. The contribution of the sector to GDP rose to 5.1% in 2013 from 1.3% in 2009. However, there were jumps in the construction sector's output, the construction sector's share of total GDP has remained unchanged, about 5%.

Ulaanbaatar is the coldest capital city in the world with an average temperature -1.3 grads Celsius which poses a challenge to the construction sector. Most of the construction companies operate from April to October due to the harsh climate. The shortness of the business activity affects materials' delivery schedules negatively, and more importantly, the labour force.

The number of female and male employees in the construction sector is illustrated in Figure 3.5 (from the first quarter of 2012 until the third quarter of 2017). Due to seasonal construction work, the number of female employees in the construction sector is relatively more stable than male workers. Female workers are usually office employees in financial or managerial positions. Every first quarter the number of male employees is the lowest while every third quarter the number is highest. In the second quarter of 2015, the construction sector constituted 8.28% of the total workforce, which was the highest during the given period. The seasonal business activity poses a challenge to the construction companies to find well-trained workers since the workers are not in the long term. It is a common scenario that people who work in the construction sector to be paid daily after work without paying social insurance or income tax. That is why construction companies are usually lack of source documents of expenditure which resulted in higher profits than the actual.

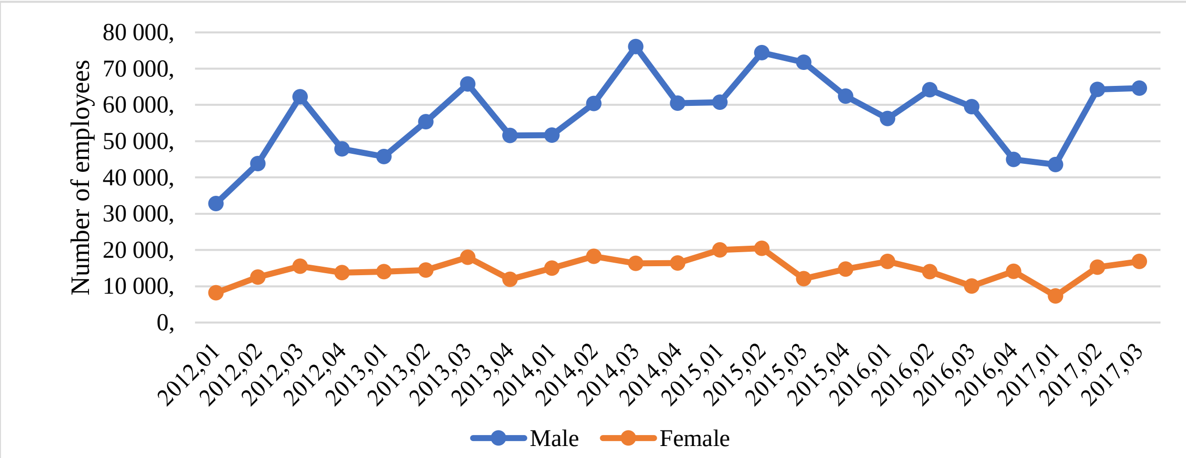


Figure 3.5 Employees in the construction sector by gender

Source: Mongolian Statistical Information Service's database and author's calculation

The Mongolian service sector also plays an important role in the Mongolian economy. It constitutes 41.65% of total GDP (9,971.58 million MNTs) in 2016 and employed 37.35% of the workforce. Wholesale, retail trade and repair of motor vehicles and motorcycles made up 11.18% of GDP in 2016, which is the highest in the service sector. Transportation and storage services had the highest in productivity (23.1%), followed by accommodation and food service 22.4%, while information and communication services were the least productive -12.4%.

3.2.2 Mongolian economic growth and its determinants

The determinants of Mongolian economic growth were calculated in this subchapter. National Domestic Product (NDP) was used as a dependent variable that determines Mongolian economic performance. To better understand the Mongolian economy, descriptive statistics of its variable are given in Table 3.6.

It is clear from Table 3.6 that the growth of copper export and the gold export were fluctuated extremely, which were the results of the economic recession. For example, the quantity of copper export increased by 0.7% in 2009; however, the amount of money from copper export plummeted from 835.6 million USD to 501.9 million USD (39.9%). Likewise, the export of gold plunged from 599.8 million USD to 308.4 million USD (48.5%). On the contrary, the dollar exchange growth rate and the unemployment rate were the highest, while the growth of NDP was the lowest. These statistics imply that the Mongolian economy is dependent on exports, especially the export of mining products.

Table 3.6 Descriptive statistics of variables relative to the Mongolian economy

Variables	Minimum	Maximum	Mean	Std. Deviation
Growth rate of NDP	0.53	48.04	20.63	12.83
Domestic investment to NDP ratio	6.94	21.83	14.68	4.14
Foreign investment to NDP ratio	6.92	49.32	17.52	11.82
Government debt to NDP ratio	8.19	61.23	36.98	16.69
Export to NDP ratio	35.96	51.41	44.39	4.62
Import to NDP ratio	32.29	69.11	50.19	9.10
Dollar exchange growth rate	-6.65	19.29	4.67	6.91
Human development index	0.67	0.76	0.72	0.03
Unemployment rate	2.80	11.60	6.03	2.94
Inflation rate	1.10	22.10	9.12	5.74
Poverty gap	18.80	33.20	27.36	4.55
Depth of poverty	4.90	9.40	7.53	1.48
Export growth rate	-25.61	65.64	17.86	26.14
Import growth rate	-34.11	106.19	16.19	34.58
Domestic investment growth rate	-31.59	86.67	25.73	36.56

Foreign investment growth rate	-56.59	144.08	25.85	49.01
Central bank's interest rate	6.54	15.51	11.26	2.46
Commercial bank's interest rate	16.61	37.35	25.08	7.29
Copper export growth rate	-39.94	171.21	22.83	51.95
Gold export growth rate	-88.75	155.41	15.99	67.59
Output growth of animal husbandry	-46.67	89.19	16.20	43.94

Source: Central Bank and National Statistical Office's data 2000-2016

The correlation coefficients between explanatory variables and the NDP growth rate are in Appendix 2. The correlations between the economic growth and five variables were statistically significant at the 0.05 level (2-tailed), namely: dollar rate growth, inflation rate, export growth, import growth, and the growth of the domestic investment. However, four variables that were statistically significantly correlated at the 0.1 level (2-tailed) were not used, namely: the growth of foreign investment, copper export growth rate, foreign investment to NDP ratio, and import to NDP ratio. Somewhat surprisingly, the livestock output growth was shown to be statistically insignificant to the NDP growth rate, although Mongolia has traditionally been based on agriculture.

Although the variables are significantly correlated with its explanatory variable, however, macroeconomic variables are often judged by their multicollinearity. In the thesis, variables were examined for potential multicollinearity via the Variance Inflation Factor (VIF). A rule of thumb states that if the values of VIF larger than 10, the multicollinearity of a model can be considered a serious problem (Mazurek, 2017). In the thesis, variables that have VIF less than 3.0 are selected; therefore, import growth and growth of domestic investment were disregarded for further analysis. After correlation and multicollinearity testing, the growth rate in NDP, dollar rate growth, inflation rate, and export growth rate were chosen as independent variables.

The growth rate in NDP and the growth rate of export have a robust positive correlation. Moreover, dollar rate growth played an important role in stimulating economic growth in Mongolia. It shows a very strong negative relationship with the rate of economic growth: the correlation coefficient is -0.65 with a p-value of 0.005. The inflation rate has a significant correlation with economic growth: the correlation coefficient is 0.60, with a p-value of 0.01. Correlation and regression analysis allows for identifying economic growth determinants. The correlation matrix of variables is shown in Table 3.7.

Table 3.7 Correlation matrix of variables

Indicators	Growth rate in NDP	Dollar rate growth	Growth rate of export
Growth rate in NDP	1.00		
Dollar rate growth	-0.65	1.00	
Growth rate of export	0.79	-0.55	1.00
Inflation rate	0.60	-0.03	0.40

Source: Author's calculation

The adjusted $R^2 = 0.814$, which means dollar rate growth, inflation rate, and growth of export, are responsible for 81.4% of the variation in NDP growth rates of Mongolia. The export growth rate contributed much to economic growth in Mongolia. Export growth itself can explain 63.9% of Mongolian economic growth (Appendix 2).

In Figure 3.6, mineral products (such as copper, coal, gold, and crude oil) are shown with a continuous line, while textile products with a dotted line. Textile products' export was almost stable compared to mineral products' export amount. Before 2005, the export amount of textile and mineral products were close each together.

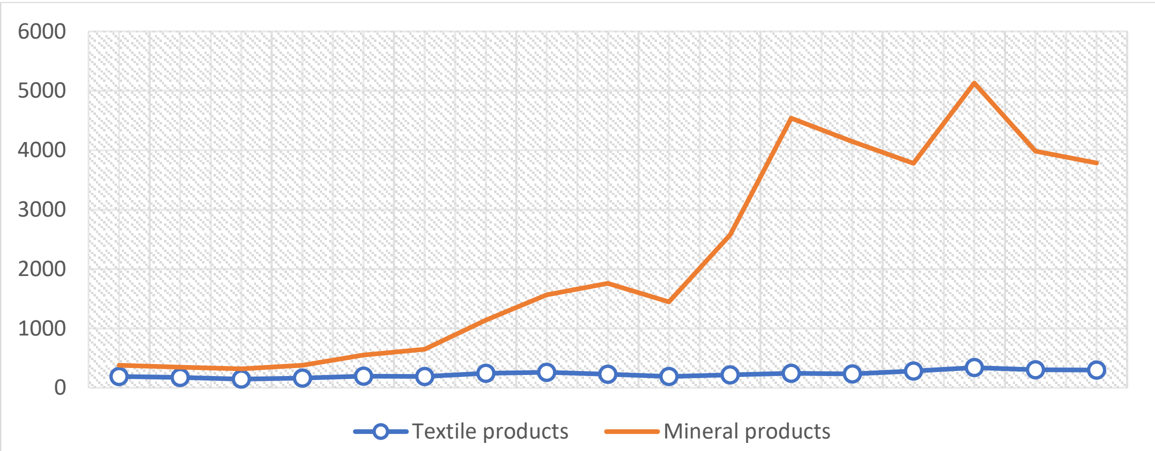


Figure 3.6 Exports by commodity groups (2000-2016)
Source: author's calculation

Figure 3.7 shows that most of the total Mongolian export directly goes to China (from 48.2% to 92.5%), which implies that the Mongolian economy is highly dependent on China. Mongolian main export products are mineral products, cashmere products, and animal products in this direction.

Dollar exchange rate growth is responsible for 42.2% of the economic growth (Appendix 2). However, there is an interrelationship between the dollar exchange rate growth and export growth rate. Exports are usually made in USD; therefore, export growth relates to an increase in dollar reserve. When the dollar reserve increases, the dollar rate decreases.

The empirical analysis indicates that the inflation rate is an essential factor of economic growth (36.8%) (Appendix 2). Simionescu et al. (2017) noted that the relationship between inflation and GDP growth, especially in the short and middle term, tends to be specific for the country. For example, they mentioned that Poland has a positive correlation between economic growth and inflation rate, as it has been found in the Mongolian case.

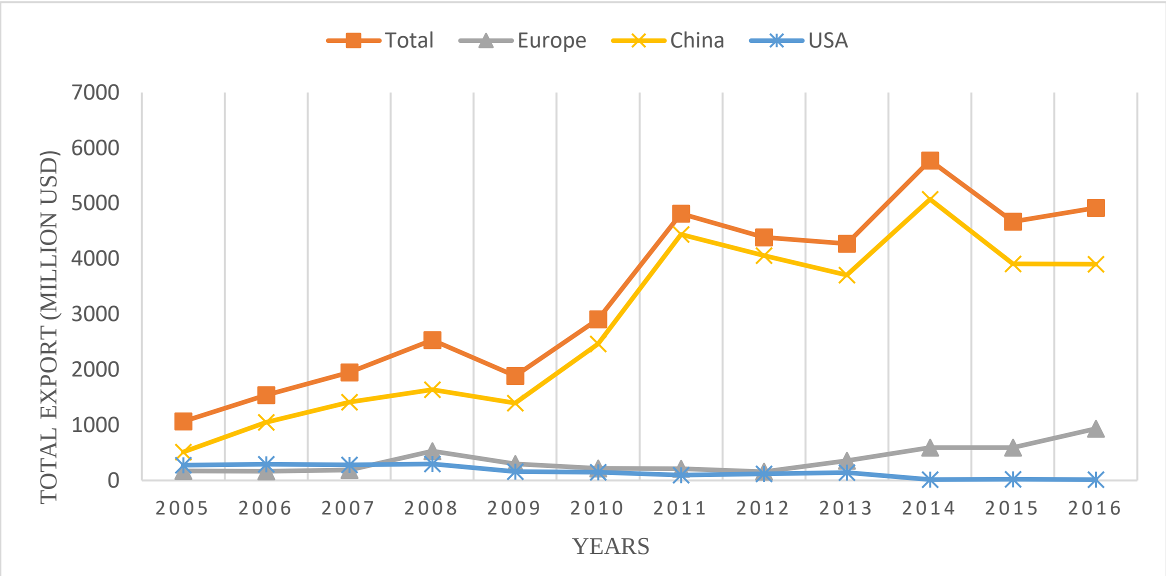


Figure 3.7 Exports by location

Source: author's calculation

3.2.3 Descriptive analysis of the variables of further analysis

Initially, ROA, ROE, and ROS were selected as output variables, and 20 input variables were chosen for the research. One of the drawbacks of the financial ratios' usage is the multicollinearity. Therefore, the "mctest" function of RExcel was used to exclude multicollinearity (Table 3.8). Highlighted variables were excluded from further research. Variables that had VIF score above three were excluded from research due to multicollinearity (i.e., Quick ratio 5.08 and Current ratio 5.02). After excluding the quick ratio and current ratio, the remained variables explain 82.9% of ROS, 86.9% of ROA, and 63.9% of ROE, respectively.

Although the operating cycle and net operating cycle had a VIF score below 3, the operating cycle is the sum of receivables turnover and inventory turnover. In contrast, the net operating cycle is calculated by subtracting payables turnover from the operating cycle. Therefore, the net operating cycle and operating cycle were excluded. When DEA is used to calculate efficiency, choosing appropriate variables is the most crucial. Since the return on cost was highly correlated with all the output variables, efficiency scores are calculated artificially high than the reality; therefore, return on cost was also excluded. The ANOVA test was used To test whether the chosen ratios are significantly different among the sectors (Table 3.9).

Table 3.8 Multicollinearity of the variables

Name of the variable	**ROS**	**ROA**	**ROE**
Operating cycle	1.76	1.76	1.76
Net operating cycle	1.68	1.68	1.68
Operating CF ratio	1.61	1.61	1.61
WC turnover ratio	1.26	1.26	1.26
Cost to revenue ratio	2.17	2.17	2.17
ATO	1.52	1.52	1.52
Current assets/Total assets	1.42	1.42	1.42
Assets to equity ratio	1.27	1.27	1.27
Debts to total asset	1.13	1.13	1.13
Quick ratio	5.08	5.08	5.08
Current ratio	5.02	5.02	5.02
Cash ratio	1.90	1.90	1.90
Receivable turnover	1.22	1.22	1.22
Inventory turnover	1.42	1.42	1.42
Payable turnover	1.44	1.44	1.44
Sales growth	1.03	1.03	1.03
Assets growth	1.02	1.02	1.02
Return on costs	1.86	1.86	1.86
R-squared (%)	*82.90*	*87.20*	*67.00*
R-squared (%)	*82.90*	*86.90*	*63.90*

Source: author's calculation

As we can see from Table 3.9, ROS, the cost to revenue, GPM, current assets to total assets ratios, and cash ratio have a significant difference among the sectors.

The descriptive statistics of the inputs and output by all companies' cases and each sector's case are illustrated in Appendix 3. From the result, we can observe considerable high values of standard deviations among the companies, which indicate that relatively big and small companies are included in the data. As we can see from Appendix 3-a, the coefficients of variation are remarkably high, especially for the last variable ATO, Assets to equity ratio, Asset growth, Debts to total assets ratio, and NWC turnover ratio (> 200%). The high values of the coefficients of variation indicate that the variability and inhomogeneity are also enormously high. From Appendix 3.1, it is apparent that ATO, Assets to equity ratio, Asset growth, Debt to total assets, and NWC turnover ratio's kurtosis indicator are high positive values, which is the results of outliers. Also, a high positive kurtosis indicator shows the data are thickening around the average value. The values of skewness are also positive numbers, which indicate the density functions of the variables have longer tails on the right side, and the mass of the distribution is concentrated on the left side.

Table 3.9 ANOVA results of variables

Variables	***Significance level***
ROA	
ROE	
ROS	***
Cost to revenue ratio	*
Gross profit margin	***
ATO	
Assets to equity ratio	
Debts to total asset	
WC turnover ratio	
Current assets to total assets	***
Operating CF ratio	
Cash ratio	*
Receivable turnover	
Inventory turnover	
Payable turnover	

Significance. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '

Source: author's calculation by RExcel

The Interquartile Range (IQR) indicators, which show the range of the middle 50% of the data, were calculated by using the average values of the variables. IQR to total range ratio of those variables, i.e., ATO, Assets to equity ratio, Asset growth, Debt to total assets, and NWC turnover ratio represents only a fraction of their total ranges (0% - 2.19%). Therefore, more than 97% of the total range of the variables is in the fourth quartile. The variables have huge variability, and the more significant part of their total range is in the fourth quarter. It shows that further analysis could be incorrect without using the classification (clustering) method, and it could lead to misinterpretations. It is essential to group them into clusters and use clusters individually for further analysis.

3.2.4 K-medoids clustering

DEA is sensitive when the data are heterogeneous. Clustering is employed for the data to overcome the drawback of DEA. Clustering helps to know the characteristics and the pattern of data as well as to identify homogenous groups. There are many kinds of research used clustering in efficiency analysis, for instance, Bi et al. (2014); Dai and Kuosmanen (2014); Gandhi and Srivastava (2014); Griffin (2011); Jahangoshai Rezaee et al. (2018); Kianfar et al. (2017); Kim et al. (2018); Po et al. (2009); Thakare and Bagal (2015), etc.

In this subchapter, the companies were grouped by k-medoids clustering, and by DEA was evaluated each cluster's efficiency. The thesis applies PAM (Partitioning Around Medoids) algorithm, which is the most common k-medoids clustering method to determine clusters, and DEA to evaluate the performance of each cluster. Various packages of the R statistical program were used for the analysis, such as 'facto extra', 'fpc', 'cluster', 'kmed', and 'cluster' packages for k-medoids analyses while the Benchmarking package was used for DEA. The R statistics were used from RStudio, which provides a more user-friendly platform than the original R software (Gandrud, 2015).

Arora and Varshney (2016) compared k-means and k-medoids in their research. Their results proved that k-medoids is better than k-means; as execution time, sensitivity to outliers, and space complexity of overlapping are all less. Particularly, there are few researches used the k-medoids clustering method: Narayana and Vasumathi (2018); Park and Jun (2009); Patel and Singh (2013); Zhang and Couloigner (2005), etc.

It is worth recalling that the clustering results are not the final results of research in general, but they are possible inputs of the other calculations. This chapter aims to integrate the k-medoids' results with DEA. The first step is to determine the clusters by the k-medoids algorithm, and the second step is to make the DEA calculations using clusters. The k-medoids clustering requires to determine the number of clusters calculated. The optimal number of clusters was established by the 'factoextra' package of R statistical program. For cluster analysis, revenue and total assets were selected as variables.

The descriptive statistics of the seven years' average values are presented in Table 3.10. The Interquartile Range (IQR) indicators, which show the range of the middle 50% of the data, were calculated by using the average values of the variables. It is apparent from Table 3.10 that the IQRs of given variables represent only a fraction of their total ranges (0.56% - 5.76%). Additionally, more than 90% of the total range of the variables is in the fourth quartile. The variables have huge variability, and the more significant part of their total range is in the fourth quarter regarding revenue. It shows that further analysis could be incorrect without using the classification (clustering) method, and it could lead to misinterpretations. It is essential to group them into clusters and use clusters individually for further analysis.

Table 3.10 Descriptive statistics of variables investigated (All companies)

(million tugriks)

Statistical characteristics	Current assets	Noncurrent assets	Assets	Revenue	COGS	Operating cost	Pretax Profit
Minimum	0.6	4.5	23.7	-	-	-	-3,910
1. Quartile	146.5	374.6	746.0	140.0	66.3	117.5	-81.4
Mean	8,603.0	20,167.1	28,770.1	18,275.9	12,718.5	3,161.9	1,984
Median	1,286.5	1,681.7	3,738.0	1,158.5	586.9	405.7	2.5
3. Quartile	7,067.3	8,884.1	17,161.9	9,487.2	6,891.2	1,697.7	280
Maximum	120,225	360,671.6	387,080.1	255,839.4	168,084.0	58,414.9	61,08
Range	120,225	360,667.1	387,056.4	255,839.4	168,084.0	58,414.9	64,994
IQR	6,920.8	8,509.5	16,415.9	9,347.1	6,824.9	1,580.2	361.4
IQR / Total range	5.76%	2.36%	4.24%	3.65%	4.06%	2.71%	0.56%
Std. Deviation	20,852.6	55,811.8	69,669.5	46,111.2	30,897.1	9,035.5	8,995
Coefficient of variation	242.39%	276.75%	242.16%	252.31%	242.93%	285.76%	453%
Skewness	3.97	4.07	3.66	3.69	3.49	4.49	5.40
Kurtosis	16.58	18.06	13.95	14.42	12.72	21.36	30.70

Source: Own calculation by RStudio

Figure 3.8 shows the cluster validation executed by the silhouette method. When the average silhouette width (ASW) is closer to 1, it indicates the object is well clustered. The dashed vertical lines in the graphs in Figure 3.8.a indicate the optimal number of clusters by the silhouette method, which determined two clusters. Therefore, two clusters are made according to the obtained annual ASW values (Figure 3.8 b). According to 2 clusters, there are 90 companies in the 1st cluster, while only ten companies are in the 2nd cluster. The k-medoids cluster analysis was performed in case of an average of 7 years, using the revenue and the total assets as variables. The results of the k-medoids cluster analysis are presented in Table 3.11.

The k-medoids cluster analysis was performed with the average data of the years. Although we can see that there is an overlap between the maximum amount of assets in SME and a minimum amount of assets in big companies, those companies earned much higher revenue than other companies, which made them classified as big according to their revenue. Table 3.11 illustrates that the differences between the medoids of the two clusters' means are extremely high, 23.22 times more in the case of total assets, and 24.73 times more in the case of revenues. Based on Table 3.11, it can be concluded that small and medium-sized enterprises (SME) are in the first cluster, while cluster 2 includes large corporations (big companies).

a. Optimal number of clusters *b. Cluster plot*

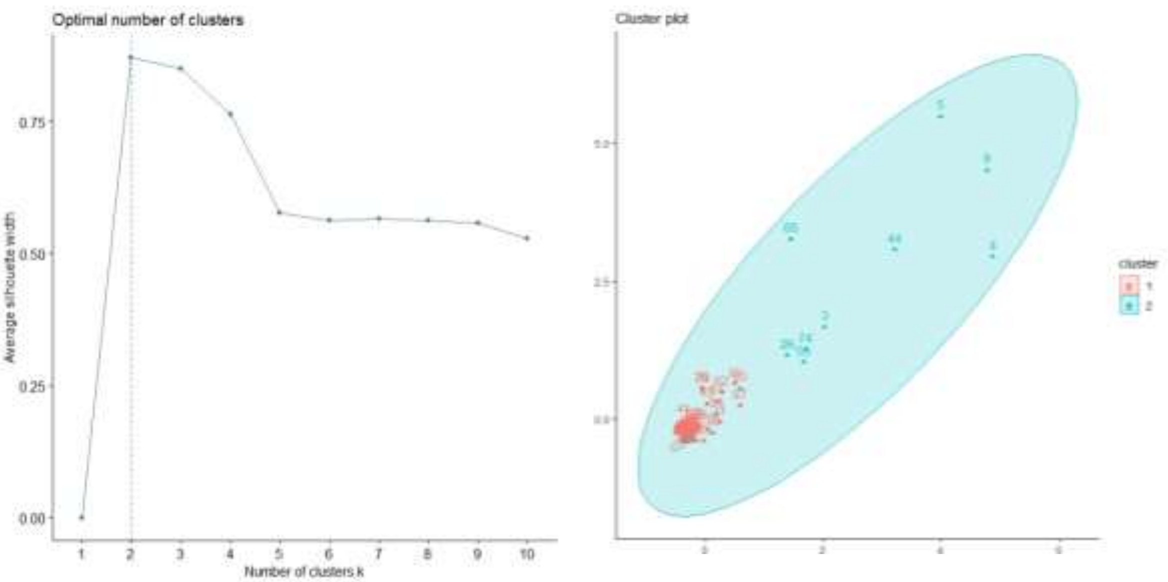


Figure 3.8 Silhouette method results

Source: author's calculation

Table 3.11 Descriptive analysis of big companies and SMEs (million tugriks)

	All		SME		Big	
	Assets	Revenue	Assets	Revenue	Assets	Revenue
Minimum	23.7	-	23.7	-	62,342.0	48,608.1
1. Quartile	746.0	140.0	617.4	115.8	131,983.2	70,165.4

Mean	28,770.1	18,275.9	8,925.7	5,417.0	207,369.1	134,006.8
Median	3,738.0	1,158.5	2,771.4	714.1	159,335.4	123,374.0
3. Quartile	17,161.9	9,487.2	10,086.0	3,900.2	312,695.9	186,040.3
Maximum	387,080.1	255,839.4	65,243.2	47,043.5	387,080.1	255,839.4
Std. Deviation	69,669.5	46,111.2	13,750.2	10,642.8	110,193.9	75,718.1
Skewness	3.66	3.69	2.32	2.65	0.59	0.63
Kurtosis	13.95	14.42	5.57	6.48	-1.03	-0.92

Source: author's calculation by R excel

Table 3.12 shows which industries belong to the big companies and which ones are rather smaller companies. Four Thermal Power Stations (TPS) are considered as big companies where heat energy is converted to electric power and distribute it throughout Ulaanbaatar (the capital city of Mongolia) and Darkhan (the second-largest city in Mongolia after Ulaanbaatar). Thermal Power Stations require huge amounts of investment in plants and equipment. Since the thesis used Total assets and Revenue as criteria to decide which cluster the company belongs to many of TPS considered as big. There are four mobile phone operators in Mongolia: Mobicom Corporation, Unitel Group, Skytel Group, and G-mobile LLC. Three of them were classified as big corporates. Interestingly, only one company in the mining sector was classified as big, while none of the companies in construction was in the big corporation cluster.

Table 3.12 Sectors in clusters

Industry	Big companies	SMEs	Total
Heavy Industry (total):	5	28	33
- *Thermal Power Station*	4	6	10
- *Construction*	-	9	9
- *Heavy manufacturing*	-	3	3
- *Mining*	1	10	11
Manufacturing (total):	2	29	31
- *Food industry*	1	12	13
- *Light industry*	1	7	8
- *Agriculture*	-	10	10
Service (total):	3	33	36
- *Transportation*	-	5	5
- *Trade*	-	6	6
- *Other services*	3	22	25
Total number of financial statements	10	90	100

Source: author's calculation

In Table 3.13, the skewness and kurtosis indicators were also decreased significantly, which means the distributions of 1st cluster (SMEs) data are approximate to the normal distribution. Although the standard deviation and coefficient of variation are still high, the standard deviation of pre-tax profit is significantly decreased. IQR to total range indicator is also improved considerably. These changes in the statistical characteristics confirm the necessity of the separation of companies. Clustering gives possibilities to analyze a more homogeneous database.

Table 3.14 illustrates the main statistical characteristics of big companies. It can be seen from Table 3.14 that the maximum values of the variables, along with their total range values, have been significantly reduced. Not only the minimum value but also the quartile values of the variables are reduced. These decreases are extremely significant in the case of the maximum and total range values.

Table 3.13 Descriptive statistics of SMEs (million tugriks)

Statistical characteristics	Current assets	Noncurrent assets	Assets	Revenue	COGS	Operating cost	Pre-tax Profit
Minimum	0.6	4.5	23.7	-	-	-	-3,910.5
1. Quartile	111.6	338.6	617.4	115.8	51.1	94.1	-84.1
Mean	3,651.8	5,273.9	8,925.7	5,417.0	4,213.4	979.8	114.3
Median	927.5	1,341.4	2,771.4	714.1	434.1	353.4	0.6
3. Quartile	3,947.5	5,724.7	10,086.0	3,900.2	2,919.2	1,148.6	89.0
Maximum	27,163.0	54,406.3	65,243.2	47,043.5	43,003.8	10,594.7	3,472.2
Range	27,162.4	54,401.7	65,219.5	47,043.5	43,003.8	10,594.7	7,382.8
IQR	3,835.9	5,386.1	9,468.6	3,784.4	2,868.1	1,054.5	173.1
IQR / Total range	14.12%	9.90%	14.52%	8.04%	6.67%	9.95%	2.34%
Std. Deviation	6,214.3	9,828.8	13,750.2	10,642.8	8,608.9	1,707.5	931.8
Coefficient of variation	170.17%	186.37%	154.05%	196.47%	204.32%	174.27%	815.47%
Skewness	2.37	3.16	2.32	2.65	2.72	3.32	-0.56
Kurtosis	5.21	11.27	5.57	6.48	7.26	13.33	8.46

Source: Own calculation by RStudio

Table 3.14 Descriptive statistics of Big companies (million tugriks)

Statistical characteristics	Current assets	Noncurrent assets	Assets	Revenue	COGS	Operating cost	Pre-tax Profit
Minimum	8,632.5	10,736.4	62,342.0	48,608.1	23,965.0	1,688.2	-1,337.6
1. Quartile	10,668.1	51,946.9	131,983.2	70,165.4	46,174.4	5,104.4	-14.3
Mean	53,163.1	154,206.0	207,369.1	134,006.8	89,264.4	22,800.7	18,819.1

Median	46,562.0	145,922.6	159,335.4	123,374.0	83,582.6	15,347.6	11,051.2
3. Quartile	94,534.8	232,602.9	312,695.9	186,040.3	140,682.4	43,538.5	35,524.9
Maximum	120,225.5	360,671.6	387,080.1	255,839.4	168,084.0	58,414.9	61,083.8
Range	111,593.0	349,935.2	324,738.1	207,231.3	144,119.1	56,726.6	62,421.4
IQR	83,866.7	180,656.0	180,712.7	115,875.0	94,508.0	38,434.1	35,539.3
IQR / Total range	75.15%	51.63%	55.65%	55.92%	65.58%	67.75%	56.93%
Std. Deviation	44,157.7	105,491.4	110,193.9	75,718.1	50,342.2	19,825.7	23,056.4
Coefficient of variation	83.06%	68.41%	53.14%	56.50%	56.40%	86.95%	122.52%
Skewness	0.44	0.56	0.59	0.63	0.36	0.69	1.06
Kurtosis	-1.53	0.18	-1.03	-0.92	-1.21	-0.86	-0.17

Source: Own calculation by RStudio

Table 3.14 represents the main statistical characteristics of big companies, which shows similar changes, as in Table 3.13. However, the changes in Table 3.14 are more significant for the following indicators: IQR to the total range, the coefficient of variant, skewness, and kurtosis than that of in Table 3.13. These changes also justify the necessity of clustering.

Table 3.13 and Table 3.14 explain the descriptive analyses of two clusters. Companies with total assets less than 65,243.2 million tugriks and revenue less than 47,043.5 million tugriks are classified in the first cluster (as SMEs). The second cluster's companies (big companies) earn approximately 108 times more profit than SMEs on average, which also demonstrates the substantial difference between the two clusters.

Table 3.15 reveals the financial ratios of two clusters and the whole dataset. Regardless of which sector, all big companies have positive profitability ratios. As for SMEs, only manufacturing companies have positive profitability ratios, while service and heavy industry have negative profitability ratios.

SMEs has a low and negative amount of NWC turnover ratio (-21.03), especially SMEs in heavy industry sector has the lowest (-73.54) NWC turnover ratio, which indicates that those companies are investing in too many accounts receivable and inventory to support their sales, which could lead to an excessive amount of bad debts or obsolete inventory. However, manufacturing companies (5.97-6.03) have the highest NWC turnover ratio regardless of their sizes. The high ratio shows the companies are being very efficient in using their short-term assets and liabilities for supporting sales.

Big companies’ ROS ratio is much higher than that of SMEs, which means that larger companies pay greater attention to cost management than the smaller ones. Moreover, the value of the ROA ratio is about ten times higher in the second cluster than in the first cluster, which means the efficiency of asset management in larger companies is much better than in smaller companies. For the GPM ratio, smaller companies also perform better, but in this case, the difference is much smaller, which may indicate that smaller companies have relatively higher fixed costs.

Table 3.15 Financial ratios of clusters

	SME				Big				All			
	all	**Heavy**	**service**	**manufacture**	**all**	**heavy**	**Service**	**manufacture**	**all**	**heavy**	**service**	**manufacture**
ROA	-0.04	-0.06	-0.06	0.01	0.08	0.09	0.09	0.06	-0.03	-0.04	-0.05	0.02
ROE	-0.04	-0.05	-0.08	0.02	0.15	0.14	0.14	0.18	-0.02	-0.03	-0.06	0.04
ROS	-0.39	-0.82	-0.09	-0.30	0.09	0.07	0.13	0.08	-0.34	-0.71	-0.06	-0.26
Cost to revenue ratio	1.98	1.69	1.10	3.28	0.87	0.91	0.81	0.89	1.86	1.59	1.07	3.05
Gross profit margin	0.38	0.17	0.52	0.44	0.30	0.17	0.52	0.24	0.37	0.17	0.52	0.42
Return on cost	-0.18	-0.19	-0.28	-0.06	0.12	0.11	0.16	0.10	-0.15	-0.15	-0.25	-0.04
ATO	0.63	0.57	0.79	0.50	0.72	0.69	0.65	0.83	0.64	0.58	0.78	0.53
Assets to equity ratio	1.94	1.91	2.29	1.58	1.90	1.42	1.56	2.87	1.94	1.85	2.23	1.70
Debts to total asset	0.54	0.51	0.67	0.42	0.38	0.28	0.35	0.55	0.52	0.48	0.64	0.43
WC turnover ratio	-21.03	-73.54	2.15	6.03	5.41	9.41	-0.49	5.97	-18.39	-63.49	1.93	6.03
Current assets/Total assets	0.39	0.32	0.41	0.45	0.35	0.29	0.19	0.60	0.39	0.31	0.39	0.47
Operating CF ratio	0.35	-0.16	-0.01	1.30	0.15	0.16	0.25	0.02	0.33	-0.12	0.02	1.17
Quick Ratio	3.17	1.63	5.30	2.24	1.28	2.19	0.70	0.65	2.98	1.70	4.92	2.08
Current Ratio	4.13	2.29	6.63	3.07	1.83	2.75	0.77	1.68	3.90	2.35	6.14	2.94
Cash ratio	0.07	0.05	0.09	0.06	0.08	0.15	0.02	0.04	0.07	0.06	0.08	0.06
Operating Cycle	294.70	353.3	251.80	277.8	126.2	50.2	53.2	300.6	393.8	312.8	232.6	703.4
Net Operating Cycle	57.30	111.8	10.4	48.4	69.1	32.0	-42.8	230.5	62.3	101.2	-1.0	94.2
Receivable turnover	396.40	108.7	82.4	1,092.7	36.9	28.1	30.0	55.5	160.0	98.7	77.9	339.1
Inventory turnover	147.90	140.1	161.7	137.8	89.3	22.1	23.2	245.1	245.7	208.3	148.3	425.9
Payable turnover	199.20	104.0	250.7	246.1	57.1	18.2	96.1	70.15	171.6	175.1	191.9	138.7
Assets growth	1.56	1.25	2.18	1.14	1.46	1.98	1.09	1.15	1.55	1.34	2.09	1.14
Sales growth	1.98	3.35	1.12	1.26	1.57	2.08	1.06	1.40	1.93	3.18	1.11	1.28
MVIAC	2.64	3.04	3.70	0.90	5.89	8.03	5.55	3.38	2.97	3.65	3.86	1.15

Source: author's calculation by RExcel

3.3 Performance evaluation

Performance can be explained in many ways, such as the fulfilment of an obligation, the accomplishment of a task, etc. In the thesis, the performance was evaluated using financial ratios in case of size and sector. Financial performance was analyzed by several kinds of research from different countries, including; Hornungová and Milichovský (2016); Kopp (2016); Liu (2011); Luo (2003), etc. The thesis compares multiple frontier efficiency techniques across parametric and non-parametric approaches. Four different frontier efficiency estimations are considered, which are output-oriented DEA, input-oriented DEA (DEA-CRS and DEA-VRS), PCA-DEA, and SFA. Moreover, the thesis compares three different sectors' efficiencies and ranks the sectors by its efficiencies'.

3.3.1 Panel regression

This subchapter is aimed at examining what ratios can determine the financial performance of Mongolian 3 main sectors. Financial statements were evaluated by panel regression covering the period of 2012-2018. As the data contains companies with corresponding years, panel regression was employed to choose variables (Table 3.16). The FE model is an appropriate specification if we are focusing on a specific set of *N* firms and our inference is restricted to the behaviour of these sets of firms, while the RE model is an appropriate specification if we are drawing *N* individuals randomly from a large population (Baltagi, 2005).

Table 3.16 Panel regression results of the whole dataset

Variables	ROE	ROA	ROS
WC turnover ratio		***	
Gross profit margin	(***)	(***)	***
Cost to revenue ratio	(.)	(***)	***
Return on costs	***	***	***
ATO	(.)	***	
Assets to equity ratio	(***)		
Debts to total asset	***	*	*
Receivable turnover			***
Sales growth		*	
Assets growth		*	
R-Squared (%)	62.53	88.34	82.49
Adj. R-Squared (%)	53.52	85.54	78.28

*Significance. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Source: Author's compilation

Three ratios were used as dependent variables (ROE, ROA, and ROS) separately, and their results were examined to determine the financial performance impacts for each sector. There were used 20 independent variables ratios are used. FE or RE model, whichever is appropriate, is used to find the results based on the Hausman specification test in this thesis.

Operating CF ratio, quick ratio, inventory turnover, payable turnover, cash ratio, and current assets to total assets are not significant for any of the dependent variables. GPM, cost to revenue ratio, debt to total assets, and return on costs were significant determinants of all the dependent variables, which will be called – "General determinants" – for further analysis. However, multicollinearity is a critical issue to consider when financial ratios are used. Based on the Hausman test results, I used the FE model for the whole dataset. Panel regression was employed separately in each sector to determine sector-specific determinants (Table 3.17.). Output variables, determined as significant in each sector, will be called as "sector-specific" determinants.

Table 3.17 Hausman test results

Variables	Manufacturing			Service			Heavy		
	ROE	ROA	ROS	ROE	ROA	ROS	ROE	ROA	ROS
Random Effect									
R-Squared:	74.01	87.48	75.56	69.30	90.93	95.55	79.74	94.73	92.45
Adj. R-Squared:	71.66	86.35	73.35	66.95	90.23	95.21	78.05	94.29	91.82
Fixed Effect									
R-Squared:	64.76	87.12	73.51	68.45	91.35	96.70	79.19	95.36	93.33
Adj. R-Squared:	53.10	82.86	64.75	58.65	88.66	95.68	72.54	93.88	91.20
Hausmann test results:									
P-value	0.42	0.00	0.98	0.02	0.00	0.03	0.02	0.00	0.13
Chosen Model	RE	FE	RE	FE	FE	FE	FE	FE	RE

Source: Author's compilation

Table 3.17 explains the panel regression results of sectors along with their Hausman test results. According to the Hausman test, each variable, which has significant P-value (<0.05), uses the Fixed Effect model, if not the Random Effect model is chosen.

In Table 3.18, we can see that debts to total assets ratio have significant positive impacts on ROE only, while this ratio has significant impacts on all output variables in the case of the whole dataset. Although sales growth and assets growth have significant positive impacts on the ROA of the whole dataset, growth does not determine the manufacturing sector significantly. As for the service sector, its operational flow is tightly connected with current assets rather than non-current assets. Therefore, it can be concluded that the proportion of liquid assets influences the service sector's profitability positively.

Table 3.18 Panel regression results of sectors

Variables	**Manufacturing**			**Service**			**Heavy**		
	ROE	ROA	ROS	ROE	ROA	ROS	ROE	ROA	ROS
	RE	FE	RE	FE	FE	FE	FE	FE	RE
WC turnover ratio	.	**		(***)					
Gross profit margin	(***)	(*)	***			**	(**)	(***)	***
Cost to revenue ratio	(**)	(**)	**	(.)	(***)	***			***
Return on costs	***	***	***	***	***	***	***	***	***
ATO		**		***	***		.	***	
Current assets/total assets	*	(**)		**	**	**			
Assets to equity ratio	(**)			(***)			(***)		**
Debts to total asset	***		.	***			***	***	**
Receivable turnover			***			*			***
Inventory turnover							(.)		
Payable turnover					(.)		*		
Sales growth						(*)		*	
Assets growth					*				

Source: Author's compilation

When we compare whole dataset variables with service sector-specific variables, we can see that the NWC turnover ratio negatively effects on ROE of the service sector. GPM significantly affects all output variables, except the service sector ROA and ROE. Some service companies tend to record all the expenses as operating expenses, while some service companies record them as COGS. Because of this, GPM might be an inappropriate determinant in the service sector. An important service-specific variable is the current assets to total assets ratio, which has positive impacts on all the output variables. Like the manufacturing sector, debts to total assets ratio is significant for only ROE. Although assets growth has significant positive impacts, sales growth effects negatively in the case of ROS in the service sector. As for manufacturing, it is required to produce a large number of products, which makes amounts of current assets relatively higher than that of the other sectors. We can conclude that the proportion of liquid assets influences the manufacturing sector's profitability positively.

The heavy industry is the only sector that is not determined by the NWC turnover ratio and current assets to total assets ratio significantly. Moreover, payables turnover has a significant positive impact on only heavy industry. GPM, the cost to revenue ratio, receivables turnover, and sales growth have the same impacts on the whole dataset as well as sector-specific cases. The Debt to assets ratio is a fundamental determinant of heavy industry, which has a significant positive effect. The heavy industry has a longer life cycle compared with the other sectors, particularly construction. In Mining and Construction businesses, the first revenue is mostly expected after the business operation. Therefore, there is a period the total costs must be paid from equity before the cash comes from the revenue. A positive relationship of debt to total assets ratio conflicts with the results of Dasuki (2016) and Mirza and Javed (2013).

GPM has the same significant impacts on manufacturing and heavy industry, while this ratio explains only ROS in the service sector. It can be explained that manufacturing and heavy industry produce products which have their own costs, while in the service sector the main cost is operating costs which are not connected with COGS. Current assets to total assets ratio is an important factor for the service sector. Return on cost ratios determines all sectors for all three ratios significantly, although this ratio is highly correlated with dependent variables. Therefore, the return on cost is not used for further analysis. The operating cycle determines only the service sector. The Payable turnover ratio is significant only for heavy industry. Operating CF ratio, cash ratio, and inventory turnover are not significant. Also, it is noteworthy that the liquidity of the company does not determine the financial performance of Mongolian companies.

3.3.2 The efficiency of Service sector

The main method used in the research is DEA, which is a widely used non-parametric approach to measure the efficiency of DMUs based on multiple inputs and outputs. Panel regression was used for the whole dataset as well as each sector to determine if there are any sector-specific determinants exist. Current assets to total assets ratio is a sector-specific ratio, which determines ROE, ROA, and ROS. Although there are different determinants for every sector, it is not appropriate to use different variables for each sector and compare their efficiencies. Therefore, the efficiency of the service sector is determined by using sector-specific variables and general determinants separately. Efficiency determined by general output variables is compared for further analysis. The service sector consists of five transportation companies, six commercial companies, and 25 others (one of the companies went bankrupt in 2016).

Every sector was evaluated in 8 different ways; different models (VRS, CRS), different orientation (input and output), different input variables (sector-specific and general), and different output variables (ROA, ROE, and ROS). That calculation of the sector's efficiency was also compared the efficiency results without dividing it into the group. The service sector includes 36 companies, while the dataset consists of 100 companies. Therefore, the discriminative power of DEA will be better in the case of all data set than the individual sector.

Financial ratios were calculated on 7 years average, from 2012 to 2018. Therefore, abnormal changes in the variables were reduced. Three dependent variables, i.e., ROA, ROE, and ROS, were calculated separately.

In Table 3.19, VRS and CRS technology of sector-specific input orientation results are illustrated. As we can see from Table 3.19, input efficiency by VRS shows much higher efficiency scores than CRS for each three output variables' cases. VRS technology revealed 20 ROA, 13 ROE, and 22 ROS companies are working efficiently, which are 55.5%, 36.1%, and 61.1%. However, the number of efficient companies is reduced significantly according to CRS technology, which is 9 (25% by ROE variable) and 10 (27.7% by ROA and ROS variables). When the input and output variables vary greatly, the VRS model is suggested. Efficient companies by the VRS model turned into inefficient in the case of the CRS model; moreover, the efficiency score of inefficient companies has increased significantly.

Since the results produced by VRS and CRS differ widely, I employed the same methods for input efficiency, which is determined by general variables (Table 3.20). Sector-specific determinants showed slightly higher mean efficiency than that of whole dataset variables, except VRS technology by ROA and ROE variables.

In the case of the CRS model, efficiency scores by sector-specific determinants were higher. Interestingly, the majority of the companies (61.1%-63.8%) are determined as working in an efficiency range of 0-0.4, which means that we could still produce the same output if we decreased the inputs by 60%.

Table 3.19 Summary of input efficiency by sector-specific variables

Efficiency Range	ROA		ROE		ROS	
	CRS	VRS	CRS	VRS	CRS	VRS
0.0-0.4	21	3	21	7	11	-
0.4-0.5	2	3	1	6	3	-
0.5-0.6	-	6	1	1	2	1
0.6-0.7	-	1	2	3	-	-
0.7-0.8	1	1	1	4	4	1
0.8-0.9	1	-	1	2	4	2
0.9-1.0	1	2	-	-	2	10
1.0	10	20	9	13	10	22
Minimum	0	0.299	0	0.219	0.073	0.596
1st Quartile	0	0.573	0	0.415	0.320	0.983
Median	0.053	1	0.315	0.714	0.733	1
Mean	0.393	0.807	0.407	0.697	0.650	0.961
3rd Quartile	1	1	0.854	1	1	1
Maximum	1	1	1	1	1	1

Source: Author's compilation

Table 3.20 Summary of input efficiency by whole dataset variables

Efficiency Range	ROA		ROE		ROS	
	CRS	VRS	CRS	VRS	CRS	VRS
0.0-0.4	22	-	23	1	14	2
0.4-0.5	1	-	2	3	2	4
0.5-0.6	1	1	-	4	2	2
0.6-0.7	2	-	1	5	1	5
0.7-0.8	-	-	4	3	4	2
0.8-0.9	2	3	1	6	3	5
0.9-1.0	1	8	-	1	2	2
1.0	7	24	5	13	8	14
Minimum	0	0.596	0	0.380	0.072	0.366
1st Quartile	0	0.987	0	0.624	0.276	0.632
Median	0.047	1	0.142	0.842	0.617	0.826
Mean	0.356	0.968	0.340	0.792	0.587	0.791
3rd Quartile	0.844	1	0.744	1	0.937	1
Maximum	1	1	1	1	1	1

Source: Author's compilation

Output efficiency results are given in Table 3.21. The output-oriented model's efficiency scores were determined between 1.35 to 49.26, which means that the given company, compared to effective firms, could increase its output by 1.3 to 49.26 times without involving any additional input source. The maximum efficiency scores from ROA and ROE were extremely high (900.72 and 649.83), which means there is a possibility to increase its output 900.72 or 649.83 times.

The mean efficiency scores of the service sector are slightly higher when it is evaluated separately than the other sectors. It can be explained in 2 different ways. Firstly, current assets to total assets ratio is sector-specific determinants, which is not used general determinants. This ratio could have explained efficiency more than the general ratios. Second, DEA determines at least one efficient company for every observation. However, those efficient companies in the service sector might not be as efficient as other companies in different sectors.

Table 3.21 Output efficiency summary

Efficiency range	Sector-specific			Whole dataset		
	ROA	ROE	ROS	ROA	ROE	ROS
1.0	12	10	21	14	11	14
1.0-1.1	-	1	3	1	1	2
1.1-1.2	1	1	4	1	-	5
1.2-1.3	-	-	-	1	1	2
1.3-1.5	-	3	-	-	1	-
1.5-2.0	1	2	3	1	-	2
2.0-5.0	3	4	5	1	5	8
5.0-inf	5	4		3	6	3
Minimum	1	1	1	1	1	1
1st Quartile	1	1	1	1	1	1
Median	1	1.312	1	1	1.232	1.135
Mean	49.266	30.311	1.354	2.399	21.795	2.17
3rd Quartile	3.501	2.204	1.168	1.264	3.299	2.318
Maximum	900.729	649.832	4.967	14.616	388.634	13.317

Source: Author's compilation

VRS - ROA model (general determinants) defined 24 companies as efficient out of 36, while sector-specific determinants revealed 20 companies as efficient. Interestingly, the number of efficient companies had reduced significantly to 12, when all the sectors calculated together. It shows some of the companies are not efficient, but within the sector, they are assumed as efficient. VRS model determines more efficient companies than the CRS model. For example, the CRS-ROA model defined only seven efficient, and this number slightly increases by the VRS-ROA model (24 companies).

Moreover, this number even reduces when the sectors are combined, i.e., only three companies by the CRS-ROA model. It shows the discriminative power declines as the number of DMUs is reduced. Only one company was determined as efficient consistently throughout all the models and variables. However, its financial statement looked suspicious (lack of information except for the proportionate amount of revenue and COGS without other expenses). Mongolian biggest mobile phone operator – Mobicom Corporate - was determined as efficient by all the models and variables; however, it was inefficient when all the sectors combined. Therefore, it can be concluded that Mobicom Corporate is the most efficient company in the service sector, but not as efficient as companies in other sectors.

As for ROA and ROE output variables, the number of efficient companies by the VRS and CRS model differ significantly, while the ROS output variable showed closer results between the models.

3.3.3 The efficiency of the Manufacturing sector

Financial leverage and growth ratios do not significantly determine the manufacturing sector. Profitability ratios, i.e., GPM and cost to revenue ratio, are significant for each output variables (whole dataset and sector-specific case). Debts to total assets ratio determine each output variable in the case of the whole dataset. But it determines only ROE in the manufacturing sector. Current assets to total assets ratio is the sector-specific determinant, but not for the ROS output variable. The manufacturing sector consists of 13 companies in the food industry, ten agricultural companies and, eight light industries from one of the light industry company went bankrupt in 2016 and one more in 2017.

Every sector is evaluated in 8 different ways; different models (VRS, CRS), different orientation (input and output), different input variables (sector-specific and general), and different output variables (ROA, ROE, and ROS). That calculation of the sector’s efficiency is also compared the efficiency results without dividing it into a group. The manufacturing sector includes 31 companies, while dataset consists of 100 companies. Therefore, the discriminative power of DEA will be improved in the case of all data set than the individual sector.

Financial ratios are determined using an average of 7 years of financial statements from 2012 to 2018. Therefore, any abnormal changes in some of the years are reduced. Three dependent variables, i.e., ROA, ROE, and ROS, are calculated separately.

In Table 3.22, VRS and CRS technology of sector-specific, input-oriented results is illustrated. As we can see from Table 3.22, input efficiency by VRS shows much higher efficiency scores than that of CRS for each output variable. Efficiency results from the CRS model were similar to each other, while VRS results differ significantly.

CRS technology revealed only 3 (9.7%) efficient companies in case of ROA output, while 4 (12.9%) efficient companies from ROE output, and 6 (19.3%) efficient companies from ROS output are determined. Efficient companies by the VRS model turned into inefficient in the case of the CRS model. Furthermore, the efficiency score of inefficient companies has increased significantly in the VRS model. Similar to service sector's efficiency results from CRS model, majority of the companies are determined as working in efficiency range of 0-0.4 particularly ROA (83.9%) and ROE (80.6%), which means that we could still produce the same output if we decreased the inputs by 60%.

Table 3.22 Summary of input efficiency by sector-specific variables

Efficiency Range	**ROA**		**ROE**		**ROS**	
	CRS	VRS	CRS	VRS	CRS	VRS
0.0-0.4	26	2	25	1	11	6
0.4-0.5	-	3	1	-	2	-
0.5-0.6	-	-	1	1	1	3
0.6-0.7	1	1	-	2	1	1
0.7-0.8	1	-	-	7	3	5
0.8-0.9	-	6	-	2	3	4
0.9-1.0	-	2	-	4	4	3
1.0	3	17	4	14	6	9
Minimum	0	0.360	0	0.269	0.048	0.264
1st Quartile	0	0.816	0	0.727	0.151	0.586
Median	0	1	0.012	0.931	0.737	0.819
Mean	0.198	0.858	0.203	0.864	0.587	0.745
3rd Quartile	0.238	1	0.191	1	0.964	1
Maximum	1	1	1	1	1	1

Source: Author's compilation

Since the results produced by VRS and CRS differ widely, I employed the same methods for input efficiency, which is determined by general input variables (Table 3.23). When general input ratios are used, the mean efficiency scores are slightly higher than that of sector-specific ones. In the case of the CRS model, efficiency scores from sector-specific and general input variables are fundamentally comparable.

Output efficiency results are given in Table 3.24. Like input efficiency results, output efficiency scores from whole dataset determinants were slightly better than that of sector-specific ones. The output-oriented model's efficiency scores are determined between 2.39 to 3.21 (general determinants), which means that the given company, compared to effective firms, could increase its output by 2.39 to 3.21 times without involving any additional input source. Maximum efficiency scores were 79.79 from generally determined input variables, and 80.28 from sector-specific. Although those results are reasonable compared to the service sector's results, those results are still high.

Table 3.23 Summary of input efficiency by general input variables

Efficiency Range	ROA		ROE		ROS	
	CRS	VRS	CRS	VRS	CRS	VRS
0.0-0.4	22	-	25	-	11	6
0.4-0.5	1	-	1	1	2	-
0.5-0.6	-	-	1	1	1	3
0.6-0.7	1	-	-	2	1	1
0.7-0.8	1	-	-	6	3	5
0.8-0.9	1	3	-	4	3	4
0.9-1.0	1	5	-	2	3	3
1.0	4	23	4	15	7	9
Minimum	0	0.818	0	0.328	0.048	0.264
1st Quartile	0	0.996	0	0.744	0.151	0.587
Median	0	1	0.012	0.933	0.744	0.819
Mean	0.278	0.979	0.206	0.868	0.589	0.746
3rd Quartile	0.538	1	0.215	1	0.964	1
Maximum	1	1	1	1	1	1

Source: Author's compilation

Table 3.24 Output efficiency summary

Efficiency range	Sector-specific			Whole dataset		
	ROA	ROE	ROS	ROA	ROE	ROS
1.0	10	9	9	10	10	9
1.0-1.1	-	-	4	-	-	4
1.1-1.2	-	-	-	-	-	-
1.2-1.3	-	-	3	-	-	3
1.3-1.5	-	-	1	-	-	1
1.5-2.0	-	-	3	-	-	3
2.0-5.0	1	2	5	-	1	5
5.0-inf	4	5	6	2	5	6
Minimum	0	1	1	1	1	1
1st Quartile	1	1	1	1	1	1
Median	1	1	1.297	1	1	1.29
Mean	4.986	10.483	3.224	2.395	9.599	3.214
3rd Quartile	5.143	6.309	2.798	1	5.642	2.783
Maximum	33.096	80.28	20.416	17.241	79.799	20.416

Source: Author's compilation

Only one company was determined as efficient throughout the different models and different variables. However, that efficient company is one of the fast-growing companies; the three biggest manufacturing companies that are well-known and considered as the most efficient companies turned inefficient. The mean efficiency score of the VRS model is much higher than that of the CRS model. Regardless of what determinants are used as input variables (sector-specific, general ratios for every sector), the mean efficiency scores are approximate in the CRS model. The manufacturing sector covers 31 companies, including the three biggest manufacturing companies. Twenty-three companies are efficient according to the VRS-ROA model using general ratios, which is the highest number. On the contrary, only three companies are efficient by the CRS-ROA model from sector-specific determinants as inputs. As the service sector, there were many efficient companies by VRS, which are turned inefficient according to the CRS model, which is consistent with Büschken's (2003) result.

3.3.4 The efficiency of Heavy industry

GPM and debts to total assets ratio are significant for each output variables (both general and sector-specific cases). There is not sector-specific input variable, which determines all three output variables. The heavy industry consists of 10 Thermal Power Stations, three companies in heavy manufacturing, 11 mining companies and, nine construction companies. One of the construction company went bankrupt in 2016.

Like the service and manufacturing sectors, efficiency was determined in eight different ways. Financial ratios were determined using an average of 7 years of financial statements from 2012 to 2018. Therefore, any abnormal changes in some of the years are reduced. Three dependent variables, i.e., ROA, ROE, and ROS, were calculated separately.

In Table 3.25, VRS and CRS technology of sector-specific, input-orientation results are illustrated. CRS technology revealed only one efficient company from ROA, three companies from ROE, and seven companies from ROS, which are 3.0%, 9.1%, and 21.2%, respectively.

Like previous two sectors, heavy industry's efficiency results from CRS model, majority of the companies were determined as working in efficiency range of 0-0.4 particularly ROA (93.9%) and ROE (87.9%), which means that we could still produce the same output if we decreased the inputs by 60%.

Table 3.25 Summary of input efficiency by sector-specific variables

Efficiency Range	ROA		ROE		ROS	
	CRS	VRS	CRS	VRS	CRS	VRS
0.0-0.4	31	-	29	3	18	-
0.4-0.5	-	-	-	2	-	-
0.5-0.6	-	-	-	8	2	-
0.6-0.7	1	1	1	2	-	-
0.7-0.8	-	2	-	1	3	-
0.8-0.9	-	7	-	2	-	-
0.9-1.0	-	11	-	3	3	4
1.0	1	12	3	12	7	29
Minimum	0.676	0	0	0.237	0	0.919
1st Quartile	0.886	0	0	0.560	0	1
Median	0.964	0	0.006	0.803	0	1
Mean	0.928	0.096	0.151	0.754	0.401	0.995
3rd Quartile	1	0.040	0.117	1	0.952	1
Maximum	1	1	1	1	1	1

Source: Author's compilation

The efficiency results are similar to the other two sectors as VRS determined too many efficient companies (up to 23 out of 33 companies), while the CRS model determines only 1-3 efficient companies. Only one company is efficient regardless of model and output variables – Tavan Tolgoi coal mining company – which constituted ≈ 5% of Mongolian GDP in 2017. Since the results produced by VRS and CRS differ widely, I employed the same methods for input efficiency, which is determined whole dataset variables (Table 3.26).

In ROA and ROE output variables' case and for both model determinants from the whole dataset gave a slightly higher mean efficiency score than determinants from sector-specific ones. On the contrary, the ROS output variable has the opposite results by having a higher efficiency score in sector-specific case.

Output efficiency results are given in Table 3.27. Unlike input efficiency results from the CRS model, the number of efficient companies is higher 15.1% - 39.4%. The maximum efficiency score was also extremely high as the service sector, which is 246.67 from general input variables, 136.78 from sector-specific variables. It shows there is a chance to increase its output by 246.6 or 136.78 times without involving any additional input source.

Table 3.26 Summary of input efficiency by whole dataset variables

Efficiency range	ROA		ROE		ROS	
	CRS	VRS	CRS	VRS	CRS	VRS
0.0-0.4	29	-	29	-	28	-
0.4-0.5	-	-	-	-	-	-
0.5-0.6	-	-	-	-	1	1
0.6-0.7	-	-	-	-	1	2
0.7-0.8	1	-	-	-	1	-
0.8-0.9	-	1	1	3	-	7
0.9-1.0	1	6	-	12	-	9
1.0	2	26	3	18	2	14
Minimum	0	0.886	0	0.807	0	0.545
1st Quartile	0	1	0	0.936	0	0.857
Median	0	1	0.003	1	0	0.963
Mean	0.153	0.988	0.158	0.969	0.152	0.916
3rd Quartile	0.069	1	0.062	1	0.099	1
Maximum	1	1	1	1	1	1

Source: Author's compilation

VRS model using general ratios determined more than half of the companies as efficient regardless of sector and output variables (ROA, ROE, ROS). Therefore, either the input ratios are too many compared with the number of DMUs, or the VRS model is not appropriate as it cannot discriminate between efficient and inefficient companies. If the number of companies vs. the number of variables decreased discrimination power, it would be solved by the PCA-DEA model.

Table 3.27 Output efficiency summary

Efficiency range	**Sector-specific**			**Whole dataset**		
	ROA	ROE	ROS	ROA	ROE	ROS
1.0	5	6	13	9	9	6
1.0-1.1	-	-	1	1	-	-
1.1-1.2	1	-	1	-	-	-
1.2-1.3	-	-	-	-	-	1
1.3-1.5	-	-	-	-	1	-
1.5-2.0	2	1	-	-	1	-
2.0-5.0	1	3	-	-	1	3
5.0-inf	6	7	-	5	5	5
Minimum	1	1	1	1	1	1
1st Quartile	1	1	1	1	1	1
Median	1.86	2.90	1	1	1	2.29
Mean	13.86	20.14	1.01	8.04	22.61	7.27
3rd Quartile	18.82	22.95	1	9.39	11.89	9.47
Maximum	78.72	136.78	1.10	55.53	246.67	26.03

On efficiency scores, unrelated ANOVA was executed using the sector as a factor. The F-test is significant (significance level = 0.05). Therefore, it is concluded that the significant difference exists efficiency results among the sectors. To identify which sector differ from other sectors, I continued unrelated ANOVA on pair of sectors separately. As for the Heavy industry and Service sector, unrelated ANOVA on CRS (sector as a factor), revealed significant difference, F-test is significant at the significance level 0.01. Likewise, there is also a significant difference between the Heavy industry and Manufacturing sector, F-test also is significant at the significance level 0.01. However, the efficiency of the Service and Manufacturing sectors does not differ significantly.

From those sectors' efficiency results, we can see that determinants from the sector-specific case do not necessarily mean better efficiency results; therefore, for the sake of simplicity and comparability, determinants from the whole dataset will be used for further analysis. Since the efficiency results from CRS and VRS models differ significantly, it is assumed to due to outliers in the dataset. Therefore, the next subchapter is aimed to determine if size matters in efficiency results.

3.3.5 Efficiency analysis of sizes

Clustering gives possibilities to analyze a more homogeneous database. To determine whether size difference matters in efficiency analysis, DEA was applied for the entire population and the two clusters separately. The main interest of this subchapter was identifying the effects of cluster-specific analysis that influenced the number of effective companies. For better comparability, some of the statistical characteristics of the efficiency coefficients were calculated. The results of the CRS model are presented in Table 3.28.

Table 3.28 Summary of input efficiency by CRS

Efficiency range	ROA			ROE			ROS		
	Big	SME	All	Big	SME	All	Big	SME	All
0.0-0.4	3	74	80	4	78	83	4	38	39
0.4-0.5	1	3	7	1	-	4	1	7	11
0.5-0.6	2	4	3	-	3	1	1	10	8
0.6-0.7	-	1	-	3	-	1	-	8	11
0.7-0.8	1	-	1	-	2	2	-	10	10
0.8-0.9	-	1	-	-	1	1	1	1	1
0.9-1.0	-	-	1	-	1	-	-	3	6
1	3	7	8	2	5	8	3	13	14
Minimum	0	0	0	0	0	0	0	0.012	0.012
1st Quartile	0.403	0	0	0.138	0	0	0.101	0.208	0.213
Median	0.567	0	0.009	0.519	0.007	0.012	0.536	0.486	0.508
Mean	0.575	0.179	0.186	0.471	0.163	0.182	0.527	0.501	0.513
3rd Quartile	0.944	0.254	0.278	0.628	0.203	0.226	0.973	0.746	0.743
Maximum	1	1	1	1	1	1	1	1	1

Source: Author's compilation

In Table 3.28, big companies have a much higher mean efficiency score, while SMEs have a much less mean efficiency score. Since the number of SMEs are greater than the number of big companies, the mean efficiency scores of whole datasets are also less. However, mean efficiency scores are similar before and after clustering for ROS output efficiency. The efficiency results of ROA and ROE are fundamentally similar. To verify out results from CRS, input efficiency results from the VRS model are illustrated in Table 3.29.

In Table 3.29, big companies' mean efficiency scores are extremely high, from 96.7% - 99.9%, which means almost all big companies are efficient. It might be caused by the small number of big companies, which is only ten compared to 90 SMEs.

Table 3.30 describes the output efficiency results of before and after clustering. Similar to input efficiency results, big companies are mostly determined as efficient (50%-70%) by output efficiency. On the other hand, the number of efficient companies is much less for SMEs (17.7%-24.4%).

Table 3.29 Summary of input efficiency by VRS

Efficiency range	ROA			ROE			ROS		
	Big	SME	All	Big	SME	All	Big	SME	All
0.0-0.4	-	-	-	-	6	5	-	19	18
0.4-0.5	-	-	-	-	10	8	-	12	13
0.5-0.6	-	3	2	-	11	12	-	10	9
0.6-0.7	-	4	5	-	16	15	-	9	11
0.7-0.8	-	3	3	-	8	14	-	13	18
0.8-0.9	-	12	17	-	7	10	2	5	5
0.9-1.0	1	27	28	1	11	15	1	4	6
1	9	41	45	9	21	21	7	18	20
Minimum	0.995	0.518	0.520	0.998	0.267	0.287	0.870	0.248	0.259
1st Quartile	1	0.903	0.897	1	0.570	0.608	0.933	0.423	0.458
Median	1	0.985	0.977	1	0.739	0.765	1	0.650	0.677
Mean	0.999	0.927	0.928	0.999	0.739	0.755	0.967	0.650	0.671
3rd Quartile	1	1	1	1	0.979	0.978	1	0.854	0.919
Maximum	1	1	1	1	1	1	1	1	1

Source: Author's compilation

DEA's many advantages; however, the discrimination power declines and might prove the majority of DMUs as efficient when the number of inputs and outputs is relatively high, and the number of DMUs is less. It also might be the cause that most of the big corporates are determined as efficient (only 10 big companies). To identify whether a significant difference exists between the efficiency of big corporates and SMEs, unrelated ANOVA is executed using clusters as a factor. The F ratio = 2.416 (insignificant) in the case of efficiency results from the VRS model. In contrast, unrelated ANOVA on CRS revealed significant differences. F-test is significant at the significance level 0.05.

To overcome the curse of dimensionality in DEA, the PCA can be combined with DEA. PCA is a multivariate technique to reduce the dimensionality of a multivariate dataset while accounting for as much of the original variation as possible present in the dataset. Therefore, PCA-DEA is applied for the next subchapter to reduce the curse of dimensionality in DEA.

Table 3.30 Output efficiency summary

	Big			**SMEs**			**Whole**		
Efficiency range	ROA	ROE	ROS	ROA	ROE	ROS	ROA	ROE	ROS
1.0	7	7	5	22	16	18	26	15	20
1.0-1.1	-	1	-	-	-	9	-	1	9
1.1-1.2	-	-	-	1	1	7	-	1	6
1.2-1.3	1	-	-	1	-	3	-	1	8
1.3-1.5	-	-	-	1	1	12	1	1	11
1.5-2.0	-	-	1	3	2	8	5	3	10
2.0-5.0	-	-	2	4	10	21	5	13	22
5.0-inf	-	-	-	12	20	12	15	23	14
Minimum	1	1	1	1	1	1	1	1	1
1st Quartile	1	1	1	1	1	1.06	1	1.01	1.07
Median	1	1	1	1.08	3.62	1.43	1.19	3.37	1.43
Mean	1.02	1.00	1.56	9.29	63.68	4.15	9.61	57.13	4.16
3rd Quartile	1	1	1.68	6.97	25.98	2.91	6.17	25.86	2.95
Maximum	1.22	1.01	3.90	134.61	1204.28	74.48	144.87	1140.27	79.6

Source: Author's compilation

3.3.6 PCA-DEA

This subchapter applies PCA to reduce the dimensionality of the dataset and DEA to evaluate companies' input efficiencies using the R statistical program. PCA is executed on the 'psych' package of the R statistical program. PCA is applied to the same inputs and outputs as conventional DEA to determine PC scores.

The procedures for the efficiency analysis of the integrated PCA-DEA model in this thesis can be seen in Figure 3.9.

The PCA was applied to both input and output variables separately. There are different criteria for determining the number of components, which should be extracted, such as eigenvalues greater than one and/or PC account for more than 80%. Table 3.31 shows the PCA results of output variables.

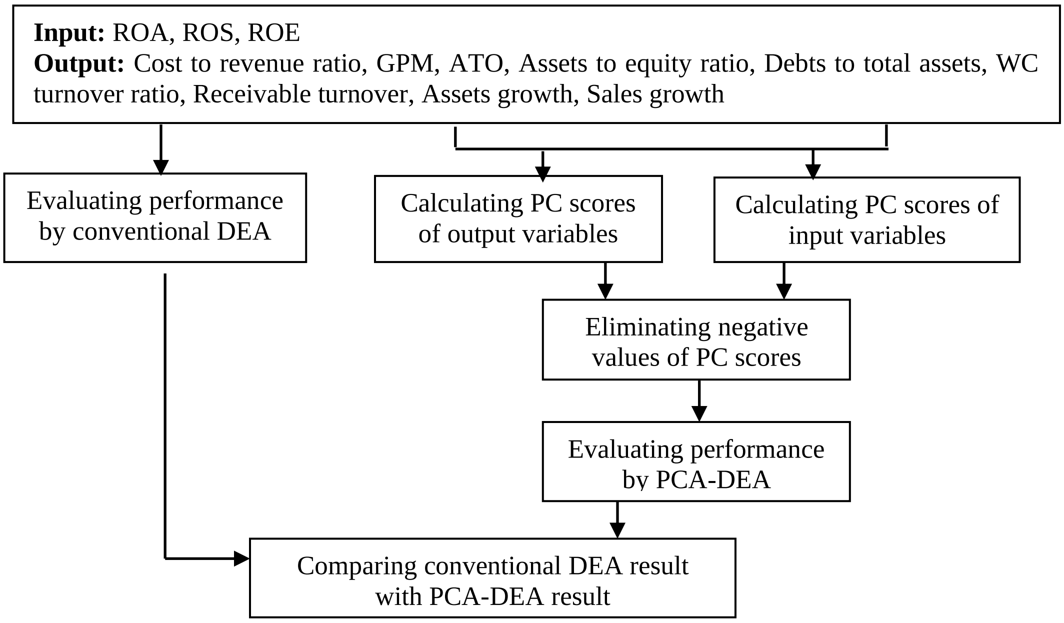


Figure 3.9 Flowchart of the stages of the thesis

Source: Author's compilation

Table 3.31 PCA results of output variables

Principal components (PC)	**Eigenvalue**	**Proportion (%)**	**Cumulative proportion %**
PC1	*1.20*	*48.68*	*48.68*
PC2	*0.96*	*30.86*	*79.54*
PC3	0.78	20.45	100

Source: Author's compilation

From Table 3.31, one can see that only the first component has an eigenvalue above one, which can explain 48.68% of the total variance. The second component can explain 30.86% of the total variance, and the cumulative proportion of this level is 79.54%. Therefore, the first two components are chosen as output variables of PCA-DEA (Figure 3.10).

According to the Kaiser criterion, an eigenvalue above 1.0 is not the only way to decide the number of extracted components. One of the other common ways is to see the scree plot ('*elbow diagram*') of PCA results, as shown in Figure 3.10. There is not any clear break between components. Therefore, the first two-component are used for further analysis as an input variable.

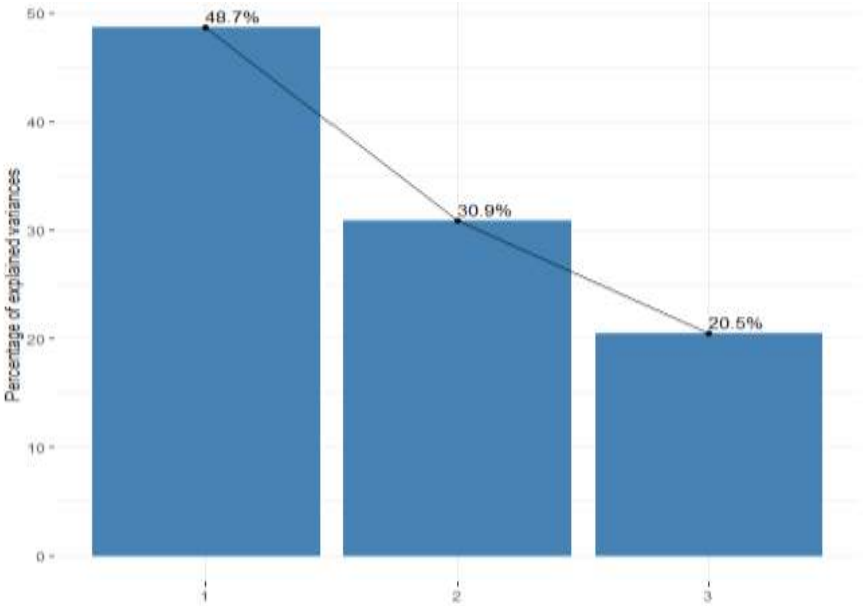


Figure 3.10 Scree plot of output variables PCA results

The labels of bars in Figure 3.10:
1st bar (1): First PC 2nd bar (2): Second PC 3rd bar (3): Third PC

Source: Author's compilation

It is also possible to see which variables contribute more to the components. Figure 3.11 describes the contribution of variables. ROS is dominated in the first component, while ROA is dominated in the second PC. The first two PCs are used as output variables for PCA-DEA. Figure 3.11 indicates that ROS and ROA play essential roles as output variables of PCA-DEA.

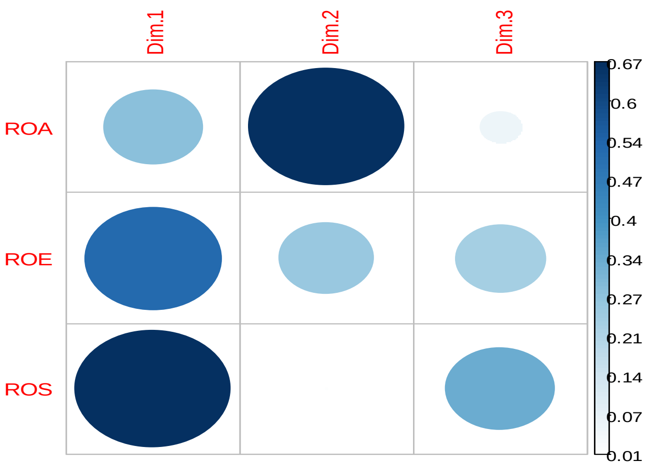


Figure 3.11. The contribution of variables to the components

Source: Author's compilation

The eigenvalue-analysis of input variables is provided in Table 3.32. According to the eigenvalue greater-than-one rule, the first three PCs were chosen for further analysis, which explains only 47.83% of the total variance. Therefore, the first five PCs explain 69.21% of the total variance is used for further analysis (Figure 3.12). Values between 70% until 90% is usually suggested; therefore, the first five components (69.2%) were used as input variables. It is also possible to see which variables contribute more to the components. Figure 3.13 describes the contribution of variables for the chosen components. Those five PC scores were used as input variables for the PCA-DEA method.

Table 3.32 PCA results of input variables

Principal components	**Eigenvalue**	**Proportion (%)**	**Cumulative proportion (%)**
PC1	*1.83*	*20.32*	*20.32*
PC2	*1.45*	*16.07*	*36.39*
PC3	*1.03*	*11.44*	*47.83*
PC4	*0.99*	*11.02*	*58.86*
PC5	*0.93*	*10.36*	*69.21*
PC6	0.85	9.49	78.70
PC7	0.79	8.72	87.42
PC8	0.70	7.76	95.19
PC9	0.43	4.81	100.00

Source: Author's compilation

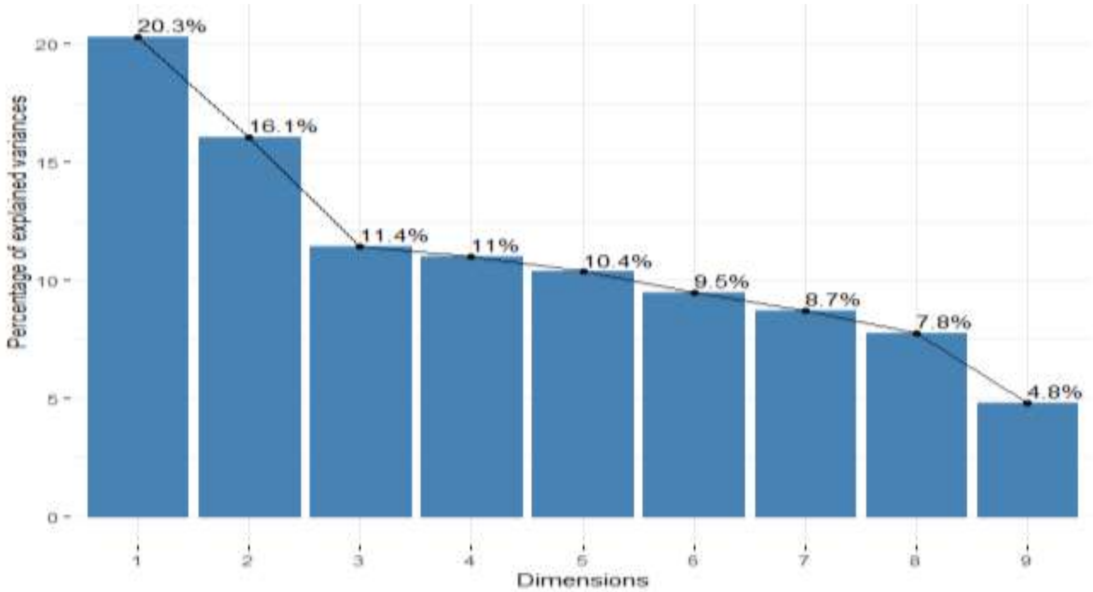


Figure 3.12 Scree plot of input variables PCA results

Source: Author's compilation

The labels of bars in Figure 4.12:

1st bar (1): First PC
2nd bar (2): Second PC
3th bar (3): Third PC
4th bar (4): Fourth PC
5th bar (5): Fifth PC
6th bar (6): Sixth PC
7th bar (7): Seventh PC
8th bar (8): Eighth PC
9th bar (9): Ninth PC

Figure 3.13 indicates that debts to total asset ratio is the least essential indicator, and sales growth is the indicator only for the first component. The efficiency results of the conventional DEA model and the PCA-DEA model - to analyse consistency - are illustrated in Figure 3.14.

Figure 3.14 indicates the efficiency result of PCA-DEA shows normal distribution compared with conventional DEA results. These comparison results are consistent throughout each sector and size (Appendix 6). It can also be stated in Appendix 6 that the PCA-DEA efficiency scores are closer to reality, which are normally distributed. Table 3.33 presents the efficiency scores of PCA-DEA along with descriptive statistics.

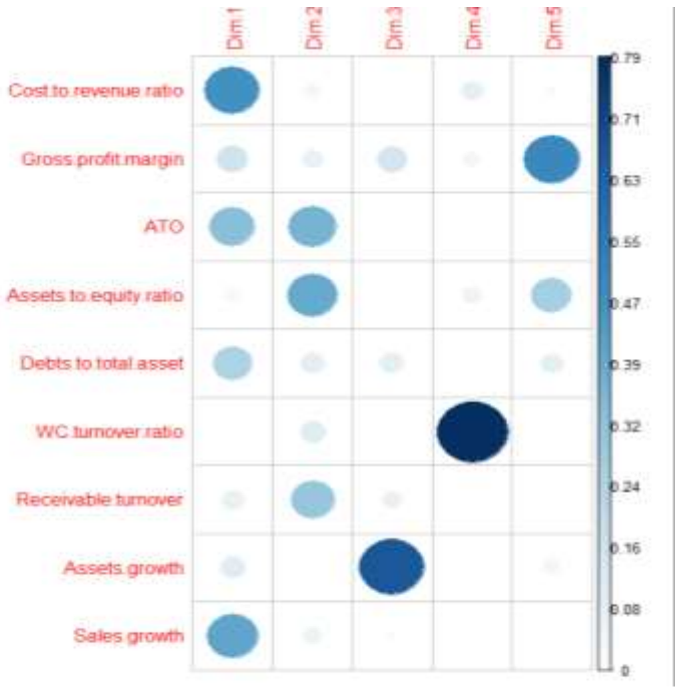


Figure 3.13. The contribution of variables to the first five components

Source: Author's compilation

In the conventional DEA model, efficiency scores were calculated using the original data (sector-specific and general inputs; three output variables), and the PCA-DEA model used the first two PCs of output variables and the first five PCs of input variables. It was hard to distinguish which model to use what variables to use, as the efficiency results differ greatly from model to model. Also, the efficiency scores were either too low (between efficiency range 0.0-0.3) or too high (more than half of the companies are efficient) in conventional DEA. However, PCA-DEA gave similar consistent results in the case of three sectors and two sizes. In PCA-DEA, efficiency scores fitted in a better way to normal distribution. This shows that the reduction of variables has a considerable effect on the classification of efficiency.

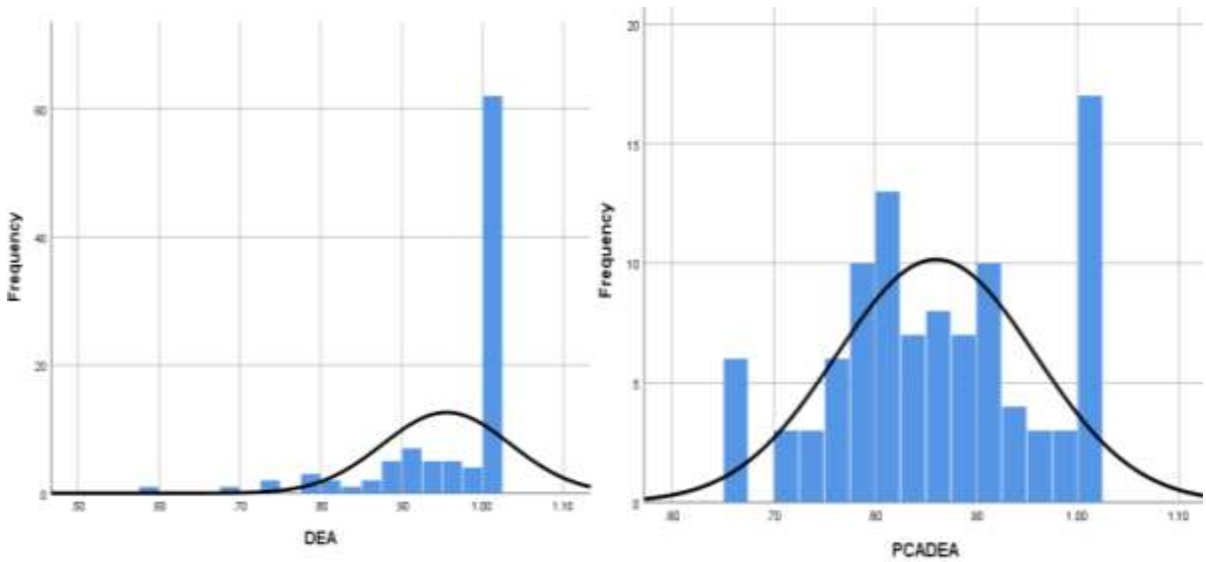


Figure 3.14 Comparison of DEA and PCA-DEA results (All dataset)

Source: Author's compilation

Table 3.33 Efficiency results of PCA-DEA

Efficiency Range	Size			Sector		
	All	SME	Big	Heavy	Manufacturing	Service
0.6-0.7	6	5	-	-	-	-
0.7-0.8	22	20	2	3	2	5
0.8-0.9	35	32	1	12	2	12
0.9-1.0	20	17	3	9	13	9
1.0	17	16	4	9	14	10
Minimum	0.65	0.65	0.72	0.72	0.77	0.77
1st Quartile	0.79	0.79	0.85	0.85	0.94	0.81
Median	0.86	0.86	0.98	0.91	0.99	0.91
Mean	0.86	0.86	0.92	0.91	0.95	0.90
3rd Quartile	0.93	0.93	1.00	1.00	1.00	1.00
Maximum	1.00	1.00	1.00	1.00	1.00	1.00

Source: Author's compilation

VRS and CRS efficiency scores differ widely for every sector and both sizes. However, efficiency scores from PCA-DEA are similar in both models. For example, PCA-DEA by VRS determined 17 efficient companies, while 15 companies are efficient in the case of the CRS model. If we classify companies by sector, nine service companies are efficient, including only one big corporate (both VRS and CRS model). As for the manufacturing sector, big companies are inefficient by PCA-DEA, while four efficient companies (VRS) and three efficient companies (CRS) are determined. In heavy industry, the number of efficient companies is the same as the manufacturing sector' (4-VRS, 3-CRS); however, one of the efficient companies is the biggest mining company in Mongolia.

3.3.7 Stochastic Frontier Analysis

Like the DEA method, the SFA method is also commonly used for measuring efficiency. SFA is a parametric approach and is suited to measure the efficiencies of the industry for input/output information (Lin & Tseng, 2005). Alike the DEA method, the SFA method also receives a score of 1 for efficient companies. However, it does not require any efficient company for every observation unless possible inefficiency (u) is equal to zero. The stochastic frontier approach assumes the deviations are either due to noise or inefficiency. The additive model was used in this subchapter. The estimation of the additive model is similar to the multiplicative model, which differs only by the omission of the log of the variables.

In the case of DEA, the variables are chosen based on panel regression; however, those variables are insignificant according to the SFA model. In Table 3.34, the estimation of the SFA model is displayed.

Table 3.34 Estimation of SFA model

Variables	Coefficient	Standard error	T-value	Pr(>|t|)
(Intercept)	0.062	0.012	4.94	0.000
Cost to Revenue	-0.040	0.005	-7.06	0.000
Debt to Assets	-0.243	0.011	-21.24	0.000
GPM	-0.064	0.022	-2.90	0.004
Lambda	-4.513	1.335	-3.38	0.001

Source: Author's compilation

According to the SFA model, only cost to revenue, debts to total assets, and GPM ratios are significant to the efficiency (ROA). If the parameter is 0, there is no effect from differences in efficiency, and if it is very large, differences are almost only due to differences in the efficiency and not to other kinds of uncertainty (Bogetoft & Otto, 2011). In Table 3.34, it is seen that the estimated parameter is -4.513, which means that the total error variance is 95.3% due to inefficiency.

From Table 3.35, we see that the percentage of total variation due to variation in efficiency is 95.32%. The estimated variance for the variation in efficiency (u) is 0.022 and is considerably larger than the variation due to random errors (v), which is 0.001. 95.32% of the total variation is due to inefficiency, and the remaining 4.68% is the random variation. The variance for efficiency is larger than the variance of random errors.

Table 3.35 Estimation variation in SFA

Variance for inefficiency	U	0.022
Variance for random errors	V	0.001
Inefficiency variation to total variation (%)	100*lambdaˆ2/(1+lambdaˆ2)	95.32%

Source: Author's compilation

Efficiency scores from DEA were calculated based on the panel regression results in the previous subchapter. For the sake of comparability, DEA was calculated again using the same variables as the SFA model. The efficiency results are illustrated in Table 3.36.

Table 3.36 Comparison of DEA and COLS efficiencies

Efficiency ranges	**DEA**	**SFA**	**Descriptive statistics**	**DEA**	**SFA**
0.5-0.6	24	-	*Minimum*	*0.085*	0.63
0.6-0.7	5	3	*1st quartile*	*0.604*	0.853
0.7-0.8	17	6	*Median*	*0.807*	0.913
0.8-0.9	28	34	*Mean*	*0.748*	0.893
0.9-1.0	13	55	*3rd quartile*	*0.892*	0.953
1.0	11	-	*Maximum*	*1.000*	0.999

Source: Author's compilation

The mean efficiency score of SFA is comparatively higher than that of DEA. As for the DEA method, 11 companies are efficient, while the SFA model did not determine any efficient company. However, more than half of the DMUs are determined as working in the efficiency range of 0.9-1. As two methods showed entirely different efficiency results, the correlation of efficiency scores from DEA and SFA were calculated. According to the Pearson correlation, the efficiency scores from SFA and ROA have a moderate negative correlation (-0.34). Efficiency results are inconsistent. Also, the variables determined by Panel regression are insignificant in the case of SFA. Therefore, SFA is assumed as an inappropriate model to evaluate Mongolian companies' financial performance.

3.3.8 Intellectual Capital effect on Financial Performance

In this subchapter, ROA was used as a dependent variable representing profitability (performance), while MVAIC (Modified Value-Added Coefficient) and its four components were used as independent variables representing IC. ROA is an indicator of how profitable a company is relative to its total assets, which is measured by net income divided by average total assets (Xu & Li, 2019). Table 3.37 illustrates the variables used in this research, along with its calculations.

Table 3.37 Measurement of variables

Variables	Labels	Measurements
Dependent variable		
Return on Assets	ROA	the ratio of net income divided by total assets
Independent variables		
Value Added	VA	OUT the total revenues IN the total expenses excluding employee expenditures
Capital Employed Efficiency	CEE	the ratio of value-added divided by capital employed which is both physical and financial capital, measured by total assets-liabilities
Human Capital Efficiency	HCE	the ratio of value-added divided by human capital.
Structural Capital Efficiency	SCE	the ratio of structure capital, measured by VA - HC, divided by value-added
Relational Capital Efficiency	RCE	marketing, selling and advertising expenses
Intellectual Capital Efficiency	ICE	HCE + SCE + RCE
Modified Value-Added Intellectual Coefficient	MVIAC	ICE + CEE

Source: Author's compilation

As the firm uses its human, structural, physical, and financial capital, the firm creates value added to the firm. The more efficiently these capitals are used, the more value is added to the firm, the higher the VAIC (Clarke et al., 2011).

The results of the research were tested through descriptive statistics, correlation analysis, MANOVA, ANOVA, and unconditional quantile regression. Data includes the companies of different sizes so that they displayed extreme values. Revenue was used to classify companies to improve distribution. Unconditional Quantile Regression (UQR), uqr package in R, was applied to group the companies into four ranges by its sizes. Descriptive statistics of 4 groups are illustrated in Table 3.38.

Table 3.38 Descriptive statistics

Variables	***Range 1***	***Range 2***	***Range 3***	***Range 4***	***Range 1***	***Range 2***	***Range 3***	***Range 4***
	ROA				CEE			
Minimum	- 1.24	- 0.31	- 0.09	- 0.07	- 1.21	- 1.92	- 2.41	0.07
Mean	- 0.14	- 0.02	0.04	0.04	0.07	- 0.01	0.11	0.51
Median	- 0.01	- 0.00	0.01	0.04	0.09	0.09	0.18	0.25
Maximum	0.18	0.08	0.38	0.37	0.47	0.51	0.94	5.43
IQR/Total range (%)	6.05	8.17	17.24	13.38	7.29	6.94	9.67	4.73
Variables	SCE				RCE			
Minimum	- 1.64	- 9.63	- 1.20	- 1.85	- 4.02	- 4.63	- 4.63	0.03
Mean	0.49	- 0.31	0.44	0.30	0.86	2.65	1.53	1.03
Median	0.23	0.09	0.30	0.34	1.19	1.48	0.62	0.72
Maximum	3.16	4.52	2.70	0.96	5.68	18.88	8.69	3.48
IQR/Total range (%)	28.55	4.86	15.29	23.46	40.26	13.29	17.19	35.48
Variables	HCE				MVAIC			
Minimum	-75.50	- 5.36	- 5.81	0.35	- 75.68	- 9.16	- 4.58	1.16
Mean	- 4.19	0.82	4.25	3.00	- 3.71	4.13	6.40	4.86
Median	0.80	1.02	1.17	1.52	2.46	3.18	3.17	3.85
Maximum	4.67	4.32	75.88	24.44	11.39	17.92	75.32	25.68
IQR/Total range (%)	2.93	9.07	1.21	9.70	8.59	14.35	4.56	11.21

Source: Own calculation by SPSS statistical program

In Table 3.38, 1^{st} and 2^{nd} range companies have negative values in ROA, which are considered as smaller companies have a negative mean of ROA (-0.14 and -0.02, respectively), implying that SMEs have difficulties in making a profit. On the contrary, companies in the 3^{rd} and 4^{th} ranges have positive ROA, which shows the advantage of being big. The HCE is the most influential component of VAIC with the greatest mean values, where the lowest mean is -4.19 in the 1^{st} quartile, and the highest mean is 4.25 in 3^{rd} quartile. This is consistent with the mean values of the MVAIC that the companies in the 1^{st} range have the lowest mean, while the companies in the 3^{rd} range have the highest mean. The highest mean of MVAIC is 6.40 reveals that companies in the 3^{rd} range create MNT 6.4 for every MNT 1.00 utilized. The values of other components of MVAIC have a higher value than the values of the CEE, which indicates the companies create more value by using IC rather than by the physical and financial components.

MANOVA (Multivariate Analysis of Variance) was used to examine whether the variables differ across the quartiles. MANOVA results proved the existence of a statistically significant difference among the groups in the case of all of the independent variables; the value of the Pillai-test showed a significant difference at the 0.05 significance level. Since the MANOVA showed a statistically significant result, therefore, the ANOVA was applied for each of the variables separately. The CEE and HCE ratios were statistically significantly different among the groups at the 0.05 significance level; however, the SCE and RCE ratios were proven to be statistically insignificant. For further analysis of the variables, Pearson's correlation was applied by SPSS. The correlation coefficient analysis is given in Table 3.39.

Table 3.39. Pearson's Correlation

1^{st} range	***ROA***	***CEE***	***HCE***	***SCE***	***RCE***	***3^{rd} range***	***ROA***	***CEE***	***HCE***	***SCE***	***RCE***
CEE	-0.04					CEE	0.41				
HCE	0.27	0.12				HCE	-0.05	-0.85			
SCE	-0.54	-0.24	-0.18			SCE	0.14	-0.30	0.11		
RCE	0.50	0.19	0.27	-0.87		RCE	-0.24	0.04	-0.04	-0.68	
MVAIC	0.25	0.15	0.93	-0.31	0.38	MVAIC	-0.09	-0.83	0.98	0.00	0.16
2^{nd} range	**ROA**	**CEE**	**HCE**	**SCE**	**RCE**	**4^{th} range**	**ROA**	**CEE**	**HCE**	**SCE**	**RCE**
CEE	0.37					CEE	-0.18				
HCE	0.73	0.50				HCE	0.88	0.04			
SCE	-0.01	-0.03	0.02			SCE	0.32	0.04	0.44		
RCE	0.12	0.17	0.09	-0.92		RCE	-0.40	0.56	-0.31	-0.27	
MVAIC	0.27	0.45	0.41	-0.79	0.89	MVAIC	0.76	0.35	0.94	0.41	-0.01

Source: Own calculation by SPSS statistical program

Table 3.39 represents a correlation matrix from Pearson's correlation coefficient analysis. For the 4^{th} quartile of companies, MVAIC has significant positive correlations with ROA. In other words, IC affects big companies' performance and profitability significantly. But SMEs (1^{st} and 2^{nd} quartiles) have a weak positive correlation on MVAIC and ROA. Unexpectedly 3^{rd} quartile companies have a weak negative correlation. In the case of the big companies (4^{th} quartile), MVAIC is found to be significantly positively associated with EBIT, ROA, and ROS.

RCE demonstrates a positive relationship with ROA in the case of SMEs (1st and 2nd quartiles), while big companies (3rd and 4th quartiles) showed the opposite correlations.

As data includes outliers that have a great effect on the mean value of the data but have little effect on the median. R^2 or adjusted R^2 is based on deviations from the arithmetic mean. To clarify, OLS regressions provide a simple way of estimating the effect of explanatory variables on the conditional mean of an outcome variable, while quantile regressions provide simple estimates of the effect of the same variables on any conditional quantile of the outcome variable (Firpo et al., 2009). Therefore, the Unconditional Quantile Regression (UQR), which is calculated using the median is more appropriate than OLS calculated using mean. UQR was executed on the *'uqr'* package of the R statistical program. In quantile regression, there is not R^2 or adjusted R^2. Therefore, pseudo R^2 is used in harmony with quantile regression, which takes the value of 0-1. Unconditional Quantile Regression results are presented in Table 3.40.

Table 3.40. Unconditional Quantile Regression results

Variables	***Coefficients***	***Lower***	***Upper***	***Tprob***	***Coefficients***	***Lower***	***Upper***	***T-test p value***
	1st range - Revenue below 230.975				*2nd range - Revenue 230.975 - 1.585.870*			
Intercept	-0.0134	-0.0166	-0.0103	0.0000	0.0033	0.0009	0.0057	0.0077
CEE	0.0177	0.0140	0.0215	0.0000	0.0029	0.0025	0.0034	0.0000
HCE	0.0021	0.0015	0.0027	0.0000	0.0000	0.0000	0.0000	0.0000
SCE	0.0006	0.0004	0.0008	0.0000	-0.0001	-0.0002	0.0000	0.0327
RCE	0.0004	0.0003	0.0005	0.0000	0.0000	0.0000	0.0001	0.4931
Variables	*3rd range-Revenue 1.585.870 - 10.282.122*				*4th range - Revenue above 10.282.122*			
Intercept	0.0099	0.0057	0.0142	0.0000	0.0223	0.0188	0.0258	0.0000
CEE	0.0104	0.0082	0.0127	0.0000	0.0005	-0.0060	0.0071	0.8699
HCE	0.0000	0.0000	0.0000	0.0000	0.0018	0.0012	0.0024	0.0000
SCE	0.0010	0.0002	0.0018	0.0149	0.0227	0.0169	0.0285	0.0000
RCE	0.0006	0.0004	0.0009	0.0000	-0.0093	-0.0126	-0.0060	0.0000

Source: Own calculation from RExcel statistical program

Table 3.40 shows the unconditional quantile regression coefficients of the VAIC and its components as independent variables, using each performance measure ROA as the dependent variable. CEE has a positive and significant impact on the efficiency of SMEs (1st, 2nd, 3rd quartiles), while it fails to show a significant impact in big companies (4th quartile). All four components are found to be statistically significant in the 1st and 3rd quartiles. The coefficient of HCE ratio is positive and significant across all quartiles (1% significance level). In the case of quantile regression, R = 0.3-0.5 is considered a weak correlation (pseudo $R^2 > 0.1$), while the amount below 0.3 will be considered as insignificant. In the results, Pseudo R^2 is 0.249 for the 1st quartile, and 0.308 for the 2nd quartile, which means IC explains 24.9-30.8 percent of the variance in the dependent variable. IC has less explanatory power in the case of big companies (pseudo R^2 is 0.074 for the 3rd quartile, 0.133 for the 4th quartile), which is considered as insignificant. This result is a strong indicator that there is a relationship between the overall IC and companies' performance (profitability). CEE has greater explanatory power than SCE, HCE, and RCE, excluding the 4th quartile, shown by its larger standardized coefficients. Therefore, CEE is a more dominant component of the VAIC to predict performance. This result is consistent with prior studies, for instance, Clarke et al. (2011). RCE in the 2nd quartile is found to be insignificant in profitability (performance), which is consistent with the opinion of Vishnu and Gupta (2014) and Xu and Li (2019). Moreover, CEE in the 4th quartile is also insignificant.

4 CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions to Comparison of Some Asian Countries' Economic

Mongolian economic growth is compared with the selected three Asian lower-middle-income countries' economic growths, i.e., Kyrgyzstan, Kazakhstan, and Indonesia. Economic growth is determined by two dependent variables and 20 independent variables. ANOVA test revealed that the most independent variables are significantly different among countries, except inflation rate and consumer price index. On the contrary, none of the dependent variables is significantly different among the countries. Consumer price index and employment to population ratios are significantly important ratios for all the four countries' economic growth. The urban population significantly affects economic growth except for Kyrgyzstan. Although the inflation rate and consumer price index together determine 80.5% of the economic growth, there is high multicollinearity among the macroeconomic variables.

According to multidimensional scaling results, the Indonesian economy is significantly different from other countries' economies, while Kyrgyzstan's economy is the most similar to the Mongolian economy. As for Mongolian and Kyrgyzstan economic growth, only 38.9% and 23.8% are explained by the given variables. Moreover, both countries' economic growth is explained by different variables. Consequently, it is assumed that the Mongolian economy is unique and inappropriate to compare with that of other countries, which suggests that there are significant differences between the Mongolian economic growth and the other selected Asian countries' economic growth.

Therefore, it is not appropriate to compare Mongolian companies with foreign companies from different economic situations. Companies are compared to their sectors and sizes.

4.2 Conclusions to Mongolian Economy and Economic Growth

Mongolian economy relies heavily on mineral extraction, particularly copper, coal, and gold. The mining sector's exports can explain it constituted up to 89.2% of the total export. The mining sector constitutes 20.7% of the GDP (in 2016); however, only 3.3% of the workforce is related to the mining sector. On the contrary, the agricultural sector provides most of the workplace, which is 30.36% of the total workforce (348,487 people) in 2016, although this sector constitutes only 11.68% of the total GDP (2,796.1 million MNT). The number of herdsmen is relatively small in comparison to the total population, which is about 10% of the population; however, the number of livestock is approximately 19.72 times more than the population. Surprisingly, the output growth of the animal husbandry was shown to be statistically insignificant to the NDP growth rate, although Mongolia has traditionally been based on agriculture or rather animal husbandry. In 2016, the construction sector made up 3.96%. This sector faces challenges due to the harsh climate and the shortness of the business activity period. The service sector also plays an essential role in the Mongolian economy by constituting 41.65% of total GDP and employing 37.35% of the total workforce.

NDP is chosen as a dependent variable representing the Mongolian economy. Mongolian economic determinants are the growth rate of export, which have a robust positive correlation with the NDP growth rate. Dollar rate growth showed a very strong negative relationship with the rate of economic growth: the correlation coefficient equals -0.65 with the p-value of 0.005. The inflation rate exhibits a significant correlation with economic growth: a coefficient of 0.60 with a p-value of 0.01. The dollar rate growth, inflation rate, and growth of export were responsible for 81.4% of the variation in NDP growth rates of Mongolia. Export growth itself can explain 63.9% of Mongolian economic growth. Export growth is the most influential determinant in Mongolian economic growth. Dollar exchange rate growth is responsible for 42.2% of economic growth. The high values of the coefficients of variation indicate that the variability and inhomogeneity are also enormously high.

4.3 Conclusions to Performance Evaluation

The chosen variables had huge variability, and the more significant part of their total range was in the fourth quarter. Therefore, k-medoids is applied to classify companies based on their sizes. According to the silhouette method, 90 companies are classified in the 1st cluster (SMEs), while only 10 companies were in the 2nd cluster (big companies). The second cluster's companies (big companies) earn approximately 108 times more profit than SMEs on average, which also demonstrates the substantial difference between the two clusters.

As for SMEs, only manufacturing companies have positive profitability ratios, while service and heavy industry have negative ones. SMEs have a low and negative amount of NWC turnover ratio (-21.03). It shows that SMEs invest in excessive receivables and inventories to support their sales, which could lead to an excessive amount of bad debts or obsolete inventory. ROS ratio is much higher in big companies than SMEs, which means that larger companies pay greater attention to cost management than the smaller ones. Moreover, the value of ROA is about ten times higher in big companies than SMEs, which means the efficiency of asset management in larger companies is much better than smaller companies. Hypothesis 2 is supported. *Big corporates are more efficient than SMEs.*

Panel regression is employed on the whole dataset as well as separately on each sector to calculate sector-specific performance determinants. Debts to total assets ratio have significant positive impacts on ROE only, while this ratio has significant impacts on all output variables on the whole dataset. Although sales growth and asset growth have significant positive impacts on the ROA of the whole dataset, growth does not determine the manufacturing sector significantly. As for the service sector, operational flow is tightly connected with current assets rather than non-current assets. Therefore, it can be concluded that the proportion of liquid assets influences the service sector's profitability positively. Also, it is noteworthy that liquidity does not determine the financial performance of Mongolian companies. The operating cycle determines only the service sector. On the one hand, the payables turnover ratio is significant only for heavy industry. On the other hand, the cash ratio is significant only for the heavy industry. VRS model using general ratios determined more than half of the companies as efficient regardless of sector and output variables (ROA, ROE, ROS). In contrast, the CRS model defined most of the companies working under the efficiency range of 0.0-0.4. Therefore, the selection of VRS and CRS models is vitally important, which must be made carefully. The change of the model significantly changes the efficiency score.

Furthermore, it is assumed that either the input ratios are too many compared with the number of DMUs, or the VRS model is not appropriate as it cannot discriminate between efficient and inefficient companies.

On efficiency scores, unrelated ANOVA was executed using the sector as a factor. The F-test was significant (significance level = 0.05). Therefore, it is concluded that the significant difference exists efficiency results among the sectors. To identify which sector, differ from other sectors, I continued unrelated ANOVA on pair of sectors separately. As for the Heavy industry and service sector, unrelated ANOVA on CRS (sector as a factor), revealed significant difference, F-test showed a significant difference at a significance level 0.01. Likewise, there was also a significant difference between the Heavy industry and manufacturing sector; F-test was significant at a significance level of 0.01. However, the efficiency of service and manufacturing did not differ significantly based on F-test.

Sectors' efficiency results show that sector-specific determinants do not necessarily mean better efficiency results. Hypothesis 1 is refuted. *(H1): The heavy industry is the most efficient sector in the Mongolian economy.*

PCA-DEA model used the first two PCs of output variables and the first five PCs of input variables. The efficiency scores were either too low (between efficiency range 0.0-0.3) or too high (more than half of the companies are efficient) in DEA. However, PCA-DEA gave similar consistent results in the case of 3 sectors and two sizes. For example, PCA-DEA by VRS determined 17 efficient companies, while 15 companies were efficient in the case of the CRS model. If we classified companies by sector, 9 service companies were efficient, including only one big corporate (both VRS and CRS model). As for the manufacturing sector, big companies were inefficient by PCA-DEA, while four efficient companies (VRS) and three efficient companies (CRS) were determined. In heavy industry, the number of efficient companies was the same as the manufacturing sector' (4-VRS, 3-CRS); however, one of the efficient companies was the biggest mining company in Mongolia. In PCA-DEA, efficiency scores were closer to a normal distribution. This shows that the level of information reduction has a considerable effect on the classification of efficiency. It suggests that DEA efficiency scores can be improved by using principal component analysis.

The mean efficiency score of SFA was comparatively higher than that of DEA. As for the DEA method, 11 companies were efficient, while the SFA model did not determine any efficient company. However, more than half of the DMUs were determined as working in the efficiency range of 0.9-1. As two methods showed entirely different efficiency results, correlation of efficiency scores from DEA and SFA were calculated. Pearson's correlation results showed a moderate negative correlation (-0.34) on efficiency scores from SFA and ROA. Efficiency results were inconsistent. Also, the variables determined by panel regression were insignificant in the case of SFA. Therefore, SFA is assumed as an inappropriate model to evaluate Mongolian companies' financial performance. Hypothesis 4 is rejected. *H4: Efficiency results by SFA are compatible with that of DEA in the case of Mongolian listed companies.*

In the final stage of the research, the impact of IC on financial performance is analyzed - via UQR. ROA was chosen as dependent variables, while MVAIC and its four components were regarded as independent (CEE, SCE, HCE, and RCE). Uqr packages of the R statistical program was used for the analysis.

As data contains outliers, companies were classified into four ranges based on their sizes representing revenue. From the descriptive analysis, it can be concluded that SMEs (1st and 2nd quartiles) have difficulties with making profits as ROA has negative values -0.14 and -0.02, respectively. Moreover, the mean of CEE is highest in the 4th quartile. It indicates that big companies create value more efficiently through physical and financial assets. HCE is highly correlated with the profitability of the bigger companies, i.e., 3rd and 4th quartiles (0.73 and 0.83, respectively). It shows the importance of using human capital efficiently.

The impact of CEE on performance is greater in SMEs (1-3rd quartiles) than in big companies (4th quartile). According to Pearson's correlation, there is a weak correlation between ROA and MVAIC (0.285). ROA is significantly influenced by four components of IC, except RCE in the 2nd quartile and CEE in the 4th quartile. Based on the results, it can be concluded that IC affects significantly and positively on Mongolian public companies' financial performance regardless of their sizes. Hypothesis 5 is supported. *H5: IC has a significant positive impact on financial performance.*

However, the significant difference does not exist between IC and sectors based on F-test. Pearson correlation is executed on MVAIC and efficiency scores if each sector. The heavy industry has the highest correlation of 0.356, followed by service sector 0.34 and manufacturing 0.276.

4.4 Main Conclusions and Novelty of thesis

Performance measurement is one of the topics that attract attention and analysed in the case of many countries. However, there is not any published research that used Mongolian companies as data. The thesis aims to analyse Mongolian listed companies' financial performance, from 2012 to 2018. As listed companies are required to be audited before publishing their financial statements, their financial statements are more reliable. Data covers 100 companies' financial statements from 2012 to 2018. Four companies went bankrupt during this period; therefore, the thesis used unbalanced data.

At first, it is important to evaluate the Mongolian current economic situation to evaluate the performance of Mongolian companies. The thesis compares Mongolian economic determinants with that of the selected three Asian countries. According to Multidimensional scaling, Kyrgyzstan's economy is the closest economy to the Mongolian economy. However, it is impossible to determine well both countries' economic growth based on the given variables (adjusted R^2 are 38.9% and 23.8%). Mongolia is a mining-based unique country; therefore, it would be inappropriate to analyse horizontally.

Mongolian economic growth is analysed to figure out what sector is the most crucial in the Mongolian economy. To do so, NDP is chosen as a dependent variable representing economic growth, and 20 macroeconomic variables are chosen as independent variables. Dollar rate growth, inflation, and export are the main determinants of Mongolian economic growth (based on the regression results executed by SPSS). Mongolian economy directly depends on mining export; therefore, as export increases, so does the economy. Since the exports are made mostly by the dollar, it also affects the dollar exchange rate. Moreover, the dollar exchange rate has an effect on consumer products, which has a direct impact on inflation.

Data includes companies from different sectors and with different sizes. Some of the companies are the biggest companies in Mongolia, while some of the companies are rather start-up businesses. In performance measurement, it is advisable to use companies from the same sector as different factors determine every sector. Unfortunately, data contained companies from 17 different sectors. So, it is impossible to analyze by their exact sector and tried to generalize companies into three different sectors. When it comes to horizontal analysis, it is recommended to use financial ratios as input and output variables. Therefore, financial ratios are used as variables that allow analyzing companies with different sizes. Although financial ratios are used in the thesis, it was clear from the descriptive analysis that the data contains outliers. Therefore, k-medoids clustering is used to classify companies into two groups. Revenue and total assets are used to represent the sizes. According to the k-medoids results, only 10 companies are in the second cluster (big corporates), while the rest of the companies are SMEs (90 companies in the first cluster). Unrelated ANOVA on VRS efficiency scores is executed using cluster as a factor. The F ratio = 2.416, which is insignificant. Therefore, it is concluded that there is not a significant difference between big corporates and SMEs' performance. Hypothesis 3 is rejected. *(H3): The k-medoids clustering improves the performance measurement of the Mongolian companies investigated.*

Initially, 20 variables were chosen as input variables; however, some of the variables are excluded due to multicollinearity, i.e., cash ratio, current ratio, net operating cycle, operating cycle, and return on cost. After excluding those variables, panel regression was executed by R excel to define the determinants for each three output variables and each sector. Both FE and RE models are performed, and based on the Hausman test, it is decided which model to choose. Although there were the same variables that are specific for the sector, i.e., current assets to total assets ratio for the service sector, variables determined for a certain sector did not differ widely.

The performance of every sector was evaluated by output-oriented DEA, VRS-DEA, CRS-DEA, PCA-DEA, and SFA methods. For DEA, input variables determined for certain sectors and general ratios (same for every sector) are used separately. Efficiency results were similar to each other in the case of sector-specific variables and general input variables, however, depending on which model efficiency results significantly differ. For example, many efficient companies from the VRS model turned into inefficient in the CRS model. Even inefficient companies' efficiency scores reduced significantly. Discriminative power might be declined due to an insufficient number of DMUs in data when sectors are evaluated separately. Therefore, the DEA-VRS model is executed for all data set, and then the efficiency scores of companies are classified by sector and compared with separately performed efficiency scores. The number of efficient companies is always less when the sector unbiased efficiency scores are rearranged into the sector. It can be explained by the efficient companies in a certain sector that might not be efficient than other companies from another sector. Unrelated ANOVA is executed to reveal whether a significant difference exists in the sector's efficiency scores. According to ANOVA results, a significant difference exists between heavy industry and service, heavy industry and manufacturing sector. However, the efficiency results of the manufacturing sector and service sector do not differ significantly.

DEA determines the majority of DMUs as efficient when the number of variables is relatively high and the number of DMUs insufficient. Therefore, PCA is combined with DEA using the same variables. Also, the efficiency scores were either too low (between efficiency range 0.0-0.3) or too high (more than half of the companies are efficient) in conventional DEA. However, PCA-DEA gives similar consistent results in the case of 3 sectors and two sizes. In PCA-DEA, efficiency scores are closer to a normal distribution. This shows that the level of information reduction has a considerable effect on the classification of efficiency.

The mean efficiency score of SFA is comparatively higher than that of DEA; however, the SFA model did not determine any efficient company. SFA proved more than half of the DMUs between the efficiency range of 0.9-1. As the SFA model showed entirely different efficiency scores (efficiency scores of DEA and SFA negatively correlates -0.34) and the variables determined by panel regression are insignificant when it comes to SFA. Therefore, SFA is assumed as an inappropriate model to evaluate Mongolian companies' financial performance.

IC is an essential and integral part of revenue creating process. However, due to the hardness of valuation, IC is often ignored in performance measurement. MVAIC and its four components are used representing IC, while ROA is used representing profitability (performance). The impact of IC on financial performance is conducted by UQR on R excel.

4.5 Summary

This thesis includes four major chapters. The thesis starts with discussing the aim, objectives, research approaches, and ethical considerations.

The first chapter demonstrated the literature review of the business analysis and performance measurement. The business analysis comprises of four parts: strategy analysis, accounting analysis, financial analysis, and prospective analysis. The main scope of the thesis is financial analysis. Therefore, the financial analysis was explained in detail, while strategy analysis, accounting analysis, and prospective analysis were briefly described as they are also parts of business analysis. Financial analysis is extended by ratio analysis. Afterwards, performance measurement was explained, which started from the definition of effectiveness and efficiency and followed performance measurement approaches.

Chapter 2 described data and the general research methodology used in the thesis. The chapter examined research data sources and described a comprehensive review of the DEA, SFA, PCA, and k-medoids analysis. The basic DEA concepts, together with the formulations, were explained and moved forward to more advanced issues development of DEA. Moreover, the concepts of SFA with a discussion of its advantages and disadvantages and a comparison between DEA and SFA methods were illustrated.

Chapter 3 began with a comparison between the Mongolian economy and three other Asian countries' economies. Afterwards, an introduction to the main features of Mongolia, its current economic situation, and main sectors, which are fundamental for the Mongolian economy, were introduced in this chapter. Then the empirical results of DEA and SFA for each sector were discussed.

Chapter 4 briefly summarized each chapter's key aspects and findings of the entire research and provided the main conclusion of the thesis with the novelty of this thesis.

Abbreviation list

COGS	Cost of Goods Sold
GPM	Gross Profit Margin
OPM	Operating Profit Margin
WC	Working Capital
MSE	Mongolian Stock Exchange
FDH	Free Disposability Hull
FRH	Free Replicability Hull
IRS	Increasing Return to Scale
DRS	Decreasing Return to Scale
DEA	Data Envelopment Analysis
SFA	Stochastic Frontier Analysis
VRS	Variable Return to Scale
CRS	Constant Return to Scale
PCA	Principal Components Analysis
PCA-DEA	Principal Component Analysis with Data Envelopment Analysis
PC	Principal Components
COLS	Corrected Ordinary Least Squares
SPSS	Statistical Package for Social Sciences
MANOVA	Multivariate Analysis of Variance
ROS	Return on Sales
ATO	Assets turnover
ROA	Return on Assets
ROE	Return on Equity
DMU	Decision-Making Unit
SE	Scale Efficiency
AE	Allocative Efficiency
TFA	Thick Frontier Approach
RE	Random Effects
FE	Fixed Effects
WC	Working Capital
NDP	National Domestic Product

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2. Bayaraa, B. (2017). Financial performance measurement with the use of financial ratios : case of Mongolian companies. *International Journal of Engineering and Management Sciences*, *2*(3), 20–32. https://doi.org/10.21791/IJEMS.2017.3.3.Financial

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List of publications related to the dissertation

Articles, studies (6)

1. **Bayaraa, B.**, Tarnóczi, T., Fenyves, V.: Comparison of the economic situation of Mongolia and some similar Asian countries.
   Economics and Working Capital. 3 (4), 2-6, 2019. ISSN: 2398-9491.
2. **Bayaraa, B.**, Tarnóczi, T., Fenyves, V.: Measuring performance by integrating k-medoids with DEA: Mongolian case.
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3. **Bayaraa, B.**: Determinants of Mongolian Economic Growth.
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6. **Bayaraa, B.**: Measuring efficiency of Mongolian companies by SFA and DEA methods. *Annals of the University of Oradea Economic Science. 26* (1), 39-48, 2017. ISSN: 1222-569X.

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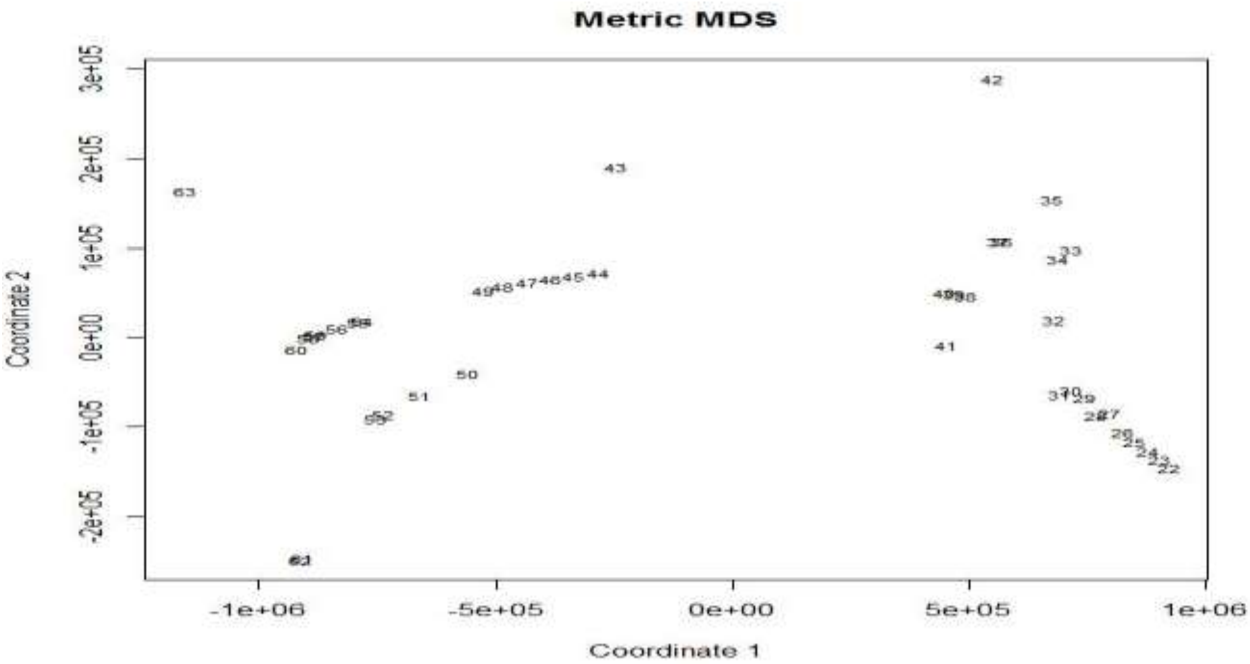
Table of Tables

Table of Figures

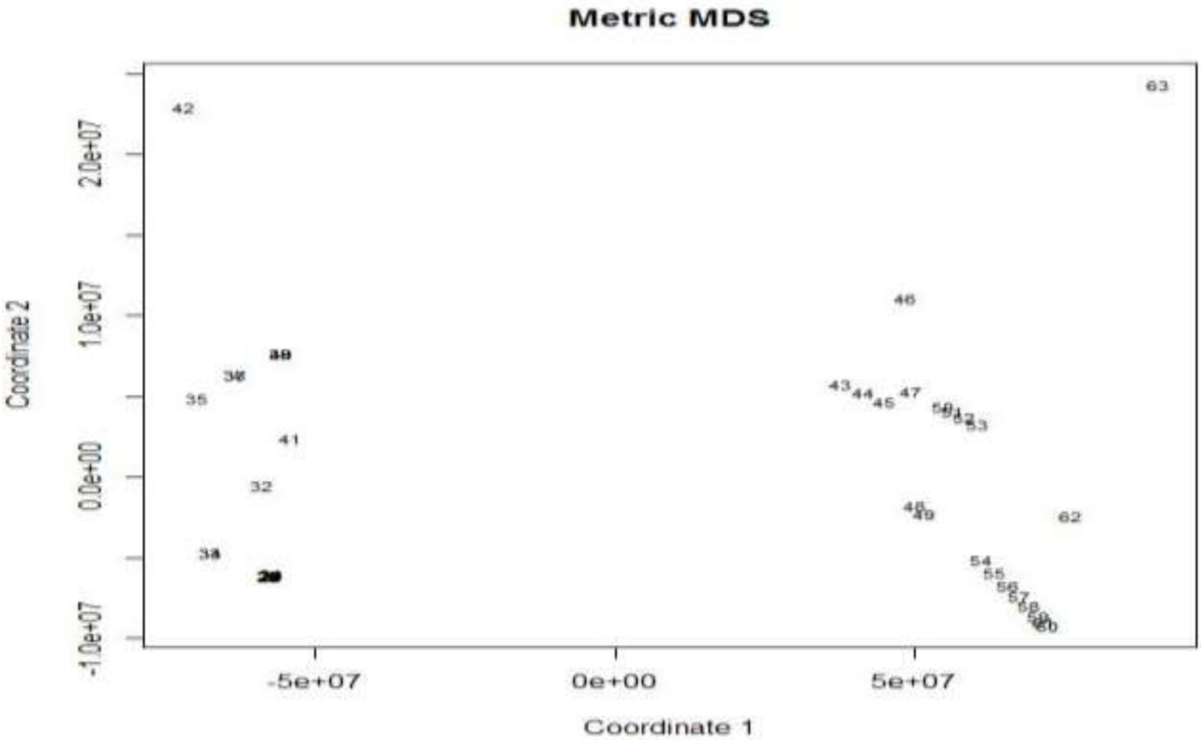
Appendices

Appendix 1: Comparison of selected Asian countries' economic

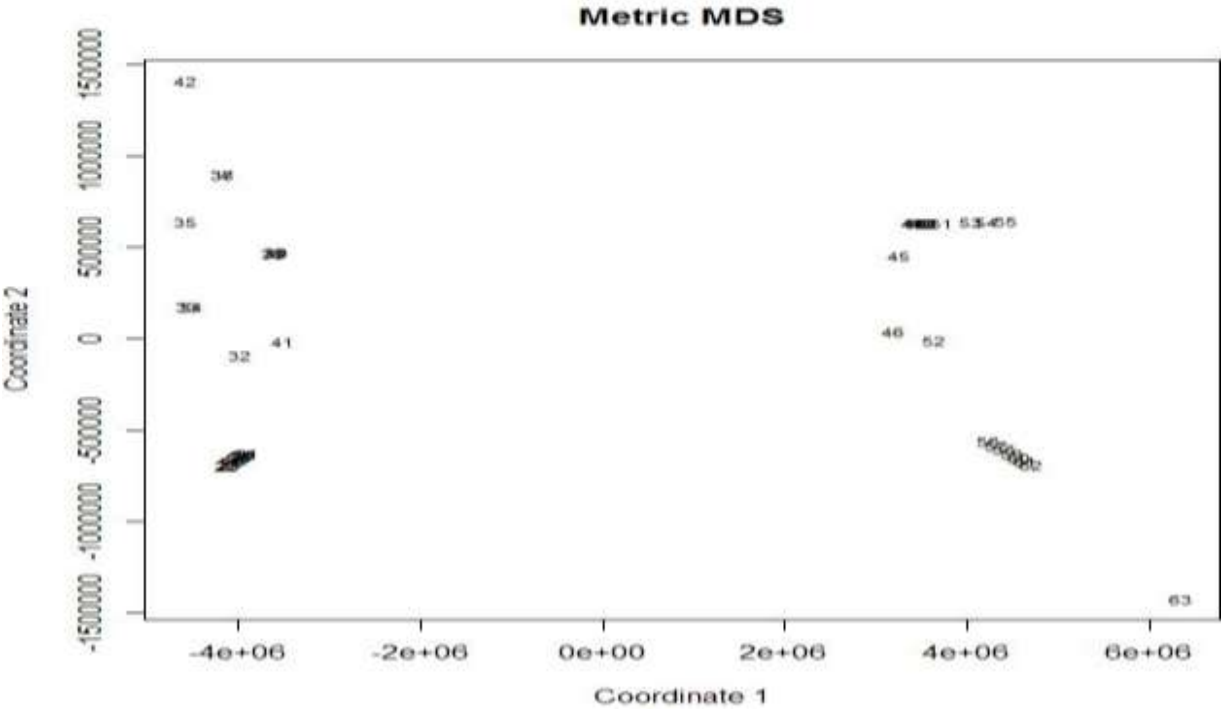
1-a. Multidimensional scaling (Mongolia 22:42 and Kyrgyzstan 43:63)



1-b. Multidimensional scaling (Mongolia 22:42 and Indonesia 64:84)



1-c. Multidimensional scaling (Mongolia 22:42 and Kazakhstan 1:21)

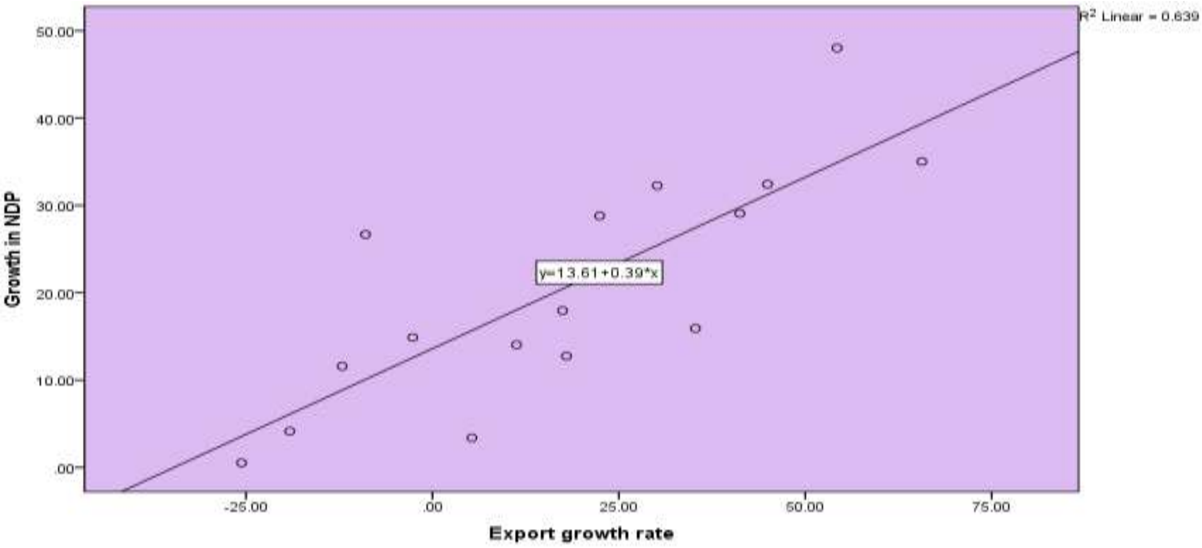


Appendix 2: Mongolian economic growth

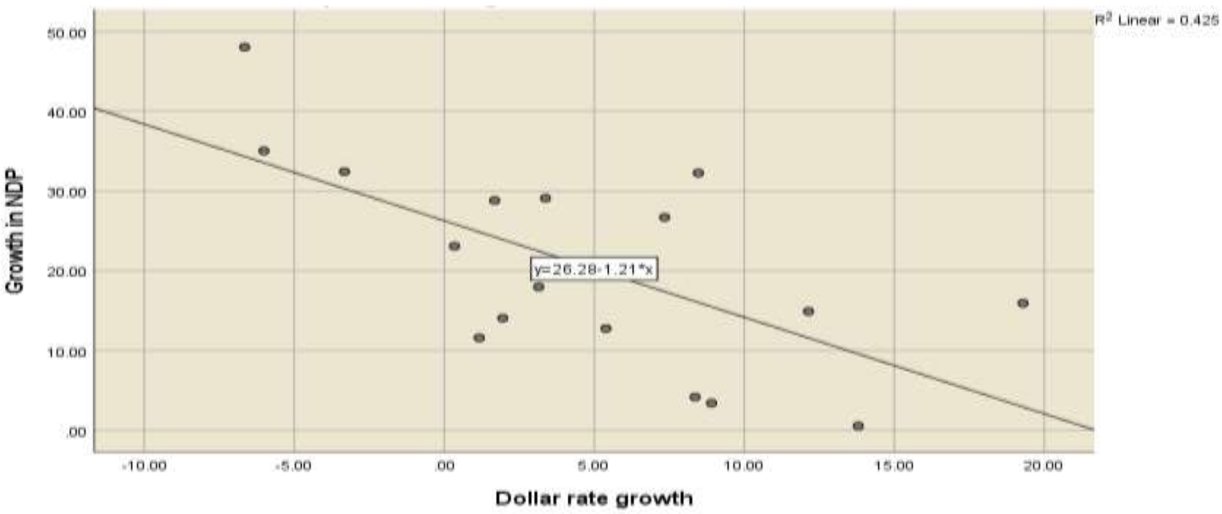
2-a. Linear Regression Results

Model	R	R squared	Adjusted R squared	Sig.lev. of F test
1	0.921	0.849	0.814	0.000

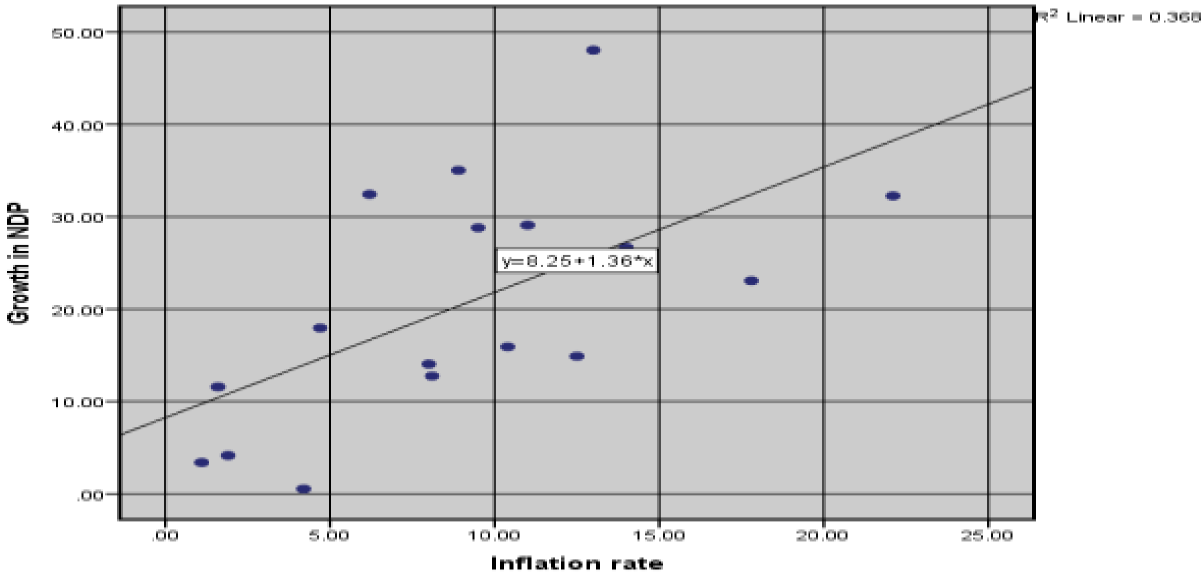
2-b. The relationship between NDP growth and the Dollar Exchange Rate Growth



2-c The relationship between NDP growth and the export growth rate



2-d. The relationship between NDP growth and inflation rate



Appendix 3: Descriptive analysis

3-a. All listed companies' case

Variables	*Minimum*	*1st Quartile*	*Mean*	*3rd Quartile*	*Maximum*	*IQR/Total range %*	*Coefficient of variation %*	*Skewness*	*Kurtosis*
ROA	1.00	147.25	291.62	436.75	584.00	49.66	57.67	0.01	-1.20
ROE	1.00	147.25	291.30	436.75	584.00	49.66	57.80	0.02	-1.20
ROS	1.00	148.25	291.19	438.75	542.00	53.70	57.10	-0.04	-1.25
Cost to revenue ratio	1.00	148.25	292.61	440.75	542.00	54.07	56.96	-0.05	-1.25
Gross profit margin	1.00	147.25	279.24	439.75	460.00	63.73	54.01	-0.25	-1.32
Return on costs	1.00	148.25	285.84	427.75	571.00	49.04	57.57	0.03	-1.18
ATO	0.00	0.12	1.73	0.83	617.25	0.12	1,471.58	24.11	581.16
Assets to equity ratio	-110.48	1.08	1.73	2.07	109.72	0.45	580.21	-2.67	81.15
Debts to total asset	0.00	0.12	0.54	0.63	23.23	2.19	230.69	12.32	200.50
WC turnover ratio	-3,552.34	-0.80	8.01	3.26	6,359.35	0.04	4,091.37	10.00	266.42
Current assets/total assets	0.00	0.13	0.38	0.61	1.00	48.30	77.09	0.52	-0.99
Operating CF ratio	1.00	148.25	290.20	433.75	578.00	49.48	57.45	0.01	-1.19
Quick ratio	1.00	147.25	293.83	440.75	584.00	50.34	57.82	-0.01	-1.20
Current ratio	1.00	149.25	296.08	442.75	586.00	50.17	57.41	-0.01	-1.21
Cash ratio	1.00	146.25	293.66	440.75	584.00	50.51	57.94	-0.01	-1.21
Operating cycle	1.00	147.25	261.64	392.00	392.00	62.60	49.93	-0.50	-1.21
Net operating cycle	1.00	148.25	261.76	392.00	392.00	62.34	49.87	-0.50	-1.20
Receivable turnover	1.00	56.25	208.69	349.75	452.00	65.08	75.14	0.11	-1.38
Inventory turnover	1.00	127.25	262.10	421.75	446.00	66.18	58.01	-0.23	-1.34
Payable turnover	1.00	77.25	215.26	370.75	395.00	74.49	67.66	-0.14	-1.46
Assets growth	0.00	0.91	7.55	1.04	2,701.01	0.00	1,514.77	22.40	519.58
Sales growth	1.00	134.00	233.80	329.00	437.00	44.72	54.23	-0.13	-0.92

Source: Author's compilation

3-b. Manufacturing sector's case

Variables	*Minimum*	*1st Quartile*	*Mean*	*3rd Quartile*	*Maximum*	*IQR/Total range %*	*Coefficient of variation %*	*Skewness*	*Kurtosis*
ROA	1.00	46.50	90.70	135.50	181.00	49.44	57.53	0.02	-1.21
ROE	1.00	46.50	90.65	135.50	181.00	49.44	57.60	0.02	-1.21
ROS	1.00	45.50	88.97	136.50	154.00	59.48	55.63	-0.14	-1.33
Cost to revenue ratio	1.00	46.50	89.55	137.50	154.00	59.48	55.26	-0.16	-1.32
Gross profit margin	1.00	45.50	83.55	129.00	130.00	64.73	51.53	-0.39	-1.29
Return on costs	1.00	45.50	87.17	130.50	174.00	49.13	57.78	0.06	-1.20
ATO	0.00	0.02	3.92	0.75	617.25	0.12	1,162.97	13.30	175.86
Assets to equity ratio	-110.48	1.09	2.43	2.59	109.72	0.68	644.58	-1.35	36.57
Debts to total asset	0.00	0.13	0.60	0.72	23.23	2.54	292.39	11.96	151.70
WC turnover ratio	-3,552.34	-0.08	18.35	2.47	6,359.35	0.03	2,954.66	7.18	109.49
Current assets/ total assets	0.00	0.15	0.45	0.72	0.98	57.74	68.71	0.09	-1.34
Quick ratio	0.00	0.21	4.35	1.98	129.67	1.37	353.30	6.04	39.16
Current ratio	0.00	0.67	6.65	3.92	171.92	1.89	323.04	5.96	37.93
Cash ratio	0.00	0.01	2.64	0.30	129.67	0.23	530.06	6.65	47.50
Operating cycle	1.00	46.50	77.24	110.00	110.00	58.26	47.14	-0.66	-1.06
Net operating cycle	1.00	46.50	77.24	110.00	110.00	58.26	47.14	-0.66	-1.06
Receivable turnover	1.00	16.50	62.32	107.50	125.00	73.39	73.86	0.02	-1.49
Inventory turnover	1.00	38.50	77.23	125.00	125.00	69.76	56.67	-0.35	-1.34
Payable turnover	1.00	22.50	62.67	109.00	109.00	80.09	66.16	-0.24	-1.51
Assets growth	0.00	0.89	3.21	1.05	211.72	0.07	538.10	10.49	117.72
Sales growth	1.00	108.75	237.84	376.75	437.00	61.47	61.49	-0.16	-1.21

Source: Author's compilation

3-c. Heavy industry's case

Variables	*Minimum*	*1st Quartile*	*Mean*	*3rd Quartile*	*Maximum*	*IQR/Total range %*	*Coefficient of variation %*	*Skewness*	*Kurtosis*
ROA	-2.18	-0.05	-0.04	0.02	0.55	2.90	-703.77	-5.09	35.12
ROE	-2.48	-0.05	0.05	0.06	6.37	1.24	1,159.23	5.06	55.75
ROS	1.00	49.50	97.95	146.50	191.00	51.05	57.53	0.00	-1.22
Cost to revenue ratio	1.00	49.50	97.95	146.50	191.00	51.05	57.53	0.00	-1.22
Gross profit margin	1.00	49.50	96.61	146.50	173.00	56.40	56.26	-0.10	-1.30
Return on costs	-2.86	-0.19	-0.12	0.05	2.48	4.46	-404.50	-0.96	10.48
ATO	0.00	0.13	0.62	0.80	7.57	8.93	127.83	4.68	32.69
Assets to equity ratio	-31.12	1.08	1.48	1.82	29.04	1.23	295.20	-0.58	28.56
Debts to total asset	0.00	0.11	0.47	0.54	5.09	8.56	147.35	4.14	21.04
WC turnover ratio	-144.72	-0.32	13.48	4.06	2,004.68	0.20	1,081.09	13.09	175.61
Current assets/ total assets	0.00	0.11	0.31	0.47	0.95	38.00	73.27	0.73	-0.21
Operating CF ratio	-2,199.24	-0.12	-11.11	0.77	27.01	0.04	-1,419.83	-13.68	186.74
Quick ratio	0.00	0.29	41.68	3.84	6,933.71	0.05	1,192.86	13.66	186.31
Current ratio	0.00	0.74	56.34	4.95	9,218.25	0.05	1,173.65	13.65	186.08
Cash ratio	0.00	0.01	25.17	0.62	4,434.74	0.01	1,262.10	13.72	187.47
Operating cycle	1.00	49.50	93.79	146.50	155.00	62.99	54.06	-0.24	-1.33
Net operating cycle	1.00	49.50	93.79	146.50	155.00	62.99	54.06	-0.24	-1.33
Receivable turnover	1.00	27.50	77.25	124.50	169.00	57.74	70.41	0.09	-1.30
Inventory turnover	1.00	49.50	96.70	146.50	173.00	56.40	56.34	-0.09	-1.30
Payable turnover	1.00	29.50	77.78	126.50	153.00	63.82	67.89	-0.01	-1.39
Assets growth	0.01	0.86	1.57	1.02	46.16	0.34	280.73	7.77	65.01
Sales growth	1.00	124.00	225.46	317.00	437.00	44.27	54.84	-0.02	-0.98

Source: Author's compilation

3-d. Service sector's case

Variables	*Minimum*	*1st Quartile*	*Mean*	*3rd Quartile*	*Maximum*	*IQR/Total range %*	*Coefficient of variation %*	*Skewness*	*Kurtosis*
ROA	-1.90	-0.03	-0.04	0.05	0.29	3.63	-678.25	-4.67	24.97
ROE	-18.04	-0.03	-0.06	0.10	5.35	0.56	-2,189.80	-10.10	127.46
ROS	1.00	53.75	105.02	157.25	200.00	52.01	57.23	-0.01	-1.23
Cost to revenue ratio	1.00	53.75	105.38	157.25	200.00	52.01	57.04	-0.03	-1.23
Gross profit margin	1.00	51.75	98.78	157.25	161.00	65.94	53.77	-0.29	-1.33
Return on costs	1.00	53.75	105.34	157.25	209.00	49.76	57.43	0.01	-1.20
ATO	0.00	0.19	0.85	0.93	7.27	10.22	136.19	2.71	8.24
Assets to equity ratio	-89.15	1.04	1.36	1.93	23.19	0.79	528.58	-9.13	116.69
Debts to total asset	0.00	0.13	0.55	0.63	11.07	4.53	200.42	6.47	49.49
WC turnover ratio	-2,259.89	-1.63	-5.96	3.37	583.91	0.18	-2,710.60	-12.57	176.50
Current assets/total assets	0.00	0.13	0.39	0.72	1.00	59.06	82.53	0.55	-1.19
Operating CF ratio	1.00	53.75	105.34	157.25	207.00	50.24	57.39	0.00	-1.21
Quick ratio	1.00	53.75	105.95	158.25	208.00	50.48	57.53	-0.01	-1.21
Current ratio	1.00	54.75	107.17	159.25	209.00	50.24	56.87	-0.01	-1.22
Cash ratio	1.00	53.75	105.83	158.25	208.00	50.48	57.77	-0.01	-1.21
Operating cycle	1.00	52.75	89.64	129.00	129.00	59.57	47.76	-0.62	-1.11
Net operating cycle	1.00	53.75	89.80	129.00	129.00	58.79	47.54	-0.63	-1.08
Receivable turnover	1.00	15.75	71.41	120.25	162.00	64.91	77.81	0.16	-1.37
Inventory turnover	1.00	41.75	89.21	147.25	151.00	70.33	59.26	-0.25	-1.38
Payable turnover	1.00	28.75	76.62	133.25	137.00	76.84	66.29	-0.18	-1.48
Assets growth	0.03	0.94	16.79	1.04	2,701.01	0.00	1,131.29	13.46	185.59
Sales growth	1.00	157.50	238.01	310.25	437.00	35.03	46.59	-0.22	-0.65

Source: Author's compilation

Appendix 4:Correlation analysis

4-a. All listed companies' case

	ROA	ROE	ROS	Cost to revenue ratio	Gross profit margin	Return on costs	ATO	Assets to equity ratio	Debts to total asset	WC turnover ratio	Current assets to total assets	Operating CF ratio	Quick ratio	Current ratio	Cash ratio	Operating cycle	Net operating cycle	Receivable turnover	Inventory turnover
ROE	0.82	1.00																	
ROS	0.73	0.64	1.00																
Cost to revenue ratio	-0.69	-0.48	-0.37	1.00															
Gross profit margin	-0.01	-0.01	0.28	-0.03	1.00														
Return on costs	0.91	0.72	0.85	-0.64	0.13	1.00													
ATO	0.08	0.08	0.02	0.02	-0.08	0.02	1.00												
Assets to equity ratio	-0.05	-0.16	-0.01	0.03	-0.04	-0.01	-0.42	1.00											
Debts to total asset	-0.11	0.18	0.01	0.21	0.06	-0.13	0.01	-0.02	1.00										
WC turnover ratio	0.04	-0.01	0.00	-0.03	-0.04	0.01	-0.43	0.19	-0.03	1.00									
Current assets/total assets	0.20	0.20	0.12	-0.11	-0.13	0.16	0.07	0.11	-0.04	-0.06	1.00								
Operating CF ratio	0.41	0.23	0.25	-0.42	0.03	0.37	-0.01	-0.02	-0.16	-0.02	0.01	1.00							
Quick ratio	0.27	0.08	0.26	-0.24	0.00	0.32	-0.01	0.05	-0.23	0.01	0.37	0.41	1.00						
Current ratio	0.28	0.06	0.24	-0.26	-0.02	0.32	-0.03	0.04	-0.25	0.01	0.41	0.38	0.88	1.00					
Cash ratio	0.36	0.21	0.25	-0.33	0.06	0.35	0.01	-0.02	-0.16	0.04	0.09	0.50	0.60	0.56	1.00				
Operating cycle	-0.24	-0.19	-0.01	0.26	0.34	-0.16	-0.09	0.04	0.09	0.00	-0.28	-0.10	-0.15	-0.21	-0.07	1.00			
Net operating cycle	-0.11	-0.10	0.11	0.16	0.36	-0.03	-0.09	0.07	0.05	0.01	-0.13	-0.08	0.09	0.09	0.07	0.56	1.00		
Receivable turnover	-0.02	0.02	0.25	0.19	-0.02	0.03	-0.06	0.03	0.06	-0.03	0.11	-0.03	0.15	0.11	-0.01	-0.15	-0.12	1.00	
Inventory turnover	-0.14	-0.12	0.07	0.17	0.34	-0.07	-0.07	0.03	-0.03	-0.03	-0.10	-0.05	-0.08	-0.08	-0.06	0.30	0.26	0.08	1.00
Payable turnover	-0.20	-0.13	0.06	0.25	0.39	-0.11	-0.07	0.00	0.04	-0.04	-0.10	-0.14	-0.19	-0.20	-0.19	0.25	0.21	0.09	0.49
Assets growth	0.07	0.06	0.02	-0.04	-0.02	0.03	0.00	0.00	-0.01	0.00	0.05	-0.03	-0.01	0.01	-0.01	-0.06	-0.05	0.03	-0.07
Sales growth	0.00	0.03	0.02	0.02	0.07	-0.02	0.05	-0.08	-0.04	0.04	-0.03	-0.07	-0.03	-0.02	-0.03	0.00	0.03	-0.01	-0.04

Source: Author's compilation

4-b. Heavy industry's case

	ROA	ROE	ROS	Cost to revenue ratio	Gross profit margin	Return on costs	ATO	Assets to equity ratio	Debts to total asset	WC turnover ratio	Current assets to total assets	Operating CF ratio	Quick ratio	Current ratio	Cash ratio	Operating cycle	Net operating cycle	Receivable turnover	Inventory turnover
ROE	0.79	1.00																	
ROS	0.86	0.75	1.00																
Cost to revenue ratio	-0.75	-0.44	-0.58	1.00															
Gross profit margin	0.12	0.16	0.29	-0.11	1.00														
Return on costs	0.94	0.72	0.93	-0.71	0.20	1.00													
ATO	0.25	0.12	-0.02	-0.28	-0.09	0.04	1.00												
Assets to equity ratio	-0.01	-0.23	-0.01	0.03	-0.14	0.01	-0.02	1.00											
Debts to total asset	-0.16	0.31	-0.01	0.38	0.05	-0.20	-0.16	-0.07	1.00										
WC turnover ratio	0.10	0.06	0.01	-0.05	-0.08	0.02	0.64	-0.01	-0.07	1.00									
Current assets/total assets	0.30	0.19	0.21	-0.31	0.08	0.25	0.19	0.12	-0.05	-0.10	1.00								
Operating CF ratio	0.48	0.24	0.35	-0.54	0.08	0.43	0.13	-0.10	-0.27	0.03	0.11	1.00							
Quick ratio	0.39	0.08	0.27	-0.48	0.02	0.37	0.20	0.00	-0.42	-0.01	0.34	0.60	1.00						
Current ratio	0.30	-0.03	0.20	-0.41	0.03	0.31	0.17	-0.02	-0.47	-0.01	0.36	0.53	0.88	1.00					
Cash ratio	0.41	0.18	0.29	-0.43	0.09	0.36	0.17	0.02	-0.32	0.05	0.19	0.62	0.67	0.59	1.00				
Operating cycle	-0.27	-0.18	-0.19	0.27	0.27	-0.27	0.05	-0.08	0.04	0.08	-0.22	-0.19	-0.24	-0.24	-0.14	1.00			
Net operating cycle	0.00	-0.04	0.06	0.03	0.38	-0.01	0.11	-0.05	-0.09	0.07	0.00	-0.01	0.09	0.15	0.14	0.50	1.00		
Receivable turnover	-0.04	0.03	0.10	0.04	-0.13	0.00	-0.19	0.07	0.23	-0.11	0.00	0.00	0.08	0.02	0.04	-0.12	-0.16	1.00	
Inventory turnover	-0.03	0.03	0.10	0.07	0.32	0.03	-0.12	-0.07	0.06	-0.15	-0.06	-0.12	-0.09	-0.13	-0.01	0.25	0.23	-0.01	1.00
Payable turnover	-0.14	0.06	0.01	0.21	0.34	-0.08	-0.21	-0.06	0.24	-0.05	-0.14	-0.17	-0.30	-0.31	-0.16	0.23	0.10	0.00	0.27
Assets growth	0.04	0.03	0.02	-0.03	-0.02	0.02	-0.02	0.13	0.01	0.00	-0.04	0.01	-0.02	0.02	0.03	-0.06	0.01	0.04	0.00
Sales growth	0.07	0.13	0.09	-0.01	0.13	0.05	0.06	0.03	0.08	0.10	0.01	-0.08	-0.13	-0.09	-0.10	-0.03	0.12	-0.05	-0.01

Source: Author's compilation

4-c. Service sector's case

	ROA	ROE	ROS	Cost to revenue ratio	Gross profit margin	Return on costs	ATO	Assets to equity ratio	Debts to total asset	WC turnover ratio	Current assets to total assets	Operating CF ratio	Quick ratio	Current ratio	Cash ratio	Operating cycle	Net operating cycle	Receivable turnover	Inventory turnover
ROE	0.79	1.00																	
ROS	0.81	0.69	1.00																
Cost to revenue ratio	-0.72	-0.50	-0.52	1.00															
Gross profit margin	-0.07	-0.05	0.18	0.07	1.00														
Return on costs	0.89	0.67	0.92	-0.69	0.11	1.00													
ATO	0.27	0.25	-0.12	-0.11	-0.43	-0.06	1.00												
Assets to equity ratio	0.04	-0.14	-0.01	0.00	-0.18	0.01	0.06	1.00											
Debts to total asset	-0.15	0.22	-0.11	0.26	0.04	-0.19	0.00	-0.05	1.00										
WC turnover ratio	0.08	-0.10	0.11	0.03	-0.09	0.11	0.01	0.06	-0.04	1.00									
Current assets/total assets	0.22	0.18	0.04	-0.04	-0.38	0.07	0.45	0.15	-0.08	0.07	1.00								
Operating CF ratio	0.48	0.29	0.36	-0.51	0.01	0.47	0.09	-0.02	-0.20	-0.10	0.04	1.00							
Quick ratio	0.37	0.17	0.35	-0.31	-0.03	0.45	0.03	0.11	-0.22	0.12	0.38	0.40	1.00						
Current ratio	0.37	0.16	0.35	-0.28	-0.07	0.43	0.07	0.10	-0.24	0.05	0.45	0.37	0.90	1.00					
Cash ratio	0.33	0.21	0.35	-0.22	0.08	0.39	0.04	-0.11	-0.11	0.12	0.10	0.45	0.72	0.68	1.00				
Operating cycle	-0.23	-0.16	-0.09	0.23	0.29	-0.17	-0.09	-0.10	0.14	-0.05	-0.41	-0.05	-0.21	-0.25	0.00	1.00			
Net operating cycle	-0.13	-0.06	0.01	0.20	0.25	-0.07	-0.11	-0.13	0.11	-0.03	-0.23	-0.12	0.08	0.10	0.09	0.53	1.00		
Receivable turnover	0.04	0.06	0.22	0.06	-0.02	0.10	-0.08	0.04	-0.12	0.06	0.21	-0.07	0.15	0.13	0.04	-0.35	-0.23	1.00	
Inventory turnover	-0.09	-0.10	0.02	0.16	0.21	-0.06	-0.03	-0.14	-0.19	-0.10	-0.10	0.00	-0.13	-0.09	-0.03	0.19	0.22	0.10	1.00
Payable turnover	-0.12	-0.10	0.03	0.16	0.35	-0.04	-0.15	-0.17	-0.15	-0.10	-0.11	-0.10	-0.18	-0.17	-0.12	0.15	0.22	0.09	0.54
Assets growth	0.10	0.09	0.04	-0.05	-0.07	0.05	0.08	0.00	-0.01	0.00	0.08	-0.06	-0.02	0.01	-0.04	-0.10	-0.07	0.04	-0.13
Sales growth	-0.06	-0.02	-0.01	0.11	0.06	-0.08	0.04	0.02	0.03	-0.01	0.00	-0.12	-0.09	-0.07	-0.05	-0.02	-0.05	0.10	-0.06

Source: Author's compilation

4-d. Manufacturing sector's case

	ROA	ROE	ROS	Cost to revenue ratio	Gross profit margin	Return on costs	ATO	Assets to equity ratio	Debts to total asset	WC turnover ratio	Current assets to total assets	Operating CF ratio	Quick ratio	Current ratio	Cash ratio	Operating cycle	Net operating cycle	Receivable turnover	Inventory turnover
ROE	0.87	1.00																	
ROS	0.55	0.49	1.00																
Cost to revenue ratio	-0.62	-0.50	-0.08	1.00															
Gross profit margin	-0.18	-0.23	0.33	0.03	1.00														
Return on costs	0.90	0.77	0.69	-0.54	0.00	1.00													
ATO	0.13	0.13	0.02	0.04	-0.14	0.04	1.00												
Assets to equity ratio	-0.12	-0.19	-0.04	0.04	0.04	-0.05	-0.49	1.00											
Debts to total asset	-0.08	0.13	0.09	0.14	0.06	-0.09	0.02	0.00	1.00										
WC turnover ratio	0.03	0.01	-0.04	-0.05	-0.02	-0.03	-0.47	0.23	-0.03	1.00									
Current assets/total assets	0.10	0.20	0.05	-0.06	-0.16	0.14	0.09	0.09	-0.04	-0.11	1.00								
Operating CF ratio	0.26	0.15	0.10	-0.23	0.02	0.22	-0.02	0.01	-0.10	-0.02	-0.06	1.00							
Quick ratio	0.06	-0.02	0.20	0.05	0.03	0.12	-0.02	0.06	-0.18	-0.03	0.45	0.22	1.00						
Current ratio	0.16	0.06	0.16	-0.12	0.03	0.20	-0.05	0.03	-0.20	0.00	0.47	0.24	0.85	1.00					
Cash ratio	0.34	0.22	0.17	-0.31	-0.03	0.33	0.02	0.02	-0.15	0.03	0.04	0.41	0.39	0.40	1.00				
Operating cycle	-0.25	-0.26	0.20	0.31	0.44	-0.09	-0.16	0.16	0.07	-0.01	-0.24	-0.07	0.01	-0.12	-0.09	1.00			
Net operating cycle	-0.22	-0.27	0.20	0.24	0.49	-0.07	-0.19	0.23	0.04	0.00	-0.21	-0.09	0.11	0.01	0.01	0.66	1.00		
Receivable turnover	-0.06	-0.03	0.42	0.40	0.12	-0.01	-0.09	0.02	0.13	-0.05	0.09	-0.01	0.22	0.17	-0.08	0.04	0.05	1.00	
Inventory turnover	-0.30	-0.31	0.08	0.27	0.49	-0.18	-0.12	0.15	0.06	0.01	-0.16	-0.04	-0.01	-0.03	-0.15	0.44	0.33	0.13	1.00
Payable turnover	-0.37	-0.34	0.07	0.37	0.49	-0.25	-0.11	0.10	0.10	-0.04	-0.11	-0.16	-0.09	-0.14	-0.29	0.34	0.27	0.17	0.60
Assets growth	0.05	0.03	0.01	-0.06	-0.03	0.03	-0.01	-0.01	-0.03	0.00	-0.02	0.12	0.10	0.13	0.11	-0.15	-0.12	0.06	0.04
Sales growth	-0.01	-0.02	-0.04	-0.02	-0.01	-0.04	0.07	-0.17	-0.13	0.04	-0.10	0.00	0.12	0.08	0.05	0.03	0.02	-0.06	-0.06

Source: Author's compilation

Appendix 5: Results of Data Envelopment Analysis

5-a. Service sector's case by ROA

ROA	***By sector specific variables***					***By whole dataset variables***				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
94	0.690	0.868	1.384	1.155	0.795	0.852	0.916	1.210	inf	0.930
93	0.321	0.810	4.581	0.810	0.396	0.332	0.829	4.505	0.829	0.400
92	0.539	0.959	7.057	1.179	0.562	0.609	1.000	1.000	2.421	0.609
89	0.563	0.852	2.127	0.856	0.660	0.850	0.988	1.186	inf	0.860
84	0.876	1.000	1.321	inf	0.876	0.876	1.000	1.321	inf	0.876
82	0.637	0.846	1.535	1.649	0.753	0.715	0.871	1.371	inf	0.821
81	0.929	1.000	1.000	2.549	0.929	0.999	1.000	1.000	inf	0.999
77	0.425	0.771	2.791	0.771	0.551	0.740	0.951	1.711	inf	0.778
76	0.898	0.942	1.075	inf	0.953	0.981	1.000	1.000	inf	0.981
71	1.000	1.000	1.000	2.027	1.000	1.000	1.000	1.000	inf	1.000
70	0.962	1.000	1.008	1.293	0.962	0.992	1.000	1.008	1.451	0.992
69	0.938	0.946	1.027	inf	0.992	1.000	1.000	1.000	inf	1.000
66	0.784	0.892	1.413	inf	0.879	0.866	0.969	1.403	inf	0.893
57	0.388	0.758	2.326	0.852	0.511	0.674	0.921	1.522	inf	0.732
56	0.472	0.800	2.087	0.800	0.590	0.656	0.901	1.640	1.253	0.728
54	0.626	0.921	1.581	0.983	0.680	0.660	0.948	1.560	1.124	0.696
53	0.707	0.931	2.160	0.967	0.759	0.741	0.964	1.141	1.140	0.768
49	0.229	0.835	20.199	0.835	0.274	0.246	0.859	19.535	0.859	0.287
45	0.618	0.811	1.878	0.815	0.762	0.704	0.906	1.835	0.921	0.777
44	0.988	1.000	1.013	1.331	0.988	0.988	1.000	1.013	inf	0.988
43	0.853	0.924	1.899	1.200	0.923	0.857	0.942	1.898	1.339	0.909
42	0.296	0.762	3.815	0.762	0.388	0.316	0.795	3.754	0.795	0.398
41	0.391	0.776	3.542	0.776	0.504	0.440	0.827	3.319	inf	0.532
39	0.338	0.822	6.951	0.822	0.411	0.467	0.868	6.069	inf	0.538
38	0.747	0.984	1.047	1.106	0.760	0.862	1.000	1.000	inf	0.862
37	0.526	0.911	3.033	0.979	0.577	0.657	0.941	3.022	2.941	0.698
36	0.539	0.772	1.723	0.772	0.698	0.673	0.906	1.552	0.950	0.743
34	0.520	0.926	1.100	1.349	0.561	0.555	0.953	1.096	1.560	0.583
30	0.602	0.966	15.673	3.574	0.623	0.609	0.998	1.761	5.500	0.611
25	0.787	0.932	5.516	1.888	0.844	0.872	0.982	1.043	3.784	0.887
23	0.670	0.909	1.930	1.032	0.737	0.788	1.000	1.105	1.170	0.788
18	0.722	0.911	1.050	inf	0.792	0.771	0.943	1.050	inf	0.818
10	0.833	0.915	1.121	inf	0.910	0.865	0.936	1.113	inf	0.924
5	0.615	0.807	1.877	1.393	0.763	0.639	0.832	1.841	inf	0.767
1	0.663	0.914	3.677	0.968	0.726	0.735	0.981	3.633	inf	0.750

Source: Author's compilation

5-b. Service sector's case by ROE

ROE	***By sector specific variables***					***By whole dataset variables***				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
94	0.341	0.371	1.697	inf	0.917	0.239	0.309	1.858	0.309	0.774
93	0.222	0.311	2.965	0.311	0.714	0.115	0.267	3.182	0.267	0.430
92	0.623	1.000	1.000	2.424	0.623	0.210	0.709	9.532	0.724	0.296
89	0.997	1.000	1.000	inf	0.997	0.292	0.617	3.001	0.617	0.473
84	0.902	1.000	1.000	inf	0.902	0.261	0.715	1.507	inf	0.365
82	0.401	0.425	1.379	inf	0.944	0.376	0.424	1.578	1.952	0.886
81	0.851	1.000	1.000	8.170	0.851	0.332	0.535	1.513	0.759	0.621
77	1.000	1.000	1.000	inf	1.000	1.000	1.000	1.000	inf	1.000
76	0.590	0.780	1.067	1.077	0.757	0.487	0.680	1.121	0.976	0.716
71	0.905	0.948	1.074	inf	0.955	1.000	1.000	1.000	inf	1.000
70	0.197	0.389	1.199	0.389	0.506	0.746	0.932	1.066	1.398	0.801
69	1.000	1.000	1.000	4.727	1.000	0.892	0.996	1.012	4.364	0.895
66	0.785	0.917	1.539	inf	0.856	0.464	0.679	1.700	inf	0.684
57	0.868	0.884	1.009	inf	0.982	0.224	0.606	3.043	0.606	0.369
56	0.404	0.645	1.841	inf	0.627	0.237	0.602	1.863	inf	0.393
54	0.238	0.360	4.198	0.360	0.662	0.242	0.505	4.177	0.505	0.480
53	0.740	0.957	1.351	1.281	0.774	0.186	0.415	2.883	0.415	0.448
49	0.126	0.417	15.468	0.417	0.303	0.072	0.223	16.956	0.223	0.323
45	0.242	0.435	2.167	0.435	0.556	0.208	0.398	2.190	0.398	0.522
44	0.495	0.891	1.043	inf	0.556	0.308	0.693	1.081	0.755	0.444
43	0.226	0.565	1.696	0.565	0.400	0.511	0.754	1.801	1.273	0.678
42	0.406	0.656	2.692	inf	0.618	0.227	0.330	3.623	inf	0.687
41	0.261	0.326	2.692	inf	0.801	0.337	0.512	2.677	inf	0.658
39	0.384	0.567	5.931	inf	0.677	0.084	0.228	7.221	0.228	0.369
38	0.633	0.799	3.275	inf	0.793	0.252	0.528	4.064	0.528	0.478
37	0.432	0.663	4.076	2.155	0.651	0.247	0.505	5.254	0.512	0.489
36	0.328	0.459	1.895	0.459	0.715	0.266	0.451	1.844	0.451	0.589
34	0.423	0.698	6.236	0.698	0.606	0.384	0.679	6.029	0.725	0.566
30	0.483	0.776	22.312	1.684	0.623	0.331	0.721	23.264	1.019	0.459
25	0.728	0.945	1.056	5.588	0.770	0.523	0.771	1.125	4.738	0.678
23	0.628	0.765	1.080	1.146	0.821	0.378	0.657	2.283	0.657	0.575
18	0.507	0.864	1.065	1.253	0.587	0.294	0.553	6.781	0.617	0.532
10	0.588	0.839	1.050	4.280	0.701	0.265	0.543	1.311	3.315	0.487
5	0.446	0.581	1.758	inf	0.768	0.322	0.579	1.795	inf	0.556
1	0.420	0.780	3.473	inf	0.538	0.226	0.423	3.909	0.423	0.533

Source: Author's compilation

5-c. Service sector's case by ROS

ROS	By sector specific variables					By whole dataset variables				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
94	0.570	0.798	1.685	0.820	0.715	0.407	0.632	2.105	0.632	0.643
93	0.249	0.757	8.635	0.764	0.329	0.239	0.656	8.704	0.664	0.364
92	0.484	0.733	3.455	1.192	0.660	0.583	0.905	2.162	1.330	0.644
89	0.741	0.927	1.796	2.630	0.800	0.953	0.993	1.061	3.873	0.960
84	0.665	1.000	1.000	inf	0.665	0.605	1.000	1.000	inf	0.605
82	0.555	0.801	1.740	1.604	0.692	0.535	0.728	1.754	1.531	0.735
81	1.000	1.000	1.000	57.405	1.000	1.000	1.000	1.000	57.404	1.000
77	0.778	0.973	1.908	2.703	0.800	0.700	0.909	2.267	2.480	0.771
76	0.788	0.882	1.190	0.940	0.893	0.932	0.961	1.039	1.045	0.970
71	1.000	1.000	1.000	4.794	1.000	1.000	1.000	1.000	inf	1.000
70	0.963	0.996	1.031	1.382	0.967	0.841	0.896	1.125	0.946	0.939
69	0.938	0.939	1.016	2.007	0.999	1.000	1.000	1.000	3.717	1.000
66	0.856	1.000	1.634	73.734	0.856	0.803	0.945	1.672	1.606	0.850
57	0.785	1.000	1.507	4.639	0.785	0.883	1.000	1.392	7.430	0.883
56	0.714	0.973	1.616	3.149	0.734	0.552	0.974	1.883	0.974	0.567
54	0.476	0.806	4.044	0.806	0.591	0.501	0.786	3.796	0.786	0.637
53	0.705	0.834	1.692	1.024	0.846	0.768	0.858	1.670	1.033	0.895
49	0.189	0.578	9.491	0.578	0.327	0.190	0.497	9.504	0.497	0.383
45	0.615	0.852	1.610	0.852	0.722	0.496	0.701	1.685	0.701	0.708
44	0.943	0.965	1.036	1.035	0.977	0.889	0.926	1.046	0.963	0.960
43	0.841	0.980	1.023	1.339	0.858	0.812	0.957	1.992	1.132	0.849
42	0.445	0.940	3.828	inf	0.473	0.443	0.924	3.897	inf	0.479
41	0.257	0.848	16.290	0.848	0.303	0.225	0.696	16.503	0.696	0.323
39	0.331	0.714	8.220	0.798	0.463	0.337	0.742	8.227	0.799	0.453
38	0.626	0.841	1.427	1.054	0.744	0.696	0.890	1.353	1.146	0.782
37	0.427	0.702	3.369	0.702	0.608	0.393	0.559	3.521	0.559	0.704
36	0.765	0.905	1.305	1.757	0.845	0.664	0.795	1.487	1.571	0.835
34	0.459	0.885	1.097	1.664	0.519	0.495	0.882	2.020	1.602	0.561
30	0.627	1.000	1.000	48.322	0.627	0.627	1.000	1.000	48.322	0.627
25	0.798	0.960	1.037	29.199	0.831	0.878	0.978	1.034	30.775	0.898
23	0.642	0.820	2.197	2.944	0.784	0.779	0.938	1.160	3.431	0.831
18	0.761	0.903	1.547	1.243	0.843	0.791	0.884	1.436	1.269	0.895
10	0.773	0.833	1.153	73.500	0.928	0.728	0.856	1.153	1.446	0.850
5	0.436	0.733	3.849	0.752	0.595	0.498	0.695	3.849	0.699	0.717
1	0.724	0.934	1.074	0.949	0.775	0.677	0.848	3.104	0.989	0.798

Source: Author's compilation

5-d. Manufacturing sector's case by ROA

ROA	By sector specific variables					By whole dataset variables				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
99	0.571	0.868	3.444	1.017	0.658	0.618	0.985	1.264	1.174	0.627
95	0.444	0.686	1.981	0.686	0.648	0.507	0.867	1.596	0.882	0.585
88	0.473	0.747	4.532	inf	0.633	0.496	0.924	1.535	inf	0.538
86	0.965	0.969	1.037	inf	0.995	0.970	1.000	1.037	inf	0.970
83	0.941	1.000	1.000	inf	0.941	0.607	0.958	1.940	inf	0.634
80	0.406	0.904	5.691	1.156	0.450	0.449	0.995	3.198	1.357	0.452
72	0.963	1.000	1.000	1.865	0.963	0.899	1.000	1.000	1.601	0.899
67	0.947	0.972	1.019	inf	0.975	0.980	0.998	1.004	inf	0.982
64	0.852	0.932	1.162	inf	0.915	0.893	0.982	1.141	inf	0.909
63	0.712	1.000	3.071	inf	0.712	0.691	1.000	3.071	inf	0.691
62	0.918	0.988	1.091	1.336	0.930	0.925	0.999	1.069	1.377	0.926
61	0.343	0.965	5.098	1.136	0.355	0.346	1.000	2.153	1.271	0.346
58	0.633	0.825	3.060	3.505	0.768	0.675	0.949	2.604	inf	0.711
51	0.883	0.972	1.384	inf	0.909	0.870	0.951	1.489	inf	0.915
50	0.439	0.936	4.419	inf	0.469	0.511	0.970	3.948	inf	0.526
48	0.796	1.000	1.702	inf	0.796	0.893	1.000	1.000	inf	0.893
40	0.854	0.964	2.106	inf	0.885	0.853	0.962	2.186	inf	0.887
32	0.597	0.836	3.317	inf	0.714	0.615	0.900	3.385	inf	0.683
31	0.900	1.000	1.000	1.305	0.900	0.853	1.000	1.000	1.303	0.853
29	0.585	0.989	1.677	75.042	0.591	0.718	1.000	1.260	75.090	0.718
28	0.834	0.938	33.042	146.241	0.889	0.834	1.000	38.133	146.302	0.834
26	0.912	0.926	1.119	inf	0.985	0.917	1.000	1.166	inf	0.917
20	0.781	1.000	1.001	18.920	0.781	0.590	1.000	1.879	188.573	0.590
19	0.417	0.984	8.271	inf	0.424	0.478	0.977	3.054	inf	0.489
17	0.594	0.916	6.021	3.711	0.649	0.639	0.963	5.648	6.616	0.664
14	0.693	0.969	2.406	2.218	0.715	0.850	1.000	1.087	2.572	0.850
13	0.921	0.986	1.087	3.683	0.934	0.999	1.000	1.001	inf	0.999
12	0.758	0.850	1.206	0.893	0.892	0.893	0.987	1.149	1.136	0.905
11	0.775	0.890	1.272	inf	0.871	0.963	1.000	1.022	inf	0.963
9	0.644	0.869	2.019	0.949	0.741	0.723	0.963	1.885	1.100	0.751
7	0.722	0.910	1.334	inf	0.794	0.777	1.000	1.100	inf	0.777

Source: Author's compilation

5-e. Manufacturing sector's case by ROE

ROE	By sector specific variables					By whole dataset variables				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
99	0.567	0.924	1.348	1.150	0.614	0.370	0.634	5.937	0.692	0.584
95	0.419	0.698	2.036	0.698	0.601	0.244	0.423	2.223	0.423	0.577
88	0.435	0.710	4.347	0.710	0.612	0.174	0.414	4.752	0.414	0.421
86	0.954	0.958	1.036	inf	0.996	0.890	0.896	1.044	inf	0.993
83	0.907	0.980	1.118	36.023	0.925	0.261	0.557	3.004	1.387	0.469
80	0.741	0.847	1.787	inf	0.875	0.704	0.740	1.801	inf	0.951
72	0.725	0.990	1.147	1.237	0.733	0.269	0.412	2.065	0.412	0.653
67	0.946	0.973	1.053	1.125	0.972	0.463	0.534	1.292	0.534	0.867
64	0.719	0.872	1.430	1.350	0.825	0.451	0.603	1.608	0.705	0.749
63	0.525	0.908	6.547	2.674	0.578	0.290	0.684	6.804	2.382	0.424
62	0.801	0.914	1.282	0.914	0.876	0.295	0.446	1.398	0.446	0.661
61	0.312	0.518	3.463	0.520	0.602	0.092	0.182	3.485	0.182	0.504
58	0.593	0.760	2.954	3.377	0.781	0.274	0.492	3.115	0.492	0.557
51	0.875	0.953	1.358	6.933	0.918	0.238	0.702	3.801	0.712	0.339
50	0.297	0.903	5.656	1.197	0.329	0.118	0.610	8.485	0.610	0.193
48	0.820	0.996	1.052	inf	0.823	0.417	0.974	3.416	inf	0.428
40	0.853	0.968	2.229	6.402	0.881	0.469	0.901	2.334	2.515	0.521
32	0.572	0.848	3.857	0.960	0.675	0.259	0.556	4.276	0.556	0.466
31	0.875	0.970	1.143	inf	0.903	0.551	0.678	1.368	inf	0.813
29	0.432	0.676	2.596	1.543	0.639	0.391	0.539	2.600	1.406	0.725
28	0.823	0.925	56.937	5.079	0.890	0.706	0.769	68.704	4.923	0.918
26	0.820	0.898	1.242	inf	0.914	0.275	0.393	1.647	0.393	0.700
20	0.667	0.892	3.050	inf	0.748	0.130	0.359	3.702	0.418	0.361
19	0.168	0.763	10.662	0.769	0.220	0.095	0.438	22.416	0.438	0.217
17	0.475	0.804	6.609	inf	0.591	0.414	0.695	6.632	inf	0.596
14	0.698	0.804	1.803	1.016	0.869	0.388	0.539	1.969	0.539	0.721
13	0.943	1.000	1.000	5.127	0.943	0.703	0.885	1.082	1.564	0.794
12	0.763	0.848	1.422	1.026	0.901	0.416	0.502	1.616	0.502	0.829
11	0.829	0.934	1.195	57.345	0.888	0.363	0.528	2.408	1.122	0.688
9	0.679	0.886	1.759	0.973	0.767	0.282	0.444	2.202	0.444	0.635
7	0.737	0.907	1.378	1.290	0.813	0.499	0.601	1.518	0.879	0.829

Source: Author's compilation

5-f. Manufacturing sector's case by ROS

ROS	***By sector specific variables***					***By whole dataset variables***				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
99	0.467	0.772	6.925	0.853	0.605	0.645	0.914	1.329	1.302	0.706
95	0.387	0.660	2.267	0.660	0.587	0.415	0.714	2.207	0.714	0.581
88	0.360	0.640	6.383	0.640	0.563	0.401	0.735	5.155	0.735	0.545
86	0.947	0.953	1.054	7.199	0.994	0.948	0.954	1.054	7.200	0.993
83	0.408	1.000	1.856	1.012	0.408	0.961	1.000	1.000	149.072	0.961
80	0.407	0.707	3.847	0.734	0.575	0.408	0.725	3.770	0.838	0.562
72	0.940	1.000	1.092	1.639	0.940	1.000	1.000	1.000	1.823	1.000
67	0.819	0.893	1.161	0.902	0.917	0.935	0.965	1.066	1.096	0.969
64	0.761	0.872	1.122	2.720	0.873	0.864	0.976	1.061	4.532	0.885
63	0.590	1.000	1.172	2.012	0.590	0.839	1.000	1.000	2.986	0.839
62	0.821	0.942	1.219	0.942	0.871	0.854	0.960	1.177	0.960	0.890
61	0.540	1.000	2.123	1.022	0.540	0.548	1.000	2.123	1.022	0.548
58	0.495	0.693	2.897	31.826	0.714	0.612	0.783	2.788	31.959	0.782
51	0.398	0.921	2.663	0.921	0.432	0.868	0.953	1.461	10.339	0.911
50	0.218	0.655	4.383	0.655	0.332	0.513	0.932	1.538	1.227	0.551
48	0.613	0.986	1.006	1.239	0.622	0.985	0.986	1.006	2.445	0.999
40	0.837	0.964	6.587	13.809	0.869	0.838	0.969	6.386	15.124	0.865
32	0.404	0.676	11.876	0.676	0.598	0.485	0.815	11.466	0.815	0.594
31	0.776	0.956	1.121	1.081	0.811	0.831	0.976	1.059	1.271	0.852
29	0.531	0.763	1.818	1.456	0.696	0.580	0.784	1.818	7.860	0.739
28	0.718	0.902	30.465	4.500	0.796	0.834	0.921	28.070	4.638	0.905
26	0.723	0.851	1.237	0.851	0.850	0.857	0.897	1.214	39.162	0.955
20	0.512	0.907	1.342	5.691	0.564	0.811	0.932	1.342	5.988	0.871
19	0.264	0.638	3.425	0.638	0.413	0.515	0.848	2.853	0.914	0.607
17	0.568	0.891	2.825	2.476	0.638	0.629	0.956	2.825	4.153	0.658
14	0.692	0.847	1.502	22.822	0.818	0.738	0.881	1.389	22.860	0.838
13	0.945	0.963	1.054	30.769	0.982	0.966	0.967	1.031	39.968	0.999
12	0.611	0.797	1.388	0.802	0.766	0.765	0.953	1.071	1.101	0.803
11	0.586	0.888	1.891	66.275	0.659	0.848	0.966	1.249	70.337	0.878
9	0.499	0.826	3.587	0.826	0.604	0.641	0.875	3.269	0.974	0.732
7	0.694	0.924	1.425	1.836	0.751	0.696	0.925	1.425	1.847	0.753

Source: Author's compilation

5-g. Heavy sector's case by ROA

ROA	***By sector specific variables***					***By whole dataset variables***				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
98	0.536	0.914	4.411	inf	0.587	0.639	0.999	1.873	inf	0.639
97	1.000	1.000	1.000	2.816	1.000	1.000	1.000	1.000	3.424	1.000
96	0.773	0.815	1.526	61.009	0.948	0.837	0.977	1.100	65.397	0.857
91	0.703	0.885	1.703	2.894	0.794	0.798	0.925	1.483	inf	0.863
90	0.849	0.969	1.302	1.042	0.876	0.914	1.000	1.024	inf	0.914
87	0.494	0.828	4.378	74.828	0.597	0.535	0.963	4.258	75.065	0.555
85	0.649	0.988	1.122	2.085	0.657	0.680	1.000	1.086	2.209	0.680
79	0.894	1.000	1.258	2.660	0.894	0.896	1.000	1.257	2.698	0.896
78	0.977	1.000	1.000	inf	0.977	1.000	1.000	1.000	inf	1.000
75	0.574	0.748	2.308	inf	0.767	0.634	0.874	2.250	inf	0.725
74	0.488	0.761	2.467	0.761	0.642	0.559	0.892	1.953	0.918	0.626
73	0.689	0.929	1.637	1.070	0.742	0.858	0.970	1.588	inf	0.884
68	0.939	0.991	1.003	inf	0.947	1.000	1.000	1.000	inf	1.000
65	0.681	0.995	1.764	inf	0.685	0.794	1.000	1.760	inf	0.794
60	0.444	0.831	4.092	1.138	0.534	0.592	0.950	2.292	inf	0.623
59	0.448	0.715	3.238	0.876	0.627	0.511	0.826	3.229	1.175	0.619
55	0.764	0.901	1.583	3.939	0.847	0.795	0.948	1.566	inf	0.839
52	0.531	0.806	2.339	0.862	0.659	0.844	0.893	1.099	inf	0.945
47	0.716	0.872	1.498	2.212	0.821	0.817	0.983	1.199	2.521	0.831
46	0.895	0.973	1.029	1.225	0.920	0.984	0.989	1.008	inf	0.995
35	0.665	0.926	16.157	1.630	0.718	0.671	0.977	10.148	inf	0.687
33	0.679	0.851	1.561	13.776	0.797	0.772	0.893	1.435	inf	0.864
27	0.484	0.793	4.425	1.248	0.610	0.872	1.000	1.000	inf	0.872
24	0.510	0.726	1.825	0.804	0.702	0.659	0.877	1.757	inf	0.751
22	0.660	0.855	1.354	2.402	0.772	0.926	0.961	1.092	inf	0.963
21	0.726	0.965	3.595	1.599	0.752	0.841	1.000	3.495	1.721	0.841
16	0.787	0.919	1.064	inf	0.857	0.936	0.938	1.054	inf	0.998
15	0.580	0.812	87.776	0.974	0.714	0.844	0.920	1.651	inf	0.917
8	0.910	1.000	1.198	8.953	0.910	0.932	1.000	1.000	15.811	0.932
4	0.379	0.969	4.610	1.519	0.392	0.399	0.977	4.576	2.399	0.408
3	0.737	0.962	9.935	1.427	0.766	0.745	0.974	9.109	1.514	0.765
2	0.895	0.990	1.120	1.263	0.903	0.962	1.000	1.035	inf	0.962
0	0.763	0.968	3.431	1.265	0.788	0.830	1.000	1.000	1.438	0.830

Source: Author's compilation

5-h. Heavy sector's case by ROE

ROE	***By sector specific variables***					***By whole dataset variables***				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
98	0.439	0.745	6.459	1.554	0.589	0.404	0.738	6.732	1.111	0.548
97	0.937	1.000	1.000	2.504	0.937	0.935	1.000	1.000	2.504	0.935
96	0.694	0.743	1.612	48.673	0.934	0.668	0.717	1.651	45.927	0.931
91	0.844	0.960	1.074	6.510	0.879	0.582	0.734	2.188	2.743	0.793
90	0.755	0.794	1.486	0.935	0.950	0.645	0.716	1.606	0.779	0.901
87	0.225	0.510	20.748	0.510	0.442	0.221	0.434	33.023	0.434	0.510
85	0.464	0.765	5.628	1.273	0.607	0.431	0.738	5.699	1.201	0.585
79	0.752	0.882	1.429	2.328	0.853	0.704	0.843	1.504	1.500	0.835
78	0.361	0.583	1.574	0.867	0.620	0.276	0.472	1.583	0.527	0.584
75	0.907	1.000	1.000	inf	0.907	0.734	0.876	1.264	inf	0.839
74	0.608	0.888	2.868	3.378	0.685	0.272	0.512	3.320	0.512	0.530
73	0.430	0.696	2.014	0.724	0.617	0.357	0.677	2.287	0.703	0.527
68	0.824	0.962	1.045	inf	0.857	0.772	0.944	1.045	inf	0.819
65	0.554	0.893	2.193	1.736	0.621	0.481	0.775	3.030	1.292	0.621
60	0.130	0.465	5.874	0.465	0.279	0.113	0.409	6.182	0.409	0.278
59	0.488	0.651	2.566	inf	0.749	0.468	0.646	2.572	inf	0.724
55	0.352	0.569	3.049	0.578	0.619	0.307	0.515	3.165	0.515	0.597
52	0.404	0.687	3.087	0.687	0.589	0.381	0.637	3.153	0.637	0.599
47	0.474	0.672	2.531	0.697	0.706	0.384	0.584	2.578	0.584	0.659
46	0.700	0.827	1.133	2.250	0.846	0.551	0.657	1.620	0.657	0.840
35	0.582	0.855	11.079	2.463	0.681	0.547	0.757	11.383	1.396	0.723
33	0.735	0.800	1.778	5.590	0.918	0.704	0.797	1.778	2.589	0.884
27	0.476	0.723	5.394	1.009	0.659	0.472	0.720	5.433	1.006	0.655
24	0.438	0.472	1.864	1.745	0.929	0.328	0.418	1.947	0.418	0.785
22	0.691	0.794	1.223	inf	0.871	0.624	0.691	1.224	1.241	0.903
21	0.539	0.807	4.697	1.006	0.668	0.460	0.795	4.700	0.909	0.578
16	0.597	0.809	1.104	2.154	0.738	0.522	0.773	1.104	1.545	0.676
15	0.650	0.799	44.835	7.090	0.813	0.548	0.775	44.864	0.921	0.707
8	0.872	0.918	1.221	7.310	0.950	0.809	0.907	1.308	6.335	0.892
4	0.330	0.882	12.913	0.972	0.375	0.328	0.863	12.974	0.953	0.380
3	0.655	0.823	10.341	1.050	0.796	0.621	0.818	10.341	1.024	0.759
2	0.704	0.889	1.235	1.122	0.793	0.687	0.875	1.338	1.108	0.786
0	0.438	0.688	4.337	0.814	0.636	0.436	0.685	4.600	0.811	0.637

Source: Author's compilation

5-i. Heavy sector's case by ROS

ROS	***By sector specific variables***					***By whole dataset variables***				
	CRS	VRS	Output	Super	Scale	CRS	VRS	Output	Super	Scale
98	0.613	0.861	7.012	2.487	0.713	0.619	0.865	7.046	2.491	0.716
97	1.000	1.000	1.000	2.345	1.000	1.000	1.000	1.000	2.345	1.000
96	0.758	0.836	1.595	46.196	0.908	0.802	0.908	1.442	46.272	0.883
91	0.738	1.000	3.081	8.707	0.738	0.738	1.000	3.081	8.707	0.738
90	0.796	0.914	1.866	0.996	0.871	0.840	0.947	1.613	1.042	0.886
87	0.379	0.742	6.587	2.102	0.511	0.512	0.795	5.997	2.155	0.643
85	0.655	0.812	1.944	1.635	0.807	0.737	0.867	1.737	1.709	0.849
79	0.866	0.946	1.334	2.203	0.916	0.866	0.930	1.329	2.220	0.931
78	0.741	0.962	1.192	inf	0.770	0.822	0.962	1.192	inf	0.854
75	0.743	0.901	1.257	inf	0.825	0.673	1.000	2.851	inf	0.673
74	0.367	0.657	2.594	0.657	0.559	0.674	0.894	1.595	1.034	0.754
73	0.732	0.879	1.876	1.108	0.833	0.819	0.922	1.648	1.208	0.887
68	0.964	0.978	1.038	inf	0.985	0.932	0.956	1.061	1.284	0.975
65	0.969	0.993	1.023	11.642	0.975	0.966	0.993	1.023	11.621	0.973
60	0.390	0.740	4.233	0.755	0.527	0.396	0.751	4.196	0.766	0.528
59	0.564	0.732	4.592	inf	0.771	0.505	0.733	4.654	0.891	0.689
55	0.560	0.693	1.911	0.707	0.808	0.583	0.724	1.868	0.757	0.805
52	0.582	0.788	1.856	1.217	0.739	0.711	0.790	1.321	12.403	0.900
47	0.791	0.999	1.549	inf	0.792	1.000	1.000	1.000	inf	1.000
46	0.718	0.888	2.882	0.901	0.809	0.731	0.895	2.868	0.908	0.816
35	0.534	0.889	35.667	3.499	0.600	0.522	0.909	35.667	3.519	0.574
33	0.785	0.938	1.613	22.778	0.837	0.812	0.972	1.301	22.836	0.836
27	0.459	0.761	6.205	2.605	0.603	0.489	0.817	4.970	2.661	0.599
24	0.410	0.616	2.861	0.633	0.665	0.543	0.690	2.488	0.900	0.788
22	0.445	0.686	1.743	0.701	0.649	0.826	0.891	1.406	2.047	0.927
21	0.811	0.942	23.030	1.448	0.861	0.807	0.910	23.031	1.416	0.887
16	0.896	0.915	1.093	inf	0.979	1.000	1.000	1.000	inf	1.000
15	0.569	0.807	76.955	0.853	0.705	0.664	0.867	74.066	1.153	0.766
8	0.937	0.999	1.008	8.787	0.938	1.000	1.000	1.000	8.939	1.000
4	0.300	0.937	11.529	1.071	0.321	0.444	1.000	1.000	1.523	0.444
3	0.613	0.893	5.428	1.046	0.686	0.747	1.000	1.000	1.321	0.747
2	0.715	0.991	1.117	1.253	0.721	0.725	0.991	1.117	1.358	0.731
0	0.566	0.802	6.045	0.936	0.706	0.660	0.998	5.685	1.248	0.661

Source: Author's compilation

Appendix 6. Comparison of DEA and PCA-DEA results (by sectors and by sizes)

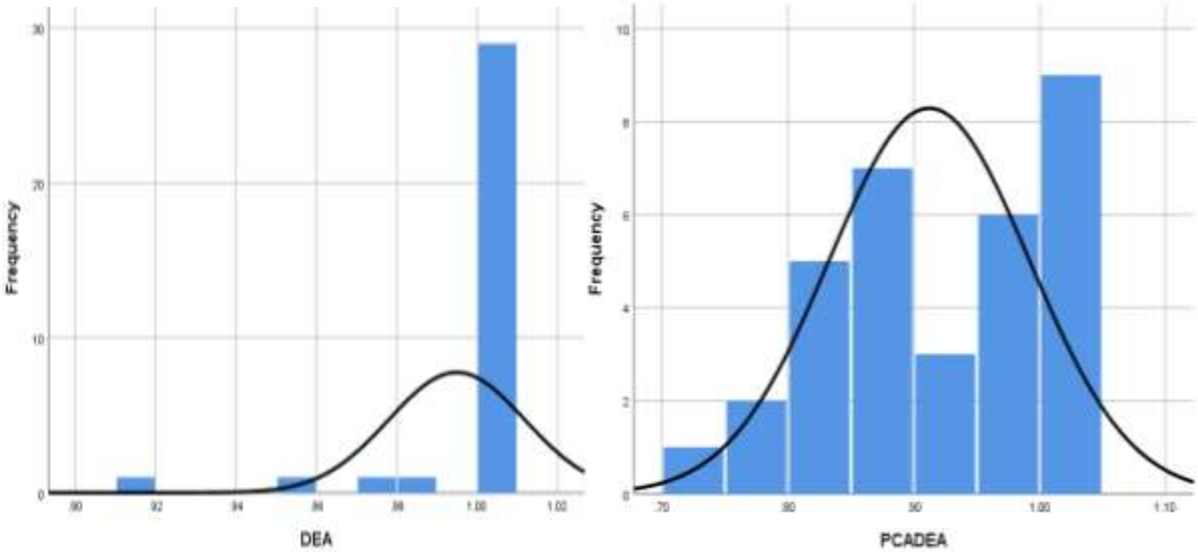


Figure 1 Comparison of DEA and PCA-DEA results (Heavy)

Source: Author's compilation

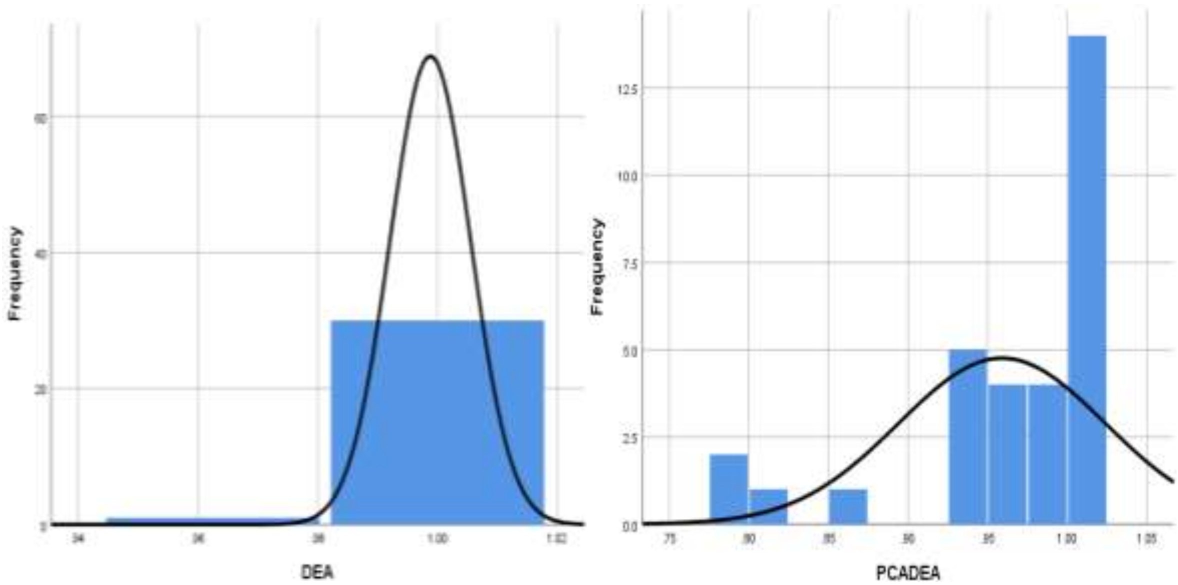


Figure 2 Comparison of DEA and PCA-DEA results (Manufacturing)

Source: Author's compilation

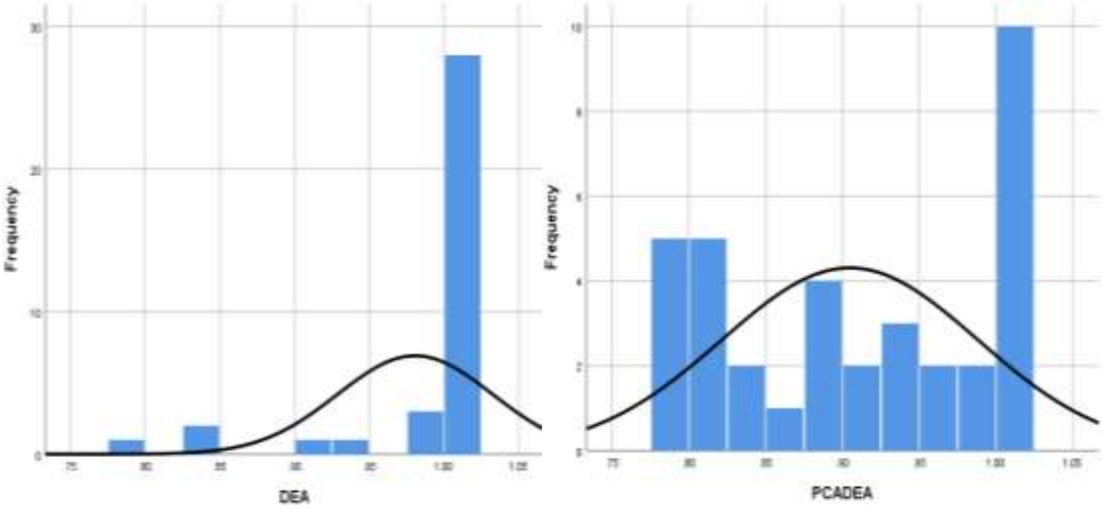


Figure 3. Comparison of DEA and PCA-DEA results (Service)

Source: Author's compilation

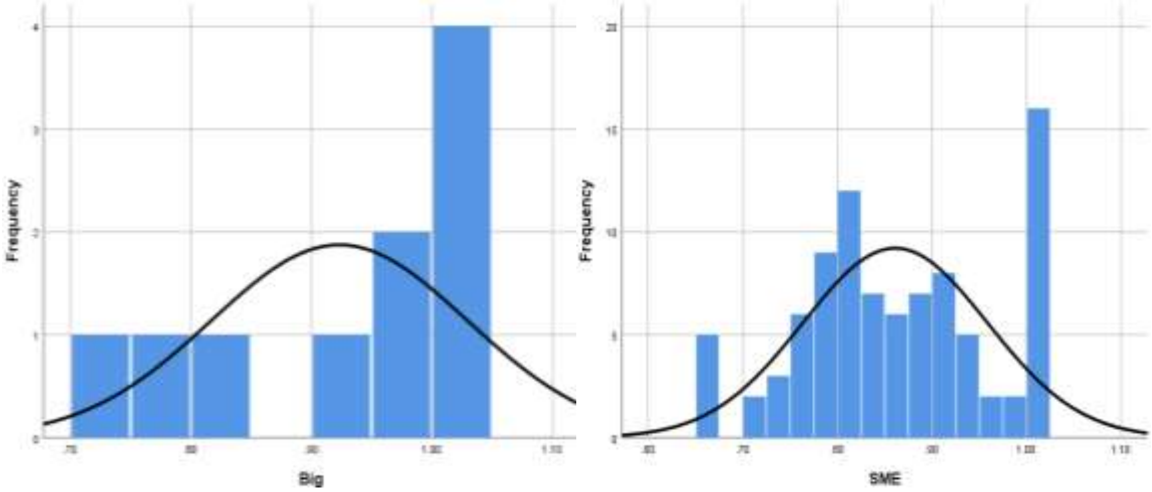


Figure 4. Comparison of DEA and PCA-DEA results (Size)

Source: Author's compilation

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