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Technical Efficiency in Norwegian Grocery Retail

An application of stochastic frontier - and data envelopment analysis on Kiwi Stores

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NORWEGIAN SCHOOL OF ECONOMICS

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With data provided by NorgesGruppen, we have been given a unique opportunity to study the technical efficiency development in the Norwegian Kiwi stores. The investigation has been challenging and educational. We have acquired new knowledge about the Norwegian grocery market, and subjects we previously had no experience with.

On a final note, we would like to express our sincere gratitude to our supervisors Frode Steen and Simen A. Ulsaker for exceptional guidance, support, and valuable feedback. Moreover, we would like to thank NorgesGruppen for the cooperation and opportunity to analyze their data.

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Abstract

The first part of the thesis outlines the historical trends in productivity and profitability in several Norwegian industries and sectors

The second part of the thesis analyzes the technical efficiency of Kiwi grocery stores in the period 2014 - 2015. Since NorgesGruppen has not been subject to any type of technical efficiency analysis, a review of the previous literature has been crucial for the various choices made in connection with the thesis. The chosen methodology is primarily based on the data envelopment analysis (DEA) as a tool for measuring Kiwi´s technical efficiency. As a supplement, the stochastic frontier analysis (SFA) is utilized to support the primary results. Both methods report the technical efficiency as a single number in the interval [0,1] (where 1 is efficient). The data set is processed using two different outlier methods. The choice of models are tested using the Banker´s parametric test and the maximum likelihood ratio test

The results indicate that the average technical efficiency in 2014 and 2015 is in the range of 70 to 84 %. The DEA and SFA approach ranks the most and least efficient Kiwi stores in a similar order, supporting that both approaches can be used complementary. In the year 2014(2015), we find 2(3) technically efficient stores when assuming a DEA model with a constant return to scale. We find 15(16) technically efficient stores when assuming a DEA- model with variable returns to scale. In the SFA- model, we find no efficient stores. Overall, the reported technical efficiencies show great potential for cost savings. Regarding the store-specific inefficiency effects, we find that longer opening hours and Sunday open stores appear to affect Kiwi´s efficiencies negatively. Regarding the inefficiency effects of the region-specific variables, we find stores located in Nord-Trøndelag and Sør-Trøndelag seem to be less efficient than stores in Oslo. When analyzing the inefficiency effects on the municipality level, we find that market concentration affets kiwi´s technical efficiency. We find no sufficient statistical evidence to conclude that factors such as higher income, higher education, higher population size and higher population density affect Kiwi´s technical efficiency.

Keywords – Technical Efficiency, SFA, DEA, CRS, VRS

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1 Introduction

1.1 Background

The increasing competitiveness, globalization of markets, and regulations have made evaluating and analyzing a business´s efficiency an increasingly important managerial activity. The grocery market is no exception, and ongoing efforts are taking place to improve its management.

From June 2021 to June 2022, Norwegian grocery prices increased by 5.6 %. From May to June 2022, the corresponding price growth was 2 %, which marked the highest price hike in four decades (Tangen, 2022). The Norwegian Consumer Council reported that the abnormal price growth was largely driven by a surge in prices of key feedstocks for fertilizer production, shipping costs, electricity prices, and low competition in the Norwegian grocery market.

According to Jan Christian Vestre, the Minister of Trade and Industry, the low competition in the Norwegian grocery market is unsustainable (Regjeringen, 2022). The ongoing inflation crisis has also brought this issue to the attention of the Norwegian government, which is currently investigating several measures to decrease the abnormal price growth. Consequently, the potential implementation of new measures implies that business owners will be incentivized to structure their operations more efficiently. By incorporating benchmark practices and studying technical efficiency scores, it is possible to identify potential areas in productivity and profitability improvement.

Following the guidance from our supervisors Frode Steen and Simen A. Ulsaker, the thesis will first analyze the productivity and profitability development in various Norwegian Industries to acquire a deeper understanding of the macroeconomic factors affecting the Norwegian grocery market. Second, a technical efficiency analysis will be conducted on the Norwegian Kiwi stores from 2014-2015 using the non-parametric data envelopment analysis (DEA) and the parametric stochastic frontier analysis (SFA). The thesis will also investigate the determinants of the obtained technical efficiencies by analyzing the influence of store-specific and region-specific environmental factors.

1.2 Previous Literature

This chapter will provide an overview of the most central productivity and efficiency studies. It is essential to review previous studies to understand the current state of research and identify potential limitations. Further, by building on the work of other authors, we can help to advance our understanding of productivity and efficiency in the Norwegian grocery market, and provide valuable insights for policymakers and business owners.

1.2.1 Productivity Studies

Gabrielsen et al. (2013) examined the buying power in the Norwegian grocery sector. They compared the productivity development against the seafood-industry, the total industry-sector, the food-industry, and the retail-sector. The results implicated that seafood-industry had the strongest labor productivity growth, followed by the retail-sector, the total industry-sector, and the food-industry. The results of the total factor productivity growth were dissimilar. It indicated that retail had the strongest total factor productivity growth, followed by the total industry-sector, seafood-industry and the food-industry.

A master thesis by Jørgen Farmen Sørlie (2017) examined the productivity and profitability development in NorgesGruppen and the Norwegian grocery market. The paper discovered that NorgesGruppen had the strongest labor productivity growth compared to its peers. Further, the paper uncovered slightly lower growth when comparing NorgesGruppen´s labor productivity against the development in total factor productivity. The paper concluded that NorgesGruppen´s productivity development was not that different from retail in general. The findings in this thesis are rational as the Norwegian grocery sector constitutes approximately 39 percent of the entire retail industry, where NorgesGruppen is the largest player.

1.2.2 Efficiency Studies

Upon reviewing the literature on the technical efficiency in the grocery retail, we noticed that only non-parametric data envelopment analysis (DEA) has been utilized to study technical efficiency. To the best of our knowledge, none of the authors have jointly employed both stochastic frontier analysis (SFA) and DEA to compare their results. In this thesis, we will therefore use both methodologies to provide a more comprehensive analysis of the technical efficiency in the grocery retail. Below, we have compiled a list of some relevant studies that have utilized the DEA methodology:

Badin (1997) used the non-parametric DEA-approach to evaluate the technical efficiency of the supermarkets in Brazil. The study concluded that approximately 78% of the sample was technically inefficient. Total supermarkets, or Decision Making Units(DMUs) corresponded to 600. The selected input variables were total store size, number of employees and the average income per capita. The corresponding output was revenue.

Sonza and Ceretta (2008) used the DEA-approach to analyze the relationship between technical efficiency and store size. The authors concluded that larger stores were more technically efficient than smaller stores. The selected input variables were store size, checkouts and the number of employees. The selected output variable was revenue .

Sinik (2017) used the DEA-methodology to evaluate the technical efficiency of Austrian malls in 2015. The results revealed a high level of average technical efficiency (91%) in the period. Total DMUs (malls) corresponded to 32. The selected input variables were store size, items, number of employees and rent. The selected output variable was revenue.

1.3 Research Question

This thesis will be divided into two main parts. In the first part of the thesis, we will provide a brief overview of the main characteristics of the Norwegian grocery market. Followingly, we will analyze the productivity and profitability development in the Norwegian grocery market and compare it against various Norwegian sectors and industries.

In the second part of the thesis, we will present the average technical efficiencies obtained from the SFA and DEA methodologies, before discussing the determinants of technical efficiency.

The determinants of technical efficiency will be divided into two main categories: *store-specific factors* and *region-specific environmental factors*. The store-specific variables are directly related to the characteristics of each individual Kiwi store, such as the availability and quality of its inputs. Meanwhile, the region-specific environmental factors are defined as factors outside the Kiwi's control, such as the level of competition in the Norwegian grocery market.

Based on economic reasoning, it can be argued that market demand is the main driver of Kiwi´s technical efficiency. When the market demand is high, Kiwi stores can generate more revenue. This in turn can be used to support investments in improving production processes, ultimately leading to increased technical efficiency. In contrast, when the demand is low, Kiwi stores may not have the necessary resources to invest in better technology, which can lead to lower technical efficiency. We argue that the retail-sector in particular is more reliant on generating revenue from sales to improve their efficiency. This is because such investments may need to be made more quickly to keep up with the demand. In contrast, other industries such as manufacturing and agriculture may not rely heavily on sales to improve their technical efficiency. This is because the corresponding investments in production technology could be assumed to be spread out over a longer period. Thus, the investigated efficiency factors will be highly related to Kiwi´s market demand, rather than its production efficiency. The corresponding research hypotheses are presented below:

1.3.1 Hypotheses: Store-Specific Factors

In the following, we will present the hypotheses related to the store-specific factors.

In general, it is illegal for Norwegian grocery chains to operate on Sundays. However, there are some exceptions to the law. For instance, aside from convenience stores such as Narvesen and 7-Eleven, only grocery stores that are less or equal to 100 square meters are permitted to operate on Sundays (Åpningstidsloven, 1998). This leads to the following hypothesis:

H_1 = Sunday open Kiwi stores affect Kiwi´s technical efficiency.

The opening hours in the Norwegian grocery market have been strictly regulated throughout the years. However, since 2003, there have been no restrictions. Consequently, this has allowed grocery chains to decide their opening hours themselves. According to a report written by the Consumer Research Institute SIFO, the number of stores opening early and closing late has increased in the most recent years (Schjøll and Lavik, 2016). This suggests that opening hours have become an important competitive parameter, which leads to the following research hypothesis:

H_1=Longer opening hours on weekdays affect Kiwi´s technical efficiency.

1.3.2 Hypotheses: Region-Specific Environmental Factors

In the following, we will present the hypotheses related to the region-specific environmental factors on the Norwegian administrative region level, municipality level and local level.

One can argue that regional institutions influence how regional collective decisions are made. In this context, it is rational to believe that efficiency within different regions i Norway is particularly marked between urban and remote rural areas. This leads to the following research hypothesis:

H_1=The technical efficiency of Kiwi stores varies among the Norwegian administrative regions.

Radcliffe (2022) argues that an economy´s productivity rises as the number of educated workers increases. The justification for this can be argued by the fact that skilled workers could perform several tasks more efficiently. Additionally, it can be argued that higher levels of education might also affect the demand. For instance, individuals with higher levels of education tend to have higher incomes, which may increase their ability to purchase more groceries. To meet the increased demand, it may be necessary for Kiwi stores to operate more efficiently. Thus, we would like to examine whether higher levels of education on the municipality level affect Kiwi´s technical efficiency. This leads to the following research hypothesis:

H_1=Higher levels of education in the municipalities affect Kiwi´s technical efficiency.

Cingano and Schivardi (2004) argues that productivity growth is positively associated with a city´s population size. In this context, we argue that a higher population size may provide a larger customer base, which can increase the number products sold at the Kiwi stores. The increased demand may require the grocery stores to invest in new technologies, such as self-service checkouts, or even expand their selling area in order to serve the customers more efficiently. Thus, we want to examine whether technical efficiency is affected by the population size on the municipality level. Consequently, the following hypothesis is put forward:

H_1=The population size in the municipalities affects Kiwi´s technical efficiency.

Matherly et al. (2018) emphasizes that a higher population density (number of people per unit of the total land area of a geographical area) strongly affects income. In the context of Kiwi, we argue that a higher population density may result in a higher demand for groceries due to a larger number of potential customers in the area. Additionally, it can be argued that a higher population density would allow for a greater variety of products to be sold due to more potential customers with diverse preferences. To meet the increased demand, we argue that Kiwi stores located in areas with a higher population density would need to be run more efficiently. Thus, we would like to investigate whether the degree of population density on the municipality level influences Kiwi´s technical efficiency. This leads to the following research hypothesis:

H_1=The population density in the municipalities affects Kiwi´s technical efficiency.

According to the income effect, the consumption of goods increases as consumers´ income rises (Horowitz and McConnell, 2003). As emphasized, higher incomes may be associated with the ability to purchase more groceries. Additionally, it is also rational to believe that higher income may allow individuals to purchase more expensive and specialized products. This in turn could potentially incentivize the Kiwi store to improve their technical efficiency to meet the increased demand for such products. Thus, it is interesting to examine whether a higher median income on the municipality level could explain the variation in the obtained technical efficiencies. This leads to the following research hypothesis:

H_1= Higher level of median income in the municipalities affects Kiwi´s technical efficiency.

The economic theory states that competition benefits consumers by keeping the prices low and the quality of goods high (Boushey and Knudsen, 2022). Moreover, it can be argued that competition may incentivize to more innovation, which can ultimately contribute to firms becoming more efficient. In the context of Kiwi stores, increased competition could encourage them to differentiate themselves from the competitors, leading to increased innovations and improvements in how they are managed. Thus, it is interesting to determine whether the level of market concentration on the municipality level affects Kiwi´s technical efficiency. In this context, the Herfindahl-Hirschman Index (HHI) will be utilized to study the inefficiency effects. Thus, the following research hypothesis:

H_1=The level of market concentration in the municipalities affects Kiwi´s technical efficiency.

As an additional feature to the HHI-measure, the number of close competitors will be considered to determine whether competition is an important determinant on the local level. More specifically, we assume that if the number of competitors within a predetermined range is relatively high, it becomes easier for the consumer to switch stores. This in turn might affect Kiwi´s demand negatively. This leads to the following research question:

H_1=The number of close competitors on the local level affect Kiwi´s technical efficiency.

Furthermore, it is also interesting to examine whether the store density per capita (the number of stores per unit of the total population in the municipalities) is a key factor in determining technical efficiency. We argue that a higher store density per capita could result in lower demand for Kiwi's products, as the stores may need to lower their prices to remain competitive. This, in turn, could lead to decreased revenues and reduced resources available for improving production efficiency. Consequently, the following hypothesis is put forward:

H_1= The store density per capita in the municipalities affects Kiwi´s technical efficiency.

All of the above lead to the following research questions:

- How has productivity and profitability in the Norwegian grocery market and comparable industries developed throughout time?

-What is the average technical efficiency of Norwegian Kiwi stores, and to what extent do store- and region-specific factors affect Kiwi´s technical efficiency?

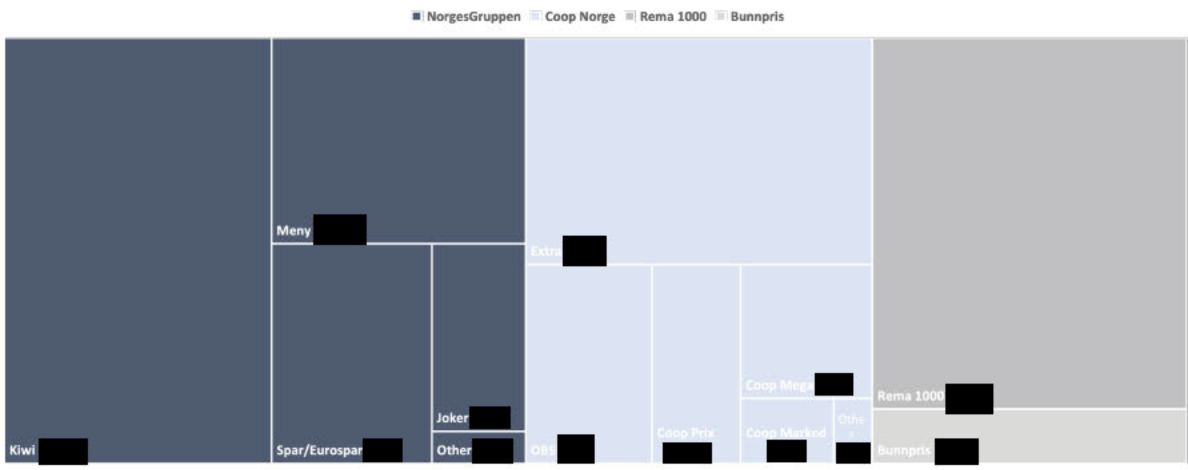
1.4 Structure of The Thesis

This thesis is divided into 8 main chapters. The previous chapter contained a brief overview of the background, literature, and a presentation of the research question. The following chapter provides a general presentation of the Norwegian grocery market. Chapter 3 examines the productivity and profitability development in various Norwegian industries and sectors. Chapter 4 introduces the data envelopment analysis (DEA) and the stochastic frontier analysis (SFA). In chapter 5, the chosen data, variables, and models are presented and discussed. Chapter 6 contains the technical efficiency results and a discussion of the efficiency determinants. In chapter 7, the results are summarized. In chapter 8, limitations and opportunities for in-depth research are suggested.

2 The Norwegian Grocery Market

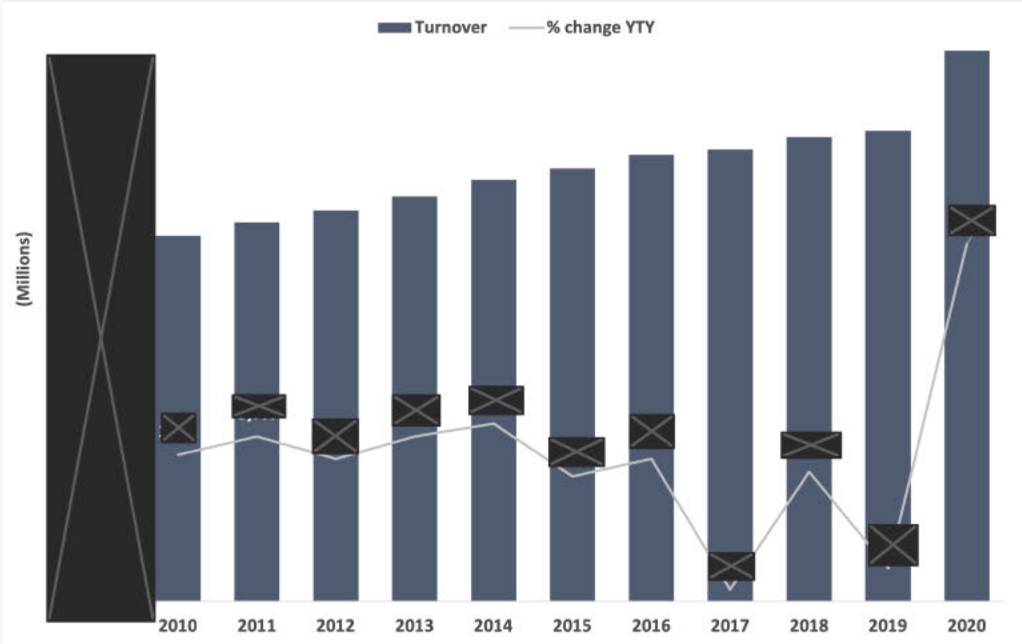
The market term is often used to describe an industry, geographical markets, consumer groups, or goods and similar. Consequently, the definition depends on which dimensions are chosen to define the market. Regjeringen (2011) defines the Norwegian grocery market as a link in the value chain for food, whereas the four "umbrella chains" are assumed to define the Norwegian grocery market. Consequently, this is also the definition we will use as a basis in the following sections. Following, we will present the development in the market shares, revenue and number of stores.

Figure 2.1: Market Shares Distributed Among Grocery Chains



The umbrella chains consist of NorgesGruppen, Coop Norge, Rema 1000 and Bunnpris with respective market shares of [redacted]%, [redacted]%, [redacted]% and [redacted]% (Nielsen, 2021). The umbrella chains consist of a portfolio of stores owned by the chains or by merchants through franchise agreements (Regjeringen, 2011). Rema 1000, Kiwi, and Extra are the largest grocery chains with market shares of [redacted]%, [redacted]% and [redacted]%, respectively.

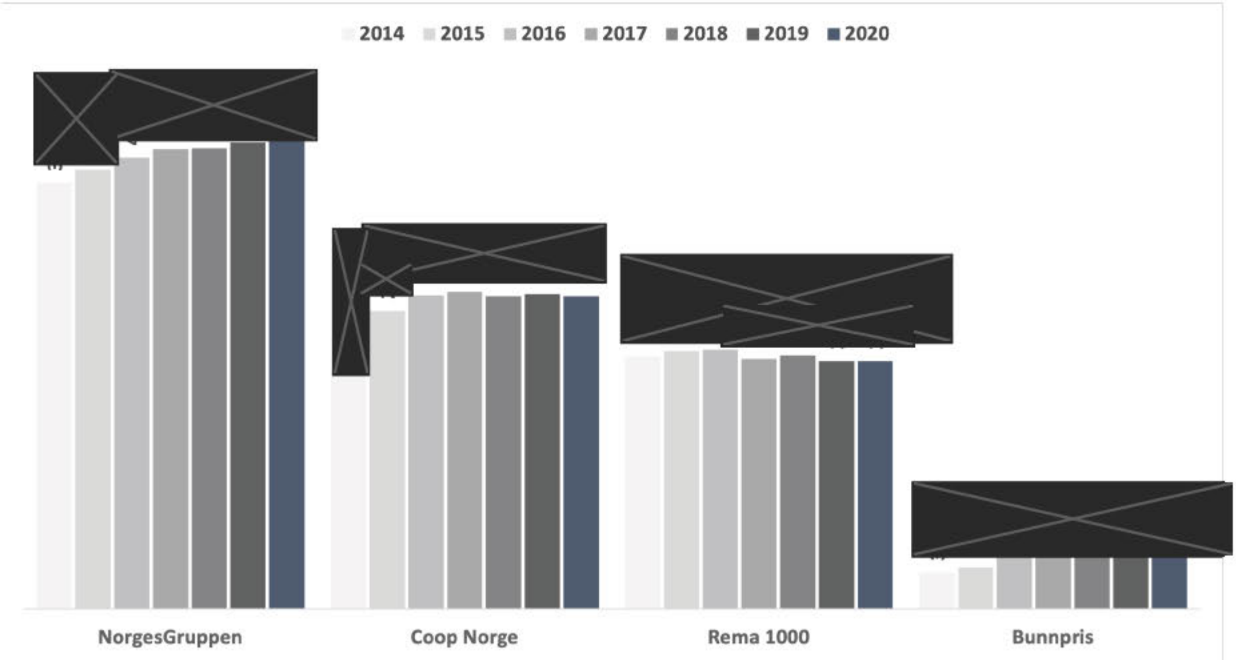
Figure 2.2: Development in Revenue



In 2020, the Norwegian grocery market achieved a revenue of NOK [redacted] excluded value-added tax (Nielsen, 2021). The turnover corresponded to an increase of [redacted]%, which marked one of the most successful years in the history of Norwegian grocery retail. Among the umbrella chains, NorgesGruppen had the largest average growth of [redacted]%, outperforming the peers by approximately [redacted]%. According to Daglivarerapporten from 2021, the record-high market growth was highly correlated with the COVID-19 pandemic. The corresponding restrictions made closing borders, cultural life, and catering establishments necessary, ultimately contributing to booming sales. The sales were particularly strong in areas with a high population and border regions, such as Viken, Oslo and Vestland, with respective year-over-year growths of [redacted]%, [redacted]% and [redacted]%, respectively.

Further, when examining the Norwegian grocery market as initially defined, the development in the corresponding market shares is presented in figure 2.3.

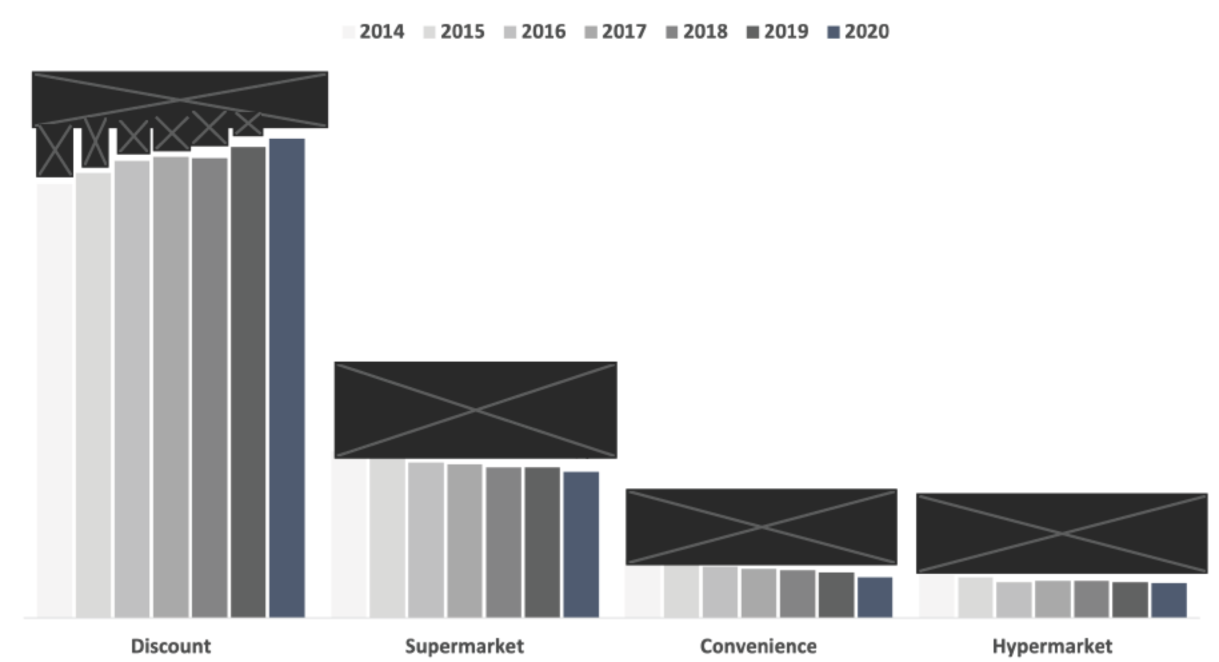
Figure 2.3: Umbrella Chains: Development in Market Shares



As illustrated, NorgesGruppen has been the most dominant umbrella chain throughout the period. In 2014, Rema 1000 was the second largest player, before it was surpassed by Coop in 2015 after acquiring ICA.

The most recent trend indicates an increasing number of market shares in the discount segment compared to the supermarket, convenience, and hypermarket. In the following, the corresponding development in market shares is presented in figure 2.4.

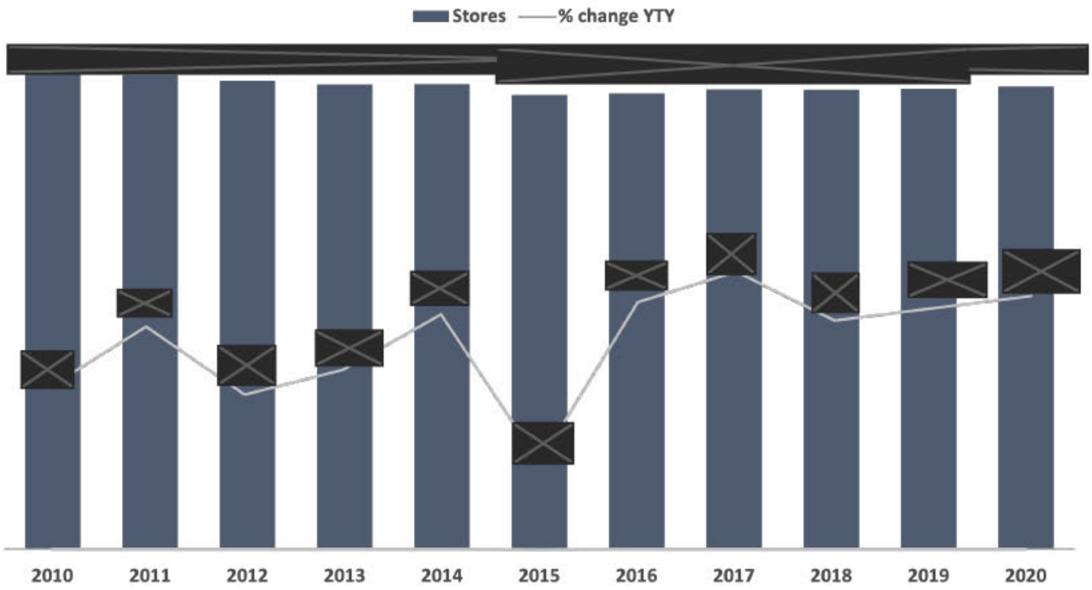
Figure 2.4: Grocery Segments: Development in Market Shares



The discount segment is currently the largest segment in the Norwegian grocery market, with a corresponding market penetration o[redacted]%. As shown in figure 2.4, the segment has experienced relatively stronger growth throughout the period, whilst the other segments have lost market shares. According to Dagligvarerapporten from 2021, the disparity was much due to rebranding, new establishments, and closed stores.

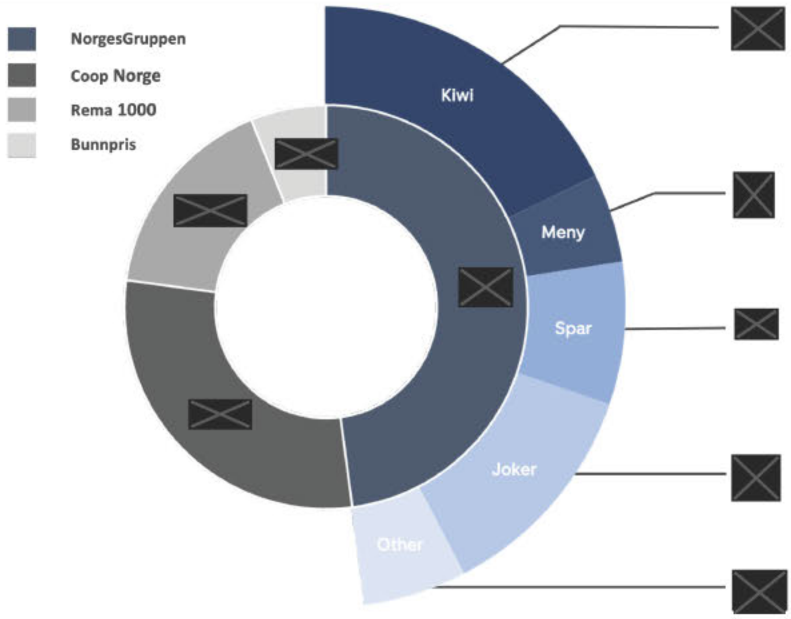
According to Wifstad et al. (2018) the Norwegian grocery market is characterized by a high store density per capita compared to Sweden and Europe in general.

Figure 2.5: Umbrella Chains: Development in Total Stores



In 2020, there were [redacted] stores in the Norwegian grocery market, which was an increase of [redacted] stores from the previous year. Among the segments, the discount segment increased by [redacted] stores. In comparison, the convenience segment decreased by [redacted] stores, whilst the supermarket segment increased by [redacted] store. Since 2010, the total number of stores has decreased by approximately [redacted]%, corresponding to [redacted] stores in absolute values.

Figure 2.6: NorgesGruppen: Total Number of Stores



Among the umbrella chains, NorgesGruppen holds the largest portfolio of stores. Around [redacted]% of NorgesGruppen´s portfolio is owned by merchants, whilst the remaining [redacted]% is owned by NorgesGruppen. In 2020, NorgesGruppen consisted of [redacted] stores, whereas Kiwi accounted for more than 1/3 of the portfolio. In addition to grocery stores, NorgesGruppen operates other chain concepts within the service trade. These concepts are Deli De Luca, Mix, Kaffebrenneriet, Jafs and Big Horn Steak House, which account to approximately [redacted] stores.

Based on the outlined market characteristics, we can conclude that the Norwegian grocery market constitutes a significant role in the Norwegian mainland economy. In the following chapter, we will examine the corresponding profitability and productivity growth.

3 Profitability and Productivity Development

In this part of the thesis, the subsequent analysis will be based on chapter 3.2 in Kjøpermakt I Daglivaresektoren (Gabrielsen et al., 2013). The study will be expanded by examining the productivity and profitability development in various Norwegian industries and sectors. Using the data from StatBank Norway (SSB), the thesis will also try to uncover the potential drivers of productivity and profitability growth.

3.1 Selection of Relevant Sectors and Industries

To be able to assess the productivity and profitability performance in the Norwegian grocery market, a selection of relevant industries and sectors was essential.

From SSB we retrieved data for the food-industry, retail-sector, total industry-sector, and the grocery-sector. According to SSB, the food-industry includes beverages and tobacco with the exclusion of fish processing, retail-sector includes the repair of motor vehicles, the total industry-sector includes many of the most important Norwegian sectors (retail, metals, etc.), whilst the grocery-sector includes grocery stores with a wide selection of goods.

The food-industry was chosen as a relevant industry since the corresponding products are sold in the Norwegian grocery market. Moreover, the retail-sector was chosen as a relevant sector as it is characterized by many physical shops and similar distribution of goods. On the other hand, the total industry-sector was selected as it measures the general economic activity in the mainland of Norway. Meanwhile, the grocery-sector was selected as a proxy to measure the development in the Norwegian grocery market. We further assume that the grocery-sector reflects the development in the Norwegian grocery market even though it includes several elements that are not directly associated with the Norwegian grocery market, as initially defined in section 2. Moreover, it is worth mentioning that selected industries and sectors are not entirely independent. For instance, the food-industry is a part of the total industry-sector, whilst the grocery-sector is a part of the retail-sector. Thus, some of the productivity and profitability growth might be highly correlated.

The selection of the relevant industries and sectors are consistent with the examined industries in Gabrielsen et al. (2013). Considering the high relevance of this study, it is important to emphasize that SSB has changed some of the industry/sector definitions. For instance, oil refining is no longer a part of the total industry-sector. Consequently, some of the obtained results in this thesis might differ from the results obtained in the study.

3.2 Profitability

Many factors can positively impact profitability, including productivity (DCED, 2022). The relationship between profitability and productivity is often symbiotic. For instance, a decline in productivity can affect economic output, increase operational costs, and ultimately decrease the profit margin. In the following section, we will first present the retrieved profitability data. Second, we will present the financial ratios and examine the profitability development in the various Norwegian sectors and industries.

3.2.1 Data

SSB was used to retrieve the profitability data for the relevant industries and sectors. The retrieved profitability data consisted of pre-calculated measurements for the operating margin, gross margin, return on equity and return on assets. Unfortunately, the profitability data for the food-industry and the grocery-sector was discontinued after 2015. Consequently, we were unable to estimate their most recent productivity growths. Furthermore, the data was converted to indexed data to allow for a better comparison of the data.

3.2.2 Financial Ratios

In financial analysis, financial profitability ratios are the most popular metrics to measure a firm´s ability to generate income relative to revenue, assets, operating costs, and equity. The most common ones are grouped into the following: gross margin, operating margin, return on assets and return on equity.

3.2.2.1 Gross Margin Ratio

$$Gross\ Margin = \frac{Gross\ Profit}{Net\ Sales} \tag{3.1}$$

The gross margin ratio compares a company's gross profit to its net sales (Bloomenthal, 2021). It reveals how much profit is generated after a company has paid off its Cost of Goods Sold. A higher gross margin ratio indicates that a company has more capital to pay its operating expenses like salaries, utilities, and rent.

3.2.2.2 Operating Margin

$$Operating\ Margin = \frac{Operating\ Income}{Net\ Sales} \tag{3.2}$$

The operating margin ratio, also known as operating profit margin, is a profitability measure that reflects the percentage of profit a company produces from its business operations before tax and interest expenses (Hayes, 2022). A higher operating margin is positive as it indicates that there are enough cash flows from the operations to cover both fixed and variable costs.

3.2.2.3 Return On Assets

$$Return\ On\ Assets\ (ROA) = \frac{Net\ Income}{Total\ Assets} \tag{3.3}$$

The return on assets ratio measures a company's profitability in relation to its total assets (Hargrave, 2022). Total assets are equal to the sum of shareholders 'equity and debt. The higher the ratio, the more efficiently a company manages its balance sheet to generate profits.

3.2.2.4 Return On Equity

$$Return\ On\ Equity\ (ROE) = \frac{Net\ Income}{Shareholder's\ Equity} \tag{3.4}$$

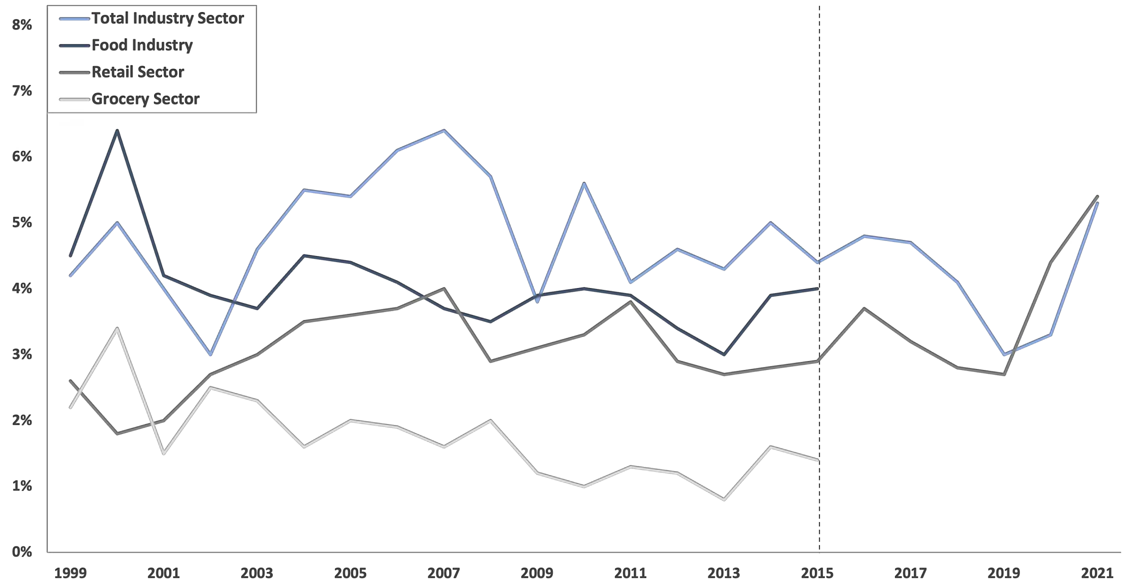
Return on Equity is a ratio used to measure a corporation's profitability in relation to its shareholders' equity (Furhmann, 2022a). The higher the ratio, the more efficient a company´s management is at converting its equity financing into profits.

3.2.3 Profitability Development

In this section, we will examine the profitability development in the food-industry, retail-sector, grocery-sector, and the total industry-sector.

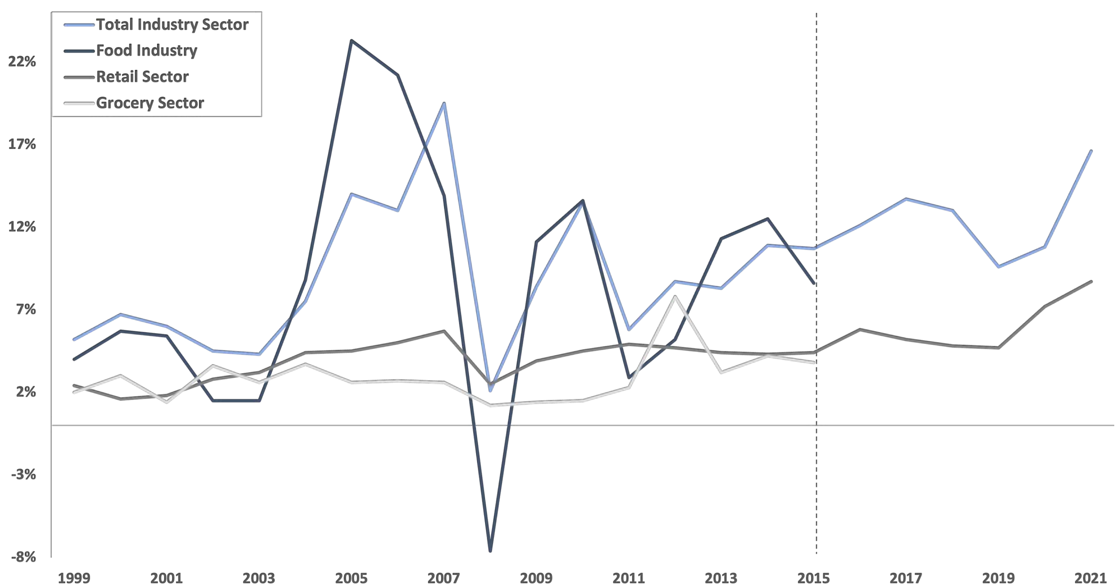
In figure 3.1, the development in gross margins is illustrated.

Figure 3.1: Development in Gross Margins



Until 2015, it can be observed that the total industry-sector and the food-industry were most profitable, followed by the retail-sector and the grocery-sector. In 2019, it can be observed that retail managed to surpass the total industry-sector. This implies that retail-sector has become relatively more efficient in managing its resources that directly contribute to the production of the goods.

Figure 3.2: Development in Operating Margins



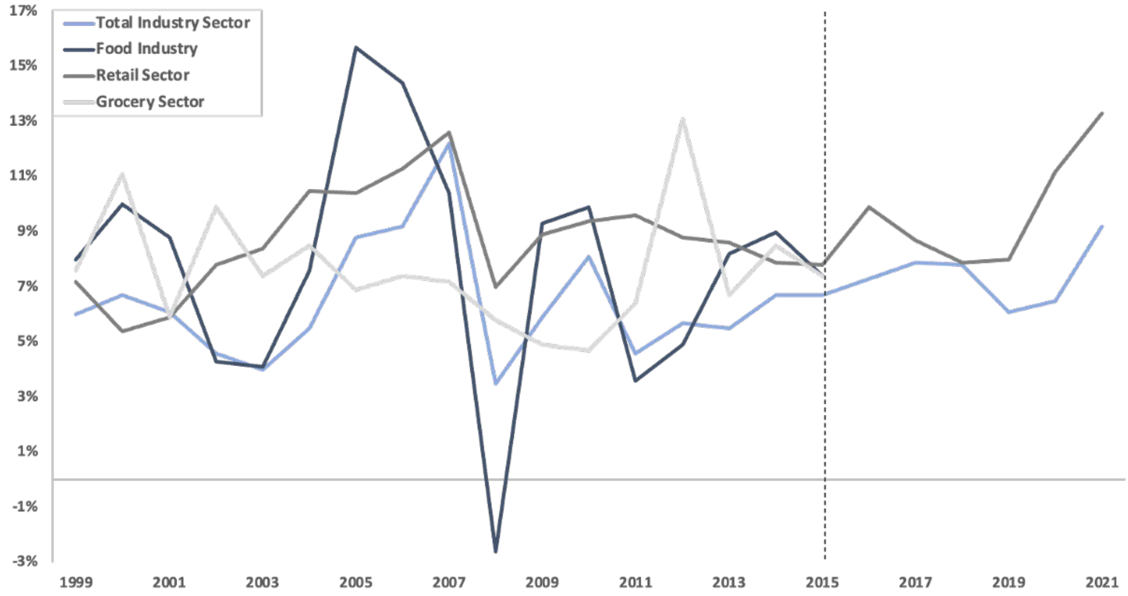
In figure 3.1 we can observe highly similar trends in the operating margins. Likewise, the total industry-sector and the food-industry are most profitable, while the retail-sector and the grocery-sector are the least profitable. Contrary to the most recent development in the gross margins, the retail-sector is relatively less profitable. This implies that business operations in the retail-sector contain relatively more financial risk.

When comparing the overall development in the gross margins against the development in the operating margins, we can observe that the development in the operating margins is generally more volatile. The higher volatility in the operating margins is rational. This is because the gross margins measure how efficiently a company manages its direct costs, while the operating margins also measure how efficiently it absorbs the fixed costs. Said differently, the higher volatility in the operating margins can be explained by the fact that more of the costs are incorporated in the profitability measure (Beers, 2021).

More generally, we can observe the largest volatility for the total industry-sector and the food-industry between 2007 and 2009. In the same period, the global financial crisis occurred, wiping out nearly 64% of the Oslo Stock Exchange´s value in a period of 6 months (Norges Bank, 2008). Surprisingly, the grocery-sector and the retail-sector did not experience as large fluctuations. The explanation can be argued to be that groceries are naturally hedged against disruption and uncertainty since food is considered a necessity. For the retail-sector, the rationalization is somewhat different. It is rational to think that the demand for products in the retail-sector would decrease significantly during an economic decline. Consequently, an explanation can be argued to be that Norwegian consumers were not particularly affected by the global financial crisis. This is in accordance with (Gjedrem, 2009), stating that economies with solid finances, such as Norway, were less severely affected by the financial crisis. Moreover, we can observe substantial profitability growth in the retail sector from the year 2020. In the same period, the COVID-19 pandemic occurred. This suggests that retail in particular is more hedged against disruption and market risk.

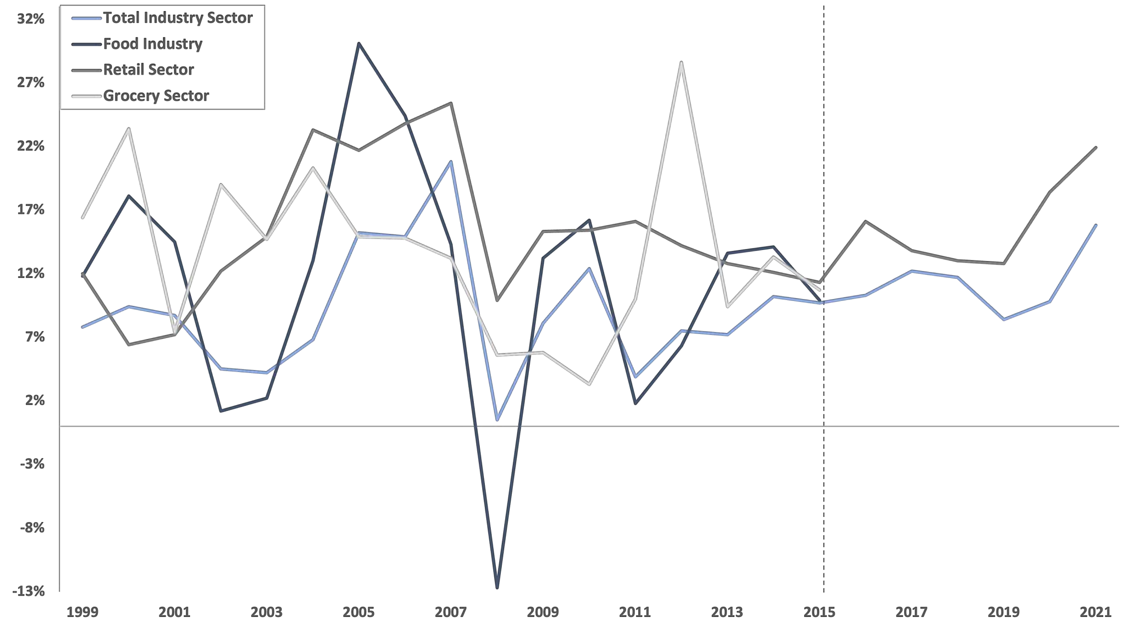
In the next section, we will examine the development in the return on assets (ROA) and the return on equity (ROE). In figure 3.3 the development in ROA is illustrated.

Figure 3.3: Development in ROA



In 2015, we can observe that food-industry and the total industry-sector are no longer dominant in terms of profitability. In contrast to the development in the gross and operating margins, the retail-sector is most profitable, followed by the grocery-sector, food-industry and the total industry-sector. In terms of the most recent development, we can observe that retail-sector is also the most profitable implying that companies in the retail-sector are relatively more efficient in converting their equity and debt financing to create profits.

Figure 3.4: Development in ROE



As in figure 3.4, we can observe highly similar trends in ROE. However, ROE is significantly more volatile, which can be observed by the lower minimum and higher maximum bounds. This is somewhat rational. Many companies issue debt to increase their cash-flow (Furhmann, 2022b). In this context, the higher volatility in ROE implicates that leverage is an important factor for stabilizing profitability. Further, when comparing the development in ROE against the gross and operating margins, we can observe more variation in ROE, especially in the retail-sector and the grocery sector. This implies that both sectors are more affected by market fluctuations than initially emphasized.

Conclusively, we argue that profitability could depend on the selection of the profitability ratios. For instance, the grocery-sector and the retail-sector are relatively less profitable when assuming gross and operating margins. Meanwhile, the food industry seems to be relatively profitable across all ratios.

Most recently, several politicians have stated that new laws need to be implemented to increase the competition in the Norwegian grocery market (NTB, 2022). Based on the findings from the profitability analysis, we cannot conclude that the Norwegian grocery market is profitable. As industries and sectors with high profitability are generally characterized by low competition, the politicians´ claims may seem counter-intuitive.

3.3 Productivity

In the following section, we will first present the data retrieved for the productivity analysis. Thereafter we will present the productivity framework and examine the productivity development

3.3.1 Data

The complete labor productivity measurements were retrieved from SSB. We analyzed the development in the food-industry, the total industry-sector and the retail-sector. It is important to mention that SSB did not have any input data nor complete productivity measurements for the grocery-sector. However, as emphasized earlier, the grocery-sector is a part of the retail-sector. Thus, we further assume that retail is an acceptable proxy for the productivity development in the Norwegian grocery market. In terms of total factor productivity, SSB did not have the complete total factor productivity measurements for the relevant industries or sectors. Consequently, we needed to calculate the total factor productivity measurements manually. Subsequently, we used SSB to retrieve the necessary inputs to estimate the total factor productivity. The retrieved inputs were capital service's cost share, fixed physical capital and labor hours. Since the data for the capital service´s cost share was incomplete, we chose to utilize the average capital service´s cost share from 1971-2012 as a proxy for the data ranging from 1971-2021. The average capital service cost for the food-industry, the total industry-sector and the retail-sector was estimated to 5.43%, 7.72% and 15.88%, respectively. Lastly, the productivity growth was converted to indexed values to allow for a better comparison of the data.

3.3.2 Definition and Measures of Productivity

The productivity definition is broad. More generally, productivity is defined as the amount of output relative to the amount of input (Kenton, 2022). An increase in productivity is often caused by the development of new technology or increased knowledge, but it can also be driven by other factors, such as factor prices. For instance, productivity will increase if factor prices increase and all the other factors stay constant. Likewise, a decrease in the factor prices will decrease productivity. Since this is not a controllable factor, it is usually adjusted. The best way of doing this is to adjust the corresponding income and costs using the price indexes. However, it is important to notice that factor effects can never be fully adjusted as the price indexes are not specified for each specific industry.

The ideal productivity measure would illustrate every possible factor and its influence on productivity. Since this is not possible, the measure of general growth will be utilized in this thesis.

Generally, Productivity is measured in labor - and total factor productivity (SSB, 2017). Labor productivity measures the production in relation to labor, whilst the total factor productivity measures the production in relation to both labor and capital. In this thesis, the estimation of labor productivity and total factor productivity is based on SSB´s estimations, illustrated in equations (3.5) and (3.6), respectively.

3.3.2.1 Labor Productivity

Labor productivity reflects the workforce's knowledge, effort, total production capital, technology, the economics of scale, and capital utilization. SSB´s labor productivity formula is presented in (3.5)

$$ln(\frac{LP_t}{LP_{t-1}}) = ln(\frac{GP_t}{GP_{t-1}}) - ln(\frac{L_t}{L_{t-1}}) \tag{3.5}$$

Where, LP_t is labor productivity in each period, while LP_{t-1} is labor productivity in the previous period. GP_t is the gross product of a given period, while L_t is the labor in each period. Altogether, $ln((LP_t)/(LP_{t-1}))$ returns the labor productivity growth between two periods.

It is important to mention that growth rates in the gross product, total hours, and labor productivity differ from the growth rates found in the national accounts. This is due to the fact that labor productivity is calculated using logarithmic growth rates. Additionally, SSB´s numbers are aggregated using the Törnquist indexes instead of the Laspeyers index (SSB, 2017). The main difference is that Törnquist calculates the price indexes using the half-splice method over a 25-month window, whilst the Laspeyers indexes uses the fixed prices in each period.

3.3.2.2 Total Factor Productivity

The total factor productivity (TFP) is the ratio between the production, the average of the capital investments, and the work effort. Factors such as technological development and organizational improvements might explain the productivity variation.

SSB´s formula for total factor productivity is presented in equation (3.6)

$$ln(\frac{TFP_t}{TFP_{t-1}}) = ln(\frac{LP_t}{LP_{t-1}}) - b(ln(\frac{C_t}{C_{t-1}}) - ln(\frac{L_t}{L_{t-1}})) \tag{3.6}$$

Where TFP_t is the total factor productivity in a period t, while TFP_{t-1} is the total factor productivity in the previous period. b is the capital services' cost share, whilst C_t and L_t are the capital services and labor hours, respectively. C_{t-1} and L_{t-1} are the capital services and labor in the previous periods. The most noticeable point of this formula is the fact that LP from (3.5) is used to calculate TFP instead of gross product (GP).

3.3.3 Productivity Development

The aim of this section is to present the historical productivity development in the retail-sector, the total industry-sector, and the food-industry. In the following sections, we will first examine the development in labor productivity. Thereafter, we will examine the development in total factor productivity and compare the results consecutively. Finally, we will elaborate on the relationship between the productivity growth and historical events in the Norwegian economy.

3.3.3.1 Labor Productivity

In figure 3.5, the development in labor productivity is illustrated.

Figure 3.5: Development in Labor Productivity

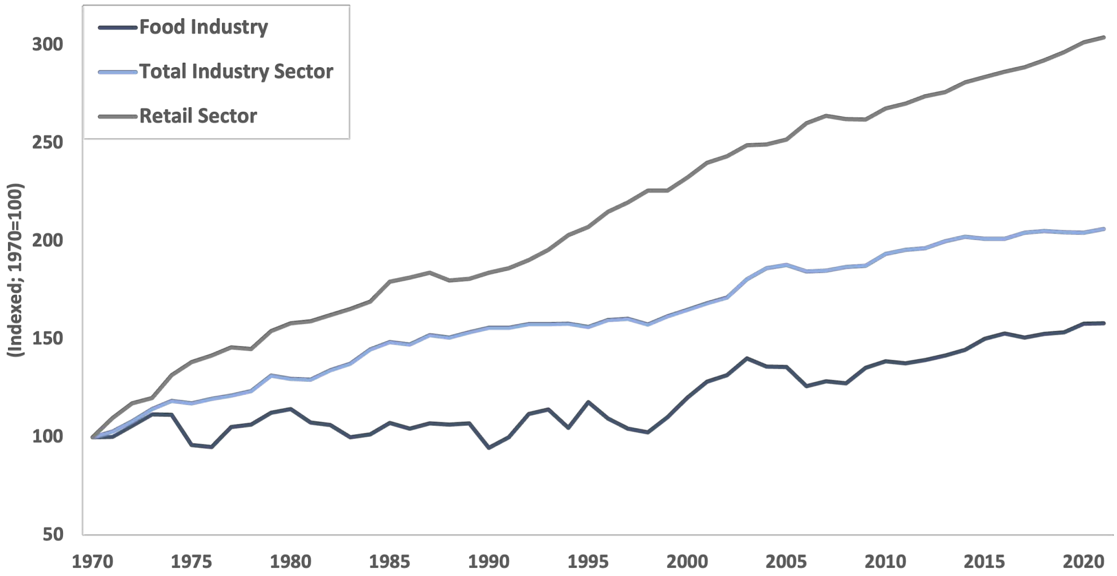


Table 3.1: Summary Statistics [Labor Productivity]

	1971-1981		**1982-1992**		**1993-2003**		**2004-2014**		**2005-2021**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Food-Industry	0.7	7.0	0.4	6.4	2.6	7.8	0.4	4.6	2.0	2.6
Total Industry-Sector	2.7	3.1	2.6	2.6	2.1	3.3	2.0	2.6	0.6	1.4
Retail-Sector	5.4	3.9	2.8	3.3	5.3	2.3	2.9	2.9	3.3	1.0

From figure 3.5, we can observe that retail has grown by more than 300% from 1970 to 2021. In comparison, the total industry-sector and the food-industry have grown by 206% and 158%, respectively. This implies that retail has experienced the largest labor productivity growth throughout the estimated period. The findings are in line with the presented summary statistics in table 3.1. The summary statistics are divided into five time periods to explore the productivity growth in more detail. The table implies that retail has been the most dominant industry. Additionally, we notice that food-industry has had the highest volatility. This is rather surprising since the corresponding industry has had the weakest productivity development throughout the period. More generally, table 3.1 discloses that productivity growth has been unstable for all industries, which is illustrated by the corresponding standard deviations and means. For the retail sector, we observe that the corresponding variation has been relatively less. In fact, from the period 1993- 2003 to the period 2005-2021, the corresponding average growth has exceeded the volatility.

Based on economic reasoning it seems that especially two factors have affected retail´s productivity growth. The first factor can be argued to be globalization, i.e., increased imports from developing countries at the end of the 1900´s (Urata, 2002). The second factor can be argued to be the increased usage of cheap materials and cheap labor from low-cost countries in the most recent decades (MacArthur et al., 2016). In addition to these factors, it can also be argued that several other economic factors have contributed to the growth. For instance, the rise of the computer and the internet era in the 1980´s and 1990´s. Meanwhile, in the most recent time, it can be argued that artificial intelligence and machine learning have become two increasingly important factors(Sébastien, 2020). Despite the corresponding events, the food-industry and the total industry-sector have not managed to keep up with the retail sector.

3.3.3.2 Total Factor Productivity

In figure 3.6, the development in the total factor productivity is illustrated.

Figure 3.6: Development in Total Factor Productivity

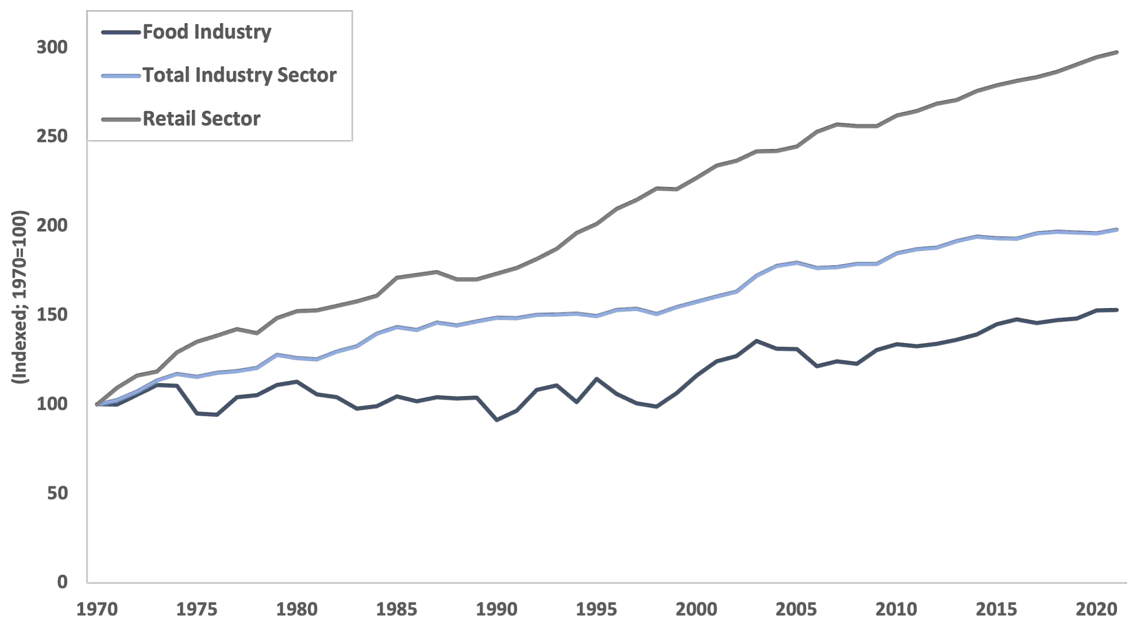


Table 3.2: Summary Statistics [Total Factor Productivity]

	1971-1981		1982-1992		1993-2003		2004-2014		2015-2021	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Food-Industry	0.5	7.0	0.2	6.4	2.5	7.7	0.3	4.5	2.0	2.6
Total industry-sector	2.3	3.1	2.3	2.6	2.0	3.2	2.0	2.5	0.5	1.5
Retail-Sector	4.8	3.9	2.6	3.4	5.5	2.6	3.1	2.7	3.1	0.8

Analogous to the development in labor productivity, the trends are highly similar for the total factor productivity. We notice a slightly lower growth for all industries partially due to the inclusion of several varying inputs, such as the capital service´s cost share. However, we observe that retail is still the most productive sector, followed by the total industry-sector and the food-industry. The fact that food-industry has consistently lower productivity growth is especially interesting since it was uncovered in section 3.2 that the corresponding profitability growth was less affected by the selection of the financial ratios. The findings are in line with (Gabrielsen et al., 2013), where the relationship between the productivity and profitability growth is argued to be unclear. However, it is conceivable that the most productive industries are also the least profitable ones. A possible explanation to this might be that productive industries put more focus on increasing their productivity to become more profitable. Moreover, it can also be argued that the most profitable industries are the least productive ones, as such industries might need less investments in productivity to become profitable. Thus, this might explain why the food-industry is not that productive.

From table 3.2 we can also observe that retail, on average, has experienced the largest and most stable total factor productivity growth. More generally, we can also observe a periodic volatiity decrease for all industries and sectors. However, the findings are dissimilar in terms of their average productivity growths. For instance, from table 3.2 we can observe that food-industry was the only one with a positive productivity growth from the period 2004-2014 to the period 2015-2021.

When comparing the overall findings against Gabrielsen et al. (2013), we can observe similar results. If we disregard the seafood-industry, we notice that retail is also the most productive sector in terms of the labor and total factor productivity, followed by the total industry-sector and the food-industry. Meanwhile our findings suggest that the total industry-sector and food-industry are much less productive industries than retail, the study suggest otherwise. However, as emphasized earlier, this might be due to modifications in the industry/sector definitions.

3.3.3.3 Historical Events Affecting the Productivity Development

In this section, we will explore the relationship between the productivity growth and historical events in the Norwegian Economy in more detail.

In the 1980´s, the Norwegian banks had a large lending growth, which eventually resulted in a banking crisis that lasted from 1987 to 1992. The crisis occurred as result of both household and corporations having solvency problems (SSB, 1999). From the summary statistics, presented in table 3.1 and 3.2, one can observe that food-industry and retail-sector experienced relatively large productivity declines in the periods from 1971-1981 to 1982-1992. Thus, it can be argued that the banking crisis might have affected their productivity. The fact that retail sector experienced the largest decline in productivity is rational as people generally buy less goods when their purchasing power falls.

The period 1993-2003 is highly interesting in the examination of the food-industry. From the summary statistics in tables 3.1 and 3.2 it can be observed that both labor and total factor productivity growth increased by 2.2 and 2.3 percentage points from the period previously, respectively. In the same period the value of the Norwegian NOK increased substantially (Norges Bank, 2022). Consequently, when it becomes relatively cheaper to import goods, the productivity increases. Since the same amount of output can be produced with less input, the corresponding productivity growth seems highly rational.

In 2008 the financial crisis occurred. In the examination of the summary statistics, it becomes clear that the corresponding crises did not only affect the profitability growth, but also the productivity growth. Furthermore, in the first quarter of 2020, the outbreak of the covid-19 pandemic occured(Fredriksen, 2021). From the summary statistics, it is difficult to obtain any clear effects on the productivity development. However, based on the economic intuition we do argue that such events play a significant role. For instance, as more people lose their jobs, or are unable to work, the production is normally set to decrease. Given that the corresponding decrease in input and output is not proportional, the productivity should also decline. However, according to the European Central Bank, the labor productivity measured in GDP per hours increased at the onset of the Covid-19 pandemic (Lopez-Garcia and Szörfi, 2021). This contradicts the general notion of productivity being procyclical, which reflects the unique nature of the corresponding crisis.

So far, a solid understanding of the Norwegian grocery market and the corresponding productivity and profitability development has been established. From this point on, a more specific area of the grocery market will be investigated. More specifically, the data retrieved from NorgesGruppen will be utilized to analyze the technical efficiency of Kiwi stores. In the following section, we will first present the chosen methodologies. Second, we will discuss the corresponding data, variables and models. Third, we will present the technical efficiency results and discuss the determinants of technical inefficiency. Lastly, we will summarize the findings of this study, including any limitations, and suggest areas for further research

4 Methodology

The main objective of this chapter is to present the theoretical framework of the technical efficiency estimation. The following section will be organized as follows: In section 4.1, the production frontier will be presented. In section 4.2, measurements of firm efficiency will be outlined. In section 4.3, the parametric and non-parametric estimation procedures will be introduced. In section 4.4 two outlier methods will be presented. In section 4.5 the efficiency step ladder will be introduced. In section 4.6, the banker´s statistical test will be presented. Lastly, in section 4.7, the second-stage and first-stage regressions will be presented.

4.1 The Production Frontier

Since the development of the production frontier function (Aigner et al., 1977), evaluating firm efficiency has become an increasingly important managerial activity. Throughout time, its popularity has grown, and different techniques have been developed to estimate technical efficiency, including parametric and non-parametric approaches.

Theoretically, a production function returns the maximum possible output given a set of inputs, which is much different from its regression counterpart specifying the conditional mean. Unlike the cost, revenue, and profit frontiers, the production frontier exploits only input and output quantity data (Kumbhakar, 2000). Said differently, the production function defines a boundary or a frontier, whereas deviations from the frontier can be interpreted as inefficiency. Consequently, all the production units positioned on the frontier are fully efficient.

In the following, the deterministic production frontier can be written as:

$$y_i = f(x_i; \beta)TE_i \tag{4.1}$$

Where, y_i is defined as the output of the producer i (i=1,. . . ,N), x_i is a vector of M inputs used by the producer i, $f(x_i; \beta)$ is the deterministic production frontier, whereas β is a vector of parameters to be estimated.

The technical efficiency of producer i is denoted as TE_i;

$$TE_i = \frac{y_i}{f(x_i; \beta)} \tag{4.2}$$

Whereas TE_i is defined as the ratio of observed output y_i to maximum feasible output $f(x_i; \beta)$. More specifically, if $TE_i = 1$, y_i has achieved the maximum feasible output of the $f(x_i; \beta)$. Otherwise, if $TE_i < 1$, y_i is below the maximum feasible output and provides a shortfall in the observed output. Since the production frontier is deterministic, the entire shortfall is attributed to technical inefficiency. TE_i is a non-negative measure, thus $0 \leq TE_i \leq 1$.

To incorporate the fact that the observed output Y_i can be affected by random shocks v_i, the following stochastic production frontier is specified:

$$y_i = f(x_i; \beta)exp(v_i)TE_i \tag{4.3}$$

Where $f(x_i;)exp(v_i)$ is defined as the stochastic frontier, while $exp(v_i)$ is defined as the producer specific component capturing the effects of randoms shocks for each individual producer.

Given that production frontier is stochastic, the TE_i in (4.2) becomes (4.4).

$$TE_i = \frac{y_i}{f(x_i; \beta)exp(v_i)} \tag{4.4}$$

If $TE_i = 1$, y_i has achieved the maximum feasible output of the stochastic production frontier $f(x_i;)\ exp(v_i)TE_i$. Otherwise, if $0 \leq TE_i \leq 1$, the observed output is below the feasible output and the random shocks $exp(v_i)$ are incorporated in the estimation

4.2 Measurement of Firm Efficiency

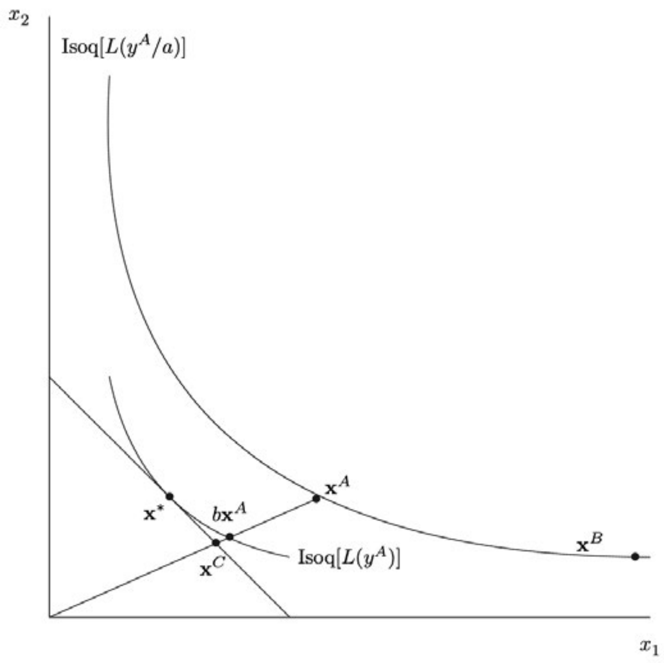
There are many reasons why it is favorable to measure a firm´s efficiency. The most important justification can be argued to be that it facilitates comparisons across economics units, allowing undertaking a thorough investigation in the case of technical efficiency divergence. Ultimately, this can facilitate the implementation of policies that address the reduction of the efficiency gap.

Efficiencies can either be technical or allocative (Emrouznejad and Cabanda, 2014). In this thesis, the emphasis will be on technical efficiency. Technical efficiency refers to the extent to which a firm or production process is able to produce goods or services with a given set of inputs, such as labor, capital and raw material. The input-based measure evaluates the performance of a firm by comparing the actual inputs used in the production to the minimum inputs required to produce a given output, while the output-based focuses on the relationship between the actual output and the maximum possible output that could be produced. In this thesis, the emphasis will be on the input-orientated measure. The input-based measurement was first proposed by Debreu (1951) and Farrell (1957), therefore often referred to jointly as the Debreu-Farrell measure of technical efficiency (Bogetoft and Otto, 2022). The Debreu-Farrell input-based measure of technical efficiency is presented below:

$$\varphi(y, x) = Min[bf(bx)Y] \tag{4.5}$$

Holding the input ratios constant, φ indicates the proportion of x necessary to produce y. f is a standard frontier production function, illustrated in Figure 4.1.

Figure 4.1: Farell´s Measure of Technical Efficiency.



The function depicts an inefficient firm producing output y^A with an input vector x^A. The technically efficient production occurs along the isoquant, $Isoq[L\frac{y^A}{a}] = [x : \varphi(y^A, x) = 1]$, where $L(Y) = [x : (y, x)]$ is the input requirement. To produce y^A, bx^A is required. To achieve technical efficiency, both factors need to be scaled back by the factor (1-b).

4.3 Parametric and Non-Parametric Efficiency Estimation

The most common techniques to estimate production frontiers are non-parametric (also known by the name "Data Envelopment Analysis", or DEA) and parametric (Stochastic Frontier Analysis, or SFA).

The choice of procedure depends highly on data availability. With cross-sectional data, it is only possible to estimate the performance of each store at a specific period, whilst with panel data, it is possible to estimate the performance of each producer across time. The weakness of cross-sectional data comes into play in the measurement of technical efficiency, as several strong assumptions need to be imposed (Battese and Coelli, 1995). In particular, the statistical noise error term v_i is assumed to be independently and identically distributed as $N(0, \sigma_u^2)$, while the technical inefficiency component represented by u_i is assumed to be distributed independently of v_i and follows a one-sided normal distribution $N^+(0, \sigma_u^2)$. With panel data, it is possible to avoid these issues. More specifically, panel data allows the relaxation of these assumptions. Thus, the parametric procedure will be based on panel data estimation. Due to DEA´s limitations, it is more complex to use panel data estimation. Thus, the corresponding procedure will be based on cross-sectional data.

4.3.1 Stochastic Frontier Analysis (SFA)

The first use of panel data in SFA was first introduced by Pitt and Lee (1981) and was later specified by Battese and Coelli (1995). In comparison to the DEA, the SFA approach does have the advantage of allowing for statistical inference. Said differently, the efficient frontier is empirically estimated based on a regression model with a pre-specified product function.

The approach to estimate the stochastic frontier model consists of a representation of a technology component along with two part composed error term. Given that $f(x_i; \beta)$ is a production function of type Cobb-Douglas, we can rewrite (4.3) in log form as follows:

$$y_i = \alpha_i + \beta x_{it} + \varepsilon_{it} \tag{4.6}$$

$$i = 1, 2, ..., N; t = 1, 2, ..., T$$

Where, y_{it} is defined as the logarithm of the production for the i_{th} firm at the n_{th} period of observations; x_{it} represents the vector of the logarithmic inputs associated with the production of the i_{th} firm in the t_{th} period of observations, and β being a vector of unknown parameters to be estimated. The two-part error component, ε_{it}, is presented in equation 4.7.

$$\varepsilon_{it} = v_{it} - u_{it} \tag{4.7}$$

The two-part composed error term consists of a random error term (v_{it}) and a systematic error term (u_{it}), where the latter is a measure of technical inefficiency. The estimation of the stochastic frontier parameters is facilitated by Battese and Corra (1977):

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \tag{4.8}$$

$$\gamma = \frac{\sigma_u^2}{\sigma^2} \tag{4.9}$$

Where:

$$(0 \leq \gamma \leq 1)$$

If the gamma parameter $\gamma = 0$, the variance of the technical inefficiency effect is equal to 0. Said differently, the deviation from the efficient frontier is the exclusive result of the effects of the specification error. In such case, the stochastic production function is equivalent to the traditional average response function which can be estimated by the ordinary least-square (OLS) regression. If $\gamma > 0$, it indicates that the proportion of the total deviation from the frontier is associated with technical inefficiency. Thus, if $\gamma = 1$, the frontier contains no systematic noise, and is equal to the DEA frontier.

Alternatively, using the variance of two-part composed error term, one can construct the lambda parameter(λ):

$$\lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}} \tag{4.10}$$

The higher the variance of the systematic error term relative to the variance of the stochastic error term, the higher (λ) is. If (λ) = 0, there is no technical inefficiency in the model.

Before proceeding with the estimation method for the unknown parameters σ^2, γ and λ a distinction regarding the time dimension of the inefficiency term must be clarified. In the following section, we will present two model specifications of the stochastic frontier model. First, we will present a model with a time-invariant efficiency. Then, we will present a model where the efficiency term is relaxed.

4.3.1.1 Time-Invariant Efficiency

In this section, the time-invariant efficiency model is presented. We can rewrite equation 4.6 to:

$$y_i = \alpha_i + \beta x_{it} + v_{it} - u_{it} \tag{4.11}$$

$$i = 1, 2, ..., N; t = 1, 2, ..., T$$

By defining $\alpha_i = \alpha - u_i$, the standard panel data model is presented in equation 4.12.

$$y_i = \alpha_i + \beta x_{it} + v_{it} \tag{4.12}$$

From the viewpoint of the panel data literature, 4.11 is a standard unobserved-effects model. Unless otherwise noted, the following assumptions for the model are applicable.

$$E(v_{it}|x_i^o, \alpha_i) = 0, t = 1, \ldots, T$$

$$E(v_i v_i'|x_i^o, \alpha_i) = \sigma_v^2 IT$$

Where $x_i^o = (x_{i1}, x_{i2}, \ldots, x_{iT})$ and v_i is T x 1. The error term v is assumed to be independently and identically distributed $(0, \sigma_v^2)$ and uncorrelated with the regressors. This assumption is required for consistency of the within and generalized estimators of the parameter vector β, derived from OLS estimation under a fixed and random effects model. Unlike the fixed effects model, which allows arbitrary correlation between x_{it} and α_i, a random effects specification often denies this possibility.

4.3.1.2 Time-Variant Efficiency

In this section, the time-variant model with the exponential specification of firm behavior is presented, i.e., the assumption of the time-invariant efficiency term is relaxed. Battese and Coelli (1992) defines the time-variant model as:

$$y_{it} = f(x_i; \beta) exp(v_{it} - u_{it}) \tag{4.13}$$

And the exponential specification of firm behavior effects is presented in (4.14):

$$u_{it} = \eta_{it} u_i = (exp[-\eta(t-T)])u_i \tag{4.14}$$

$$t \in g(i); i = 1, 2, ..., N$$

Where v_{it} is assumed to be i.i.d as $N(0, \sigma^2)$ and u_{it} is assumed to be i.i.d with a one-sided normal distribution $N^{+}(0, \sigma^2)$. *g(i)* represents the T_i time periods among the total T time periods for which the objects for the i_{th} firm are obtained. The exponential specification (4.14) sets a constrain that technical efficiency must either increase at a decreasing rate ($\eta > 0$), decrease at an increasing rate ($\eta < 0$) or remain constant at ($\eta = 0$).

Alternatively, (4.13) can be rewritten to:

$$y_{it} = \alpha_{it} + \beta x_{it} + v_{it} \tag{4.15}$$

Where $a_{it} = a_t - u_{it}$ only if $u_{it} \geq 0$. Given that a_{it} can be estimated, the estimates of the inefficiency error term can be obtained:

$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it}$$

Where:

$$\hat{\alpha}_t = Max_i(\hat{\alpha}_{it})$$

4.3.1.3 Maximum Likelihood Estimation

The stochastic frontier models are usually estimated by the econometric maximum likelihood estimation (MLE) (Battese and Corra, 1977). The method requires a set of distributional assumptions of the error term ε. First, it is assumed that the stochastic noise term v is normally distributed with zero mean and constant variance σ_v^2. Second, it is assumed that the inefficiency term u has a half-normal distribution or a positive truncated normal distribution with a constant scale parameter σ_u^2. Third, it is assumed that v and u are distributed independently of each other and of the regressors:

$$v \sim N(0, \sigma_v^2) \tag{4.16}$$

$$u \sim N + (\mu, \sigma_u^2)$$

Where μ is 0 for the positive normal distribution, while $\mu \neq 0$ for the positive truncated normal distribution.

4.3.2 Data Envelopment Analysis (DEA)

Initially, one of the earliest attempts at the quantification of production efficiency treated the production frontier as deterministic, thus ignoring the role of random shocks to producers. The DEA method was based on Farrell´s research in Farrell (1957) and first got its name in 1979 when Charnes, Cooper and Rhodes published a scientific paper in which they assumed a production technology under the assumption of constant returns to scale, the CCR model (Charnes et al., 1979). A couple of years later, the trio developed a new model in which they proposed variable returns to scale, naming it the BCC-model (Banker et al., 1984). We will provide a brief outline of these models in section 4.3.2.1. In the following section, the DEA framework is presented.

Data Envelopment Analysis (DEA) is a non-parametric methodology that uses linear programming to estimate the technical efficiency of decision-making units (DMUs), or in this case defined as Kiwi stores that control their own consumption of input factors. The DEA frontier technology consists of convex input and output sets enveloping the data points with linear facets. In a way, the DEA method becomes a form of benchmarking, as the DMUs´ technical efficiency are measured against the best performing producers. For each DMU, rates are constructed for the output/input ratio, providing weights that are further optimized in the construction of the efficiency ranking. In the case of inefficiencies, the corresponding weights of the inefficient DMUs will help to clarify how the producers can move towards the frontier by changing their output/input ratio.

One of the most important assumptions of the DEA framework is the homogeneity of the DMUs. More specifically, the DMUs must operate within the same environment and under the same technological conditions. In terms of disadvantages, the procedure postulates the absence of random errors (v) by assuming that all deviations from the efficient frontier is denoted as technical inefficiency (u). Additionally, it is also highly sensitive to extreme observations (DMUs) in the data. Consequently, removing outliers is essential to obtain non-biased DEA estimates. However, in contrast to SFA, the DEA procedure does not require a priori hypothesis about the analytical form of the production function, making it more flexible(Zhu, 2009).

4.3.2.1 CCR- and BCC- Model

As introduced, both the CCR and BCC models can be used to estimate technical efficiency. While the CCR methodology is based on identifying the most efficient DMUs and shaping the efficient production frontier based on the assumption of a constant return to scale (CRS), the BCC model considers variable returns to scale (VRS). In contrast to VRS, the CRS refers to a situation in which the output of a production changes in proportion to the changes in inputs. Said differently, if the inputs are increased or decreased by a certain factor, the corresponding output will also change by the same factor. The relaxed constraint of constant returns in the assumption of VRS makes it possible to investigate whether each DMU has an increasing, decreasing or constant return to scale in multiple outputs and inputs situations.

In the following, the input-orientated CCR and BCC models (multiplier form) are presented in equation 4.1a and 4.1b respectively.

Table 4.1: CCR - and BCC- Input Oriented Models

$$\begin{aligned} \max \quad & \theta = \sum_{j=1}^{m} u_j y_{j0} \\ \text{s.t.} \quad & \sum_{i=1}^{s} v_j x_{j0} = 1 \\ & \sum_{j=1}^{m} u_j y_{j0} - \sum_{i=1}^{s} v_j x_{j0} \leq 0, \quad && \forall i \\ & v_i, u_j \geq 0 && \forall k, j \end{aligned}$$

(a) Input- Oriented CCR Model

$$\begin{aligned} \max \quad & \theta = \sum_{j=1}^{m} u_j y_{j0} + u_o \\ \text{s.t.} \quad & \sum_{i=1}^{s} v_j x_{j0} = 1 \\ & \sum_{j=1}^{m} u_j y_{j0} - \sum_{i=1}^{s} v_j x_{j0} + u_o \leq 0, \quad && \forall i \\ & v_i, u_j \geq 0 && \forall k, j \end{aligned}$$

(b) Input- Oriented BCC Model

In the two equations the relative efficiency score for DMU_0 is noted as θ_o, x_i is the vector input at DMU_0, y_{j0} is the vector output at DMU_0, x_{jk} is the actual value of input i used by DMU_k, y_{jk} is the actual value of output j produced by DMU_k. The weights u and v are attached to inputs and outputs, respectively. DMU_0 is normalized to 1. DMU_0 is CCR and BCC-efficient if $\theta_o = 1$. Otherwise, $DMU_0$is inefficient. The additional constant variable that permits variable returns to scale is u_0. For $CCR : u_0 = 0$. For $BCC : u_0 = unconstrained$ (Aminuddin and Ismail, 2016).

The linear programming problem is solved for each $DMU_0, o \in (1, \ldots, N)$ so that all combinations of the respective DMUs´ inputs and outputs are benchmarked against one other. The limitation of each model requires that the weighted use of input factor i for DMU_0 is normalized to 1. The normalized input weight ensures that in a case of two DMUs having equal production, the DMU with the lowest input consumption will be ranked the highest. Additionally, the weights are ranked so the weight of the output (v_i) is maximized, while the weight of the input (u_j) is minimized. These weights must be greater than or equal to 0 and are unique for all DMUs.

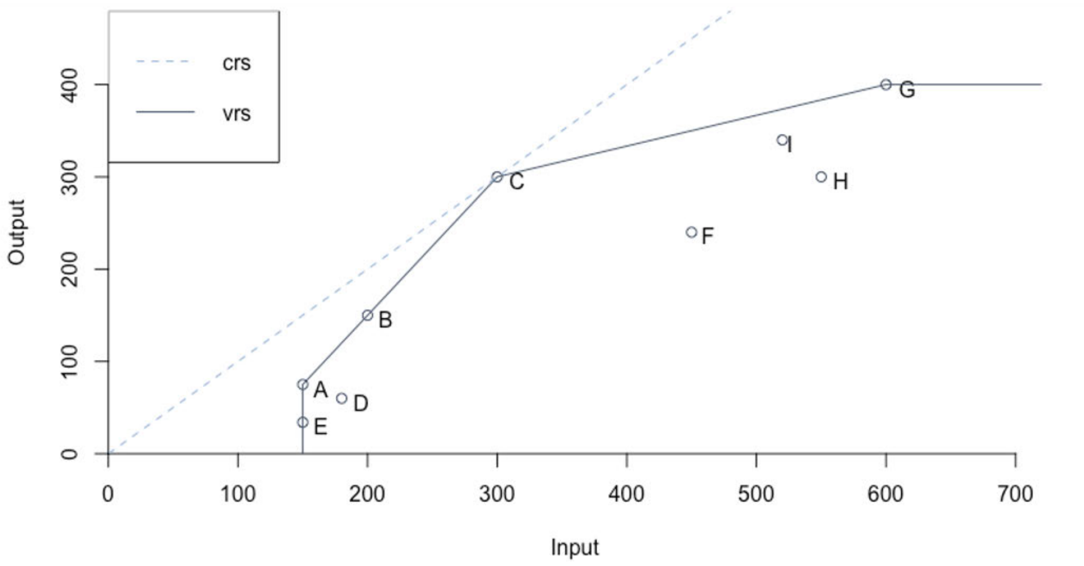
4.3.2.2 Scale Efficiency

VRS and CRS can be used to separate pure technical inefficiency from scale inefficiency (Yang, 2006). Scale inefficiency is present if the technical efficiencies in VRS and CRS models varies. The measurement of scale efficiency is showcased in equation 4.17.

$$Scale\ Efficiency = \frac{TE_{CCR}}{TE_{BCC}} \tag{4.17}$$

In chart 4.2, the VRS and CRS efficiency frontiers are presented. The corresponding example data is attached in appendix A1.1.

Figure 4.2: DEA Plot



As illustrated in figure 4.2, the dashed line represents the constant return to scale production frontier (CRS), while the concave line represents the variable return to scale frontier (VRS). The CRS-line runs from the origin and through point DMU_c with the best observed output/input ratio. Meanwhile, the concave line(VRS) runs on the assumption of scale differences. As observed, the VRS model envelopes the observations more closely to the frontier compared to the CRS model, resulting to a higher average technical efficiency. Consequently, DMU_A, DMU_E and DMU_G go from being technically inefficient to technically efficient. Further we can observe that the slope of VRS is significantly larger until point DMUc and slacker afterwards. The interpretation is as follows: To the left of DMU_C, a relative increase in input will result in higher relative output, implying increasing return to scale (IRS). Contrary is the case to the right of the DMU_C, where a relative increase in input will result in relatively lower output, which is called diminishing return to scale (DRS).

4.4 Outliers

One of the disadvantages in using non-parametric estimators, such as DEA, is the fact that it cannot detect measurement error. The existence of measurement error leads to the possibility that the estimated frontier is not feasible, thus making it highly sensitive to outlying observations. Said differently, if the data sample consist of extreme observations with low probability of occurrence, the observed input vector must be considered an outlier. Wilson (1995) quoted that “Outliers are observations that do not fit in with the pattern of the remaining data points and are not at all typical of the rest of the data" (Gunst and Mason, 1980).

According to Khezrimotlagh (2015) a DMU is called an outlier if one or several conditions are satisfied:

1. The technical efficiency score of DMU_x is much greater than most of DMUs´ technical efficiency scores.
2. The best technical efficiency score of DMU_x is much greater than most of DMU´s best technical efficiency score.
3. The best technical efficiency score of DMU_x moderately decreases in comparison with its technical efficiency score.
4. It is a technically efficient DMU_x,and has a great sensitivity score.

The most common methods to detect outliers is visualization. In parametric models, outliers can be easily detected by examining OLS residuals of each individual input and noticing large deviations. However, with non-parametric approaches such as DEA and other LP-based efficiency models, the identification of outliers is more complex, as outlier diagnostics based on residuals analysis cannot be used. Thus, in the next section two suitable methods to identify outliers in DEA models will be presented.

4.4.1 Super Efficiency

Occasionally, several DMUs are shown to be efficient when using non-parametric approaches, such as DEA. To overcome such problem, super-efficiency technique is utilized by ranking the most efficient DMUs and assigning them an efficiency value above 1. If large deviations occur, i.e., if one efficient DMU have a significantly higher efficiency score than other efficient DMUs, then the observed object can be considered an outlier. BCC´s input-orientated measure of super-efficiency is presented equation 4.18.

$$
\begin{aligned}
\max \qquad & \theta = \sum_{j=1}^{m} u_j y_{j0} + u_o \\
\text{s.t.} \qquad & \sum_{i=1}^{s} v_j x_{j0} = 1 \\
& \sum_{j=1}^{m} u_j y_{j0} - \sum_{i=1}^{s} v_j x_{j0} + u_o \leq 0, \quad \forall i \neq DMU_o \\
& v_i, u_j \geq 0 \qquad\qquad\qquad \forall k, j
\end{aligned}
\tag{4.18}
$$

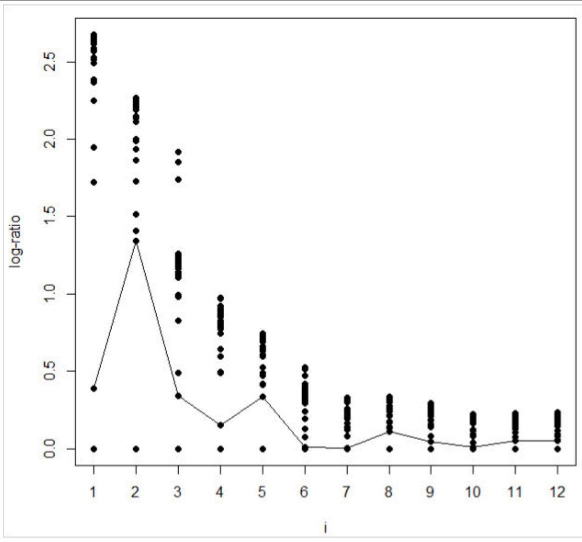
Without solving the BCC model directly, it is possible to evaluate the efficient units directly by solving for super efficiency. The DMU being evaluated, DMU_0, is removed from the constraint set, thereby allowing the efficiency score to exceed 1. In more practical terms, this means that none of the DMUs can use themselves as a reference, implying that these must locate a previously inefficient or less super-efficient DMU. Consequently, the estimated efficiency scores can now be higher than 1 with some of the DMUs laying outside of the original efficiency range.

It is important to notice that this method has some shortcomings. According to (Adler et al., 2002), super-efficiency is a rather poor ranking system since each DMU is assigned with different weights. Additionally, some of the DMUs may receive a ranking that is unreasonably high due to their "specialized" nature. Therefore, as a supplement to this method, we will examine an additional methodology for detecting outliers.

4.4.2 Wilsson's Outlier Detection

Based on the research of Andrews and Pregibon (1978), Wilson (1993) developed a statistical methodology for identifying outliers with multiple inputs and outputs in non-parametric frontier models. The advantage with this methodology lays in its usefulness in identifying observations that may contain measurement error and ranking of dissimilarities among observations. The FEAR (Functional Outlier Detection) package in r is a tool that can be used to identify potential outliers in the data. The procedure provides both a graphical and numerical representation of the results. An example of the procedure with 3 inputs and 2 outputs is illustrated in figure 4.3. The corresponding example data can be found in Appendix A1.2.

Figure 4.3: Wilsson's Outlier Plot



[1]	[2]	[3]	[4]	[5]	[5]	[6]	[7]
[1]	7	NA	NA	NA	NA	NA	NA
[2]	8	7	NA	NA	NA	NA	NA
[3]	4	8	7	NA	NA	NA	NA
[4]	4	59	8	7	NA	NA	NA
[5]	4	44	59	8	7	NA	NA
[6]	4	33	44	59	8	7	NA
[7]	4	35	33	44	59	8	7

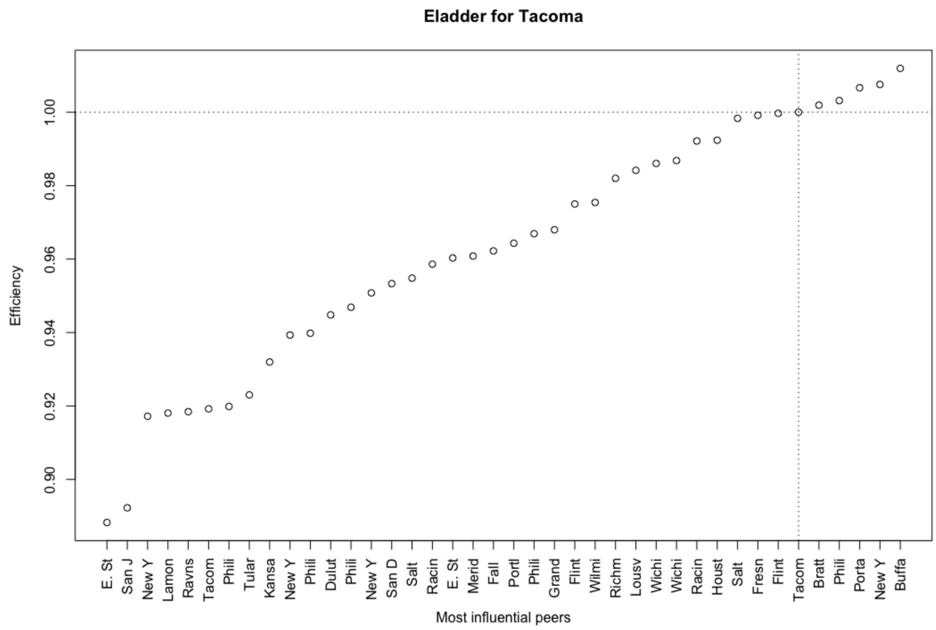
The Wilson outlier detection method minimizes $R^{(i)}$ for all DMUs. The $R^{(i)}$ is the logarithm ratio between the DMUs that are removed from the data set and the DMU that is the closest to the removed observations. The figure shows that the log-ratio has a clear peak in the range 2.5-2.6. The threshold line in the plot indicates the cutoff point for identifying outliers. Values above the threshold line are considered to be unusually large or small, and may warrant further investigation. In the matrix to the right, we can observe that most of the potential outliers in the data set occurs between [R1] and R[3], indicating that they are significantly different from the other observations. This implicates that DMUs 4,8 or 7 could be potential outliers in the data.

Contrary to super-efficiency outlier detection, the most important implication of Wilson´s outlier approach is the fact that it considers that not all efficient DMUs are outliers. Wilson argues that a DMU or group of DMUs who appear to be outliers might simply have a different composition of inputs or outputs compared to other DMUs. Therefore, in further analysis, both methods will be utilized to detect and remove potential outliers.

4.5 Sensitivity of Efficiency Estimates

Some studies have identified issues in relation the robustness of DEA procedures (Edvardsen, 2004). To investigate the robustness of the DEA models, a method known as the efficiency step ladder (ESL) is proposed. The corresponding methodology allows to investigate the changes in the technical efficiencies when sequentially removing the most influential peers (efficient stores) of an inefficient DMU until the inefficient DMU itself becomes efficient. If an inefficient DMU gets a dramatic increase in technical efficiency after removing its most influential peer, the efficiency estimates can be considered sensitive in the sense that measurement error could have a large impact on the model and the results. In figure 4.4, the efficiency step ladder is illustrated.

Figure 4.4: Efficiency Step Ladder Plot



The eladder function in R is used to calculate the efficiency step ladder for a DMU(School) named Tacoma. The corresponding example data is attached in appendix A1.2. We can observe that it takes 34 steps before Tacoma becomes technically efficient. The growth seems to be linear, which implies that Tacoma´s corresponding growth rate is the same from step 1 to step 34. Thin in turn, implicates low sensitivity. After step 35, Tacoma´s super efficiency (TE>1) is estimated.

4.6 Banker's Statistical Test

Banker (1993) constructed a parametric test enabling a comparison between the efficiencies of two groups of DMUs. The background was to access whether a specific group of DMUs are more efficient than others. The null hypothesis of no technical efficiency differences can be tested for the assumptions of exponential and half normal distributions of the efficiency term. Given that the logarithm of the true efficiency term has an exponential distribution for the two groups of DMUs, the test statistic can be calculated:

$$T_{EK} = \sum_{j=1}^{N}(1-\theta_j^1)/\sum_{j=1}^{N}(1-\theta_j^2) \tag{4.19}$$

In comparison to a critical value from the F-test, with (2N, 2N) degrees of freedom.

For the half normal distribution, the test statistic is presented in (4.20):

$$T_{HN} = \sum_{j=1}^{N}(1-\theta_j^1)^2/\sum_{j=1}^{N}(1-\theta_j^2)^2 \tag{4.20}$$

In comparison to a critical value from the F-test, with (N, N) degrees of freedom.

$\theta_j^1$is the efficiency of a specific DMU in the original model. θ_j^2 is the efficiency of the alternative model. We reject the null hypothesis in favor of scale differences/alternative model if $T_{HN} > F(N, N)$ or $T_{EK} > F(2N, 2N)$.

4.7 Second-Stage [DEA] and First-Stage Regression [SFA]

Following the DEA efficiency results, the parametric Tobit model(regression) is implemented as a second stage approach to reveal how the store-specific(internal factors) and region-specific environmental factors(external factors) affect the obtained technical efficiencies. In contrast to the internal factors, which is considered in the management action plans, such as the size of a firm and opening hours, the external factors can influence the technical efficiencies without being internally controlled (education level, economic development, etc.).

Since the technical efficiencies varies between 0 and 1 , the ordinarily least square regression is not appropriate. In this context, the Tobit model is an appropriate tool since efficiencies obtained through DEA can be censored between 0 and 1. Previous studies indicate that technical efficiencies obtained from the first stage are often highly correlated with the explanatory variables obtained from the second stage. To overcome the problem of inconsistent and biased efficiency estimates, a bootstrap specification of the Tobit model can be employed (Coelli et al., 2005). The bootstrapped Tobit regression is a computer-based method used to assign measures of accuracy to statistical estimates. The method was first introduced by Tobin (1958) and since then it has become a powerful statistical tool to study internal and external determinants of technical efficiency. For n^{th} DMUs, the Tobit model is presented in equation 4.21.

$$\theta = \alpha + \beta(x) + \varepsilon \tag{4.21}$$

Given:

$$\theta \geq 0, otherwise, \theta \leq 1$$

Where θ is the technical efficiency score. β is the set of parameters which is being measured, while x is the set of internal and external variables to be explained.

To reveal how the internal and external factors affect the obtained technical efficiencies in the parametric SFA procedure, it is possible to use a one-stage or a two-stage regression model (Kumbhakar et al., 1991). In the one-stage approach, the technical efficiency and the parameters of internal and external variables can be simultaneously estimated using the maximum likelihood estimation. Meanwhile, in the two-stage approach, the efficiency estimates are regressed against the explanatory variables of the inefficiency, generally using the Tobit model (Ahmad et al., 2017; Schnedler, 2005). The Tobit model requires that the explanatory variables of the inefficiency (Internal and external variables) and the independent variables(inputs) are uncorrelated. If correlation exist, the unknown parameters (β) and the two-part composed error term (ϵ) could become biased. To avoid this problem, the one stage procedure is often preferred when dealing with technical efficiencies obtained through SFA.

5 Data - Variables, Models and Outliers

In this section, we will first present and discuss the data used in the technical efficiency analysis. Thereafter, a thorough elaboration on variables, models, and outliers will be provided.

5.1 Data

The efficiency data was provided by NorgesGruppen and ranged from 2002-2015. Unfortunately, NorgesGruppen could not provide the newest available data due to confidentiality reasons. However, we still believe the provided data is sufficient to obtain satisfactory results. The raw data contained information regarding total revenue, labor costs, operating costs, total sales area, number of employees, and opening hours of each individual store. Since we were not given the complete data considering the total sales area, we had to assume that total square meters were fixed and did not vary across time, meaning that each individual store had the exact same store size (square meters) across different time periods.

5.1.1 Homogeneity

One of the main assumptions in the DEA methodology is the fact that the selected data must be homogeneous (Bogetoft and Otto, 2022). Our data set consists of homogeneous Kiwi stores in the sense that they are furnished based on the same standards and offer homogeneous products. In contrast to NorgesGruppen´s other grocery chains, Kiwi has the lowest number of merchants (16.8%), owning and running their own stores through a franchise (NorgesGruppen, 2021). A franchise is a type of business arrangement in which a company (NorgesGruppen in this case) grants a license to an individual or a group (the franchisee) to use Kiwi´s trademarks, business model, and other intellectual property to sell its products. Since merchants in grocery retail are given more flexibility in their business operations, such stores cannot be compared directly against stores that are not merchant-owned. Consequently, selecting the Kiwi chain as the main object of this analysis makes the obtained efficiency estimates more reliable and comparable across entities. Thus, we assume that the homogeneity requirement is satisfied.

5.1.2 Data Wrangling and Cleaning

It was essential to assess and clean the selected data before we could start selecting the variables. Since we were only interested in utilizing the newest available data, the data prior to 2014 was omitted from further analysis.

First we started the process by merging all potential variables into a single data frame in excel. The selected variables were yearly revenue, yearly labor costs, store size, total employees and a set of store- and region- specific variables.

Second, all missing values (N/A) were removed from the data. Thereafter, the labor costs were transformed to positive values since none of the product functions in the DEA and SFA allow the inclusion of negative values. Moreover, we chose to omit all stores with negative revenues. In total, we removed 165 observations due to missing values and lack of information.

Lastly, the data needed to be converted to panel data and balanced accordingly to the DEA framework's requirements. In this procedure, we chose to omit stores that had missing data points across both years. Additionally, we needed to remove the outliers, which will be further presented in section 5.4. The balanced DEA data contained 748 observations for the years 2014 and 2015. The corresponding summary statistics is presented in table 5.1.

Table 5.1: Summary Statistics [DEA]

	Mean	Median	SD	Min	Max	N
Inputs						
Labor Cost	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	748
SqM	650	642	194	235	1440	748
Output						
Revenue	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	748
Store-Specific Variables						
Open Sundays	-	-	-	[redacted]	[redacted]	748
Hours Weekdays	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	748
Region-Specific Environmental Variables						
Region	-	-	-	-	-	748
Median Income	627 305	608 000	76 596	459 000	859 000	748
Population Size	120 028	26 399	205 311	933	647 676	748
Population Density	394	147	521	1	1942	
Higher Education	31	28	9.85	15.5	51	748
HHI	0.120	0.086	0.123	0.004	1	748
Store Density Per Capita	0.000158	0.000125	0.000108	0.000027	0.00107	748
Close Competitors	2.46	2	2.35	1	20	748

As observed, the data contains 1 output variable and 2 input variables. Additionally, the data contains 2 store-specific and 8 region-specific environmental variables that will be utilized to investigate the hypotheses presented in sections 1.3.1 and 1.3.2.

It is important to emphasize that SFA´s statistical properties allow the utilization of unbalanced and noisy data in the sense that outlier removal is not necessary to obtain consistent and unbiased efficiency estimates (Battese and Coelli, 1992). Consequently, in the SFA procedure, the data prior to outlier removal will be utilized to obtain the efficiencies. The corresponding summary statistics are attached in appendix A2.1. Thus, the data sample consisting of 792 observations will be utilized in the SFA procedure, while the data consisting of 748 observations will be used in the DEA procedure. We assume that both samples are homogeneous. In the following section, the justification of the selected variables is presented.

5.2 Selection of Variables

5.2.1 Inputs

To perform a satisfactory efficiency analysis of a firm´s production process, the utilized data set must reflect the entire production process. It is therefore highly important that the selected inputs are well documented and contain as much information regarding the required resources to produce the output.

Most retail studies have utilized labor costs, employees, material costs and store size as controllable inputs. Consequently, we have chosen two inputs (1) yearly labor costs and (2) store size measured in square meters (SqM).

It is important to mention that inclusion of other variables, such as operating expenses could have been beneficial. However, since we were missing approximately 2/3 of this data, we chose to exclude it. In the following, we will elaborate more on the selected inputs.

5.2.1.1 Labor Costs

The labor costs represent the labor factor in the Cobb-Douglas product function (Bucklin, 1978). The labor cost is the yearly sum of all wages paid to all employees, both full-time and part-time employees. The cost of labor is a direct cost that is fixed in the sense that employees have fixed working hours per week. Moreover, expenses such as pension costs, vacation pay, and sick pay are included.

5.2.1.2 Store Size

SqM represents the capital factor in the Cobb-Douglas product function (Bucklin, 1978). Square meters (SqM) can be considered a proxy for capital as it measures the amount of capital that is invested in the stores. For instance, larger stores normally require larger capital investments, while smaller stores normally require less financing. In other words, store size is considered a fixed asset that is used to produce the revenue.

5.2.2 Store - and Region-Specific Environmental Variables

Regarding the selection of the external varibales, some authors include retail structure (Goldman, 1992), location (Donthu and Yoo, 1998), demographics of clientele in the area (Donthu and Yoo, 1998) and national economic development (Pilling et al., 1995). In terms of the internal variables, some authors include store size (Sonza and Ceretta, 2008). In this thesis, we have selected 2 internal (store-specific variables) and 8 external (region-specific environmental variables), as illustrated in table 5.1. These variables were then converted into dummy variables. The use of dummy variables has several advantages compared to using continuous variables in this type of analysis. Firstly, it allows examining the unique effect of each category of the categorical variable on technical inefficiency, rather than the overall trend across all categories. This can be particularly useful if there are meaningful differences between the categories. Secondly, dummy variables are easier to interpret than continuous variables, as they are binary and take on only two values.

To assess the direct relationship between the inefficiency variables and the technical efficiencies TE_{mit} obtained from DEA, a bootstrapped Tobit model with 500 replications is utilized. This implicates that the bootstrapped model is fitted to 500 different samples drawn from the population, each time using a different sample to estimate the unknown parameters. Furthermore, the technical efficiencies were transformed into technical inefficiencies U_{mit}. We assumed a censoring point between 0 and 1. This implies that efficient stores will have scores of zero, while inefficient stores will have scores greater than zero or equal to one. The corresponding procedure is illustrated in equation 5.1.

$$U_{mit} = (\frac{1}{TE_{mit}}) - 1 \tag{5.1}$$

Where, U_{mit} is technical inefficiency in year t obtained from methodology m for store i, while TE_{mit} is the technical efficiency score in year t obtained from methodology m for store i. The corresponding technically inefficiency model represented by U_{mit} is expressed in equation 5.2.

$$U_{mit} = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2it} + ... + \delta_{10} z_{10it} + \varepsilon_{it} \tag{5.2}$$

Where, $\delta_1 z_{1i}$ is the categorical variable for 18 Norwegian counties (prior to 2019) for the i^{th} store, z_{2it} a dummy for the average population size in the municipalities in year t for the i^{th} store, z_{3it} a dummy for the average population density per square meter in the municipalities in year t for the i^{th} store, z_{4it} a dummy for the average number of people with high education in the municipalities in year t for the i^{th} store, z_{5it} a dummy for the average median income in the municipalities in year t for the i^{th} store, z_{6it} a dummy for Sunday open stores of the i^{th} store in time t, z_{7it} a dummy for the average opening hours on weekdays of the i^{th} store in year t, z_{8it} a dummy for the average HHI in the municipalities in year t for the i^{th} store, z_{9it} a dummy for the average store density per capita in the municipalities in year t for the i^{th} store, and z_{10it} a dummy for the average number of close competitors in year t for the i^{th} store[1]. δ_n is the unknown vector of unknown scalar parameters to be estimated, which makes it possible to analyze the influence of each environmental variable.

The one-stage approach (SFA) automatically transforms the corresponding technical efficiencies into technical inefficiencies. The corresponding technically inefficiency model represented by U_{mit} is expressed in equation 5.3[2].

$$U_{mit} = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2it} + ... + \delta_{10} z_{10it} + v_i t - u_i t \tag{5.3}$$

It is important to notice that we have included a substantial amount of dummies to control for the effects on technical inefficiency. While it is generally not a problem to include many dummy variables in a regression, there are a few potential issues to consider. As the number of dummy variables increase, it may become more challenging

[1] A more detailed explanation of the dummy variables in the DEA sample is attached in appendix A1.5

[2] A more detailed explanation of the dummy variables in the SFA sample is attached in appendix A2.4

to understand the unique effects of each dummy variable on the outcome of technical inefficiency. Additionally, if the number of dummies is too large relative to the sample size, the models may become overfitted and lead to inaccurate predictions. Another potential issue is the phenomenon of multicollinearity, which can cause the coefficients to be unstable and difficult to interpret.

Testing for issues related to complexity and overfitting can be problematic. However, we argue that there is a small likelihood that these issues are present due to the large number of observations in our data. Meanwhile, the issues related to multicollinearity will be examined in section 5.3.1.1.

In the following, we will provide a more thorough elaboration on the selected dummies.

5.2.2.1 Store-Specific Variables

In general, the technical efficiency of a store can be determined by a variety of factors, including the quality of its products or services, the number of full-time and part-time employees, the effectiveness of its marketing and sales strategies, etc. In total, we have examined two store-specific factors in this thesis.

The dummy average *Hours Weekdays* is created to investigate whether opening hours affect Kiwi´s technical efficiency. On average, we estimate that each Kiwi store is open [redacted] hours on weekdays. Thus, if a Kiwi store is open ≥ [redacted] hours, it is assigned a value of 1. If not, it is assigned a value of 0. Moreover, a dummy for *Open Sundays* was created to investigate the effects of Sunday open stores. More specifically, this means that if a Kiwi store is open on Sundays, it is assigned a value of 1. If not, it is assigned a value of 0.

5.2.2.2 Region-Specific Environmental Variables

In 2017, the Norwegian government decided to abolish some of the Norwegian counties and merge them with other counties to form larger ones. The abolishment reduced the number of Norwegian counties from 19 to 11. Since our data consists of 2014 and 2015 figures, we will be using the 19 counties prior to the abolishment. Additionally, to avoid the dummy variable trap, we chose to use Oslo as a reference dummy in the regression. Consequently, *region* is as a categorical variable for 18 different Norwegian counties: (1:Østfold, 2:Akershus, 3:Hedmark, 4:Oppland, 5:Buskerud, 6:Vestfold, 7:Telemark, 8:Rogaland, 9:Aust-Agder, 10:Vest-Agder, 11:Hordaland, 12:Sogn og Fjordane, 13:Møre og Romsdal, 14:Sør-Trøndelag, 15:Nord-Trøndelag, 16:Nordland, 17:Troms and 18:Finnmark)

A dummy for the average *Population Size* and a dummy for the average *Population Density* were created to examine the efficiency effects of the population on the municipality level. It is rational to believe that more populated areas consist of more customers, which implies that stores in more populated municipalities are more productive. Furthermore, it can be argued that population density per square meter is also interesting to examine as more populated areas per square meter can be assumed to attract more customers.

A dummy for the average *Median Income* was created to investigate the effects of income. Generally, one could say that wealthier individuals have a higher purchasing power than those who earn less. Therefore, it can be assumed that stores in wealthier municipalities obtain higher sales. Analogous to high income, one can assume that individuals with a high degree of education have better purchasing power than those with a lower degree of education. Thus, a dummy Higher Education is created to examine the effects of high education on the municipality level.

To examine the effects of competition, we created 3 dummies. The first dummy was the average *Herfindahl-Hirschman index (HHI)*. The corresponding measure is used to assess the level of market competition in the municipalities and is presented in (5.4).

$$HHI = \sum_{i=1}^{N} (MS_i)^2 \tag{5.4}$$

Where, MS_i is the sales of store i, and N is the number of grocery stores in the grocery market. An HHI score close or below 0.2 indicates a high level of competition, while an HHI score above 0.2 indicates a low level of market competition. The average HHI on the municipality level is estimated to 0.12, which implicates a concentrated competition in the municipalities.

The second dummy was created for the average *Close Competitors* to examine the efficiency effects of close competition on the local level. This was done by using geodata. We located every Kiwi competitor in a radius of 500m for each Kiwi store. We found that each Kiwi store on average had 2.46 close competitors. Moreover, the third dummy was created for the average *Store Density per Capita* to examine the effects of stores with a higher density per capita on the municipality level. The corresponding measure was calculated by dividing the number of stores by the population size in each municipality.

5.2.3 Output

In this thesis, we will be using the accumulated yearly revenue as the monetary output. This choice is based on the availability of our data, as well as other studies such as (Sinik, 2017) (Badin, 1997) and (Sonza and Ceretta, 2008), which support the use of this measure as a sufficient representation for Kiwi's production. By using the accumulated yearly revenue as the output in our analysis, we aim to accurately capture its performance.

5.3 Choice of Model

5.3.1 DEA Model

In the previous sections, the selection of data was presented and discussed. In this section, we will present and discuss the selection of the DEA model. In total, we created two DEA models to inspect.

$Model1 : Output = Revenue, Inputs = Labor + SqM$

$Model2 : Output = \frac{Revenue}{Employees}, Inputs = \frac{Labor}{Employees} + \frac{SqM}{Employees}$

In model 1, the unspecified product function assumes yearly revenue as output, and yearly labor costs and total square meters as inputs. Contrary to model 1, the product function in model 2 considers the number of employees in each Kiwi store. Thus, the only difference between model 1 and model 2, is the fact that the efficient frontier in model 2 is calculated per unit of labor. The Debreu-Farrell input-based measure of technical efficiency is assumed to obtain the corresponding technical efficiencies. We argue that Kiwi stores can only control their flow of inputs. An output maximizing model would assume that each Kiwi store operates efficiently given its utilization of inputs, which we cannot justify since we do not have any input information on the competing grocery chains. In terms of scale, the obtained efficiencies will be presented with the assumptions of constant returns to scale and variable returns to scale.

In section 4.6, we presented the Banker test (1993) to compare the efficiency estimates of two groups of DMUs. In the following, we have conducted the corresponding test to determine whether model 1 and model 2 produce different efficiency estimates. The following hypothesis is tested:

$$H_0 : Model1 = Model2$$

$$H_1 : Model1 \neq Model2$$

In table 5.2, the test statistics are presented.

Table 5.2: Technical Efficiency Comparison [Model 1 vs. Model 2]

	VRS 2014	**CRS 2014**	**VRS 2015**	**CRS 2015**
TEX	0.45	0.44	0.46	0.44
F(TEX)	1.12	1.12	1.12	1.12
THN	0.22	0.22	0.24	0.21
F(THN)	1.18	1.18	1.18	1.18

Table 5.2 illustrates the results for both years when assuming variables returns to scale (VRS) and constant returns to scale (CRS) with a significance level of 5%. As observed, all test statistics for the exponential (TEX) and half-normal distributions (THN) are smaller than the corresponding critical f-values. Thus, the null hypothesis of no difference in technical efficiency is accepted. This implies that model 1 and model 2 obtain the same efficiency estimates. Said differently, the efficiency estimates are not affected by the selection of the model. However, since the corresponding product functions are unspecified and the fact that we do not know all the factors affecting Kiwi´s product function, it is preferred to choose a model that is consistent with previous efficiency studies within grocery retail. All studies in section 1 point in the direction of using employees as a separate variable in the product function. Consequently, we conclude that model 1 is a better fit. It is also worth mentioning that model 2 contains fewer data observations due to lack of sufficient employee data. Consequently, model 1 will be emphasized.

The Banker test is also utilized to investigate whether the scale assumptions of CRS and VRS generate different efficiency estimates in the selected model (model 1). Likewise, the

Banker test assumes exponential and half-normal distributed efficiency estimates at the 5% significance level. The following hypotheses are tested:

$$H_0 : f_{crs} = f_{vrs}$$

$$H_1 : f_{crs} \neq f_{vrs}$$

The following test statistics are presented in table 5.3.

Table 5.3: Technical Efficiency Comparison [CRS vs. VRS]

	2014	**2015**
TEX	1.46	1.47
F(TEX)	1.12	1.12
THN	2.02	2.03
F(THN)	1.18	1.18

Form table 5.3, we can observe that all test statistics for the exponential and half-normal distributions (TEX and THN) are higher than corresponding critical F-values for all years. This indicates that there are significant differences in the efficiency estimates when assuming CRS and VRS at the 5% significance level. Thus, we can reject the null hypothesis in favor of efficiency differences in CRS and VRS models. Consequently, we argue that scale might be an important factor in the estimation of technical efficiencies. Therefore, we decide to obtain technical efficiencies using both CRS and VRS models.

5.3.1.1 Correlation

Table 5.4: Correlation Matrix [DEA]

	Revenue	Labor	SqM	Population Size	Population Density	Median Income	Higher Education	Open Sundays	HHI	Hours Weekdays	Close Competitors	Store Density
Revenue	100,0%	92,8%	27,2%	-3,7%	-1,6%	13,2%	6,6%	18,2%	0,9%	13,3%	-9,1%	-0,1%
Labor	92,8%	100,0%	28,5%	-7,0%	-4,8%	11,0%	3,4%	24,8%	-1,4%	14,8%	-8,8%	2,0%
SqM	27,2%	28,5%	100,0%	-27,4%	-32,4%	6,6%	-31,2%	29,6%	27,0%	13,8%	-9,6%	21,8%
Population Size	-3,7%	-7,0%	-27,4%	100,0%	73,3%	-31,4%	63,1%	-11,4%	-43,1%	10,6%	20,7%	-35,7%
Population Density	-1,6%	-4,8%	-32,4%	73,3%	100,0%	-19,5%	66,8%	-7,5%	-50,6%	0,6%	18,4%	-41,4%
Median Income	13,2%	11,0%	6,6%	-31,4%	-19,5%	100,0%	1,9%	-8,2%	16,8%	-4,5%	-11,7%	13,7%
Higher Education	6,6%	3,4%	-31,2%	63,1%	66,8%	1,9%	100,0%	-10,6%	-50,0%	-0,1%	13,1%	-42,6%
Open Sundays	18,2%	24,8%	29,6%	-11,4%	-7,5%	-8,2%	-10,6%	100,0%	6,4%	0,5%	1,2%	6,6%
HHI	0,9%	-1,4%	27,0%	-43,1%	-50,6%	16,8%	-50,0%	6,4%	100,0%	-10,9%	-15,6%	46,4%
Hours Weekdays	13,3%	14,8%	13,8%	10,6%	0,6%	-4,5%	-0,1%	0,5%	-10,9%	100,0%	8,4%	-6,2%
Close Competitors	-9,1%	-8,8%	-9,6%	20,7%	18,4%	-11,7%	13,1%	1,2%	-15,6%	8,4%	100,0%	-16,0%
Store Density	-0,1%	2,0%	21,8%	-35,7%	-41,4%	13,7%	-42,6%	6,6%	46,4%	-6,2%	-16,0%	100,0%

According to Dyson et al. (2001) the selected DEA model should contain inputs and outputs that are positively correlated to obtain consistent estimators. Additionally, the authors state that the correlation between the inputs should not be too high. From figure 5.4, we can observe a positive and high correlation between the inputs and output, and a low correlation between the inputs. Thus, we can assume that both conditions are satisfied.

According to Banker and Natarajan (2008) the DEA model should contain uncorrelated inputs and environmental variables to obtain consistent estimators from the two-stage efficiency estimation. Further, the paper argues that it is unnecessary for the environmental variables to be distributed independently, implying that a high correlation is not problematic. From the following correlation plot, we can observe that none of the environmental variables are highly correlated with the inputs, while the correlation between the environmental variables is below 70%. Thus, we assume that both conditions are satisfied.

5.3.2 Cobb-Douglas Stochastic Frontier Model

In addition to the DEA model, the stochastic production frontier is also estimated. The Cobb-Douglas stochastic production frontier assumes that the inefficiency term u follows a positive half-normal distribution. The model is presented in equation 5.5.

$$ln(Revenue) = \beta_0 + \beta_1 ln(Labor) + \beta_2(SqM) + (v - u) \tag{5.5}$$

Where ln is the natural logarithm, β are the unknown parameters to be estimated, v is the random error term, and u is the systematic error term measuring technical inefficiency.

5.3.2.1 Cobb-Douglas Stochastic Frontier Model vs OLS

We used the likelihood ratio test to investigate whether adding the inefficiency term u significantly improves the fit of the chosen model. We did so by comparing the stochastic frontier model with an OLS model with $\gamma = 0$ using the maximum likelihood ratio test[3]. The test statistically follows a mixed $\chi^2 - distribution$ (Coelli, 1995). Under the null hypothesis, there is no inefficiency, i.e only noise. The corresponding results are attached in appendix A2.3. The highly significant p-value of the test statistically rejects the OLS model in favor of the Cobb-Douglas stochastic frontier model. This implies that there is significant technical inefficiency in the model. Thus, the stochastic frontier model can be used to determine the technical efficiency.

5.3.2.2 Cobb-Douglas Stochastic Frontier Model vs. Translog Frontier Model

In addition to the Cobb-Douglas functional form, we estimate a Translog stochastic production frontier model shown in (5.6).

$$\begin{aligned} ln(Revenue) = \alpha_0 + \alpha_1(Labor) + \alpha_2(SqM) + \alpha_3(ln[Labor])^2 + \\ \alpha_4([SqM])^2 + \alpha_5 ln(Labor)ln(SqM) + (v - u) \end{aligned} \tag{5.6}$$

The maximum likelihood ratio test is used to estimate the best model fit. The corresponding results are attached in appendix A2.3. The likelihood ratio test confirms that the stochastic frontier model fits the data significantly better compared to OLS. Consequently, we decide to compare it against the Cobb-Douglas stochastic frontier model to find the best fit. The

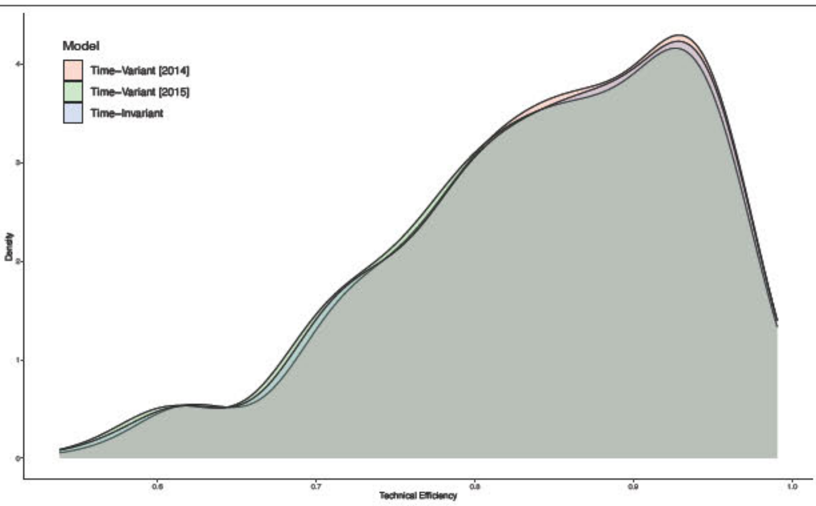
[3]The maximum likelihood ratio test is a statistical test used to compare the fit of two models. It involves calculating the ratio of the maximum likelihoods of the two models, which is then compared to a critical value based on a chi-squared distribution with a certain number of degrees of freedom.

corresponding statistical test suggests that the Translog stochastic frontier model is only significant at the 13% level. Thus, we reject the Translog stochastic frontier model in favor of the Cobb-Douglas stochastic frontier model.

5.3.2.3 Cobb-Douglas Time-Invariant Model vs Cobb-Douglas Time-Variant Model

When analyzing panel data, it is reasonable to believe that different technologies might be available in different time periods due to technological change. Hence the state of the available technology can be included as an explanatory variable to conduct a reasonable production analysis. However, in this context, we assume no technological change. Instead, we chose to consider two other model specifications of the stochastic frontier model. The first is the time-invariant individual efficiency specification, meaning that each firm has an individual fixed efficiency that is constant over time. The second specification is the time-variant individual efficiency, meaning that firms can have individual efficiencies varying over time at the same rate. Followingly, we have used the maximum likelihood ratio test to investigate the best model fit. The corresponding results are attached in appendix A2.3. The test indicates that the effect of time on technical efficiency is only significant at 35% level. This implicates that technical efficiencies do not change over time. These results are in line with findings in the density plot below, illustrating the technical efficiency distribution for the time-invariant and the time-variant models.

Figure 5.1: Technical Efficiency Density Plot [SFA]

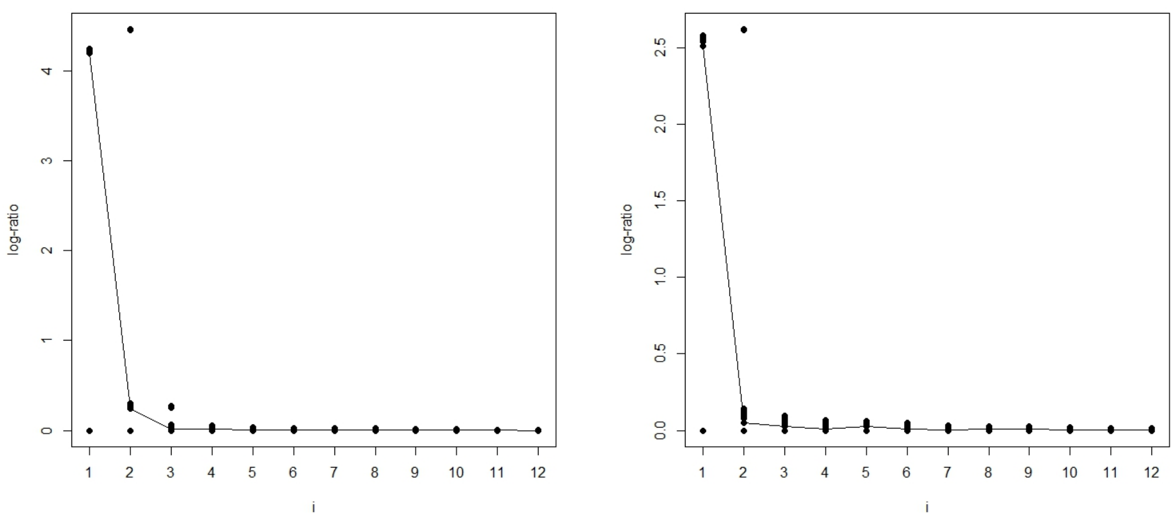


From figure 5.1, we can observe that the probability density is highly similar for all models in the interval 0 to 1. This implies that efficiency distributions are not affected by time. Considering the results from the maximum likelihood test, and the visual inspection, the time-invariant Cobb-Douglas frontier model will be further utilized in section 6.

5.4 Outliers

We remove outliers as they may represent measurement errors, data entry errors, or poor data sampling. This is especially important in the case of DEA, which assumes no noise (v).

Figure 5.2: Wilson´s Outlier Detection



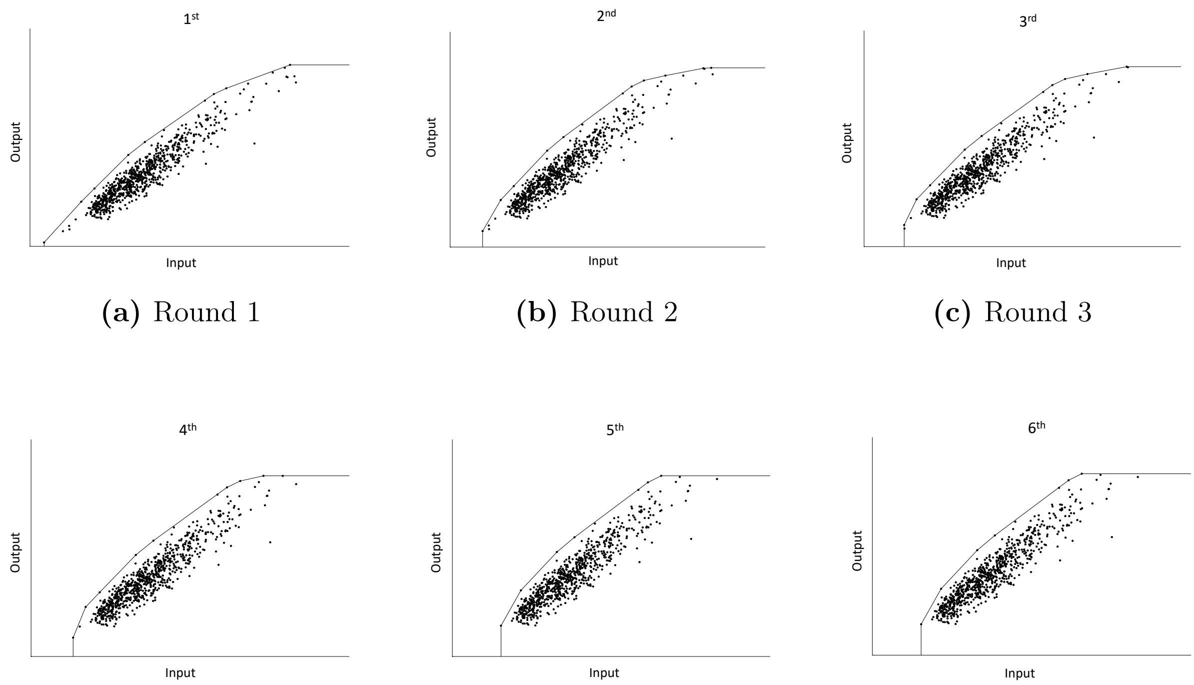
(a) 2014 **(b)** 2015

From the plots above, we notice that threshold lines drops from log ratios of 4 to 0.5 in 2014(figure 5.2a) and from 2.5 to 0.2 in 2015(figure 5.2b). It is not uncommon for the threshold line to fluctuate as the FEAR algorithm iteratively processes the data. In fact, the FEAR algorithm is designed to start with a relatively high threshold for identifying outliers and gradually lower the threshold as it processes the data. However, a sharp drop in the threshold line from one iteration to the next indicates that either one or more observations are particularly unusual or unexpected based on the data. We argue that these observations do not represent natural variability in the data. Thus, removing these outliers from the data using the super-efficiency method can be justified.

This process was done using the function SDEA in R. We implemented a threshold that the efficiency scores must satisfy. This means that, if the efficiency score of an observation is above the set threshold, we discard it. Banker et al. (2005) found that a threshold of 1.2 is optimal (with simulated data), we found that a threshold of 1.2 would discard too few observations. Hence, the threshold used during the iterations of sdea was set to 1.1. Each procedure was repeated until we were satisfied.

To visualize the outlier removal process, we constructed a plot showing the process iterated in 6 rounds.

Figure 5.3: Six Rounds of SDEA



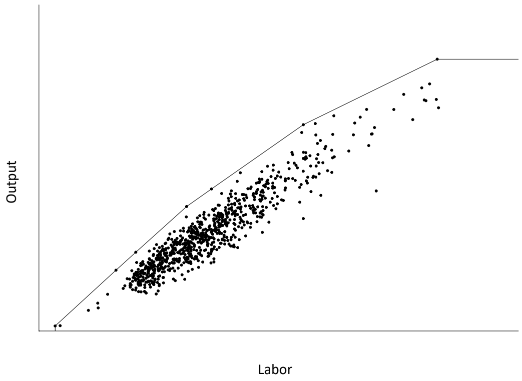
(a) Round 1 **(b)** Round 2 **(c)** Round 3

(d) Round 4 **(e)** Round 5 **(f)** Round 6

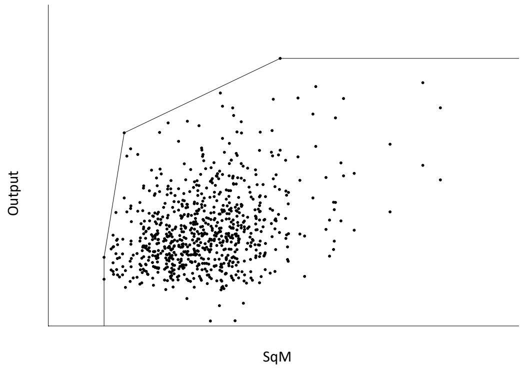
As visually observed, the number of outliers declined for each iteration. To observe the effects of outlier removal in more detail, we plotted the labor and SqM inputs against the total revenue.

In the following, the corresponding plots before and after outlier removal are illustrated in figures 5.4 and 5.5, respectively.

Figure 5.4: Input Variables Before SDEA

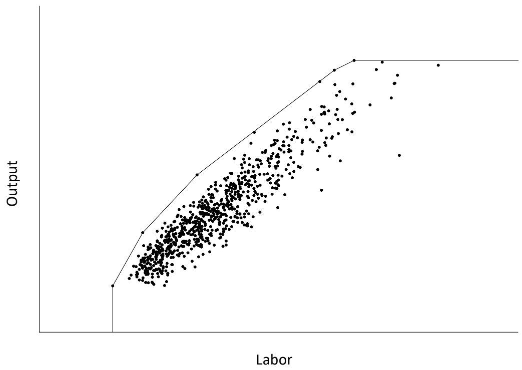


(a) Labor

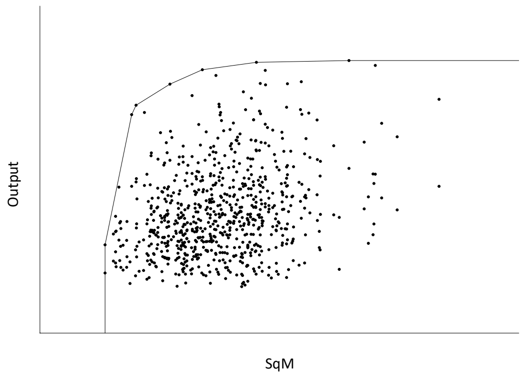


(b) SqM

Figure 5.5: Input Variables After SDEA



(a) Labor



(b) SqM

By observing Figure 5.4, it might look like there are some outliers. After removing the potential outliers (Figure 5.5), we can observe the same pattern of efficiencies, but slightly more concentrated. The smoothed efficient frontier is especially noticeable for SqM, which is important because it demonstrates that outlier removal was effective in reducing potential noise. Consequently, we assume that the potential outliers are removed from the data.

6 Results

In the following sections, we will present the technical efficiencies obtained from the frameworks of the non-parametric (DEA) and the parametric (SFA) procedures.

Various specifications tests were conducted to obtain the best model fits. First, the Banker´s parametric test was utilized to investigate whether the proposed DEA models produced statistically different efficiency estimates. The test confirmed that there was no difference in the efficiency distributions. Second, Banker´s scale test was conducted to investigate whether different scale assumptions affected the efficiency estimates in the selected model. The test rejected the null hypothesis in favor of efficiency differences when assuming constant returns to scale (CRS) and variable returns to scale (VRS) at the 5% significance level. Third, a maximum likelihood ratio test was conducted for the time-invariant and time-variant individual efficiencies. The test indicated that the effect of time was insignificant. Thus, the time-invariant functional form was retained. Consequently, input-orientated technical efficiencies of DEA will be based on the assumptions of CRS and VRS, while the SFA technical efficiencies will be based on the time-invariant individual efficiencies.

Due to confidentiality reasons, the names of the Kiwi stores will not be publicly disclosed. Consequently, each store will be named: store 1, store 2, store 3, . . . , store n in the result section.

6.1 DEA

The results of the data envelopment analysis are presented in the following subsections. The first subsection presents the DEA results for the year 2014. The second subsection presents the results for 2015 and compares the obtained technical efficiencies consecutively.

6.1.1 Technical Efficiencies in 2014

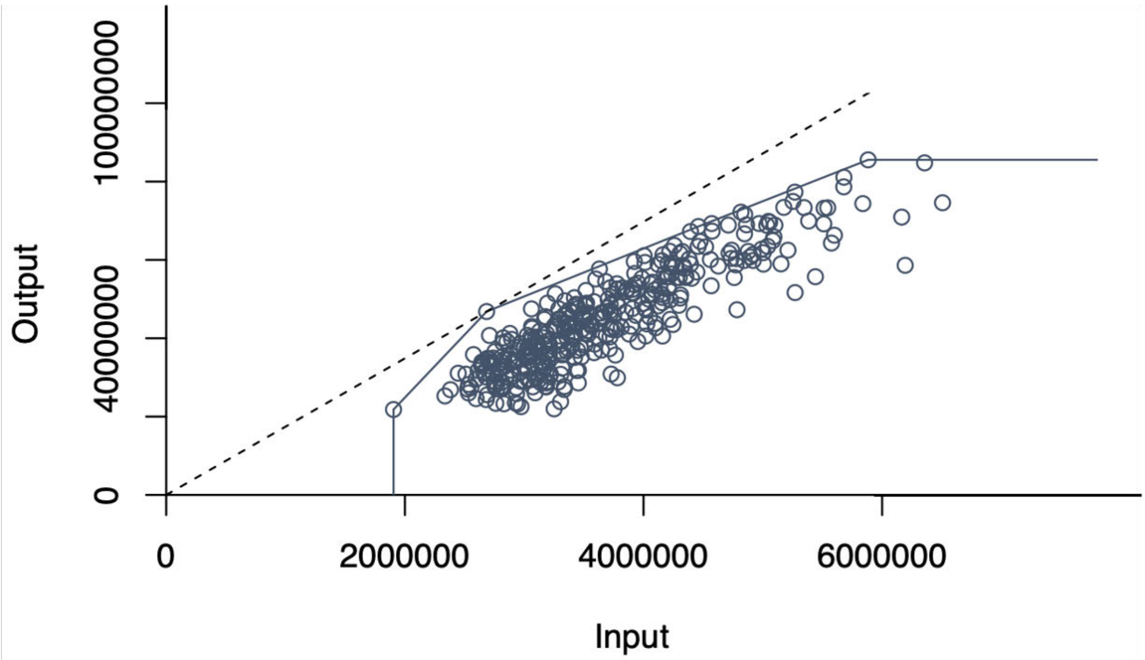
In the following, the frequency distribution of the technical efficiencies is presented.

Table 6.1: Frequency Distribution of Technical Efficiencies [DEA 2014]

Technical Efficiency Range (%)	**Frequency of Stores**		**% of Stores**	
	VRS	**CRS**	**VRS**	**CRS**
40 - 50	-	13	-	3.47
50 - 60	2	43	0.53	11.47
60 - 70	39	96	10.40	25.60
70 - 80	134	134	35.73	35.73
80 - 90	143	72	38.13	19.20
90 -100	42	15	11.20	4.0
100	15	2	4	0.53
Minimum TE	58%	41%		
Maximum TE	100 %	100%		
Mean TE	81%	72%		
Std.Error	9.0%	11%		
Scale Eff.	89%			

From table 6.1, we can observe that the lowest level of technical efficiency is 58% in the VRS model and 41% in the CRS model. The highest level of technical efficiency is 100% in both models, which is in accordance with the framework of DEA. In total, we find 15 technically efficient stores in the VRS model and 2 technically efficient stores in the CRS model. This implies that 2 stores in the CRS model and 15 stores in the VRS model define the efficient frontiers. Contrary to the most efficient stores, the least efficient stores are positioned between 59% and 42% away from the efficient frontier given CRS and VRS, respectively. Moreover, it can be observed that approximately 54% of the Kiwi stores are in the technical efficiency range of 80% - 90% to 100%, implying that a relatively high number of stores are located in the upper technical efficiency range. The estimated mean efficiencies in the VRS and CRS models are 81% and 72%, respectively. This implies that each Kiwi store on average would have produced between 19% and 28% more output with the same level of inputs if they were fully efficient given VRS and CRS, respectively. Moreover, we can observe that the average scale efficiency is estimated to be 89%, implying that 11% of the variation is due to scale inefficiency. Moreover, the reported standard deviation is 9% in the VRS model and 11% in the CRS model, implying that the technical efficiencies in the CRS model have a higher spread. The DEA plot in figure 6.1 illustrates a visual overview of the technical efficiencies.

Figure 6.1: Technical Efficiency Plot [DEA 2014]



The DEA plot allows to easily compare the technical efficiency scores for all Kiwi stores, enabling the identification of stores that are performing poorly or using more resources than necessary. While we were not able to statistically test the returns of scale, the visual interpretation of the plot suggests that many of the stores exhibit increasing and diminishing returns to scale, indicating that productivity varies across the stores and that scale differences may exist. This variation could be due to differences in the inputs and outputs of the stores, as well as their management and organizational structures. By identifying the most efficient and least efficient stores, the DEA plot provides valuable information for future analysis and potential interventions to improve Kiwi´s performance. In this thesis, we have used the peers(most efficient stores) to identify the amount of labor costs and store size (SqM) the inefficient stores would need to reduce to achieve full efficiency.

Table 6.2: Total Peers [DEA 2014]

CRS - Model		VRS - Model	
Peer	**Count**	**Peer**	**Count**
Store 98	206	Store 36	19
Store 351	372	Store 85	1
		Store 98	66
		Store 127	153
		Store 128	66
		Store 129	7
		Store 147	7
		Store 151	1
		Store 159	12
		Store188	45
		Store 202	45
		Store 277	90
		Store 351	287
		Store 355	9
		Store 373	171

Table 6.2 presents the peers for the inefficient stores and the corresponding peer count in the CRS and VRS models. When assuming CRS, we find that store 98 and store 351 are peers for 206 and 372 stores, respectively. This suggests that many Kiwi stores have discrepancies in their total labor cost and store size (SqM) and will have to refer to their respective peers (benchmarks) to become fully efficient. When assuming VRS, 13 additional stores become peers, where store 351 and store 373 are the most influential peers with respective peer counts of 287 and 171 stores. The low number of peers, especially in the CRS model, suggests that technical efficiencies could be highly sensitive to the omission of the most influential peers. Thus, the matter will be investigated in section 6.3. Moreover, we notice that 50% of the peers in the CRS model and 46.6% of the peers in VRS model are located in the county of Oslo, implying that location might be an important determinant for technical efficiency. The matter is illustrated in figure 6.2.

Figure 6.2: Average Technical Efficiencies in Norwegian Regions [CRS 2014]

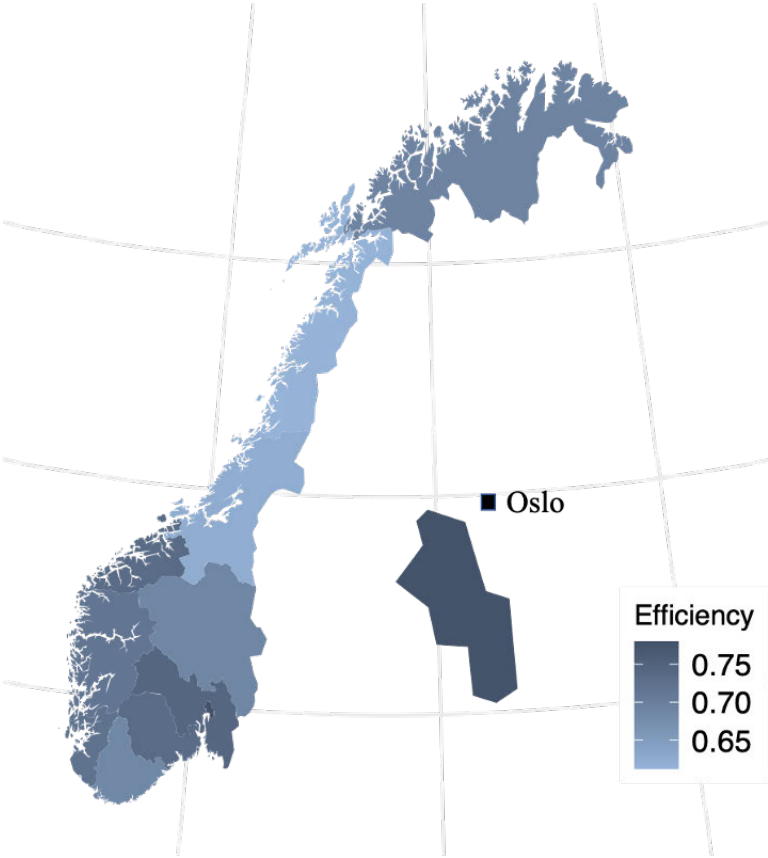


Figure 6.2 illustrates the average technical efficiency of 374 Kiwi stores in the 19 Norwegian counties for the year 2014[4]. To determine the average technical efficiency for each region, we calculated the mean of the technical efficiency scores for all Kiwi stores within each region. Although the map used in the figure does not perfectly match the boundaries of the 19 counties, it serves as a helpful visual representation of the data. By examining the map, we find that Kiwi stores in Oslo appear to be highly efficient, while Kiwi stores located in the northern regions, such as Sør Trøndelag and Nord Trøndelag seem to be less efficient. This prompts the question of whether location plays a role in determining technical efficiency. In section 6.4, we will delve deeper into this question by examining whether the technical efficiencies indeed vary across the 19 Norwegian regions.

Since we have identified the peers for the inefficient stores, we can obtain the amount of input each inefficient store needs to reduce to become fully efficient. The optimal

[4]The corresponding map for VRS and SFA is attached in appendixes A1.6, A1.7, A1.8 & A2.7

input-reduction plan for the CRS and VRS models is presented in table 6.3.

Table 6.3: Optimal Reduction of Inputs [DEA 2014]

	VRS - Model		**CRS - Model**	
	Labor(NOKM)	**Store Size (m^2)**	**Labor**	**Store Size (m^2)**
Min	-	-	-	-
Max	2.18	456	2.24	589
SD	0.38	80	0.39	96
Mean	0.70	130	0.99	183

From table 6.3, we can observe that the minimum reduction is estimated to be 0 in both the VRS and CRS models. This is rational as the efficient stores are peers for the inefficient stores. Consequently, the peers do not need to reduce their input consumption to become fully efficient.

When assuming a CRS model, we find the largest reduction in labor and SqM for store 207 and store 48 respectively. The corresponding reduction in labor costs is estimated to NOK 2.24M(41%), while the reduction in square meters is estimated to 589 m^2(55%). This means that both stores are recommended to reduce approximately half of their respective inputs. By reducing approximately half of their inputs, store 207 and store 48 may be able to streamline their operations and reduce overhead costs, potentially leading to increased efficiency. Likewise in the CRS model, the VRS model estimates the largest reduction in store size for store 48 (456 m^2) (42%). Contrary to the CRS model, the VRS model estimates the largest reduction in labor for store 104, which is estimated to NOK 2.18M (39.9%). On average, the CRS model estimates that each inefficient Kiwi store must reduce its labor costs and store size by NOK 0.99M and 183 m^2 to become fully efficient, respectively. In the VRS model, the respective reduction is estimated to NOK 0.70M and 130 m^2. The relatively larger input reduction in the CRS model is reasonable as it includes a higher number of inefficient stores.

More generally, the input reduction plan suggests that reducing labor costs and store size can be efficient ways to increase Kiwi´s efficiency. This is rational. In terms of labor, fewer employees may result in lower payroll expenses, which may allow the Kiwi stores to streamline their operations more efficiently. In addition, reducing labor may lead to increased productivity as employees may be motivated to work harder and more efficiently. On the other hand, reducing store size, or the space a store occupies can be an effective way to increase efficiency for a number of reasons. First, smaller stores may require fewer employees, resulting in lower labor costs. Second, smaller stores may have lower overhead costs, such as rent and utilities, which can further increase their efficiency. Overall, we argue that our results provide reasonable support for the importance of considering both labor costs and store size in efforts to increase technical efficiency.

6.1.2 Technical Efficiencies in 2015

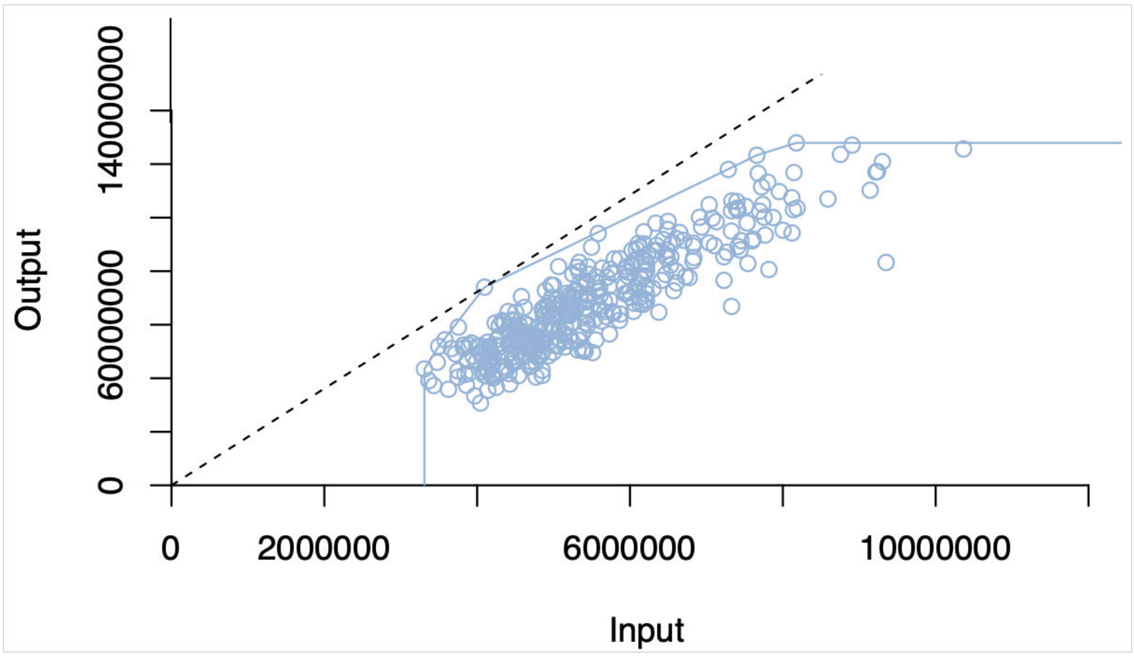
In table 6.4, the technical efficiencies frequency distribution is presented for 2015.

Table 6.4: Frequency Distribution of Technical Efficiencies [DEA 2015]

Technical Efficiency Range (%)	Frequency of Stores		% of Stores	
	VRS	CRS	VRS	CRS
40 - 50	-	10	-	2.7
50 - 60	2	51	0.53	13.6
60 - 70	42	119	11.20	31.7
70 - 80	163	135	43.47	36.0
80 - 90	118	51	31.47	13.6
90 -100	34	6	9.07	1.6
100	16	3	4.27	0.8
Minimum TE	59%	42%		
Maximum TE	100%	100%		
Mean TE	80%	70%		
Std. Error	8.9%	10.2%		
Scale Efficiency	89%			

The average technical efficiency ranges from 80% to 70% in the VRS and CRS model, respetively. This corresponds to a respective reduction of 1% and 2% from the previous year. However, it is important to notice that although the reported mean efficiencies seem ostensibly lower in 2015, the thesis cannot conclude the issue, as the matter goes beyond the scope of the DEA analysis. Thus, the matter will not be further emphasized. In the corresponding DEA plot (Figure 6.3), the technical efficiencies for the year 2015 are illustrated.

Figure 6.3: Technical Efficiency Plot [DEA 2015]



In contrast to 2014, the VRS frontier for 2015 is constructed further away from the DMUs (Kiwi stores), with a relatively higher output range. This could indicate that factors such as time may have contributed to the decreased efficiencies in 2015. However, we will not delve further into this issue as it falls outside the scope of DEA. To determine the amount of input that each inefficient store needs to reduce in order to become fully efficient, the number of peers and corresponding peer count data is obtained for the year 2015. The results are presented in the table 6.5.

Table 6.5: Total Peers [DEA 2015]

CRS - Model		VRS - Model	
Peer	**Count**	**Peer**	**Count**
Store 98	31	Store 6	93
Store 149	195	Store 36	2
Store 351	343	Store 93	2
		Store 98	21
		Store 128	67
		Store 147	13
		Store 149	96
		Store 151	1
		Store 159	58
		Store 174	88
		Store 188	83
		Store 248	2
		Store 351	295
		Store 355	14
		Store 357	72
		Store 374	64

Table 6.5 presents the peers and the corresponding peer count for the inefficient stores. In total, we find 3 peers when assuming a CRS model and 16 peers when assuming a VRS model. Contrary to the findings in 2014, store 351 is a peer for 343 stores, while store 98 is a peer for 31 stores. The additional peer (store 149) is a peer for 195 stores. Analogous to the findings in 2014, we observe that the vast majority of the peers are located in the county of Oslo, further implicating that location might be an important factor in determining technical efficiency.

The optimal input-reduction plan is presented in table 6.6.

Table 6.6: Optimal Reduction of Inputs [DEA 2015]

	VRS		**CRS**	
	Labor(NOKM)	**Store Size (m^2)**	**Labor**	**Store Size (m^2)**
Min	-	-	-	-
Max	3.24	419	3.37	495
SD	0.60	81	0.56	89
Mean	1.10	138	1.60	195

When assuming CRS, the largest reduction in labor and SqM are found for stores 198 and 48, respectively. The corresponding labor and store size reduction is estimated to NOK 3.37M (54.5%) and 495 m^2 (45.8%). Compared to estimates from 2014, the corresponding reduction in labor is slightly higher, while the reduction in SqM is slightly lower. For VRS, we find the largest reduction in labor and SqM for store 207, corresponding to a reduction of NOK 3,24M (41.5%) in labor costs and 419 m^2 (41.4%) in store size. Compared to estimates from 2014, the reduction in labor is higher, while the reduction in SqM is slightly lower. On average, the CRS model estimates that each inefficient store must reduce its labor costs and store size by NOK 1.6M and 195 m^2 to become fully efficient. In the VRS model, the respective reduction is estimated to NOK 1.1M and 138 m^2.

Conclusively, the results from the DEA analysis are supportive of what is found in other retail efficiency studies. For instance, Sinik (2017) conducted a DEA analysis of the Austrian malls and estimated an average technical efficiency of 91%. Moreover, Badin (1997) measured the technical efficiencies in the Brazilian supermarkets and found that approximately 78% of the sample wwas technically inefficient.

6.2 SFA

The following section will present the technical efficiencies obtained through the time-invariant efficiency model.

6.2.1 Time-Invariant Technical Efficiencies

Table 6.7 illustrates the maximum likelihood estimates of the time-invariant specification on the stochastic frontier model. The stochastic frontier model is estimated using the Frontier 4.1 program written by Tim Coelli from the University of England, Australia.

Table 6.7: MLE Estimates of the Stochastic Time-Invariant Efficiency Model

Variables	**Parameters**	**Coefficient**	**Std. Error**
Constant	β_o	1.252***	0.181
Ln Labor	β_1	1.095***	0.010
Ln SqM	β_2	0.004	0.019
Gamma	γ	0.908***	0.010
SigmaSqU	σ_u^2	0.048***	0.0044
SigmaSqV	σ_v^2	0.005***	0.0003
Lambda	λ	3.146***	0.2037
Loglikelihood		605.372	
Observations		792	
Number of Periods		2	
Signif. codes	0 ´***´ 0.001 ´**´ 0.01 ´*´ 0.05 ´.´ 0.1		

From table 6.7, we can observe that the coefficient of labor is positive and highly significant, implying if labor costs increased by 1%, the output would increase by 1.09%. Said differently, as more labor is employed, revenue increases. This implies that labor costs remain an important contributor to the improvement of technical efficiency. However, it is important to note that the relationship between labor costs and revenue is complex, and an increase in labor costs does not indefinitely lead to a corresponding increase in revenue. Various factors can impact this relationship and cause it to deviate from a simple scale effect. For example, the law of diminishing returns can come into play, resulting in declining marginal returns as more labor is added to the production process. Market conditions and consumer demand can also affect the relationship, as a saturated market or low demand may not support additional products or services produced with higher labor costs. Additionally, competition and technological innovations might also impact the relationship between labor costs and revenue. For instance, if a company's competitors are able to produce the same products or services more efficiently, they may be able to offer them at a lower price, which could reduce the revenue despite an increase in labor costs.

In terms of SqM, we observe that the coefficient is positive but not statistically significant at the 5% level. This indicates SqM does not meet the SFA´s apriori expectation, implying that it is not an important contributor to the improvement of technical efficiency. However, that a coefficient is statistically indistinguishable from zero does not imply that the coefficient is actually zero. This means we do not have sufficient statistical evidence to rule out that SqM has no effect on the revenue. If we decided to remove it from the regression model, and it affected the output, the estimated parameters would become biased and inconsistent. On the other hand, if SqM was affecting the output and we decided to keep it as an input, the estimation results would become inefficient but would not become biased nor inconsistent. Consequently, we chose to keep SqM as an explanatory variable in the model.

The results of the MLE estimates suggest that gamma (γ) which is the ratio of the variance of technical inefficiency effects (u_i) to the variance of random errors (v_i) has a highly significant and a positive coefficient of 0.908. This implies that about 90.8% of the variation in revenue is attributable to differences in the technical efficiencies among the stores. The implication is that about 9.2% of the variation of the revenue among the Kiwi stores is due to random shocks such as shortcomings in supply and other factors that are not under the direct control of the stores. The amount of the random variation is acceptable, which is in line with the highly significant and positive coefficient of lambda, implying that the variance of the systematic error term in relation to the random error term is relatively large. Consequently, the highly significant coefficient of lambda confirms that technical inefficiency is present. In section 5.3.2.3, the presence of technical inefficiency was also tested using the likelihood ratio test. The test returned a log-likelihood value of 605.372, which is higher than the critical chi-square value. Consequently, the null hypothesis of no technical inefficiency was rejected, implicating that the model is robust.

The following table presents the frequency distribution of the corresponding technical efficiencies.

Table 6.8: Frequency Distribution of Technical Efficiencies [SFA]

Technical Efficiency Range (%)	**Frequency of Stores**	**% of Stores**
50 - 60	5	1.3
60 - 70	25	6.3
70 - 80	91	22.9
80 - 90	138	34.8
90 - 99	137	34.5
Minimum TE	54%	
Maximum TE	99%	
Mean TE	84%	
Std. Error	9.48%	

The frequency distribution illustrates that the lowest level of technical efficiencies is 54%, whilst the highest level of technical efficiencies is approximately 99%. Contrary to the DEA estimates, approximately 34.5% of the Kiwi stores are in the technical efficiency range of 90-99. This implies that SFA considers more stores as technically efficient. Analogous to the VRS model, the mean technical efficiency of 84% is found in the technical efficiency range 80-90. This implies that an average Kiwi store would have gained 16% more revenue with the same amount of input if the stores produced at the efficient frontier. Unfortunately, we have not been able to compare the results of our SFA study with other studies due to a lack of research using the same methodology. However, our results implicate that SFA produces highly similar to those obtained through DEA. In the following section, we will therefore examine the sensitivities of the technical efficiencies.

6.3 Sensitivity of Technical Efficiencies

The efficiency step ladder (ESL) tests the robustness of the obtained technical efficiencies in the DEA procedure. In table 6.9, ESL is calculated for each Kiwi store in its first three stages towards the efficient frontier. The reported figures illustrate the average efficiency changes after removing the most influential peers. We assume no super-efficiency in this procedure.

Table 6.9: Average Sensitivity Estimates Based on ESL

CRS				**VRS**			
2014	*Step 1*	*Step 2*	*Step 3*	**2014**	*Step 1*	*Step 2*	*Step 3*
Mean	5,60%	0,70%	0,66%	Mean	3,19%	0,90%	1,22%
SD	1,60%	0,50%	0,61%	SD	2,95%	0,83%	1,61%
Min	1,73%	0,05%	0,09%	Min	0,01%	0,00%	0,03%
Max	8,64%	4,18%	6,26%	Max	9,87%	4,66%	9,45%
2015	Step 1	Step 2	Step 3	2015	Step 1	Step 2	Step 3
Mean	4,28%	3,07%	0,46%	Mean	2,52%	1,46%	0,71%
SD	0,96%	0,75%	0,67%	SD	2,38%	1,53%	1,03%
Min	2,00%	0,94%	0,01%	Min	0,01%	0,02%	0,05%
Max	6,49%	6,12%	7,74%	Max	8,84%	5,84%	16,55%

From table 6.9, we can observe that the average efficiency changes are in the range from 0.46% to 5.6% in the CRS model and from 0.71% to 3.19% in the VRS model. This implies that VRS efficiencies are less sensitive to measurement error, which is rational since the efficient frontier in the VRS model is constructed closer to the DMUs (Kiwi stores). However, when observing the maximum efficiency changes, the results indicate that VRS estimates are generally more sensitive. The highest sensitivity in the VRS model occurs in step 1 in 2014 and step 3 in 2015, with respective sensitivities of 9.87% and 16.55%. In this case, store 227 appears to be the most sensitive store in both years. In the CRS model for 2014, store 243 appears to be the most sensitive(step1), while in 2015 store 369 seems to be the most sensitive(step 3).

Since the SFA model is statistically estimated, the corresponding robustness cannot be tested using the ESL methodology. The SFA sensitivity can be tested through various statistical tests in relation to the t-scores of the parameter coefficients, measurement error, and p-values. In the SFA model, the uncertainty is mostly related to the coefficient of SqM, which is positive but not significant at the 5% level. The uncertainty of the corresponding effect is a weakness in the model, as it makes it more problematic to interpret the validity of the estimates. However, when observing the validity of the two-part composed error term in table 6.7, we can observe that are highly significant in the model. This provides reasonable evidence that the stochastic frontier model is indeed a robust model.

6.4 Comparing Technical Efficiencies Obtained through SFA and DEA

The following section will contain a graphical density compilation for the technical efficiencies obtained through the parametric SFA and the non-parametric DEA procedures. As a supplement to analysis, a correlation plot is constructed to examine the similarity of the parametric and the non-parametric efficiencies. Beyond the resemblance in the technical efficiencies, a table among the top 20 most efficient and bottom 20 least efficient Kiwi stores is included to examine whether DEA and SFA provide analogues rankings of the Kiwi stores.

Figure 6.4: Technical Efficiency Densities [DEA 2014 & SFA]

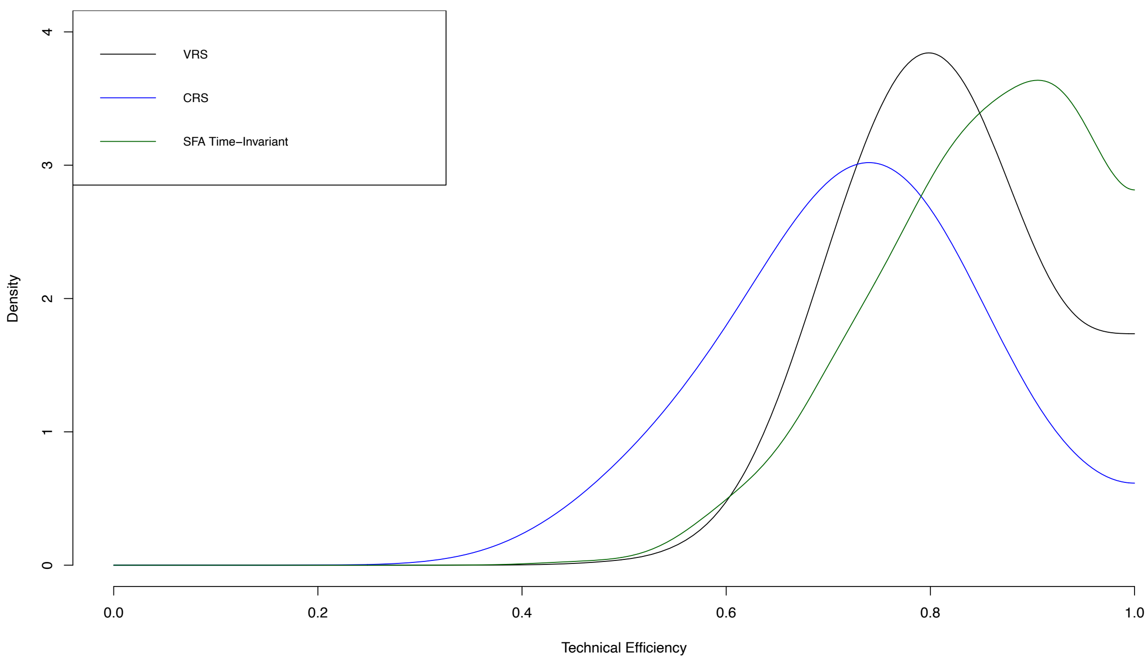
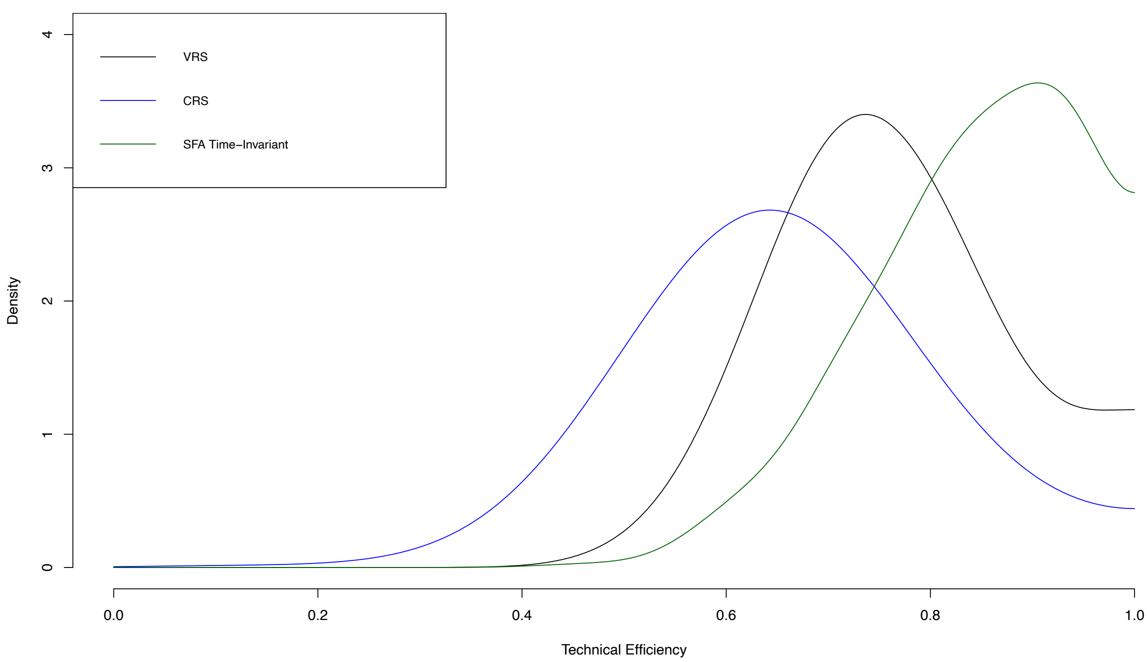


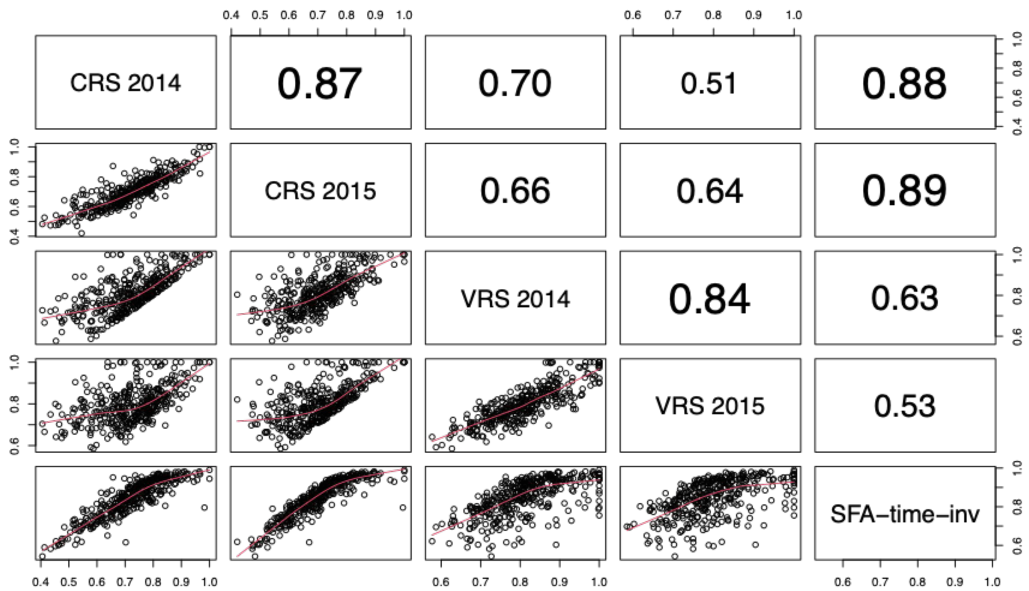
Figure 6.5: Technical Efficiency Densities [DEA 2015 & SFA]



The density plots for the years 2014 and 2015 present the distribution of the obtained technical efficiencies. The figures show that the CRS and VRS models have peaks at approximately 70% and 80%, respectively. For the technical efficiencies obtained through the time-invariant SFA model, we can observe that the corresponding vertex is at approximately 90%, which is slightly higher than the reported mean efficiency of 84%. This suggests that technical efficiencies obtained through the time-invariant SFA model are slightly higher than those from DEA. A potential explanation for this result could be due to the fact that the non-parametric DEA procedure measures all Kiwi stores from the frontier as inefficiency, whereas the parametric SFA procedure allows the deviation from the frontier to be partially caused by the random error term (v_i). Overall, we can conclude that the obtained technical efficiencies provide similar results. The results are also supported by previous studies that find that parametric and non-parametric approaches provide similar results (Cummins and Weiss, 2013).

SFA is included to test the robustness of the DEA estimates. Unfortunately, we have not been able to confirm or reject the hypotheses of variable returns to scale in neither the DEA nor the SFA model. However, we do observe that VRS add up as an average of the CRS and SFA technical efficiencies. Consequently, it is therefore conceivable that "real" technical efficiencies can be found in the interval between the CRS and SFA estimates. This is in accordance with the findings in the correlation plot presented in figure 6.6.

Figure 6.6: Correlation of Technical Efficiencies



In any case, we can derive that efficiency scores provide similar results. More specifically, we can observe that CRS 2015 and SFA-time-inv have the highest correlation, followed by the CRS 2014 and SFA-time-inv. This implies that technical efficiencies are highly similar in the CRS and SFA models, undermining the argument that "real" technical efficiencies can be found somewhere in-between the corresponding estimates. This suggests that the CRS model is a better fit than the VRS model. However, this should be viewed with some doubt, as we have not been able to statistically determine the best fit. To provide more insight into whether DEA and SFA provide analogous results, it is further interesting to examine whether Kiwi stores are roughly ranked in the same order in both procedures. In this context, a comparable ranking considers whether the same stores are included in both procedures. To determine this, we simultaneously categorized the top 20 most efficient and bottom 20 least efficient Kiwi stores for each procedure in each year. The following table presents the pairwise agreement for the top 20 most efficient and bottom 20 least efficient Kiwi stores.

Table 6.10: Pairwise Agreement on Kiwi Stores in Most and Least Efficient Tiers

Year	**2014**	**2015**
Top 20: Most efficient		
SFA - CRS	55%	40%
SFA - VRS	30%	20%
Bottom 20: Least Efficient		
SFA - CRS	70%	75%
SFA - VRS	25%	25%

From figure 6.10, we can observe that both procedures rank Kiwi stores similarly. Regarding the classification of the most efficient Kiwi stores, the rate of agreement ranges from 20% to 55%, whereas the rate of agreement for the least efficient stores ranges from 25% to 75%. Consequently, it can be argued that the corresponding correlation between the order of the Kiwi stores is strong and positive. This provides evidence that both methodologies can complement each other.

It is worthwhile mentioning that previous studies suggest that the most efficient firms are easier identified than the least efficient firms (Cummins and Zi, 1998). However, in this thesis, the agreement rate is higher in the least efficient stores. It can be argued that outlier removal in the DEA model could explain some of the divergences in the corresponding rankings. For instance, if the SFA procedure considers a specific Kiwi store as efficient, while the DEA procedure considers it an outlier, the agreement rate will naturally decrease. Overall, we cannot confirm their conclusion in this regard.

6.5 Determinants of Technical Efficiency

In the previous sections, the technical efficiency estimates were thoroughly assessed. In the following section, the corresponding technical efficiencies will be further utilized to analyze the influence of a set of store-specific and region-specific environmental factors.

Table 6.11 illustrates the technical inefficiency effects obtained from the maximum likelihood estimation and the Bootstrapped Tobit regression with C=500. Given the hypotheses in chapter 1.3, the parameter coefficients are equal to 0.

Table 6.11: First-Stage[SFA] and Two-Stage Estimation[DEA]

Variable	Parameter	Model 1 SFA Coefficient (SD)	Model 2 CRS 14 Coefficient (SD)	Model 3 CRS 15 Coefficient (SD)	Model 4 VRS 14 Coefficient (SD)	Model 5 VRS 15 Coefficient (SD)
Constant	δ_0	0.815*** (0.257)	0.354*** (0.077)	0.416 *** (0.070)	0.139** (0.045)	0.139 ** (0.043)
Store – Specific Variables						
Open Sundays	δ_1	0.053 . (0.032)	0.004 (0.032)	0.007 (0.029)	0.058** (0.018)	0.082 *** (0.018)
Hours Weekdays	δ_2	0.013 (0.045)	0.025 (0.040)	-0.027 (0.036)	0.060 ** (0.023)	0.075 *** (0.022)
Region – Specific Environmental Variables						
Median Income	δ_3	0.018 (0.038)	-0.012 (0.035)	0.014 (0.031)	0.030 (0.021)	0.044 * (0.019)
Higher Education	δ_4	-0.036 (0.046)	0.049 (0.039)	-0.054 (0.036)	-0.011 (0.026)	-0.019 (0.022)
Population Size	δ_5	0.049 (0.076)	0.019 (0.072)	0.029 (0.063)	0.020 (0.042)	0.032 (0.038)
Population Density	δ_6	0.018 . (0.052)	0.019 (0.044)	0.038 (0.043)	-0.030 (0.025)	-0.029 (0.026)
HHI	δ_7	-0.124** (0.048)	0.056 . (0.032)	0.051 . (0.028)	-0.035 . (0.018)	-0.018 (0.017)
Store Density per Capita	δ_8	0.062 (0.036)	0.059 . (0.032)	0.042 (0.029)	0.004 (0.018)	0.007 (0.017)
Close Competitors	δ_9	0.039 (0.029)	0.040 (0.026)	0.038 (0.043)	0.005 (0.015)	0.006 (0.015)
Akershus	δ_{10}	-0.080 (0.098)	0.042 (0.077)	-0.040 (0.069)	0.017 (0.045)	-0.005 (0.042)
Hedmark	δ_{11}	0.118 (0.076)	0.182 * (0.089)	0.094 (0.082)	0.151 ** (0.052)	0.132 ** (0.050)
Oppland	δ_{12}	0.143 * (0.066)	0.130 . (0.077)	0.087 (0.0719	0.135 ** (0.045)	0.144 *** (0.042)
Buskerud	δ_{13}	0.023 (0.078)	0.004 (0.074)	0.018 (0.068)	0.022 (0.042)	0.073 . (0.042)
Vestfold	δ_{14}	0.056 (0.087	0.065 (0.085)	0.060 (0.078)	0.020 (0.050)	0.066 (0.047)
Østfold	δ_{15}	0.158 ** (0.060)	0.145 (0.077)	0.172 ** (0.071)	0.114 * (0.045)	0.118 * (0.043)
Telemark	δ_{16}	0.098 (0.075)	0.064 (0.086)	0.105 (0.080)	0.069 (0.050)	0.094 . (0.049)
Aust-Agder	δ_{17}	-0.005 (0.115)	0.089 (0.089)	0.048 (0.081)	0.084 (0.052)	0.051 (0.049)
Vest-Agder	δ_{18}	0.235*** (0.062)	0.214* (0.084)	0.193 * (0.085)	0.116 * (0.054)	0.087 . (0.051)
Rogaland	δ_{19}	0.091 (0.068)	0.115 . (0.068)	0.070 (0.062)	0.042 (0.040)	0.022 (0.037)
Hordaland	δ_{20}	0.082 (0.061)	0.092 . (0.054)	0.072 (0.050)	0.050 (0.032)	0.037 (0.030)
Sogn og Fjordane	δ_{21}	0.109 (0.095)	0.161 . (0.095)	0.068 (0.088)	0.088 (0.056)	0.004 (0.053)
Møre og Romsdal	δ_{22}	0.036 (0.091)	0.092 (0.077)	-0.018 (0.070)	-0.009 (0.045)	-0.055 (0.043)
Sør Trøndelag	δ_{23}	0.288 *** (0.061)	0.314 *** (0.078)	0.253 *** (0.071)	0.150 *** (0.045)	0.120 ** (0.043)
Nord Trøndelag	δ_{24}	0.370 *** (0.077)	0.429 *** (0.111)	0.423 *** 0.102	0.237 *** (0.064)	0.174 ** (0.060)
Nordland	δ_{25}	0.293 *** (0.075)	0.356 ** (0.110)	0.210 * (0.100)	0.109 * (0.064)	0.063 (0.060)
Troms	δ_{26}	0.078 (0.140)	0.155 (0.127)	0.036 (0.115)	0.084 (0.075)	0.072 (0.070)
Finnmark	δ_{27}	0.261 ** (0.096)	0.190 (0.126)	0.244 * (0.116)	0.056 * (0.073)	0.084 (0.069)
Signif. codes	0 ´***´ 0,001 ´**´ 0,01 ´*´ 0.05 ´.´ 0,1					

The estimated parameters for the store-specific coefficients in models 1 to 3 are mostly positive, but not significant at the 5% level. Further, when examining the coefficients at the 10% level, we can observe that Open Sundays is significant in model 1, while Hours Weekdays is insignificant. Contrary to the findings in models 1-3, both Open Sundays and Hours Weekdays are positive and highly significant in models 4 and 5. The positive coefficient signs implicates that Sunday-open Kiwi stores and stores with longer opening hours are relatively less technically efficient.

Regarding the region-specific variables on the administrative region level, we can observe that both Sør-Trøndelag and Nord-Trøndelag have positive and highly significant coefficients in all models. This implicates that Kiwi stores located in the counties Nord-Trøndelag and Sør-Trøndelag are relatively less efficient than stores in Oslo. Moreover, we observe that coefficients of Østfold, Vest-Agder and Nordland are all positive and highly significant at the 5% level in four models. We argue that the significance of four models provides sufficient evidence to conclude that stores located in respective counties are relatively less efficient than those in Oslo. Moreover, we do observe that the coefficients of Hedmark, Oppland and Finnmark are all positive and significant at the 5% level in only 3 of the models. This implicates that we cannot be entirely certain that stores located in the respective counties are relatively less efficient. The Kiwi store located in the counties: Akershus, Buskerud, Vestfold, Telemark, Aust-Agder, Rogaland, Hordaland, Sogn og Fjordane, Møre og Romsdal and Troms seem to be no different from stores located in Oslo, due to the low level of consistency in the models.

Regarding the region-specific environmental factors on the municipality and local level, we can observe that only two variables are significant at the 5% level. That is HHI and Median Income, which are found in models 1 and 5 respectively. The negative coefficient of HHI suggests that Kiwi stores located in less competitive municipalities are more technically efficient, meanwhile, the positive coefficient of Median income suggests that stores located in wealthier municipalities are less efficient. When examining the corresponding effects at the 10% significance level, we can observe that HHI´s coefficient becomes significant in models 2, 3 and 4. This suggests that competition could be an important factor in determining the technical efficiency. However, there is some uncertainty related to whether the effects are positive or negative, as the coefficient sign varies across the different models. Furthermore, we can observe that the coefficients of store density per capita and Population Density are positive and significant at the 10% level, suggesting that stores located in municipalities with high population density and high store density per capita are relatively less efficient. The remaining variables: Higher Education, Population Size and Close Competitors show no significance at the 10% level.

Overall, we notice that the significance of the coefficients in the VRS, CRS, and SFA models vary. This can be explained by several factors. First, this could be to the different assumptions and methodologies used in the models. Second, the relationship between the variables and the outcome may have changed over time. For example, if a variable that was previously believed to have a strong relationship with the technical inefficiency is no longer as strongly related over time, this could lead to a decrease in its significance. On the other hand, if a previously insignificant variable has developed a stronger relationship with the outcome over time, this could lead to an increase in its significance. Third, some variables may be insignificant in the regression analysis even though they are believed to influence the technical inefficiencies. One reason could be that there is not enough variation in the variables to detect a relationship with the outcome, which would limit the statistical power of the analysis. Fourth, the significance of the environmental variables in the regression analysis may have been affected by the other variables included in the models. For instance, from table 5.4, we can observe that Population Density is highly correlated with the Population Size (73.3%). Further, we can also observe that Population Density is highly correlated with Higher Education (66.8%). This means that if a variable is confounded with other variables in the models, it can be difficult to disentangle its individual effect on the outcome. This can lead to insignificant or less significant parameters, even if the variables are believed to be important in real life. However, as emphasized by (Banker and Natarajan, 2008) the high correlation between the store- and region specific environmental variables is not problematic for the validity of the results.

Based on the results in this section, we will conclude the hypotheses presented in sections 1.3.1 and 1.3.2.

6.5.1 Investigation of Research Hypotheses

6.5.1.1 Store Specific Factors

The 1^{st} research hypothesis examined is: "Sunday open Kiwi stores affect Kiwi´s technical efficiency". In model 1, several researchers would have considered the inefficiency effect at the 10% level as not significant. For this reason, although this result would allow us to support the corresponding hypothesis, we cannot accept it based on the results from model 1. When looking at models 3 and 5, we can observe that the coefficient of Open Sundays is positive and highly significant, implying that Sunday open stores are indeed less efficient. This could be due to several reasons, including lower overall demand for their products or services on Sundays, additional wages, or difficulty in finding enough staff to work on Sundays. Without more information, it's difficult to conclude with a high level of certainty why Sunday open stores might be less technically efficient. However, (Ingvaldsen, 2016) argues that Sunday open grocery stores are generally less productive as they cannot generate enough revenue to compensate for the higher costs. For this reason, the research hypothesis can be supported.

The 2^{nd} hypothesis examined is: "Longer opening hours on weekdays affect Kiwi´s technical efficiency". From table 6.11, we find that the coefficient of Hours Weekdays is positive and statistically significant at the 1% and 0.01% level in models 4 and 5, respectively. The corresponding results imply that Kiwi stores with longer opening hours are relatively less efficient. We argue that there might be a few reasons to why longer opening hours might lead to lower technical efficiency. For instance, if a store is open for longer hours but does not get a corresponding increase in demand, it may not be able to fully utilize its employees and resources, which affects efficiency negatively. Additionally, if a store is open for longer hours, but does not have the necessary infrastructure or systems in place to support the extended operations, it could struggle to maintain high levels of productivity, which affects technical efficiency negatively. However, it should be noted, nevertheless, that staying open later may be critical in highly competitive environments. In some cases, having longer opening hours may allow a store to serve more customers, which could increase its efficiency. For example, if a Kiwi store is open for longer hours, it may be able to take advantage of peak demand periods that it would otherwise miss out on. In this context, the negative effects are dominant. We argue that high significance in 2 of the models provides sufficient evidence to conclude that longer opening hours indeed affects kiwi´s technical efficiency. Thus, the corresponding research hypothesis is accepted.

6.5.1.2 Region-Specific Environmental Factors

The 3^{rd} hypothesis examined is: "The technical efficiency of Kiwi stores varies among the Norwegian administrative regions". From table 6.11, we find that stores located in Nord-Trøndelag and Sør-Trøndelag in particular are less technically efficient than stores located in Oslo. We argue that there might be several factors to why Kiwi´s technical efficiencies might vary among the corresponding Norwegian administrative regions. The possible factors might be the quality of the local infrastructure, the level of education and training among the workforce, the level of technological development, competition and innovation, and the overall economic conditions. Additionally, the efficiency of a region may be affected by the specific industries and businesses that operate there, as well as the policies and regulations that are in place to support economic growth and development. Ultimately, even though the corresponding factors are not analyzed in this thesis, we argue that the efficiency of an administrative region is determined by the complex interplay of these factors and can vary widely from one region to another. For this reason, we can conclude that the corresponding research hypothesis can be supported.

The 4^{th} hypothesis examined is: "Higher levels of education in the municipalities affect Kiwi´s technical efficiency". From table 6.11, the coefficient of Higher education is insignificant across all models. Thus, we cannot statistically prove that higher education affects Kiwi´s technical efficiency at the municipality level. For this, the research hypothesis is not accepted.

The 5^{th} hypothesis examined is: "The population size in the municipalities affects Kiwi´s technical efficiency". From table 6.11, we find no significant inefficiency effects of population size. A possible explanation might be that population size does not have any direct effect on technical efficiency. Said differently, it can be argued that the efficiency of a store is most likely determined by a complex interplay of many different factors, and the population size in a municipality is just one potential factor among many. Thus, the result can be argued to be rational. Consequently, the corresponding hypothesis is rejected in favor of the null hypothesis: "Population size in the municipalities does not affect Kiwi´s technical efficiency".

The 6^{th} hypothesis examined is: "The population density in the municipalities affects Kiwi´s technical efficiency". We find that the coefficient of Population Density is positive and significant at the 10% level, which means that there is a greater than 5% probability that the results occurred by chance. This suggests that the relationship between population density and technical inefficiency is present, but the strength of this effect is not particularly strong. Likewise, we argue that a 10% significance level in only of the models does not provide enough evidence to accept the research hypothesis.

The 7^{th} hypothesis examined is: "Higher level of median income in the municipalities affects Kiwi´s technical efficiency". From table 6.11, we find that the coefficient of Median Income is positive and highly significant in model 5, implying that stores located in municipalities with a higher median income are less efficient. However, since the coefficient is only significant in only one of the models, it is difficult to conclude with a high level of certainty that Kiwi stores located in municipalities with higher median income are indeed less efficient. We argue that there could be several reasons to why the relationship between median income and technical efficiency is not significant in the other models. It is possible that other factors, such as the level of market concentration may be more important in determining technical inefficiency. Alternatively, it may be that the relationship between median income and technical efficiency is not consistent across all municipalities, and may vary depending on other factors or characteristics of the municipalities. We argue that further research is necessary to confirm the presence and strength of any relationship between median income and technical efficiency. Consequently, we argue that there is not enough statistical evidence to support the corresponding research hypothesis.

The 8^{th} hypothesis examined is: "The level of market concentration in the municipalities affects Kiwi´s technical efficiency". We find that the coefficient of HHI is negative and highly significant in model 1, implying that lower levels of competition positively affect Kiwi´s technical efficiency. While the high significance in only one of the models is not enough to support the hypothesis, we argue that significant results(10% level) in models 2, 3 and 4 do provide sufficient evidence to accept the hypothesis. Thus, we argue that competition may be related to Kiwi stores´ inefficiencies. Conclusively, we do accept the research hypothesis.

The 9^{th} hypothesis examined is: "The number of close competitors on the local level affect Kiwi´s technical efficiency". From table 6.11, the coefficient of Close Competitors is insignificant across all models. Thus, we cannot statistically prove that the number of close competitors affects Kiwi´s technical efficiency on the local level. For this reason, the research hypothesis cannot be accepted.

The 10^{th} hypothesis examined is: "The store density per capita in the municipalities affects Kiwi´s technical efficiency". We find that the coefficient of store density per capita is positive and significant at the 10% level, implying that Kiwi stores located in municipalities with higher density per capita are relatively less efficient. However, we argue that the 10% significance level cannot be accepted. Consequently, the research hypothesis is not supported.

7 Conclusion

In the first part of the thesis, the development in profitability and productivity were analyzed in various Norwegian industries and sectors from 1971 to 2021. In the profitability analysis, we find that total industry-sector and food-industry are the most profitable measured in gross-and operating margins. Nevertheless, they are the least productive measured in labor and total factor productivity. We find that the retail-sector is by far the most productive and least volatile in terms of productivity growth. Overall, the results indicate that profitable industries are not necessarily associated with high levels of productivity growth.

In the second part of the thesis, the technical efficiency in Kiwi stores has been analyzed using both the parametric stochastic frontier analysis (SFA) and the non-parametric deterministic data envelopment analysis (DEA). By using both methodologies, we have been able to (1) compare the average technical efficiency scores (2) compare the sensitivity of the technical efficiencies (3) compare the rankings of the most and least efficient Kiwi stores and (4) compare how the one-stage and two-stage regressions statistically assess the determinants of technical inefficiency.

We find that technical efficiencies in the SFA procedure are slightly higher compared to those in the DEA procedure. In the stochastic time-invariant model, we find an average technical efficiency score of 84%. In the DEA models with constant returns to scale for the year 2014 (2015), we obtain an average technical efficiency score of 72% (70%), while in the DEA model with variable returns to scale we find an average efficiency score of 81% (80%). The DEA results are supported by Baldin (1997) and Sinik (2017). We argue that SFA estimates are slightly higher due to the random error term (systematic noise).

To further compare the obtained technical efficiencies, we estimate the correlation between the efficiency scores retrieved from SFA and DEA, finding efficiency scores strongly and positively correlated. Additionally, the relationship between the efficiency rankings is examined. The pairwise agreement provides highly similar rankings of the top 20 most efficient and bottom 20 least efficient Kiwi stores. For the most efficient Kiwi stores, the agreement rate varies between 20% to 55%, whereas the agreement rate for the least efficient Kiwi stores ranges from 25% to 75%. This implies that both methodologies can complement each other. Overall, the results of this study are in line with previous research that has found SFA and DEA approaches to be comparable in their ability to measure efficiency (Cummins and Weiss, 2013).

Further, our investigation of DEA efficiencies revealed that the lowest average sensitivity was obtained when assuming VRS. In terms of SFA, the highly significant two-part composed error term revealed that the selected model is robust. Conclusively, we argue that both DEA and SFA provide relatively robust estimates.

In the last part of the thesis, the obtained technical efficiencies are utilized to analyze the influence of store-specific and region-specific environmental factors. By using the one-stage approach for SFA, and the two-stage approach for DEA we find that Kiwi stores that are open on Sundays and Kiwi stores that have longer opening hours are relatively less technically efficient. Additionally, we find that technical efficiencies vary across the Norwegian administrative regions, whereas especially Kiwi stores located in Nord-Trøndelag and Sør-Trøndelag seem to be less technically efficient than those located in Oslo. When investigating the inefficiency effects on the municipality level, we find that lower levels of market concentration affect kiwi´s technical efficiency. Further, we argue that there is not enough statistical evidence to conclude that factors such as education, higher median income and population affect Kiwi´s technical efficiency.

To compete efficiently in the grocery market, like in any other market, it is essential that grocery chains like Kiwi know how to analyze their current efficiencies compared to their competitors. Thus, studying technical efficiencies and recent trends might help to identify potential areas of profitability or productivity improvement. The results in this thesis implicate that there are sufficient costs to be saved. On average, we estimate that each inefficient Kiwi store could save NOK[0.70,1.6]M in labor costs and use [130,195] less store space (SqM) if run efficiently. Conclusively, we argue that both parametric and non-parametric procedures should be utilized to assess the technical efficiencies rather than substitute one another.

8 Limitations and Further Research

The data in the technical efficiency analysis ranges from 2014-2015. The grocery industry, like all industries, is subject to changes over time. As such, the results in this thesis should be interpreted with this time lag in mind and should not be assumed to fully reflect the current economical state of the Kiwi stores.

Another limitation of the thesis is that it did not consider the potential inefficiency effects of certain internal factors, such as the use of part-time versus full-time employees, the ownership status of the stores (franchise vs. non-franchise) and the age of the stores. Including an analysis of these factors could have provided valuable insights. For example, examining the use of part-time versus full-time employees may have revealed the extent to which labor practices impact the efficiency of the stores. Similarly, analyzing the ownership status of the stores (franchise vs. non-franchise) could have shed light on the role of ownership structure in determining efficiency. Meanwhile investigating the age of the stores could have revealed to which extent experience is an important determinant of technical efficiency. Unfortunately, the lack of data made it impossible to examine these effects. Consequently, future research should also examine the influence of these factors to gain a more comprehensive understanding of the determinants of Kiwi´s technical efficiency.

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Appendix

A1 DEA

A1.1 Example Data [Scale Efficiency]

DMU	Input	Output
1	150	75
2	200	150
3	300	300
4	180	60
5	150	34
6	450	240
7	600	400
8	550	300
9	520	340

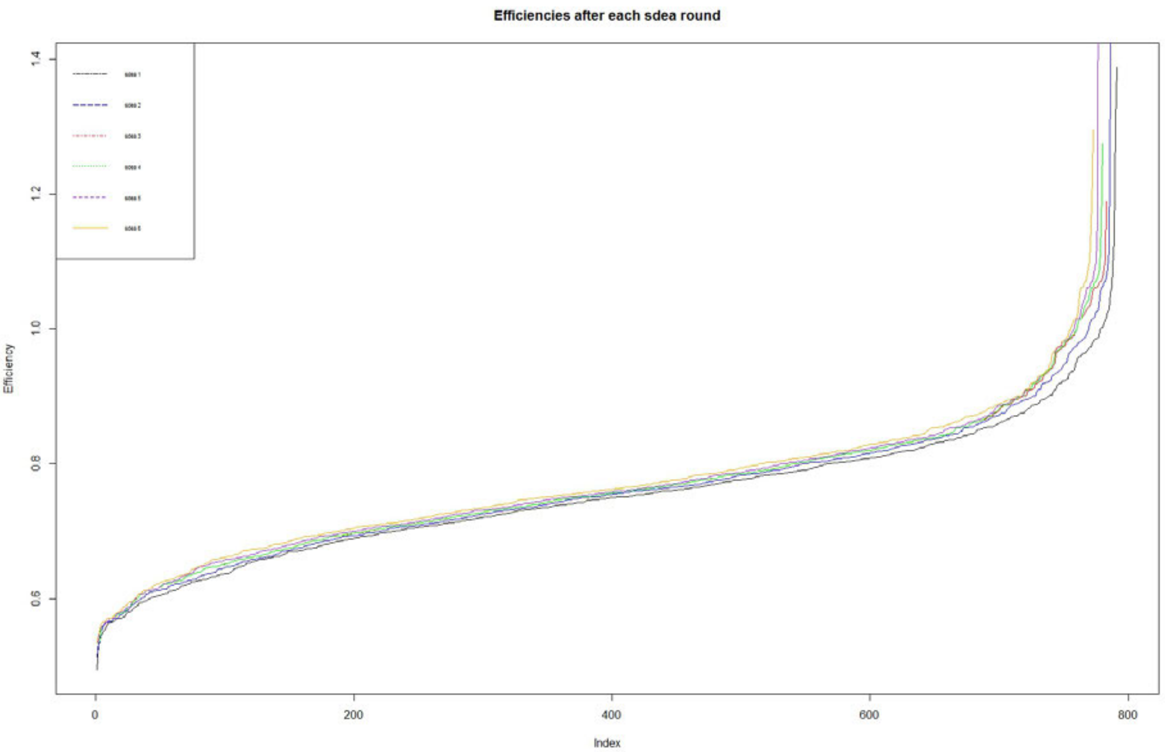
A1.2 Example Data (10 first observations) [Efficiency Step Ladder & Wilson's Outlier Detection]

Firm	x1	x2	x3	x4	x5	y1	y2	y3	pft	Name
1	86.13	16.24	48.21	49.69	9	54.53	58.98	38.16	1	Berkely
2	29.26	10.24	41.96	40.65	5	24.69	33.89	26.02	1	Buffalo
3	43.12	11.31	38.19	35.03	9	36.41	40.62	28.51	1	Duluth
4	24.96	6.14	24.81	25.15	7	14.94	17.58	16.19	1	Fresno
5	11.62	2.21	6.85	6.37	4	7.81	6.94	5.37	1	Lebanon
6	11.88	4.97	18.73	18.04	4	12.59	16.85	12.84	1	Salt Lake
7	32.64	6.88	28.1	25.45	7	17.06	16.99	17.82	1	Tacoma
8	20.79	12.97	54.85	52.07	8	20.29	30.64	33.16	1	Baltimore
9	34.4	11.04	38.16	42.4	8	26.13	29.8	26.29	1	Lakewood
10	61.74	14.5	49.09	42.92	9	46.42	51.59	35.2	1	Lincoln

A1.3 Omitted Stores

Round of SDEA	Number of stores removed
1	4
2	4
3	3
4	3
5	4
6	4
Total: 6	22

A1.4 Super Efficiencies after Removing Outliers



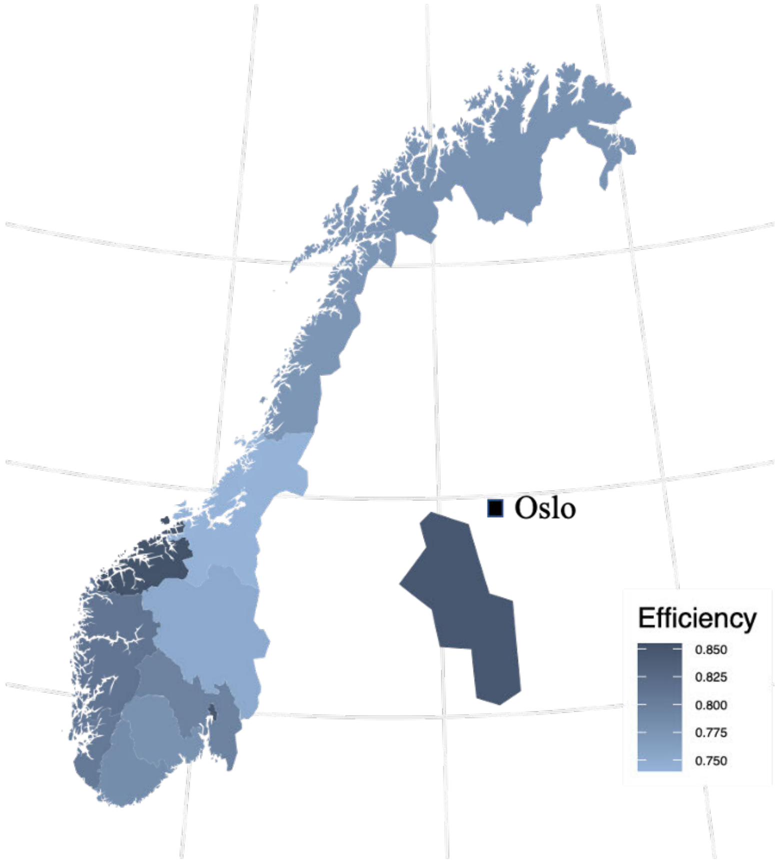
A1.5 Selected Store-Specific and Region-Specific Environmental Variables [DEA]

Dummy	Logical Explanation	Mean
Population Size	1: If Population Size $\geq$ 120 028 0: If Population Size <120 028	120 028
Population Density	1: If Population Density $\geq$ 394 0: If Population Density <394	394
Median Income	1: If Median Income $\geq$ 627305 0: If Median Income <627 305	627 305
Higher Education	1: If Higher Education $\geq$ 31 0: If Higher Education <31	31
Open Sundays	1: If Open Sundays 0: If Closed Sundays	[redacted]
HHI	1: If HHI $\geq$ 0.120 0: If HHI<0.120	0.120
Hours Weekdays	1: If Hours Weekdays $\geq$[redacted] 0: If Hours Weekdays <[redacted]	[redacted]
Close Competitors	1: If Close Competitors $\geq$ 2.46 0: If Close Competitors <2.46	2.46
Store Density Per Capita	1: If Store Density Per Capita $\geq$ 0.00015 0: If Store Density Per Capita <0.00015	0.00015

A1.6 Average Technical Efficiencies in Norwegian Regions [CRS 2015]

A1.7 Average Technical Efficiencies in Norwegian Regions [VRS 2014]

A1.8 Average Technical Efficiencies in Norwegian Regions[VRS 2015]



A2 SFA

A2.1 Summary Statistics

	Mean	Median	SD	Min	Max	N
Inputs						
Labor Cost	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	792
SqM	662	649	208	235	1652	792
Output						
Revenue	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	792
Store-Specific Variables						
Open Sundays	-	-	-	[redacted]	[redacted]	792
Hours Weekdays	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	792
Region-Specific Environmental Variables						
Region	-	-	-	-	-	792
Median Income	627 873	608 000	76 969	459 000	859 000	792
Population Size	123 856	26 711	208 757	933	647 676	792
Population Density	402	149	525	1	1942	792
Higher Education	31.25	28.3	10	15.5	51.1	792
HHI	0.118	0.086	0.121	0.004	1	792
Store Density Per Capita	0.000158	0.000125	0.00010	0.000027	0.00107	792
Close Competitors	2.54	2	2.42	1	20	792

A2.2 Correlation [Inputs, Output, Environmental Variables]

	Revenue	Labor	SqM	Population Size	Population Density	Median Income	Higher Education	Open Sundays	HHI	Hours Weekdays	Close Competitors	Store Density
Revenue	100,0%	94,2%	33,3%	-4,2%	-0,4%	14,1%	7,1%	19,1%	-0,9%	13,6%	-10,3%	-1,0%
Labor	94,2%	100,0%	34,2%	-7,5%	-3,0%	12,3%	4,6%	25,1%	-2,4%	14,6%	-10,6%	0,7%
SqM	33,3%	34,2%	100,0%	-24,3%	-28,5%	4,5%	-27,9%	29,4%	21,8%	14,4%	-7,9%	17,2%
Population Size	-4,2%	-7,5%	-24,3%	100,0%	73,0%	-32,4%	63,3%	-11,3%	-42,3%	10,5%	22,6%	-35,4%
Population Density	-0,4%	-3,0%	-28,5%	73,0%	100,0%	-18,2%	67,7%	-4,7%	-50,3%	1,1%	20,4%	-41,7%
Median Income	14,1%	12,3%	4,5%	-32,4%	-18,2%	100,0%	2,0%	-6,7%	16,1%	-4,4%	-13,1%	14,1%
Higher Education	7,1%	4,6%	-27,9%	63,3%	67,7%	2,0%	100,0%	-9,3%	-49,4%	0,1%	14,0%	-42,7%
Open Sundays	19,1%	25,1%	29,4%	-11,3%	-4,7%	-6,7%	-9,3%	100,0%	5,3%	1,0%	2,0%	5,6%
HHI	-0,9%	-2,4%	21,8%	-42,3%	-50,3%	16,1%	-49,4%	5,3%	100,0%	-11,5%	-17,4%	46,2%
Hours Weekdays	13,6%	14,6%	14,4%	10,5%	1,1%	-4,4%	0,1%	1,0%	-11,5%	100,0%	8,7%	-6,6%
Close Competitors	-10,3%	-10,6%	-7,9%	22,6%	20,4%	-13,1%	14,0%	2,0%	-17,4%	8,7%	100,0%	-17,7%
Store Density	-1,0%	0,7%	17,2%	-35,4%	-41,7%	14,1%	-42,7%	5,6%	46,2%	-6,6%	-17,7%	100,0%

A2.3 Maximum Likelihood Ratio Test

Null Hypoteses	Log Likelihood	P- Value	Decision
H0: OLS = SFA H1: OLS $\neq$ SFA	OLS: 415.11 SFA: 605.37	$2.2 * 10^{-14}$ (***)	Reject H0
H0: Trans-Log = OLS H1: Trans-Log $\neq$ OLS	OLS: 427.73 Trans-Log: 607.37	$2.2 * 10^{-14}$ (***)	Reject H0
H0: Trans-Log = SFA H1: Trans-Log $\neq$ SFA	SFA: 605.37 Trans-Log: 607.37	0.13	Accept H0
H0: SFA Time-Inv = SFA Time-Var. H1: SFA Time-Inv. $\neq$ SFA Time-Var.	Var: 605.37 Inv: 605.81	0.3503	Accept H0
Signif. Codes: 0 ’***’ 0.001 ‘**’ 0.01 ‘*’ 0.5 ‘.’ 0.1 ‘ ‘ 1			

A2.4 Selected Store-Specific and Region-Specific Environmental Variables [SFA]

Dummy	Logical Explanation	Mean
Population Size	1: If Population Size $\geq$ 123 856 0: If Population Size <123 856	123 856
Population Density	1: If Population Density $\geq$ 402 0: If Population Density <402	402
Median Income	1: If Median Income $\geq$ 627 856 0: If Median Income <627 856	627 856
Higher Education	1: If Higher Education $\geq$ 31.25 0: If Higher Education <31.25	31.25
Open Sundays	1: If Open Sundays 0: If Closed Sundays	[redacted]
HHI	1: If HHI $\geq$ 0.118 0: If HHI<0.118	0.118
Hours Weekdays	1: If Hours Weekdays $\geq$ [redacted] 0: If Hours Weekdays < [redacted]	[redacted]
Close Competitors	1: If Close Competitors $\geq$ 2.54 0: If Close Competitors <2.54	2.54
Store Density Per Capita	1: If Store Density Per Capita $\geq$ 0.00015 0: If Store Density Per Capita <0.00015	0.00015

A2.5 Top 20: Most Efficient Kiwi Stores

2014				2015				2014-2015	
CRS		**VRS**		**CRS**		**VRS**		**SFA**	
ID	*Efficiency*	*ID*	*Efficiency*	*ID*	*Efficiency*	*ID*	*Efficiency*	*ID*	*Efficiency*
[redacted]	1	[redacted]	1	[redacted]	1	[redacted]	1	[redacted]	0,990405
[redacted]	1	[redacted]	1	[redacted]	1	[redacted]	1	[redacted]	0,988476
[redacted]	0,982154	[redacted]	1	[redacted]	1	[redacted]	1	[redacted]	0,985976
[redacted]	0,966351	[redacted]	1	[redacted]	0,994983	[redacted]	1	[redacted]	0,982392
[redacted]	0,965291	[redacted]	1	[redacted]	0,9649	[redacted]	1	[redacted]	0,982308
[redacted]	0,964063	[redacted]	1	[redacted]	0,951516	[redacted]	1	[redacted]	0,979968
[redacted]	0,956554	[redacted]	1	[redacted]	0,91773	[redacted]	1	[redacted]	0,979042
[redacted]	0,949463	[redacted]	1	[redacted]	0,911142	[redacted]	1	[redacted]	0,978073
[redacted]	0,944653	[redacted]	1	[redacted]	0,906422	[redacted]	1	[redacted]	0,977788
[redacted]	0,939982	[redacted]	1	[redacted]	0,897782	[redacted]	1	[redacted]	0,973745
[redacted]	0,924384	[redacted]	1	[redacted]	0,896026	[redacted]	1	[redacted]	0,973531
[redacted]	0,921876	[redacted]	1	[redacted]	0,895454	[redacted]	1	[redacted]	0,972016
[redacted]	0,918097	[redacted]	1	[redacted]	0,892745	[redacted]	1	[redacted]	0,971882
[redacted]	0,916336	[redacted]	1	[redacted]	0,888528	[redacted]	1	[redacted]	0,97104
[redacted]	0,911673	[redacted]	1	[redacted]	0,88847	[redacted]	1	[redacted]	0,969467
[redacted]	0,911539	[redacted]	0,998194	[redacted]	0,888262	[redacted]	1	[redacted]	0,968689
[redacted]	0,90334	[redacted]	0,989551	[redacted]	0,880494	[redacted]	0,998551	[redacted]	0,968626
[redacted]	0,899987	[redacted]	0,989248	[redacted]	0,879353	[redacted]	0,995562	[redacted]	0,967845
[redacted]	0,898885	[redacted]	0,985845	[redacted]	0,871254	[redacted]	0,987947	[redacted]	0,967138
[redacted]	0,895989	[redacted]	0,984509	[redacted]	0,870115	[redacted]	0,983278	[redacted]	0,966841

A2.6 Bottom 20: Least Efficient Kiwi Stores

2014				2015				2014-2015	
CRS		**VRS**		**CRS**		**VRS**		**SFA**	
ID	*Efficiency*	*ID*	*Efficiency*	*ID*	*Efficiency*	*ID*	*Efficiency*	*ID*	*Efficiency*
[redacted]	0,405746	[redacted]	0,576977	[redacted]	0,420351	[redacted]	0,585055	[redacted]	0,543374
[redacted]	0,413143	[redacted]	0,586905	[redacted]	0,469328	[redacted]	0,591815	[redacted]	0,56959
[redacted]	0,434651	[redacted]	0,601994	[redacted]	0,472825	[redacted]	0,602522	[redacted]	0,582091
[redacted]	0,451991	[redacted]	0,620355	[redacted]	0,474314	[redacted]	0,617735	[redacted]	0,589732
[redacted]	0,454007	[redacted]	0,624419	[redacted]	0,476659	[redacted]	0,634069	[redacted]	0,59596
[redacted]	0,462891	[redacted]	0,627211	[redacted]	0,482087	[redacted]	0,636446	[redacted]	0,60138
[redacted]	0,465598	[redacted]	0,628398	[redacted]	0,489439	[redacted]	0,641297	[redacted]	0,603345
[redacted]	0,474809	[redacted]	0,629973	[redacted]	0,496464	[redacted]	0,641919	[redacted]	0,603786
[redacted]	0,475028	[redacted]	0,632269	[redacted]	0,497628	[redacted]	0,642712	[redacted]	0,609845
[redacted]	0,475585	[redacted]	0,633727	[redacted]	0,499351	[redacted]	0,642718	[redacted]	0,615657
[redacted]	0,483851	[redacted]	0,633759	[redacted]	0,516751	[redacted]	0,645059	[redacted]	0,618119
[redacted]	0,485598	[redacted]	0,648925	[redacted]	0,5185	[redacted]	0,650038	[redacted]	0,621436
[redacted]	0,496545	[redacted]	0,649987	[redacted]	0,522825	[redacted]	0,650662	[redacted]	0,624002
[redacted]	0,505424	[redacted]	0,664288	[redacted]	0,523586	[redacted]	0,650885	[redacted]	0,630873
[redacted]	0,514714	[redacted]	0,665523	[redacted]	0,524795	[redacted]	0,651308	[redacted]	0,632811
[redacted]	0,51544	[redacted]	0,666201	[redacted]	0,525484	[redacted]	0,662059	[redacted]	0,633435
[redacted]	0,519805	[redacted]	0,671633	[redacted]	0,526504	[redacted]	0,662272	[redacted]	0,634669
[redacted]	0,520443	[redacted]	0,672963	[redacted]	0,529365	[redacted]	0,662482	[redacted]	0,65079
[redacted]	0,521498	[redacted]	0,673067	[redacted]	0,533625	[redacted]	0,664779	[redacted]	0,667651
[redacted]	0,522708	[redacted]	0,67335	[redacted]	0,535629	[redacted]	0,665164	[redacted]	0,674523

A2.7 Average Technical Efficiencies in Norwegian Regions [SFA]