BI

WISEflow
Europe/Oslo(CEST)
03 Jul 2023

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	Ulrik Rasch Bakke og Kristian Hasleengen

Informasjon fra deltaker

Tittel *:	Operating performance following mergers and acquisitions
Navn på veileder *:	Jiri Woschitz

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	29
Andre medlemmer i gruppen:	

BI Norwegian Business School

Oslo, Spring 2023

Operating performance following mergers and acquisitions

An Empirical Analysis of M&As on the Norwegian market

Ulrik Rasch Bakke & Kristian Hasleengen

Supervisor: Jiri Woschitz

Master Thesis in Business

Major in Finance

BI NORWEGIAN BUSINESS SCHOOL

Table of Contents

1. Abstract 2

2. Introduction 2

3. Literature review 4

3.1 M&A and operating performance: key findings from prior research 4

3.2 Limitations and biases from prior research and how we encounter these in our study. 5

4. Hypothesis and Methodology 8

4.1 Research design 8

4.2 Statistical models 9

4.3 Matching methods 12

4.4 Justification for the use of book value over market value of assets 13

5. Data 15

5.1 Sample selection 15

5.2 Accounting data 17

5.3 Performance measurements 18

6. Results 19

6.1 Cash flow return on assets relative to industry firms 20

6.2 Cash flow return on assets relative to matched firms 21

6.3 Cash flow margin relative to matched firms 23

6.4 Operating expenses relative to matched firms 25

6.5 Labor costs relative to matched firms 26

6.6 Synthetic Control Method 28

7. Conclusion: Does operating performance improve following M&A? 31

8. Bibliography 34

9. Appendix 36

10. Tables and Figures 42

1. Abstract

We investigate the long-term operating performance of corporate mergers and acquisitions of 133 acquiring companies in Norway from year 2000 to 2020. We employ three different methods and four different measures of operating performance that allow us to compare and overcome several measurement limitations of previous literature. Acquiring companies significantly outperform the median peers in their industry prior to the acquisitions. However, this difference becomes less significant after the performance of the matched companies that are chosen to control for size and pre-event performance is controlled. For all models employed, we find no statistical evidence of improvement in operating performance following M&A activity.

2. Introduction

The study of mergers and acquisitions (M&A) and how they impact firm performance has been a topic of interest in financial research for several decades. This research paper aims to contribute to the understanding of the long-term operating performance of Norwegian mergers and acquisitions.

The relevance of our research question is highlighted by the mixed results presented in previous studies and the potential implications for various stakeholders, including academics, private and institutional investors, and policymakers. By focusing on the Norwegian market, this study aims to provide insights into the impact of M&A in different market conditions, thereby offering a more complete view. This research is driven by both professional and personal motivations, as we aspire to contribute to the field of M&A and wish to build our careers within this field.

Previous financial theory suggests potential benefits from M&As, such as synergies, economies of scale, and increased market power. However, other theories propose that M&A may not necessarily result in improved performance due to challenges such as integration difficulties, agency problems, and overpayment for target firms. We use a combination of methodologies proposed by Healy et al. (1992), Barber and Lyon (1996), Ghosh (2001) and Abadie and Gardeazabal (2003).

The research design involves matching treated firms (firms undergoing an M&A) to control groups (comparable firms that are not undergoing M&A) by the amount of total assets before the deal date. Then we compare performance three years prior and post the M&A transaction using difference-in-differences models. We examine how different methods of payment and the relatedness of acquiring and target companies affect operating performance using OLS regressions. The non-parametric Wilcoxon test statistic is used to establish the statistical significance of the results.

Given the large concentration of companies in the energy sector on the Oslo Stock Exchange (OSE), we examine the effect of M&A in this sector more closely. We use the Synthetic Control Method (SCM) proposed by Abadie and Gardeazabal (2003) to compare the treated firm to a synthetic firm made by a weighted average of similar companies from the Western world not undergoing M&A during the same period.

This research paper is structured as follows: Chapter 3 provides a literature review of key research papers and their methodological differences; Chapter 4 outlines our research question, testable hypotheses and methodology used to investigate the research question; Chapter 5 describes the sample used in the study and the data collection process; Chapter 6 presents the analysis and results of the research; and finally, Chapter 7 concludes the paper and discusses the implications of our findings.

We answer the research question by combining empirical evidence and financial theory. The study's results add to the ongoing discussion about the effect of M&A on firm performance, especially in the Norwegian market and in the energy sector.

3. Literature review

3.1 M&A and operating performance: key findings from prior research

Healy et al. (1992) investigate the impact of M&A on operating performance by using an intercept model and a Difference in Difference, (hereafter DiD), model to compare pre-event cash flows of merging firms with industry median firms. They measure operating performance as the change in operating cash flow return on assets, using pretax operating cash flow measures, which in contrast to earnings, are unaffected by the method of accounting and the method of payment (Healy et al, 1992). The paper concludes that the operating performance of acquiring firms improves considerably after an acquisition due to increasing asset productivity relative to their industries.

Ghosh (2001) proposes a different methodology that involves matching each acquiring firm with a single comparable matched firm. This approach is based on the findings of Barber and Lyon (1996). The matched-firm methodology addresses economic challenges by considering the similarities in size and past performance between the merging firms and the matching firms. This procedure overcomes issues related to whether the merging firms outperform the industry median they are compared to and whether any observed superior performance is driven by permanent or temporary factors.

Contradictory to Healy et. al 1992, Ghosh (2001) finds that the operating performance of acquiring firms declines following a merger. This study highlights the importance of selecting an appropriate control group for comparison. Ghosh also addresses the effect the method of payment used in the M&A has on operating performance. Prior research has presented varying conclusions regarding the impact of payment methods on operating performance. Myers and Majluf (1984) and Fishman (1989) found that cash transactions lead to higher post-merger operating performance, while Brown and Ryngaert (1991) found no significant difference in operating performance based on the method of payment.

When estimating the economic impact of conflict in the Basque Country, Abadie and Gardeazabal introduced the Synthetic Control Method (SCM). Using a combination of different Spanish regions in a weighted average to create a "synthetic" Basque Country as a control unit, they establish a credible way to estimate the impact and causal effect of an event when a control group is unavailable, which can be applied to all sorts of event studies (Abadie & Gardeazabal, 2003). In his recent work, Abadie (2021) provides technical and methodological details on implementing SCM, emphasizing the importance of pre-treatment fit and appropriate control group selection, underlining that a good fit in the pre-event period is important for the validity of the results. The paper also addresses concerns regarding inference and proposes solving it using permutation tests or bootstrapping.

The research by Renneboog and Vansteenkiste (2019) focuses specifically on firms' performance around and after a takeover. Their study reveals that despite the high costs related to M&A transactions annually, acquiring firms often underperform compared to non-acquiring firms, especially in public takeovers. Short-term returns are often not sustained in the long run, and the anticipated synergies are overestimated due to factors such as merger integration friction and behavioral biases. They also identify CEO overconfidence, serial acquisitions, method of payment, and the relatedness of acquiring company and target company as the key determinants of post-deal performance. Gugler et al. (2003) conducted an international comparison of the effects of mergers on the operating performance of acquiring firms. They found that the impact of M&A on operating performance varies across countries and industries and is influenced by factors such as market structure, regulatory environment, and managerial incentives, suggesting it is smart to limit the scope of future research to a specific geographical region.

3.2 Limitations and biases from prior research and how we encounter these in our study.

According to Ghosh (2001), the industry-focused intercept model and DiD model by Healy et al. will likely lead to biased results due to several econometric challenges, specifically, the possibility of acquiring firms outperforming industry-median firms, and the potential influence of superior performance stemming from either permanent or temporary factors. Such biases will be absorbed in the intercept of these regressions, while in the DiD model, cash flows in pre-acquisition periods can include such factors that need to be adjusted for not to yield biased results.

One economic reason why acquiring firms will outperform industry-median firms over pre-acquisition periods can be explained by economies of scale. Financial theory provides concrete evidence that performance is related to size (Hall and Weiss, 1967; Mueller, 1986; Fama and French, 1992). Therefore, bigger firms are more efficient and thus more profitable due to permanent factors. Another economic reason why acquiring firms will outperform industry-median firms can be explained by managerial competence and superior pre-event performance. Firms with good managers tend to outperform firms with bad managers (Morck et al., 1990). Further, acquiring firms tend to engage in acquisitions after a period characterized by superior performance, signifying that differences in performance also rely on temporary factors (Ghosh 2001).

To show that the existence of permanent or temporary factors can yield biased results, we have included a demonstration of the intercept model and the DiD model in appendix 1 of this paper, where the two models are redefined to incorporate both permanent and temporary differences. By making necessary assumptions and assigning expected values to these factors, we analyze the direction and the extent of the bias. In summary, when acquiring firms outperform industry-median firms due to a combination of permanent and temporary factors, where both factors have expected values that are not equal to zero, it can be concluded that both the change model and the DiD model will produce biased results. The intercept of the intercept model will signify expected acquisition-induced improvements in cash flow in the presence of permanent and/or temporary factors in the pre-acquisition periods, resulting in an upward bias. On the other side, the DiD model will produce unbiased results if we assume that permanent differences in the pre-acquisition periods persist into post-acquisition periods and that there are no temporary differences. This is because the pre – and post permanent components will simply cancel each other out. Only when including temporary differences in the pre-acquisition periods will the DiD model produce biased results.

To mitigate nonrandom measurement errors, such as temporary and permanent factors, we follow the research design proposed by Barber and Lyon (1996), which involves matching the merging firms with more accurate firms based on pre-event relationships. The use of matched firms provides a better comparison group because they are chosen based on their similarity to the merging firms in terms of size and performance. In the presence of permanent and/or temporary differences in the DiD model, both acquiring firms and matched firms will have similar proportions of these components, making it an even comparison. The model also accounts for acquiring firm's superior pre-acquisition performance compared to an industry group by matching it with peers based on pre-acquisition data.

However, one limitation of using the matched firm method is the survivorship bias. Since we only include matched firms and industry firms that have survived throughout the entire analysis as comparables to acquiring firms, where some have survived and others have not, our results may not accurately represent the overall population of non-M&A firms. This bias may lead to an underestimation of the impact of M&A on operating performance because every company we compare with still exists today and is therefore, likely a solid company. If the non-M&A firms we compare with did not survive we would probably experience more positive effects from M&A.

Both DiD and SCM require that the parallel trends assumption holds (Abadie, 2021). For our study, this means that the treated unit and the control units would have followed the same trend in the absence of an M&A. As we cannot observe a counterfactual scenario, we cannot definitively say that the parallel trend assumption holds. To ensure accurate results with SCM, it is necessary to have enough pre-treatment periods and a good pretreatment fit. However, there may be a decrease in efficiency when examining multiple units or varying treatment times. Due to the lack of standard statistical inference methods, alternative methods like permutation tests and bootstrapping are necessary (Abadie et al., 2015).

4. Hypothesis and Methodology

4.1 Research design

We examine the impact of mergers and acquisitions on the operating performance of acquiring firms listed on the Oslo Stock Exchange, thus our research question is "*Do acquiring firms improve their operating performance in Norway after mergers and acquisitions?*" By combining the methodologies that we now have discussed in detail by Healy et al. (1992), Barber and Lyon (1996), and Ghosh (2001) we match treated firms to control groups by the amount of total book value of assets and compare performance 3 years prior and post to the deal date. We examine how different methods of payment and the relatedness of acquiring and target companies affect operating performance using OLS regressions and use two DiD models to examine change in operating performance measures to answer our main research hypothesis (1). The non-parametric Wilcoxon test statistic is used to establish the statistical significance of the results. This approach allows us to estimate the effect of M&A on our entire population of 133 firms.

$$H_0: M\&A \ does \ not \ improve \ operating \ performance \ in \ Norway \tag{1}$$

Given the large concentration of energy-related companies on the OSE, we want to examine the effect of M&A in this sector more closely. We had difficulty finding appropriate matches for some of the large energy companies using the industry and matched firm methods, as there are none listed on the OSE within our selected range of total assets. Using the SCM proposed by Abadie and Gardeazabal (2003), we compare the treated firm to a synthetic firm made by a weighted average of similar companies from the Western world not undergoing M&A during the same period to examine the causal effect of M&A and answer our second hypothesis (2).

$$H_0: M\&A \ does \ not \ improve \ operating \ performance \ in \ the \ energy \ sector \ in \ Norway \tag{2}$$

4.2 Statistical models

We employ the nonparametric Wilcoxon test statistic instead of the parametric t-statistic in our DiD analysis. Barber and Lyon (1996) found that the Wilcoxon test demonstrated greater power when analyzing operating performance, mainly due to the high correlation between treated and control firms and non-normality. The Wilcoxon signed-rank test compares the difference between pairs (M&A and non-M&A at each given time-period) and sorts and ranks them, so the smallest difference is ranked one.

When sgn denote the sign function: $sgn(x) = 1 \ if \ x > 0 \ and \ sgn(x) = -1 \ if \ x < 0$

The test statistic is the signed-rank sum T for $_{i}$pair and can be seen in equation (1). We use the SciPy stats package in Python to calculate if the difference between M&A and non-M&A is statistically different from zero in each year before and after the deal.

$$T = \sum_{i=1}^{N} sgn(X_i)R_i \qquad (1)$$

We run OLS regressions for each performance measure we examine as in equation (2). The dependent variable is the change in the measure we examine, and shares, cash, and mixed are dummy variables representing the method of payment used, while related is a dummy variable representing the similarity between acquiring and target company based on TRBC code. Each OLS regression is tested for breach of the standard OLS assumptions by conducting the following diagnostic tests: Durbin-Watson test, White´s test, and visually inspecting with Q-Q plots for normality.

$$\Delta OperatingPerformance = \beta_0 + B_1 Stock + \beta_2 Cash + \beta_3 Mixed + \beta_4 Related + \varepsilon \qquad (2)$$

Further, we use two DiD models to examine operating performance of acquiring firms. These models allow us to compare various performance measures of acquiring firms using two different reference points. The adjustment between the two DiD models is that one compares the acquiring firm's cash flow with an *industry median* cash flow, as in Healy et al. (1992), while the other DiD model compares acquiring firm's cash flow with a *matched-firm median* cash flow as in Ghosh (2001). The industry DiD model is given by equation (3), while the matched firm DiD model is given by equation (4):

$$\Delta\text{CF} = CF\ (IND)_{post,i} - CF\ (IND)_{pre,i} \tag{3}$$

$$\Delta\text{CF} = CF\ (MTC)_{post,i} - CF\ (MTC)_{pre,i} \tag{4}$$

Where $CF\ (IND)_{post,i}$ and $CF\ (IND)_{pre,i}$ represent the post – and pre – acquisition cash flows of the i_{th} acquiring firm, respectively, after subtracting its correspondent industry median cash flow. Similarly, the $CF\ (MTC)_{post,i}$ and $CF\ (MTC)_{pre,i}$ represent the post – and pre – acquisition cash flows of the i_{th} acquiring firm, respectively, after subtracting the median cash flow of the matched firms. The cash flows, (CF)'s, notate the different performance measures we examine.

The SCM method posits that in the absence of treatment, undergoing an M&A in our case, the performance of the treated firm is a linear combination of the weighted performance of the control firms plus an unobservable term specific to the treated firm and time period. We define the γ_{1t}^{N} as the potential outcome or the operating performance for a given firm in the absence of an M&A. We assume that our data spans over T periods and that the first T_0 observations are before the M&A. For each unit j and the time t, we define the treated firm affected by the M&A as j=1 and the post-intervention period as $t>T_0$ (Abadie 2021). We separate the pre-intervention period from the post-intervention period using dummy variables.

The control firms of a single treated firm can be represented by a J x 1 vector of weights, W = $(w_2, \dots, w_{j+1})'$. Each w_j corresponds to one of the J control units, and the objective of the optimization problem is to find the weighted combination of the control units that replicate the pre-treatment performance of the treated unit by minimizing equation (6), and the synthetic control estimators are then given by (5) and (6).

$$\hat{\gamma}_{1t}^{N} = \sum_{j=2}^{J+1} w_j \gamma_{jt} \tag{5}$$

$$\hat{\tau} = \gamma_{1t} - \hat{\gamma}_{1t}^{N} \tag{6}$$

We calculate these weights using the *minimize* function from the SciPy library in Python as seen in Appendix 2. Since our synthetic control consists of publicly listed companies with the possibility of short-selling it could be possible to allow for negative weights to make the replication more precise, but following Abadie, Diamond, and Hainmuller (2015) and Abadie (2021) we restrict the weights to be non-negative and set $(w_2 + \dots + w_{j+1}) = 1$ in order to avoid extrapolation by having a bound on the weights of [0, 1]. They posit that non-negative weights ensure that the synthetic group maintains a convex relationship with the control units. This makes the contribution from each control firm directly proportional to its weight and makes the results more intuitive to interpret. After creating the synthetic control group that represents the counterfactual performance of the firm in the absence of M&A, the estimated causal effect of the M&A is given by the post-treatment difference between the outcome of the treated unit and the synthetic control unit.

We employ bootstrapping as a resampling technique to empirically estimate the sampling distribution and statistical significance of our SCM results. By using the *resample* package from the Sklearn library in Python as shown in Appendix 3 we iterate 100 000 resamples of our SCM results. This non-parametric method avoids underlying assumptions regarding the distribution of the population. The resampling allows us to make statistical inference about our results to calculate more robust p-values, confidence intervals, statistical mean, and estimated standard errors. The p-value is calculated as in equation (7) with $D*_i$ is the difference between treated and control firm in each of bootstrap iteration and D_{obs} being the actual observed by the number of iterations. The standard error calculated as in (8) with each bootstrap iteration difference as $D*_i$ and the mean of the bootstrap differences as D.

$$p - value = \frac{Number\ of\ D* \geq D_{obs}}{n_{iterations}} \tag{7}$$

$$SE = \sqrt{\frac{1}{n_{iterations} - 1} \sum_{i=1}^{n_{iterations}} (D *_i - D *)^2} \tag{8}$$

4.3 Matching methods

To generate the industry groups for the industry matching we employ Eikon´s peer analysis tool in combination with the TRBC code (Thomson Reuters Business Classification), to create a list of comparable firms for each of our acquiring firms. The TRBC code is a global industry classification system that is used to classify companies based on their primary line of business. It is related to the two-digit SIC code commonly used by researchers, however we find the two-digit TRBC code to be more convenient to use since our accounting data is obtained from Thompson Reuters Eikon as well. To find appropriate matches we sort the companies within the same TRBC code listed on OSE by total assets one year prior to the acquiring firms' deal date.

We filter out companies outside the range of 15-250% of the total assets of the acquiring firm. Given our smaller sample compared to previous research who match within a range of 25-200%, we broaden the matching range to match appropriately. This is applied to all 133 M&A observations from the years 2000 to 2020. The sorting of industry groups resulted in six different sectors. The same procedure is employed for the matched firm method. The matched firm is selected as the firm with the same TRBC code with the most similar total assets one year prior to the deal.

To ensure that our control groups and matched firms had not undergone an M&A during the same time-period as the treated firm, we assigned a dummy variable to all potential matches based on the timing of potential deals for both the M&A firm and its match. We then filtered out matches that had an overlapping deal activity with the acquiring firm we examine. There were certain instances where we could not find a comparable firm within the desired range of total assets. To mitigate this issue, we expanded our scope beyond the Norwegian market and looked for more suitable matches in the Swedish and Danish markets.

The control groups for the SCM are created in a similar manner. Here, we match each treated firm within the energy sector with 6-9 control firms each, from the Western world within the same TRBC sector code that have the most similarity in total assets to ensure the best possible match and to increase the chance of parallel trends assumption to hold (Abadie, 2021). Due to the nature of the energy sector, we expand the geographical scope to include the Western world as there are not 6-9 comparable companies similar enough in total assets. Due to potential variances in political and economic factors, we exclude companies outside the Western world. With this method, we matched control firms to be within the range in total assets of 70%-130% to that of the treated firm one year prior to the deal.

4.4 Justification for the use of book value over market value of assets

To standardize the value of assets, we consistently use book values to compare companies across periods. One of the fundamental ideas in financial theory is that the current market value of a company is equal to the discounted future cash flows, indicating that the market value of assets is a forward-looking measure. A forward-looking measure may not be appropriate to use when comparing current numbers because it reflects expectations of future performance and growth potential rather than the actual value of the assets (Barber & Lyon, 1996).

Healy et. al (1992) argue that the use of the market value of assets eases the comparison of assets over time and across different companies, nevertheless, they acknowledge the limitation of their approach as changes in cash flow can alter expectations about future cash flows, which can, in turn, affect the market value of assets. To mitigate the issue of forward-looking market values, Healy et al. (1992) implement a methodological approach of excluding changes in equity values during the year of the merger. However, findings from Agrawal et al. (1992) suggest that market values continue to decline in a systematic manner for up to five years following an acquisition. Therefore, despite the exclusion of equity values in the merger year, Healy et al.'s approach will yield consequently biased results in cash flow ratios where market values of assets are utilized (Ghosh, 2001).

In contrast, the book value of assets reflects the cost of acquiring the assets. Book value of assets is because of this less affected by market fluctuations, which makes book values more stable over time. Therefore, book value of assets provides a more accurate comparison measure, since it can provide a more consistent and reliable measure of a firm's financial performance, especially over longer periods of time (Francis & Schipper, 1999). Throughout this paper, we consistently employ book value of assets in all metrics where both market and book value are feasible options to avoid uncertainties and to achieve a more objective representation of operating performance.

5. Data

5.1 Sample selection

The sample of deals that we use in our paper is gathered from the Zephyr database of Bureau of Van Djik which is a collected dataset of corporate acquisitions that took place between 01/01/2000 and 31/12/2020. Our sample meets the following criteria: (1) the acquiring company is publicly traded on Oslo stock exchange and is based in Norway; (2) all deals are announced and completed; (3) we only focus on transactions classified as mergers or acquisitions, other deal types such as management and leveraged buyouts/inns, share buyback and minority stake sales are eliminated; (4) we exclude M&As within the banking sector due to differences in accounting and reporting methods. The banking sector does not report numbers for cost of goods sold, cash flows, and selling, general, and administrative expenses among others; (5) the final percentage of acquired stake is between 50-100%; (6) finally, acquirer must have accounting data available for at least three years prior to the acquisition date, and three years post to the acquisition date. This search resulted in a final sample of 133 pairs of acquiring and target firms with a distribution as shown in Table 1.

Table 1

Distribution of sample firms based on sector, method of payment and year of the deal.

Sector	M&A deals	Year	Number of acquisitions
		2020	4
Basic Materials	6	2019	4
Consumer Cyclicals	10	2018	4
Consumer Non-Cyclicals	31	2017	2
Energy	39	2016	2
Industrials	24	2015	3
Technology	23	2014	4
		2013	8
		2012	4
		2011	3
Method of payment	M&A deals	2010	6
		2009	6
Shares	42	2008	12
Cash	69	2007	16
Mixed	22	2006	21
		2005	9
		2004	4
Related or unrelated	M&A deals	2003	4
		2002	3
Related	111	2001	7
Non-related	22	2000	7

The Zephyr database sample also provides us with information about the method of payment used in the transaction and the takeover date. Liability payments are treated as cash payments in our paper, and the distribution of the method of payment in our sample is shown in Table 1. We use TRBC codes to assign relatedness to both acquiring and target firms, allowing us to determine the distribution of relatedness.

5.2 Accounting data

The accounting data is collected using the Refinitiv Eikon database and its formula builder plug-in in Microsoft Excel. The formula builder serves as an extraction tool for specific financial statements used to calculate performance measures for all firms included in our analysis.

To precisely capture the effects of M&As we gather accounting data for acquiring, industry and matched firms 3 years prior to and post the M&A deal date, following Magenheim and Mueller (1988), Franks et al. (1991), Rau and Vermaelen 1998, and Ghosh (2001). There is consensus among researchers that this timeframe is sufficient for capturing the long-term effects of M&A. We use the International Securities Identification Number (ISIN) as an identifier to extract financial statements for all 133 observations. We use the currency reported by each individual company. This approach ensures that our ratio-based metrics are based on the company's actual financial data and are not affected by currency reporting or approximation errors when comparing companies with different currencies.

To capture short-term effects and improve responsiveness, we collect quarterly data for the SCM analysis. By employing consistent performance measures of operating performance, we ensure a fair comparison across different approaches. Dummy variables are implemented to distinguish between the pre- and post-intervention periods, which are determined based on the deal date. After collecting data for all the acquiring companies in the energy sector and their respective control groups, we transform the data into a panel data format and import it into Python for analysis.

5.3 Performance measurements

We use operating cash flow returns on assets prior to taxes as a measure of improved operating performance. By focusing on cash flows, which directly reflect the actual economic benefits generated by the assets, we can capture the true value of performance measurement. We find operating cash flow to be a useful metric for comparing companies subject to disparate tax treatments and capital costs. Recognizing that the extent of economic benefits is influenced by the assets employed, we scale the cash flows by the book value of total assets. This allows for a meaningful Cash Flow Return on Assets (CFROA) measure that can be compared consistently over time and across different firms (Healy et. al, 1992).

We define operating cash flow as sales, minus costs of goods sold, minus selling and administrative expenses, plus depreciation, plus amortization. This measure aligns closely with the commonly used EBITDA measure, although we take additional steps to exclude the systematic allocation of intangible assets, particularly the expenses related to goodwill. Goodwill expenses represent the premium paid for the acquired company beyond the fair value of its identifiable net assets. By removing goodwill from the analysis, we eliminate a potential factor that can affect the CFROA ratio for acquiring companies when compared to non-acquiring companies. Given the variations in EBITDA definitions, some of which include goodwill, we use the term operating cash flow to avoid confusion.

By excluding interest expenses and taxes, we aim to consider differences in the method of financing the acquisition. When an acquisition is financed using cash or debt, it typically leads to lower earnings compared to stock acquisitions (Ghosh, 2001; Martynova, Oosting and Renneboog, 2007). There are several factors contributing to this trend, and one reason is because income or earning-based measures account for the cost of debt. However, income calculations do not consider the cost of equity. The method of payment and the systematic allocation of intangible assets both have an impact on earnings, which may not necessarily reflect the underlying economic performance. The operating cash flow is then deflated by the total book value of assets to create a cash flow return on assets ratio.

In addition to deflating operating cash flows by the total book value of assets, it is important to note that total assets alone may have limitations in fully explaining operating performance. Therefore, to gain further insights into the profitability and efficiency of a company, we also deflate operating cash flows by net sales (Cash Flow Margin) and operational expenses by net sales to examine the potential synergy effects resulting from the acquisition. Operating expenses are defined in Eikon as the sum of cost of goods sold, general selling and administrative expenses and depreciation. To account for potential restructurings and employee layoffs, we examine labor costs by net sales, as Zephyr nor Eikon reports the number of employees for all companies. We incorporate the Cash Flow Return on Assets (CFROA) and Cash Flow Margin (CF Margin) metrics in all three methods utilized in our analysis, including the DiD industry model, DiD matched firm model, and the SCM model, meanwhile the two latter metrics are only examined in DiD matched firm model.

6. Results

Section 6.1 display the results from the DiD model and the intercept model when we use the industry matching method by Healy et al. (1992) before we apply the matched-firm method proposed by Ghosh (2001) in 6.2-6.4. Finally, we display the results from the SCM on the Norwegian energy sector in 6.5.

Notably, all DiD results reported in tables and mean-difference SCM numbers are reported as percentages, i.e., the *Δ cash flow* of -1.61 in Table 3 is equal to -1.61%. We report both mean and median numbers, but we prefer using medians where possible to reduce the effect of extreme observations. All p-values from the Wilcoxon signed-rank tests and the OLS coefficients are reported in chapter 10, Table 2.

6.1 Cash flow return on assets relative to industry firms

The results from Table 3 show our findings of a decline in median cash flow returns from 10.68% in year -3 to 9.40% in year +3 for merging firms. Unlike merging firms, the industries appear to be experiencing an increase in median cash flow returns from 8.27% in year -3 to 10.61% in year +3. The difference between the merging firm and the industry group shows the yearly over or under-performance of merging firms relative to the industry they operate in before and after the merger. In year -3 the difference is 2.41%, and the number declines to -1.21% in year +3, both statistically significant at the 1% and the 10% level, respectively.

Table 3

Cash flow return on assets relative to industry-median firms. Cash flow is calculated as under chapter 5.3 Performance Measurement. We scale the operating cash flows by the total book value of assets for each year. To account for industry variations, we construct an industry-adjusted variable (MRG*i* - IND) for each firm and year. This is done by calculating the difference between the specific value of the firm and the median value of the same variable for all other firms within the same industry. The Δ cash flow is calculated as [(MRGi - IND)post - (MRGi - IND)pre], where (MRGi - IND)post is the median diference between the merging firm and its relative industry group for year 1, 2, and 3, while (MRGi - IND)pre is the median difference between the merging firm and its relative industry group for year -3, -2, and -1. Each acquisition is denoted by the subscript i. The OLS regressions estimate the change in CF ROA based on different methods of payment and relatedness.

Year from deal	Merged firm (MRG)		Industry (IND)		Difference (MRG*i* - IND)		
	Mean	Median	Mean	Median	Mean	Median	
-3	10.78 %	10.68 %	9.35 %	8.27 %	1.43 %	2.41 %	***
-2	10.52	10.71	9.49	8.92	1.03	1.79	
-1	8.58	8.27	10.15	9.17	-1.57	-0.91	***
1	10.01	10.40	10.05	9.32	-0.04	1.08	
2	8.99	9.06	9.16	9.19	-0.17	-0.14	
3	9.43	9.40	9.33	10.61	0.10	-1.21	*
Δ cash flow						-1.61	

Regression 1:

*ΔCFROA = - 0.98(0.4)** + 0.13(0.7)Cash - 0.71(0.8)Shares - 0.40(1.1)Mixed* $R^2 = 0.04$

Regression 2:

$\Delta CFROA = -0.63(1.0) + 0.23(0.7)Cash - 0.52(0.9)Shares - 0.34(1.1)Mixed - 0.56(1.5)Related$ $\qquad R^2 = 0.05$

* Denote the significance at the 10% level for the two tailed Wilcoxon signed rank test

** Denote the significance at the 5% level for the two tailed Wilcoxon signed rank test

*** Denote the significance at the 1% level for the two tailed Wilcoxon signed rank test

The observed differences of 2.41% and 1.79% between merging firms and industry median firms in the pre-acquisition years (-3 and -2) support the hypothesis that acquiring firms experience a superior pre-acquisition period prior to engaging in M&A activities. These findings are consistent with expectations that the merged firm's performance declines relative to the industry in the years following the merger. The median industry-adjusted cash flows show a positive trend, which then turns negative in the long term, with values of -0.14% in year 2 and -1.21% in year 3.

Although none of the coefficients of the method of payment or relatedness variables are statistically significant, the results in regression 1 and 2 show that cash payments slightly increase CFROA. This aligns with previous findings from Mayers and Majluf (1984), while coefficients for shares and mixed suggests a reduction in CFROA for the acquiring firm compared to the industry groups, supported by our results from the DiD model. In regression 2, the related coefficient shows that when acquiring and target company with the same TRBC code merge, the CFROA decrease by -0.56% annually. This contradicts previous studies but has low explanatory power, statistical insignificance, and low economic significance.

6.2 Cash flow return on assets relative to matched firms

The use of the matched firm method in the DiD model reveals smaller variations in median adjusted cash flow return on assets, compared to the industry-firm method. This outcome verifies that matching on pre-acquisition size and performance variables in the matching process results in improved matching

Table 4

Cash flow return on assets relative to matched firms. Cash flow is calculated as under chapter 5.3 Performance Measurement. We scale the operating cash flows by the total book value of assets for each year. To account for matched-firm variations, we construct a matched firm-adjusted variable (MRG_i - MTC_i) for each firm and year. This is done by calculating the difference between the specific value of the acquiring firm and the specific value of the same variable for the matched-firm. The Δ cash flow is calculated as [(MRGi - MTCi)post - (MRGi - MTCi)pre], where (MRGi - MTCi)post is the median difference between the merging firm and matched firm for year 1, 2, and 3, while (MRGi - MTCi)pre is the median difference between the merging firm and the matched firm for year -3, -2, and -1. Each acquisition is denoted by the subscript *i*. The OLS regressions estimate the change in CF ROA based on different methods of payment and relatedness.

Year from deal	Merged firm (MRG)		Matched firms (MTC)		Difference (MRG_i - MTC_i)		
	Mean	Median	Mean	Median	Mean	Median	
-3	10.78 %	10.97 %	11.23 %	10.33 %	-0.46 %	0.64 %	***
-2	10.52	10.92	10.26	10.61	0.25	0.31	
-1	11.38	11.52	10.42	11.14	0.96	0.39	**
1	10.40	10.01	10.11	10.30	0.29	-0.29	
2	8.99	9.06	10.23	9.30	-1.24	-0.24	
3	9.43	9.40	10.64	10.41	-1.21	-1.01	***
Δ cash flow						-0.89	

Regression 3:

ΔCFROA = - 0.96(0.5) - 0.40(0.8)Cash - 0.06(0.9)Shares - 0.50(1.2)Mixed*

$R^2 = 0.01$

Regression 4:

$R^2 = 0.03$

ΔCFROA = - 0.39 (1.1) - 0.23(0.8)Cash + 0.24(1.1)Shares - 0.40(1.2)Mixed - 0.92(1.7)Related

* Denote the significance at the 10% level for the two tailed Wilcoxon signed rank test

** Denote the significance at the 5% level for the two tailed Wilcoxon signed rank test

*** Denote the significance at the 1% level for the two tailed Wilcoxon signed rank test

While matched firms show a stable median cash flow return on assets of approximately 10% each year, the acquiring firms experience a decline in median CFROA during the same period. In contrast to the industry-firm method which shows a steady incline in CFROA for the industry, we now see a flat state. However, our results show that the overall trend persists, merging firms outperform matched firms over the pre-acquisition period leading up to the acquisition date. In general, the DiD model indicates a decrease in the efficiency of assets in generating operating cash flows for acquiring firms compared to matched firms after the merger. Specifically, CFROA decline from 0.35% in year -3 to -1.01% in year 3, both of which are statistically significant at the 1% level. The relative change in cash flow from the pre-acquisition period to the post-acquisition period, as indicated by Δ cash flow, is -0.89%.

Based on the OLS estimation we found that the use of shares as payment form in acquisitions yields the most positive effect on change in CFROA with -0.06% in regression 3 and +0.24% in regression 4. Cash and mixed payment both contribute negatively to the post-acquisition CFROA. The related variable shows a yearly decrease of 0.92% in CFROA following a merger which is consistent with our results from industry-matching. However, these results lack statistical significance due to high p-values and the low explanatory power.

6.3 Cash flow margin relative to matched firms

By using a CF margin measure we analyze how effectively merging firms generate cash from its sales activities relative to its matched counterparties, regardless of the asset structure of the company. Also, the analysis becomes independent of the debate regarding the use of book value or market value of assets.

Table 5

Cash flow margin relative to matched firms. Cash flow is calculated as under chapter 5.3 Performance Measurement. We scale the operating cash flows by the net sales for each year. To account for matched-firm variations, we construct a matched firm-adjusted variable (MRG*i* - MTC*i*) for each firm and year. This is done by calculating the difference between the specific value of the acquiring firm and the specific value of the same variable for the matched-firm. The Δ cash flow is calculated as [(MRGi - MTCi)post - (MRGi - MTCi)pre], where (MRGi - MTCi)post is the median difference between the merging firm and matched firm for year 1, 2, and 3, while (MRGi - MTCi)pre is the median difference between the merging firm and the matched firm for year -3, -2, and -1. Each acquisition is denoted by the subscript i. The OLS regressions estimate the change in CF Margin based on different methods of payment and relatedness.

Year from deal	Merged firm (MRG)		Matched firms (MTC)		Difference (MRG*i* - MTC*i*)		
	Mean	Median	Mean	Median	Mean	Median	
-3	16.36 %	14.10 %	15.15 %	13.23 %	1.21 %	0.87 %	***
-2	16.90	13.72	15.95	14.11	0.94	-0.39	*
-1	18.06	14.15	17.45	16.18	0.61	-2.03	
1	19.38	16.05	15.97	13.71	3.41	2.35	**
2	17.46	15.08	16.96	13.49	0.50	1.60	
3	17.83	14.81	16.97	16.03	0.86	-1.22	***
Δ cash flow						0.47	

Regression 5:

Δ*CF margin* = - 0.01(0.9) - 0.57(1.5)Cash + 1.71(1.7)Shares - 1.14(2.2)Mixed

$R^2 = 0.01$

Regression 6:

$R^2 = 0.02$

ΔCF margin = - 2.26(2.2) - 1.22(1.6)Cash + 0.50(2.0)Shares - 1.50(2.3)Mixed + 3.66(3.2)Related

---

* Denote the significance at the 10% level for the two tailed Wilcoxon signed rank test

** Denote the significance at the 5% level for the two tailed Wilcoxon signed rank test

*** Denote the significance at the 1% level for the two tailed Wilcoxon signed rank test

The results from Table 5 shows variations in CF margin with both positive and negative shifts over time. We found median differences in cash flow margins between merging firms and matched firms to be 0.87% in year -3 and -1.22% in year +3, Both differences are statistically significant at the 1% level, aligning with our findings presented in Table 4. However, in the first year after the deal, merging firms are outperforming matched firms by 2.35%, a number that is statistically significant at the 5% level, expressing that the analysis of CF margin for both M&A companies and non-M&A companies during the examined time-period does not reveal a distinct trend of consistent increases or decreases. This lack of a consistent trend is further supported by the conflicting results obtained from the Δ cash flow, as the change of median differences in pre-acquisition years to the post-acquisition years shows a positive change of 0.47%.

Regression 5 and 6 indicate that changes in cash flow margins are not significantly different when acquisitions are partitioned based on the method of payment. The coefficients for Shares, Cash, and Mixed acquisitions shows an increased margin with share payment and a reduction with cash and mixed. The coefficient for the related is 3.66, estimating a 3.66% annual increase in CF margin when acquiring a company with the same two-digit TRBC-code, but the estimated effects are without statistical significance for all the variables.

6.4 Operating expenses relative to matched firms

In Table 6, we find that merging firms are not able to reduce their operating costs relative to matched firms. Operating expenses increased from 92.46% of net sales in year -3 to 96.06% in year +2, and 93,75% in year +3 for merging firms. Matched firms are more stable in terms of operating expenses, drifting around 92.5% in all years, except for year +3 where operating expenses rose to 95.14% for the matched firms. The differences between merging firms and matched firms show that operating expenses are higher for merging firms in all years, except for the first and last year, where the difference is negative, indicating a reversal in the long run. All differences are significant at the 1% level.

Table 6

Operating expenses to net sales relative to matched firms. Operating expenses is calculated as under chapter 5.3 Performance Measurement. We scale the operating expenses by the net sales for each year. To account for matched-firm variations, we construct a matched firm-adjusted variable (MRG*i* - MTC*i*) for each firm and year. This is done by calculating the difference between the specific value of the acquiring firm and the specific value of the same variable for the matched-firm. The Δ operating expenses is calculated as [(MRGi - MTCi)post - (MRGi - MTCi)pre], where (MRGi - MTCi)post is the median difference between the merging firm and matched firm for year 1, 2, and 3, while (MRGi - MTCi)pre is the median difference between the merging firm and the matched firm for year -3, -2, and -1. Each acquisition is denoted by the subscript i. The OLS regressions estimate the change in OPEX based on different methods of payment and relatedness.

Year from deal	Merged firm (MRG)		Matched firms (MTC)		Difference (MRG*i* - MTC*i*)		
	Mean	Median	Mean	Median	Mean	Median	
-3	90.45 %	92.46 %	89.05 %	92.68 %	1.39 %	-0.23 %	***
-2	112.57	94.70	90.00	93.28	22.57	1.42	***
-1	103.75	94.94	88.71	92.46	15.04	2.49	***
1	105.28	94.16	92.13	92.90	13.15	1.26	***
2	105.43	96.06	89.92	92.44	15.51	3.62	***
3	91.98	93.75	91.29	95.14	0.69	-1.39	***
Δ operating expenses						0.70	

Regression 7:

$\Delta OPEX =$ 0.40(1.6) + 2.20(2.6)Cash - 5.38(3.0)*Shares + 3.59(3.9)Mixed

$R^2 = 0.03$

Regression 8:

$\Delta OPEX$ = - 6.47(3.8)* + 0.22(2.7)*Cash - 9.09(3.5)**Shares + 2.38(3.9)Mixed + 11.11(5.5)**Related $R^2 = 0.06$

* Denote the significance at the 10% level for the two tailed Wilcoxon signed rank test

** Denote the significance at the 5% level for the two tailed Wilcoxon signed rank test

*** Denote the significance at the 1% level for the two tailed Wilcoxon signed rank test

The Δ in operating expenses indicates an increase of 0.70% from the pre-deal period and into the post-deal period for the DiD model. However, the results from the OLS regressions indicate that operating expenses decline following stock acquisitions, with the coefficients for shares being -5.38% in regression 7 and -9.09 in regression 8, statistically significant at the 10% and 5% level respectively. In contrast, the coefficients for cash and mixed acquisitions are not statistically significant, indicating that there is no clear evidence of a reduction in operating expenses for these types of deals. The coefficient for the related variable is 11.11 which estimates that acquiring a firm within the same sector is associated with an 11.11% yearly increase in operating expenses relative to matched firms only statistically significant at the 5% level.

6.5 Labor costs relative to matched firms

Our findings show that acquiring firms experience a reduction in labor costs following a merger or acquisition relative to matched firms. Specifically, the difference in labor costs to net sales ratio between merging and matched firms are 3.06% for year -3, 6.51% for year -2, 6.14% for year -1, 0.95% for year +1, -0.69% for year +2, and -4.56% for year +3. The results for all years are statistically significant at the 1% level. The labor costs to sales declined rapidly by more than 5% the first year after the merger and another decline by almost 4% from year +2 to year +3, resulting in a change in labor costs (Δ Labor costs) between post and pre–acquisition periods by -5.82%.

Table 7

Labor costs to net sales relative to matched firms. We scale the labor costs by the net sales for each year. To account for matched-firm variations, we construct a matched firm-adjusted variable (MRG*i* - MTC*i*) for each firm and year. This is done by calculating the difference between the specific value of the acquiring firm and the specific value of the same variable for the matched-firm. The Δ labor costs is calculated as [(MRGi - MTCi)post - (MRGi - MTCi)pre], where (MRGi - MTCi)post is the median difference between the merging firm and matched firm for year 1, 2, and 3, while (MRGi - MTCi)pre is the median difference between the merging firm and the matched firm for year -3, -2, and -1. Each acquisition is denoted by the subscript i. The OLS regressions estimate the change in Labor Costs (LC) based on different methods of payment and relatedness.

Year from deal	Merged firm (MRG)		Matched firms (MTC)		Difference (MRG*i* - MTC*i*)		
	Mean	Median	Mean	Median	Mean	Median	
-3	26.16 %	24.13 %	19.41 %	21.07 %	6.75 %	3.06 %	***
-2	28.15	25.31	20.57	18.80	7.58	6.51	***
-1	27.88	25.00	20.41	18.86	7.47	6.14	***
1	26.63	23.07	21.81	22.13	4.81	0.95	***
2	25.52	19.93	22.43	20.62	3.09	-0.69	***
3	26.15	19.54	24.33	24.10	1.82	-4.56	***
Δ Labor costs						-5.82	

Regression 9:

ΔLC = - 2.02(0.7)*** + 0.34(1.0)Cash - 1.19(1.2)Shares - 1.17(1.6)Mixed

$R^2 = 0.06$

Regression 10:

ΔLC = - 5.92(1.5)*** - 0.78(1.1)Cash - 3.28(1.4)**Shares - 1.85(1.6)Mixed + 6.28(2.2)***Related

$R^2 = 0.06$

* Denote the significance at the 10% level for the two tailed Wilcoxon signed rank test

** Denote the significance at the 5% level for the two tailed Wilcoxon signed rank test

*** Denote the significance at the 1% level for the two tailed Wilcoxon signed rank test

Regression 10 shows that labor costs reductions are more significant following stock acquisitions, with an estimated effect of -3.28% yearly, statistically significant at the 5% level. Cash and mixed variables are also estimated to yield a negative effect, but less economically and not statistically significant. However, the related variable shows a 6.28% annual increase in labor costs and is statistically significant at the 1% level.

6.6 Synthetic Control Method

The findings of our study, which examined the effects of M&A on the Norwegian energy sector using the Synthetic Control Method (SCM), are in line with our earlier results from the two other models employed. Tables 8 and 9 present the summary statistics, illustrating that firms involved in M&A transactions underperform non-M&A firms in terms of CFROA and CF margin in the post-M&A period. The small difference in the pre-treatment period is due to the weighted averages being minimized to zero in the pre-treatment period. However, Figures 1 and 2 illustrate that over the 3-year period following the M&A, the control group consistently outperforms the M&A companies with an average quarterly difference of -0.71% and -13.011% for CFROA and CF margins, respectively. Although the bootstrap p-values for the two performance metrics are not statistically significant (0.4879 and 0.4969), the decrease in CFROA and CF margin hold economic significance.

Table 8

Cash flow return on assets relative to the Synthetic Control Method (SCM). Cash flow is calculated as under chapter 5.3 Performance Measurement. We scale the operating cash flows by the total book value of assets for each quarter.

Mean pre-treatment difference:	0,1828
Mean Post-treatment difference:	-0.7178
Bootstrap p-value:	0.4879
Standard deviation:	0.6605
95% confidence interval:	[-1.95 , 0.62]

Table 9

Cash flow margin relative to the Synthetic Control Method (SCM). Cash flow is calculated as under chapter 5.3 Performance Measurement. We scale the operating cash flows by the net sales for each quarter.

Mean pre-treatment difference:	2,8007
Mean Post-treatment difference:	-13,011
Bootstrap p-value:	0.4969
Standard deviation:	2.7098
95% confidence interval:	[-18.26 , -7.72]

As the SCM data does not fit the normality assumptions required for standard inference procedures, we employ bootstrapping, as described in the methodology chapter of this paper, to estimate the sampling distribution. With 100 000 resamples for each of the performance measures, we get insignificant p-values and a standard deviation of 0.6605 for CFROA and 2.7098 for CF margin. With a mean post-treatment difference of -0.7178, we consider the standard deviation on CFROA to be relatively high, which is also reflected in the wide 95% confidence interval from the resampling. Histograms for the 95% confidence intervals from the resampling can be examined in Chapter 10, Figures 3 and 4, and in combination with relatively high standard deviations, they reveal a high variability and the data. Based on our estimated results, with a 95% confidence, the causal effect of an M&A on CFROA and the CF margins of a Norwegian energy company is expected to be between -1.95% and + 0.62% and -18.26% and -7.72% respectively, in the 3-year period after acquiring another company.

Figure 1, Energy sector vs. Synthetic Energy sector CF ROA

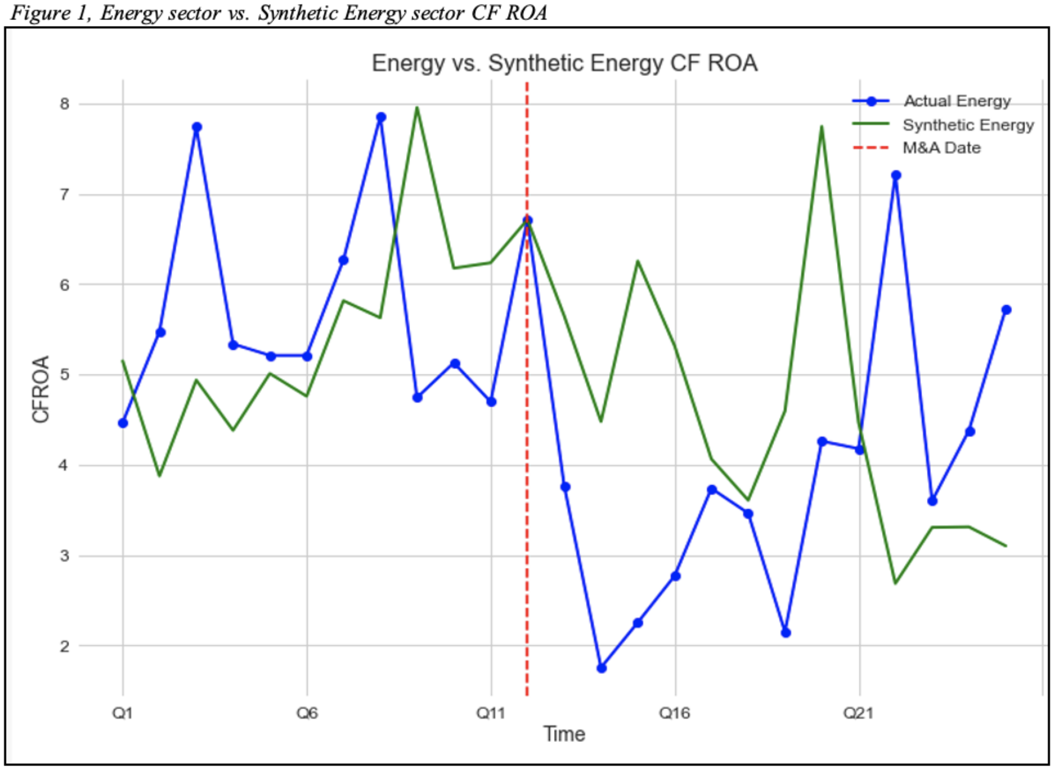
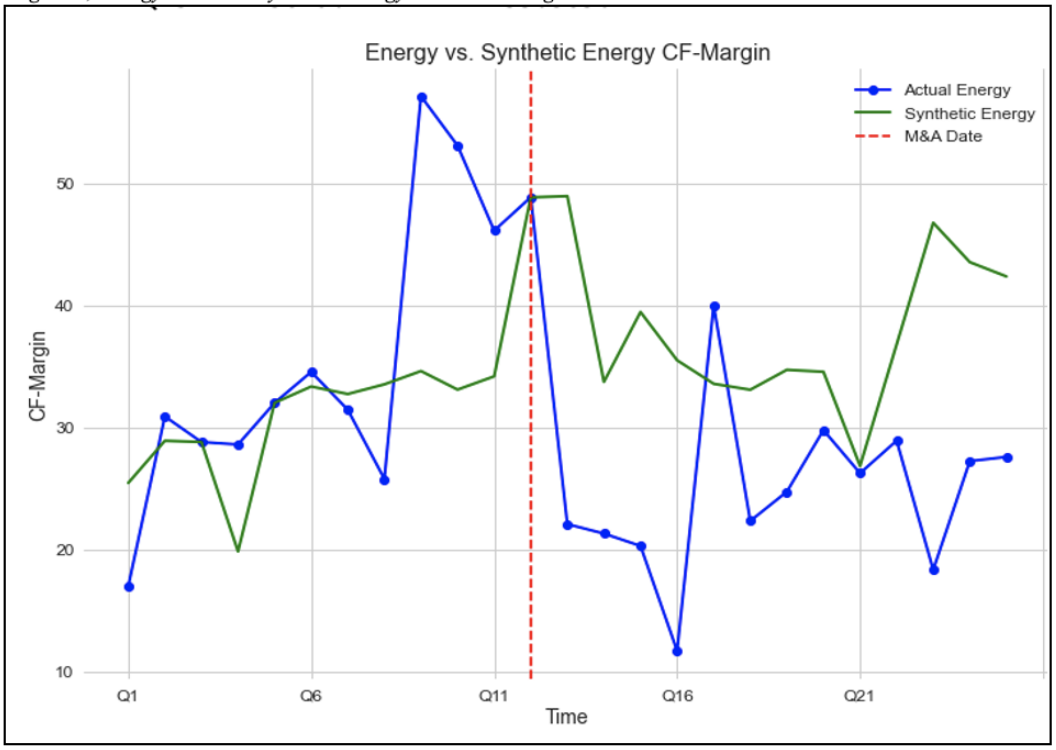


Figure 2, Energy sector vs. Synthetic Energy sector CF Margin



Figures 1 and 2 are plots of the treated and control group before and after the deal date. A clear trend is observed, indicating an instant and large decrease in both CFROA and CF margin for the M&A firms in the first quarters following the M&A deal.

A majority of the quarterly datapoints in Figure 1 show negative differences in post-acquisition periods between the treated firms and the control firms, meaning that treated firms are not able to improve cash flow return on assets after the merger date compared to its synthetic counterpart. These results are also consistent with our earlier findings in both the industry - and matched firm models. By averaging the differences of all quarterly data points in each year, we observe a difference of -26.8%, -16.09%, -7.45%, and -17.19% in year 0, +1, +2, and +3 respectively. Treatment firms are only able to outperform the control firms in two quarters, namely the last quarter in year +1 and the first quarter in year +3, the other 10 quarterly datapoints are negative.

From Q16 in Figure 2, 1 year post deal, the M&A firms decrease their CF margins before it stabilizes and the difference between the treated and control firms becomes smaller. The trend is consistent with our results in the DiD model, but much more economically significant in the

SCM test. After the merger, the yearly difference between treated and control firms are -16.09%, -7.45% and -12.95%. The volatility of the CF margin for the treated firms in the energy sector are much higher than with the regular sample from the DiD model, which leads to a wider spread in the differences.

7. Conclusion: Does operating performance improve following M&A?

Based on our study's results, acquiring firms do not consistently outperform their industry or matched counterparties following a merger or acquisition, whether we examine the energy sector or the Norwegian market as a whole. Thus, we fail to reject our hypotheses. Specifically, our findings indicate a decline in cash flow return on assets and an increase in operating expenses for acquiring firms in the three years post-acquisition. Our analysis provided evidence that stock acquisitions as a payment method in M&A transactions resulted in increased operating margins and decreased operating costs after accounting for temporary and/or permanent differences. In contrast, cash acquisitions appear to reduce cash flow return on assets, cash flow-margin, and increase operating expenses, although the empirical evidence supporting this is weak. This suggests that acquiring firms might struggle to realize the often-promised synergy effects of a merger or acquisition.

This study revealed that related acquisitions had a negative impact on CFROA and operating expenses, potentially due to CEOs overestimating synergy effects and a higher willingness to pay premiums in related acquisitions (Morck, Shleifer, and Vishny, 1990; Renneboog and Vansteenkiste, 2019). This emphasizes the importance of due diligence and realistic synergy estimation in the merger and acquisition process. Additionally, the findings of Kose and Knyazeva (2015) support our results, demonstrating that strong labor rights acquirers are motivated to target companies with similar labor rights and higher labor costs, indicating a positive relationship between relatedness and labor costs. Furthermore, employees in countries with strong labor rights, like Norway, typically have strong bargaining power, enabling employees to negotiate deal terms. As a consequence, acquiring firms may experience increased operating expenses due to such labor protections, which may also restrict them from implementing certain restructuring measures intended to achieve synergy effects. Our study's findings strengthen this relationship by demonstrating the statistically and economically significant impact of relatedness on labor costs and operating expenses.

Regarding the positive effects from M&A, our results align with the findings of Magenheim and Mueller (1988), who observed that acquiring firms experience an upward trend in abnormal returns over roughly three years prior to the acquisition's announcement. This suggests that the benefits of a merger or acquisition may be more pronounced in the pre-acquisition period.

These results provide interesting insights when compared with the findings in prior research. Martin and McConnell (1991) find that top-level target managers are more likely to be fired following cash acquisitions, whereas Ghosh and Ruland (1998) find that these managers are more likely to retain their jobs when the acquiring firms use stock. Shleifer and Summers (1988) argue that cash acquisitions are more likely to be hostile, leading to higher reductions in labor costs in cash acquisitions rather than acquisitions financed by shares. Hostile acquisitions are associated with lower post-merger performance according to results from Martynova, Oosting, and Renneboog (2007) and Ghosh (2001), among others. Contrary to the expectations of Shleifer and Summers, our study demonstrates that share-financed acquisitions outperform cash acquisitions in terms of labor cost reductions. The significant reduction in labor costs observed for share-financed acquisitions in our dataset suggests that the labor cost reductions are more prevalent among target lower/middle-managers and workers, while target top managers are more likely to retain their positions. The link between stock-financed acquisitions and the retention of top managers for target firms seems to have a positive impact on all performance measures we analyze, although the results are not statistically significant for CFROA and CF margin. Our data also supports the notion that cash acquisitions, characterized as hostile, are associated with lower post-merger performance. However, our findings do not provide statistical evidence of cash acquisitions reducing CFROA or CF margin.

We also found a consistent underperformance of firms involved in M&A transactions compared to their non-M&A counterparts in the post-M&A period when employing the SCM for the Norwegian energy sector. This was evident in both CFROA and CF margin metrics, with an average quarterly difference of -0.71% and -13.011%, respectively. Although the p-values were not statistically significant, the economic significance of the decrease in CFROA and CF margin cannot be overlooked. The variability in the data, as indicated by the high standard deviations and wide 95% confidence intervals, suggests a high degree of uncertainty in the post-M&A performance of firms.

The SCM demonstrated the best fit in terms of size and pre-deal performance of the three matching methodologies we employ in this paper. The methodological challenges encountered in earlier studies underscore the importance of robust methodologies in investigating the effects of M&A on operating performance. The SCM, with its ability to construct a synthetic control group that closely matches the pre-treatment characteristics of the treated firms, provides a robust approach to estimate the causal effect of M&A. Given these advantages, we recommend future financial research to implement the SCM to examine the causal effect in event studies.

In conclusion, our study offers a detailed perspective on how acquiring companies perform in the years before and after a merger or acquisition. While some firms may experience benefits, the overall trend suggests a decline in operating performance relative to industry or matched counterparts. Thus, the answer to our research question, “Do acquiring firms improve their operating performance in Norway after mergers and acquisitions?” seems to be no, if by after we mean the three years post to the time of the deal, and if the definition of operating performance is based on the specific performance metrics employed throughout this study. This suggests that the decrease is caused by changes other than what we specify as operating performance or macroeconomic changes unrelated to M&A.

8. Bibliography

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative Politics and the Synthetic Control Method. American Journal of Political Science. https://doi.org/10.1111/ajps.12116

Abadie, A., & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. American Economic Review, 93(1), 113-132.

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. Journal of the American Statistical Association, 105(490), 493-505.

Abadie, A. (2019). Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. Journal of Economic Literature, 57(2), 278-330.

https://www.aeaweb.org/articles?id=10.1257/jel.20191450

Agrawal, A., Jaffe, J. F., and Mandelker, G. N., (1992). The Post-Merger Performance of Acquiring Firms: A Re-Examination of an Anomaly. Journal of Finance, (47), 1605-1621.

Barber, B. M., and Lyon, J. D. (1996). Detecting abnormal operating performance: The empirical power and specification of test statistics. Journal of Financial Economics, 41(3), 359-399.

Brakman, S., Garretsen, H., and Schramm, M. (2006). The strategic benefits of mergers: Evidence from the European Union. Journal of Industrial Economics, 54(1), 1-28.

Deli, Y., and Kutan, A. M. (2008). Do mergers create value? Evidence from emerging markets. Emerging Markets Review, 9(3), 246-262.

Dittmar, A. K., and Mahrt-Smith, J. (2008). Corporate acquisitions and the informativeness of accounting earnings. Journal of Accounting and Economics, 45(2), 221-247.

Fama, E.F., & French, K.R. (1992). The Cross-Section of Expected Stock Returns. Journal of Finance, 47(2), 427-465.

Francis, J., and Schipper, K. (1999). Have financial statements lost their relevance? Journal of Accounting Research, 37(2), 289-302.

Franks, J., Harris, R., & Titman, S. (1991). The post-merger share-price performance of acquiring firms. Journal of Financial Economics, 29(1), 81-96.

Ghosh, A. (2001). Does operating performance really improve following corporate acquisitions? Journal of Corporate Finance, (7), 151-178.

Gugler, K., Mueller, D. C., Yurtoglu, B. B., and Zulehner, C. (2003). The effects of mergers: an international comparison. International Journal of Industrial Organization, 21(5), 625-653.

Gugler, K., Yurtoglu, B. B., and Zulehner, C. (2008). The effects of mergers and acquisitions on firm performance: New evidence from matched sample studies. Industrial and Corporate Change, 17(4), 773-813.

Hall, M. & Weiss, L. (1967). Firm size and profitability. The Review of Economics and Statistics, 49(3), 319-331.

Healy, P., Palepu, K., and Ruback, R. (1992). Does corporate performance improve after mergers? Journal of Financial Economics, 31(2), 135-175.

Magenheim, E.B., & Mueller, D.C. (1988). Are acquiring-firm shareholders better off after an acquisition? In A. Auerbach (Ed.), Knights, Raiders and Targets: The Impact of Hostile Takeovers (pp. 171-193). National Bureau of Economic Research: Cambridge, MA.

Martynova, M., Oosting, S., and Renneboog, L. (2007). The long-term operating performance in European mergers and acquisitions. Academic Press, 79-116.

Morck, R., Shleifer, A., & Vishny, R.W. (1990). Do Managerial Objectives Drive Bad Acquisitions? Journal of Finance, 45(1), 31-48.

Myers, S. C., and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics, 13(2), 187-221.

Mueller, D.C. (1986). Profits in the long run. Cambridge University Press.

Rau, R.P., & Vermaelen, T. (1998). Glamour, value, and the post-acquisition performance of acquiring firms. Journal of Financial Economics, 49(2), 223-253.

Renneboog, L. & Vansteenkiste, C. (2019). Failure and success in mergers and acquisitions. Journal of Corporate Finance, (58), 650-699.

9. Appendix

Appendix 1:

How permanent and/or temporary differences in pre – and post – acquisition cash flows can produce biased results when using an industry matched comparison group to an acquiring firm.

Consider the intercept model (1) and the DiD model (2) from Healy et. al 1992:

$$CF\ (IND)_{post,i} = \alpha + \beta\, CF\ (IND)_{pre,i} + \epsilon \qquad (1)$$

Where $CF\ (IND)_{post,i}$ and $CF\ (IND)_{pre,i}$ are the cash flows of merging firms after subtracting industry median cash flow for the post - and pre – acquisition period. The intercept coefficient α capture acquisition-induced improvements in cash flow (abnormal cash flow), while the slope coefficient β captures the persistence in industry-adjusted cash flow. The DiD model, which compares post-acquisition cash flow with pre-acquisition cash flow is then given by equation (2):

$$CF\ (IND)_{post,i} - CF\ (IND)_{pre,i} \qquad (2)$$

To illustrate how permanent and temporary changes in cash flow can provide biased results, let $CF\ (IND)_{pre,i}$ and $CF\ (IND)_{post,i}$ be described as:

$$CF\ (IND)_{pre,i} = PermDiff_{pre,i} + TempDiff_{pre,i} \qquad (3)$$

$$CF\ (IND)_{post,i} = PermDiff_{post,i} + TempDiff_{post,i} \qquad (4)$$

Where $PermDiff_{post/pre,i}$ and $TempDiff_{post/pre,i}$ are post - or pre – acquisition permanent and temporary differences between the cash flow of the i^{th} acquiring firm minus the cash flow of the i^{th} firm's industry median. Since temporary differences are not expected to persist over time and are uncorrelated with other variables or factors affecting the cash flows of merging firms, temporary differences are in these equations random errors which are independently distributed.

From now on, we will no longer use the subscript *i* to simplify the explanation. The change model, which is the expected improvement in operating performance can now be rewritten as:

$$\Delta\text{CF} = [E(PermDiff_{post}) + E(TempDiff_{post})] - [E(PermDiff_{pre}) + E(TempDiff_{pre})] \quad (5)$$

Now let us rearrange the intercept model to look at the expected effects on the intercept coefficient, $E(\alpha)$ and β, where we use the covariance and variance formulas to define the slope coefficient:

$$E(\alpha) = [E(PermDiff_{post}) + E(TempDiff_{post})] - \beta\,[E(PermDiff_{pre}) + E(TempDiff_{pre})] \quad (6)$$

$$\beta = \frac{Cov[(PermDiff_{post} + TempDiff_{post}),(PermDiff_{pre} + TempDiff_{pre})]}{Var(PermDiff_{pre} + TempDiff_{pre})} \quad (7)$$

However, by acknowledging that temporary differences are random errors which are independently distributed, meaning they do not contribute to the persistence or relationship between the cash flows of merging firms in the pre- and post-acquisition periods. We can exclude temporary differences in the formula for the slope coefficient and express the formula for β as follows:

$$\beta = \frac{Cov(PermDiff_{post}, PermDiff_{pre})}{Var(PermDiff_{pre} + TempDiff_{pre})} \quad (8)$$

By incorporating assumptions of the expected values for the permanent – and temporary – differences, we can now finally look at how the intercept model and the DiD model can yield unbiased and biased results. We will now describe and examine two different sets of scenarios:

Scenario 1: No permanent nor temporary changes:

Let us first illustrate the easiest example when both permanent and temporary differences between the merging firm's cash flow and the industry-median cash flow in the pre-acquisition period are equal to zero, that is: $E(PermDiff_{pre}) = 0$ and $E(TempDiff_{pre}) = 0$.
We can make the following conclusions regarding biases in the intercept – and DiD model:

1. Intercept model:

The intercept term $E(\alpha)$, will now only capture abnormal changes in cash flow resulting from the merger or acquisition alone since equation (6) will reduce to equation (4):

$$E(PermDiff_{post}) + E(TempDiff_{post}) \tag{4}$$

Since there are no pre-existing differences or biases accounted for, the intercept model would yield unbiased results.

2. DiD model:

For the DiD model, when $E(PermDiff_{pre})$ and $E(TempDiff_{pre})$ in equation (5) are equal to zero, this implies that there are no pre-existing differences between the merging firms' cash flow and the industry-median cash flow. Therefore, any changes observed in the cash flow (ΔCF) can be directly attributed to the merger or acquisition. Equation (5) will also reduce to equation (4), same as for the intercept model. In this case, the DiD model would also yield unbiased results.

Scenario 2: Both permanent and temporary changes

Let us in this scenario first examine the case when there exists permanent differences and no temporary differences to simplify the point of the proof, that is: $E(PermDiff_{pre}) > 0$ and $E(TempDiff_{pre}) = 0$. For further simplification, let us also assume that the permanent difference persists into the post – acquisition period, so $E(PermDiff_{pre}) = E(PermDiff_{post})$.
We can make the following conclusions regarding biases in the intercept – and DiD model:

1. Intercept model:

Let us first analyze the slope coefficient based on these assumptions. Since $E(PermDiff_{pre}) = E(PermDiff_{post})$, then both these variables will be positive. The covariance numerator in equation (8) will equal the variance of the permanent difference for the pre-acquisition period. The denominator will also be positive as $E(PermDiff_{pre}) > 0$ and the variance of the temporary difference in the pre-acquisition period will be greater than zero, $Var(TempDiff_{pre} > 0$. Equation (8) will because of this change to:

$$\beta = \frac{Var(PermDiff_{pre})}{Var(PermDiff_{pre}) + Var(TempDiff_{pre})} \tag{10}$$

Since both the numerator and the denominator are positive, and $Var(TempDiff_{pre} > 0$, this means that β must be lower than one. ($\beta < 1$). Using the assumptions, we can factorize equation (6) into:

$$E(\alpha) = (1 - \beta)\,[E(PermDiff_{pre})] \tag{11}$$

With $\beta < 1$, $E(\alpha)$ will be positive. This means that the intercept will signify expected acquisition-induced improvements in cash flow, resulting in a positive bias in the intercept model. The extent of the bias will depend on the size of the cash flow difference in the pre-acquisition period between acquiring firms and industry median firms due to permanent factors, $[E(PermDiff_{pre})]$, and the level of variability in the cash flow difference between acquiring firms and industry-median firms due to temporary factors, $Var(TempDiff_{pre})$.

2. DiD model:

By incorporating the assumptions of scenario 2 into the difference – in – difference model we can see from equation (5) that the permanent differences in the pre - and post - acquisition periods cancel each other out and the equation equals zero because permanent differences are expected to persist into post - acquisition periods. This means that the model does not show any improvements in operating performance after an acquisition, resulting in an unbiased conclusion, provided there are no temporary differences, $E\left(PermDiff_{pre}\right) = 0$. However, if there exist temporary differences in the pre – acquisition periods, which do not persist into post – acquisition periods, then we see from equation (5) that the DiD model will produce biased results:

$$\Delta\text{CF} = \left[E(PermDiff_{post})\right] - \left[E(PermDiff_{pre}) + E(TempDiff_{pre})\right] \tag{12}$$

Appendix 2:

Minimize function in Python for SCM

```
df = pd.read_excel('scg.xlsx', sheet_name='CF_TA_SCG')
print(df.head())


# Oil-sector CF_TA_SCG without short-selling allowed

import pandas as pd
import numpy as np
from scipy.optimize import minimize
import matplotlib.pyplot as plt

np.set_printoptions(precision=4, suppress=True)


# Pre-process the data
pre_mna_data = df[df['MNA'] == 0]
post_mna_data = df[df['MNA'] == 1]

# Separate treated and control firms
treated_firm = 'Treated'
control_firms = [col for col in df.columns if col not in ['Date', 'MNA', treated_firm]]

treated_pre_mna = pre_mna_data[treated_firm].values
control_pre_mna = pre_mna_data[control_firms].values

# Define the objective function to minimize the difference in CF/TA during the pre-M&A
def objective_function(weights, treated_outcome, control_outcomes):
    weighted_outcome = np.dot(weights, control_outcomes.T)
    return np.mean(np.abs(treated_outcome - weighted_outcome))

# Optimize weights
initial_weights = np.full(control_pre_mna.shape[1], 1 / control_pre_mna.shape[1])
bounds = [(0, 1) for _ in range(control_pre_mna.shape[1])]
constraints = {"type": "eq", "fun": lambda x: np.sum(x) - 1}

result = minimize(
    objective_function, initial_weights, args=(treated_pre_mna, control_pre_mna),
    bounds=bounds, constraints=constraints
)

optimal_weights = result.x

# Construct synthetic Oil-company during pre-M&A period
synthetic_pre_mna = np.dot(optimal_weights, control_pre_mna.T)

# Construct synthetic Oil-company during post-M&A period
control_post_mna = post_mna_data[control_firms].values
synthetic_post_mna = np.dot(optimal_weights, control_post_mna.T)

# Combine the actual and synthetic Oil-company data
actual_oil = np.concatenate((treated_pre_mna, post_mna_data[treated_firm].values))
synthetic_oil = np.concatenate((synthetic_pre_mna, synthetic_post_mna))

# Create a table comparing the actual Oil performance and synthetic Oil performance
comparison_df = pd.DataFrame({'Date': df['Date'], 'Actual_OIL': actual_oil, 'Synthetic_
```

Appendix 3:

Bootstrapping using Python

```
# Import required libraries
import numpy as np
from sklearn.utils import resample

# Define a function for bootstrapping
def bootstrap(data, n_iterations):
    bootstrap_distribution = np.zeros(n_iterations)
    for i in range(n_iterations):
        # Resample the data (with replacement)
        resampled_data = resample(data)
        # Compute the statistic of interest
        bootstrap_distribution[i] = np.mean(resampled_data)
    return bootstrap_distribution

# Compute the actual difference between the actual firm and the synthetic firm
actual_difference = np.mean(post_mna_comparison['Actual_OIL'] - post_mna_comparison['Sy

# Compute the bootstrap distribution of differences
n_iterations = 1000000
bootstrap_distribution = bootstrap(post_mna_comparison['Actual_OIL'] - post_mna_compari

# Compute the p-value as the proportion of bootstrap iterations where the difference is
p_value = np.sum(bootstrap_distribution >= actual_difference) / n_iterations

# Compute standard deviation
bootstrap_std = np.std(bootstrap_distribution)

# Compute a 95% confidence interval
alpha = 0.05
lower_bound = np.percentile(bootstrap_distribution, 100 * alpha / 2)
upper_bound = np.percentile(bootstrap_distribution, 100 * (1 - alpha / 2))
# Calculate the mean of the bootstrap results
mean_bootstrap = np.mean(bootstrap_distribution)

print("Mean of the bootstrap results:", mean_bootstrap)

print("Bootstrap p-value:", p_value)
print(f"Standard deviation of the bootstrap results: {bootstrap_std}")
print(f"The 95% confidence interval for the effect size is ({lower_bound}, {upper_bound
```

```
Mean of the bootstrap results: -0.7178439020922153
Bootstrap p-value: 0.487944
Standard deviation of the bootstrap results: 0.660538843941063
The 95% confidence interval for the effect size is (-1.9525530246001892, 0.62778938514
9291).
```

10. Tables and Figures

Table 2

Wilcoxon Signed rank test results, significance at the 5% level.

Variable	Year from M&A	Test-Stat	P-value	Significance
CF ROA	-3	2877	0,0006	Significant
CF ROA	-2	4046	0,4359	Not Significant
CF ROA	-1	3487	0,0296	Significant
CF ROA	1	4360	0,9475	Not Significant
CF ROA	2	3768	0,1226	Not Significant
CF ROA	3	3116	0,0026	Significant
CF Margin	-3	2265	0,0000	Significant
CF Margin	-2	3608	0,0761	Not Significant
CF Margin	-1	3814	0,1497	Not Significant
CF Margin	1	3275	0,0114	Significant
CF Margin	2	3989	0,2948	Not Significant
CF Margin	3	2979	0,0009	Significant
OPEX_NS	-3	2385	0,0070	Significant
OPEX_NS	-2	3100	0,0034	Significant
OPEX_NS	-1	2984	0,0010	Significant
OPEX_NS	1	2931	0,0006	Significant
OPEX_NS	2	2337	0,0000	Significant
OPEX_NS	3	3036	0,0014	Significant
LABOR_NS	-3	367	0,0032	Significant
LABOR_NS	-2	872	0,0024	Significant
LABOR_NS	-1	945	0,0076	Significant
LABOR_NS	1	1340	0,0064	Significant
LABOR_NS	2	1279	0,0085	Significant
LABOR_NS	3	883	0,0069	Significant

Figure 3:

Sample distribution of CF ROA

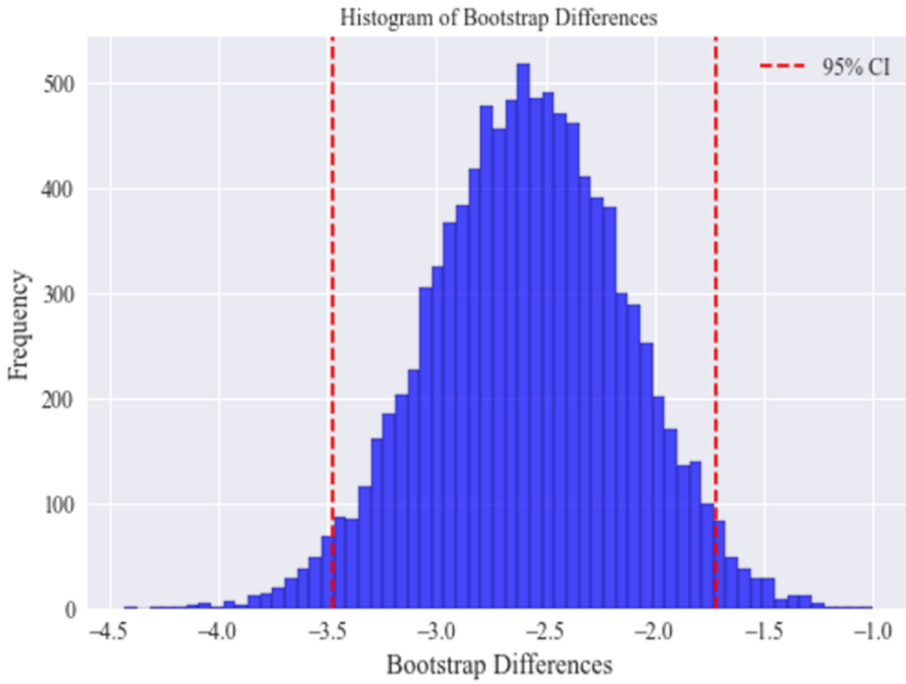


Figure 4:

Sample distribution of CF Margin