Norwegian School of Economics
Bergen, Spring 2023

The Effect of M&A on Employee Performance

An empirical study on post-M&A employee performance in private Norwegian target companies

August S. Aarbakke & Adrian Aasheim

Supervisor: Carsten Gero Bienz

Master thesis, Economics and Business Administration

Major: Business Analysis and Performance Management

&

Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This thesis represents our learning outcome from five years at NHH. We are grateful for the knowledge, challenges, and experiences we have obtained from working on this thesis. We are proud of our work and hope that others may use our findings or algorithm in the future.

We chose our topic to gain insight into the human aspects of M&A. The human aspect should never be overlooked in any financial transaction. We hope that future research will investigate the human reactions further, both internationally and in Norway.

First of all, we would like to thank our supervisor Carsten Gero Bienz. His constructive feedback and knowledge has been immensely helpful for our work. We are especially grateful for his constant attention to improvements. Secondly, we would like to thank SNF, Aksel Mjøs, and Simon Selle for providing us with our data. Lastly, we would like to thank friends and family for supporting us throughout the process.

Norwegian School of Economics

Bergen, January 2023

August S. Aarbakke

Adrian Aasheim

Abstract

This paper analyses post-M&A employee performance for private Norwegian target companies using accounting data between 2007 and 2016. We have created an algorithm which identifies ownership changes in firms from accounting data. Our model is based on the Cobb-Douglas productivity function to measure firm productivity, and utilizes Propensity Score Matching (PSM) to control for confounding variables. Additionally, we research if the effect of M&A are different based on labor size or sector. As a robustness test we use Nearest Neighbour matching combined with a Difference-In-Difference (DD) analysis to control for possible bias in the PSM analyses. Our results conclude that M&As do not have an effect on employee performance in Norwegian private companies. Furthermore, results indicate a negative effect on firm performance post-M&A. We neither find any reliable differences on employee performance from labor size nor sector. However, we find that the firm performance for the companies with the largest labor force, in the retail industry, and in the remaining sectors are negatively affected post-M&A. The DD analysis mostly support the PSM findings on employee performance and strengthens the validity of our findings. However, we cannot exclude potential confounding of the firm performance outcome variable.

Keywords – M&A, Post-M&A employee performance, Post-M&A firm performance

Contents

List of Figures

List of Tables

1 Introduction

Mergers and Acquisitions (M&As) are common strategies to increase the growth of a firm (Krishnan et al. (2007)).[1] In a M&A transaction, the acquiring firm often pays a premium for the acquired firm (Zhang (2019)). This premium reflects the estimated added value from more efficient operations in the merged entity, which is known as synergies (Feldman and Hernandez (2022)). Previous research do not present an unambiguous answer on the post-M&A performance of firms and the realization of synergies (Homberg et al. (2009)). Even though there are examples of positive post-M&A effects on firm productivity, the consensus is that M&As under-perform.[2] Post-M&A employee performance is a lesser researched topic (Siegel and Simons (2015)). M&As often represent major changes for employees, which may impose an impact on their working-performance (Kansal and Chandani (2014)) (Degbey et al. (2021)). Researching the effect on employees may contribute to a better understanding of why most M&As fail, and whether employee performance contribute to the failures.

This thesis analyzes the causal effect of M&As on employee performance in Norwegian private target firms between 2007 and 2016. Additionally, we analyze firm performance post-M&A to control for firms' overall reaction to M&As. We use accounting data for private Norwegian companies to perform our analysis.[3] To detect M&As from accounting data, we have created an algorithm which identifies the change of ownership in firms. We measure the causal effect on employee performance by utilizing Propensity Score Matching (PSM). As a robustness analysis we conduct a Nearest Neighbour (NN) matching combined with a Difference-in-Difference (DD) analysis (Rosenbaum and Rubin (1983)) (Caliendo and Kopeinig (2008)). Our analysis finds that M&As have no significant effect on employee performance. However, we find that firm performance decrease post-M&A. Our DD robustness analysis mostly agrees with our main findings on employee performance, but weakens our findings on firm performance.

Previous research indicate that M&As fail to achieve their goals or even destroy value for stakeholders.[4] Research suggest that the performance of merged firms decrease post-

[1]We will use the terms mergers, acquisitions, and M&As interchangeably throughout this paper.
[2]As studied by King et al. (2004), Christensen et al. (2011), and Meckl and Röhrle (2016)
[3]We will use the terms firm and company interchangeably in this paper.
[4]As studied by Bekier et al. (2001), André et al. (2004), Tuch and O'Sullivan (2007), Grigorieva and

M&A. However, there are some examples which show that M&As create excess value through increased productivity (Healy et al. (1992)) (Dimopoulos and Sacchetto (2017)). The excess value creation in a M&A transaction is often materialized in layoffs and restructurings (Krishnan et al. (2007)). Employees' resistance to change and uncertainty may affect their performance negatively if their interests are not acknowledged (Nyberg and Trevor (2009)) (Kaetzler et al. (2019)). Increased workload, resistance to change, and new allocation of working tasks are some of the proposed causes. If the remaining employees under-perform in the post-M&A firm, synergies may be overvalued (Recardo and Toterhi (2015)). On the other hand, successful M&As may include incentive systems and more efficient allocation of working tasks (Devos et al. (2008)) (Schweizer and Patzelt (2012)). Such measures may explain some of the successful M&As in previous research.

In total, previous research present unambiguous results for firm and employee performance post-M&A. Even though the consensus is that merged firms under-perform, studies on employee performance find a positive effect in target firms. On the other hand, psychological research on post-M&A employee performance find negative effects for workers. In light of these contradictory findings, our expectations are to find different effects on employees and firms. We have no clear expectations for employee performance, and thus assume that there is no effect from M&As. For firm performance, we expect to find a negative effect. Therefore, our null hypothesis is to find no effect of M&As on employee performance, and a negative effect on firm performance.

This paper uses accounting data for private companies in Norway between 2007 and 2016 to analyze the effect of M&As on employee performance. Initially, M&As are not identified in the accounting data. Therefore, we have created an identification algorithm to detect M&As from accounting data by recognizing changes in the ownership of firms. To our knowledge, the algorithm is the first to identify M&As in such a way for Norwegian accounting data. By using data for private firms combined with the algorithm, we can measure firm and employee performance pre- and post-M&A. Our analysis utilizes PSM to control for the counterfactual. Additionally, we perform a robustness analysis by combining a Nearest Neighbour (NN) matching with a DD analysis to control for the unconfoundedness assumption in PSM. The unconfoundedness assumption states that all factors which influence outcomes and an acquisition must be simultaneously observable in

Petrunina (2015), Pereiro (2016), and Meckl and Röhrle (2016).

a study. This assumption could be breached in our paper as accounting data does not control for all factors, such as technological competencies. Finally, we measure the effect on employee performance as the Average Treatment effect on the Treated (ATT). Similar to our expectations, we find no significant effect on employee performance following M&As. Additionally, we find decreasing firm performance post-M&A. The robustness analysis mostly support our findings, but does not remove concerns regarding confounding of the firm performance outcome variable.

To perform our analysis, the following structure will be utilized. Firstly, we will outline past research on post-M&A performance and employees' reactions to change. Then we will describe our data and present our identification algorithm. Furthermore, our model and the methodological background will be outlined. Lastly, we will present our findings and discuss their applications.

2 Background

To outline the background for our hypothesis we will discuss previous literature related to M&As and employee performance. Firstly, we will outline the consensus of previous M&A research on firm performance. Most of the previous research focuses on the performance of the acquiring firm or the merged entity (King et al. (2004)) (Meckl and Röhrle (2016)). Therefore, we will outline general research on post-M&A firm performance. Then, we will outline post-M&A effects on employees in the acquired firm and the merged entity. Furthermore, we will outline research on employees' reaction to changes in their working environment. Lastly, we will discuss previous approaches to analyzing private M&As on accounting data.

2.1 Effects of M&As on Firm Performance

Even though M&As are common, there is substantial evidence that most M&As are unsuccessful and can decrease firm performance.[5] This is evident in a meta analysis conducted by Meckl and Röhrle (2016) who found that most M&As are unsuccessful based on stock market reactions. Another meta analysis by King et al. (2004) found that the acquiring firms experience no effect or a moderate decrease in firm performance post-acquisition. The two studies suggest that overall, M&As either do not affect performance, or destroy value.

On the other hand, several studies and examples find increased firm performance following mergers.[6] A common goal of an acquisition is to increase the efficiency of the merged entity, which is know as synergies. Synergies are often caused by operational improvements (Homberg et al. (2009)). Healy et al. (1992) researched the post-acquisition operating performance of merged US firms. The paper found post-acquisition increases in asset productivity compared to industry median firms. They note that the improvements are not caused by increased cash-spending nor short-term gains that negatively affect long-term performance. Their findings suggested that overall, following a M&A, assets are more efficiently utilized if there are potential synergies between the firms' assets.

[5] As studied by Bekier et al. (2001), André et al. (2004), Tuch and O'Sullivan (2007), Grigorieva and Petrunina (2015), and Pereiro (2016)

[6] Such as Healy et al. (1992), Powell and Stark (2005), and Dimopoulos and Sacchetto (2017)

Dimopoilos and Sacchetto (2017) researched whether markets are more efficient with occurrences of M&As. Firstly, they found that firms become more efficient following M&As. Secondly, the overall market efficiency increased in markets where M&As exist, and they credit the effect to the realization of synergies. They devote this effect to be a part of the total factor productivity (TFP) in a market. The consensus of Healy et al. (1992) and Dimopoulos and Sacchetto (2017) is that firms experience greater efficiency following M&As if there are potential synergies which can be realized between the two companies.

Ghosh (2001) also researched US firms operating performance post-M&A. The paper criticizes the previously discussed paper by Healy et al. (1992) for its comparison of acquiring firms to median firms. The paper presents evidence that acquiring firms systematically outperform the industry median companies because of permanent or temporary factors. Thus, comparing merged firms to median-performing firms do not present a suitable benchmark. The paper performed a matching of merging firms and non-merging firms to control for the confounding of variables based on pre-acquisition years (Loughran and Ritter (1997)). Additional to the confounding of variables, Ghosh (2001) controlled for the size of firms (Barber and Lyon (1996)). Linn and Switzer (2001) and Switzer (1996) also researched the effect of size in acquisitions. Their findings suggested that that larger merged firms typically outperform smaller merged firms post-acquisition. In total, Ghosh (2001) found that once the confounding of covariates and size was controlled for, there were no evidence for improvements in operating performance post-M&A.

Most of the previously discussed research is based on US data. However, multiple studies find differences in M&A performance between countries. Dickerson et al. (1997) find a significant decline in post-acquisition performance in UK acquiring firms. On the other hand, Powell and Stark (2005) conclude with significant positive growth for UK firms. Martynova et al. (2007) reviewed 155 European M&As and found that the merged entity does not experience a significant change in profitability compared to peer firms. In total, there seem to be differences in firm performance post-M&A between countries. Therefore, the effect of M&A may be different in Norway compared to other countries.

2.2 Post-M&A employee performance

Post M&A, managers are often in a dilemma of reducing costs and keeping competencies (Krishnan et al. (2007)). Krishnan et al. (2007) describe the dilemma in the context of value creation from a premium acquisition. The premium paid is often justified by the predicted synergies which could be realized between the two companies. The objective of the acquisition could differ, but acquisitions are often a strategic action to increase the value creation to shareholders (Jemison and Sitkin (1986)) (Tantalo and Priem (2014)). Cutting costs may increase profitability and may be materialized through layoffs. On the other hand, labor layoffs reduce the human capital of the acquired organization, which could also negatively influence profitability post-acquisition. Krishnan et al. (2007) find a positive relationship between premiums paid in an acquisition and layoffs. Furthermore, the results could imply that the size of the layoffs could have a relationship with a negative profitability development.

Some studies have further researched the effect on employees by isolating labor productivity post-M&A. Schiffbauer et al. (2017) researched whether target firms experience improved productivity following an acquisition by a foreign company. They found a positive effect on labor productivity isolated in the five years following an acquisition. This effect was mainly found in the manufacturing industry and not the service industry. Furthermore, the target company's capital increased while the labor force decreased. Siegel and Simons (2015) researched plant workers' reactions to acquisitions. The paper found that plant productivity increased post-acquisition. However, acquisitions also resulted in layoffs and more efficient allocation of workers and plants. In total, the consensus of these two papers suggests a positive effect on employees' performance post-M&A in target firms.

2.3 Employees' Reaction to Change

Change management will be outlined to better understand employees' experiences post-M&A. Change management theory outlines approaches to achieve greater success in transitioning people, processes, and resources (Miller (2020)). The reasons for the transition or transformation of an organization will differ, but such changes will always impose uncertainty regarding the future. Kaetzler et al. (2019) note that it is in human nature to resist an unsettling change. Acquisitions often present major cultural and organizational changes for employees (Degbey et al. (2021)). Research has shown that many M&As fail due to poor adaptation of change management (Kansal and Chandani (2014)). However, the acquired firm can impose an active strategy to deal with challenges to keep employees. An active approach is characterized by the target firm taking control of the transition (Williams (2011)). By imposing active measures to manage employees in the desired direction, an active approach could be central to a successful transformation. Failings of adaptation can often be attributed to a lack of communication, support, and a proper reward system, no clear vision, and a loss of competency. Strategies which could be implemented by the leaders of the organization include an Integration plan, HR structuring, Downsizing, and Employee Involvement. The Employee Involvement strategy relates to employees needing to be well informed of the changes and aware of why the changes are required, and the consequences the changes imply. Ultimately, many aspects can negatively affect employees' post-M&A performance, although effective integration can limit these consequences.

2.4 Measuring Private M&As

M&A research is often divided between public and private firms. Golubov and Xiong (2020) compared the post-acquisition performance of private and public firms. They found that private firms experience greater improvements in operating performance compared public firms. These findings are related to better management, lower overhead costs, and lower capital expenditures. Accounting data is a commonly used data source for analyses of private acquisitions. Using accounting data has, however, received criticism compared to market data (Thanos and Papadakis (2012)). Fisher and McGowan (1983) argue that *"there is no way in which one can look at accounting rates of return and infer anything about relative economic profitability..."*. However, Thanos and Papadakis (2012) present two arguments in favour of using accounting based measures to evaluate potential synergies of M&As. 1) Accounting data present measures for actual post-M&A performance reported in annual financial statements (Grant et al. (1988)). Additionally, the data is not a representation of investors' future believes. (Hitt et al. (2002)). 2) The literature argue that long-term accounting measures present the most suitable presentation of synergies. An example of such a measure is return on assets (ROA).

Empirical acquisition studies based on accounting data differ from stock return-based data. Accounting studies are often based on data from several years pre- and post-acquisition (Thanos and Papadakis (2012)). Stock data studies usually describe daily returns surrounding the announcement date. However, there are issues with using accounting-based data in studies. 1) Different studies use different accounting-based measures for performance. This weakens the comparability between studies. 2) There are issues with methodology development. 3) There could be a lack of available data and possible accounting errors for large panels, which could weaken studies. Ultimately, using accounting data is a common method of analyzing private M&As, but there are several caveats in relation to using accounting data.

3 Data

Our analysis aims to define and isolate the effect of M&As on employee performance. Therefore, we must identify occurrences of M&As and measure them over time. We have created an algorithm which identifies M&As from accounting data based on changes in the registered parent company. Our data consists of accounting data for all registered firms in Norway between 2007 and 2016, retrieved from Regnskapsdatabasen (Mjøs and Selle (2022)). Regnskapsdatabasen (2022) ensures data quality by performing several steps of data processing.[7] The data includes accounting data and additional descriptive characteristics for each firm in a fiscal year. Thus, the data can reflect changes in a company's performance over time. All accounting numbers are presented in thousands of NOK. Firstly, we will outline the data filtering process. Then, we will describe the identification algorithm. Lastly, we will present descriptive statistics of the data.

3.1 Data Filtering

To increase the validity of our analysis and remove errors, we performed several steps of filtering. Initially, the data set consisted of 4,549,089 observations from 1999 to 2020. The filtering process is illustrated in Table 3.1. It consists of the following steps: 1) We filtered all observations with missing values in key metrics, such as total income and earnings. The M&A identification algorithm relies on the presence of a parent company as it identifies M&As based on this variable. Therefore, we filtered all observations without a registered parent company as well. We also removed any observations with no majority owner.[8] 2) We removed any publicly listed companies to limit our scope to private companies.[9] 3) Because we are trying to isolate the effect on employees, we chose to proceed with companies with more than five employees. 4) Because we are trying to measure the same companies over time, we removed companies with less than five years of consecutive data. After the initial filtering processes, the data sample consisted of 328,065 observations.

[7] Mjøs and Selle (2022) state the following steps: 1) Selecting data from quality sources. 2) Controlling for obvious accounting errors. 3) Consistency control over time. 4) User feedback.

[8] Regnskapsdatabasen (Mjøs and Selle (2022)) states that a value of at least 0.5 in max ownership is necessary to assign a parent company. However, we still found errors where this is not the case. Therefore, we removed these observations.

[9] This removed only a few observations, as most publicly listed companies do not have a majority owner with a 50% stake or more. These observations were removed in step 2.

Table 3.1: Data Filtering Process

Action	**Observations**
Raw data – initial data from 1999 to 2020	4,549,089
Removing all NA-values in key variables	1,223,319
Removing firms not listed on a stock exchange	1,222,670
Removing firms with less than five employees	501,127
Time frame condition	328,065
Creation of Panel Data	149,956
Removing Years and Balancing	118,070
Occurrences of M&As	1,820

The table presents an overview of the total number of observations for each respective step in our data filtering process. All steps until the time frame condition is performed before the algorithm is executed. The removal of certain years and the balancing are explained in section 3.2.

3.2 The M&A Identification Algorithm

The original data does not contain identified M&As. Therefore, we have created an M&A identification algorithm. M&As can be identified by finding companies which experience a change in parent name and parent organization number between two fiscal years. This would represent a new majority owner of the firm (Mjøs and Selle (2022)). However, this method of identifying M&As is prone to be inaccurate. This is because it would identify genuine name changes or re-registrations by the original parent company, which would create false positives of M&As. Furthermore, is the ownership of a firm is changed to another firm within the same corporation, it would still be marked as a M&A. A high occurrence of false positives would decrease the validity of our analysis. Therefore, we try to remove as many occurrences of false positives as possible. After manually assessing the data, we identified several characteristics of genuine name changes which differed from M&As. Many of the changes used parts of the old parent name in the new parent name. Additionally, many of the false positives registered new holding companies as a new parent. The new holding company names often closely resemble the company names themselves. Therefore, we can eliminate some of these occurrences by checking for similarities between the old and new parent names, and the new parent and company name. Furthermore, we can remove genuine name changes by requiring a change in the parent's organization number.

We have created an algorithm which identifies changes in the parent's name and organization number between two years and evaluates the similarities between the old and new names. After manually assessing 100 M&As marked by the algorithm, we find 85% to be genuine M&As. The remaining 15% are false positives. These are caused by more complex name changes and abbreviations which require a more advanced identification process to be identified. Due to the limited time frame and scope of this thesis, we could not further optimize the algorithm's accuracy. In the future, the algorithm can be improved by implementing more sophisticated methods of textual comparison or machine learning models.[10] The final algorithm is presented in appendix A1, and the conditions and process are outlined in table 3.2. To our knowledge, our algorithm is the first to identify M&As in such a way for private Norwegian accounting data. The algorithm will enable other researchers to study Norwegian M&As on a large sample using accounting data.

The algorithm sorts the data set by organization number and year and reads through each observation chronologically. For each observation, the algorithm will check for six conditions to determine an acquisition: 1) The current observation has data for one year prior, and three years post. 2) There has been a change in the parent's name and the parent's organization number in the next year. 3) The parent's name is longer than one word. This removes instances with limited information to evaluate similarity because we need at least two words in this process. 4) No similarities between the old and new parent's name, the new parent's name, the company name, and no similar abbreviations. 5) The fiscal years within -1 to +3 years of the observation are in consecutive order. This ensures that we have observations in consecutive years when evaluating the changes over time. 6) The new parent company was not the same owner in the year before the M&A, and the new parent number is the same for the next three years following the M&A. If all six conditions are met, the observation is marked as a M&A in the given year, defined as the pre-acquisition year. M&As are marked by the binary variable MA2.[11] Lastly, as the same company can be acquired multiple times, we only kept the most recent M&A for each company. Furthermore, if an observation is marked as a M&A, we remove observations outside the M&A time frame. These two procedures are done to avoid complications in

[10]See appendix A1 for suggested improvements and comments.

[11]Initially, the algorithm creates a new variable called "MA1" for the company following the acquisition. MA1 equals one in the acquisition year and between -1 and +3 for the years before and after the M&A. MA1 will have no value if no acquisitions are found. Additionally, we created a new variable called "MA2", which equals one if MA1 equals zero, else MA2 equals zero. The MA2 variable thus marks "year zero", the last year before the firm is acquired.

the matching process. In total, 1820 observations were marked as a M&A.

Table 3.2: Algorithm Conditions

Conditions
1. The M&A has consecutive data within -1 and +3 years.
2. The parent number and name is different in the next year.
3. The parent name is longer than one word.
4. The new and old parent name, and the company name, does not have similarities.
5. The time-frame years are in consecutive order.
6. The new parent is parent for the next three years, and has not been parent in the past year.

The table presents an overview of the M&A identification algorithms conditions. The algorithm consists of six conditions in consecutive order. If all conditions are fulfilled, the observation will be marked as a M&A.

3.3 Descriptive Statistics

The following section will present the final data set and descriptive statistics. After running the identification algorithm, we turn all observations into horizontal panel data by adding each observations between -1 and +3 years to the columns of each variable. We then remove missing values which were generated from insufficient consecutive observations. The data set consisted of 149,956 observations after generating the horizontal data set. However, after inspecting the new data set, it became clear that many variables were flawed or unbalanced. Equity ratio, operating margin, and interest rate were unbalanced before the matching, as presented in appendix figure A2.1 to A2.3. Observations with values outside -1 to +1 of these variables were removed as such instances were viewed as errors. Furthermore, the number of MA2 variables in 2006 and 2017 contained errors and were removed from the sample.[12]

Table 3.3 below outlines an overview of the variables used in our analysis. Except for some generated variables, these are preexisting variables from the original data set by Regnskapsdatabasen (Mjøs and Selle (2022)). We have created binary vectors of year,

[12]In 2017, there were relatively few MA2 observations compared to surrounding years. This is illustrated in appendix table A2.1. We cannot identify any natural explanation for these differences in means, and we define them as strange. We have performed extensive research to find the cause of this problem without success. After looking through the different formats, data types, regulatory changes, and the MA2 algorithm, we conclude that none of these are the root cause of the problem. The problem occurs when comparing the parent's organization number between 2016 and 2017, and it fails to recognize changes correctly. The error also occurs in the initial data set before performing any operations. The same error, but with a relatively higher mean, happens in 2006. Ultimately, we view these occurrences as errors and choose to remove them from the sample.

sector, region and credit score to isolate the fixed effects.[13] [14] Lastly, we generated three numeric variables, the logarithm of Total Assets (TA), Interest Rate, and Return On Asset (ROA).[15] Variables selection will be outlined in section 4.2.1.

Table 3.3: Variable name, description and type.

Variable	**Description**	**Type**
Employees	Number of employees	Numeric
FA	Fixed Assets	Numeric
Operating Margin	Operating Profit divided by Revenue	Numeric
Year	Fiscal Year	Numeric
Equity ratio	Equity divided by total assets	Numeric
Profitable	1 if earnings >0, else 0	Binary
Max Ownership	Ownership share of majority owner	Numeric
TA	Total Assets	Numeric
log(TA)	Logarithm of TA	Numeric
Sector	Sector Dummy, Table A2.2	Dummy
Credit Score	Credit Score Dummy, Table A2.3	Dummy
Region	Location Dummy, Table A2.4	Dummy
Earnings	Earnings for the given year	Numeric
Interest rate	Interest expenses divided by total debt.	Numeric
TI	Total Income	Numeric
EBITDA	Earnings Before Interests, Taxation, Deprivations and Amortization	Numeric
TI/Employees	TI divided by number of employees	Numeric
EBITDA/Employees	EBITDA divided by Employees	Numeric
ROA	Return On Assets, Earnings divided by TA	Numeric

The table presents descriptions of variables names and characteristics for each of the variables used in the analysis. From the left, the table presents the variable name we use in this paper, the description of the variable, and the type of the variable.

Before performing the analysis, the final data set was split into two groups, acquired and non-acquired firms. Table 3.4 below illustrates descriptive statistics for the two groups and the total sample. The table shows that there are large differences between the two groups. Most notably in the means and standard deviations. TI/Employees and EBITDA/Employees are our outcome variables to measure employee performance. The measure ROA is used as the outcome variable for firm performance. These are described in Table 3.3 and will be further outlined in section 4.2.1. Initially, there are especially large differences in the means of the outcome variables for the two groups. Especially

[13]We will use the terms sector and industry interchangeably throughout this thesis

[14]There was some observations that had a value of zero in region, but these were removed as they were perfect predictors to not receiving the treatment. This resulted in 36 observations being removed in the creation of the horisontal data set.

[15]We use the logarithm of TA to balance this variable.

EBITDA/Employees is largely different, with means of 315 for the controls and 163 for the treated group. However, the medians differ less for all of the outcome variables. ROA is especially closer with a median of 0.07 for the controls and 0.068 for the treated group. In total, it seems that large outliers strongly skew the means of the $MA2 = 0$ group to the upside. This is especially presented in the TI/Employees, EBITDA/Employees, Employees, and log(TA) columns.

Table 3.4: Descriptive Statistics

Ma2 = 0	**Mean**	**p50**	**Min**	**Max**	**SD**	**N**
TI/Employees	2,859	1,562	.448	1,065,833	9,212	116,250
EBITDA/Employees	315	96	-25,089	846,167	4,833	116,250
ROA	.076	.070	-2.08	2.94	.151	116,250
Employees	56.5	17	5	25,507	286.5	116,250
FA	153,535	2,037	-4,161	3.84e+08	3,972,791	116,250
log(TA)	9.8	9.5	4.1	21.4	1.6	116,250
Equity Ratio	.281	.259	-1	.99	.22	116,250
Profitable	.8	1	0	1	.4	116,250
Interest Rate	.010	.003	-.097	.737	.017	116,250
Max Ownership	.93	1	.5	1	.14	116,250
Operating Margin	.055	.045	-.999	1	.12	116,250
Sector	4.6	5	0	9	3.3	1162,50
Year	2011.8	2012	2007	2016	2.86	116,250
Credit Score	2.2	2	1	6	.9	116,250
Region	3.8	4	1	6	1.4	116,250
Ma2 = 1						
TI/Employees	2,306	1,487	66.7	59,312	3,457	1,820
EBITDA/Employees	163	80.4	-3,143	6,561	393	1,820
ROA	.061	.068	-3.342	2.587	.203	1,820
Employees	52.3	19	5	4,653	189.6	1,820
FA	30,493	1,960	0	3,663,899	184,709	1,820
log(TA)	9.66	9.48	5.55	15.68	1.47	1,820
Equity Ratio	.252	.24	-.98	.90	.23	1,820
Profitable	.8	1	0	1	.4	1,820
Interest Rate	.012	.004	-.088	.424	.018	1,820
Max Ownership	.884	1	.5	1	.171	1,820
Operating Margin	.041	.042	-.916	.536	.117	1,820
Sector	4.3	4	0	9	3.4	1,820
Year	2012.1	2012	2007	2016	2.8	1,820
Credit Score	2.4	2	1	6	1	1,820
Region	3.8	4	1	6	1.4	1,820
Total						
TI/Employees	2,851	1,562	.5	1,065,833	9,152	118,070
EBITDA/Employees	312	96	-25,089	846,167	4,796	118,070
ROA	.076	.07	-3.34	2.94	.152	118,070
Employees	56.5	17	5	25,507	285.2	118,070
FA	151,638	2037	-4,161	3.84e+08	3,942,149	118,070
log(TA)	9.8	9.5	4.1	21.4	1.6	118,070
Equity Ratio	.281	.259	-1	.998	.219	118,070
Profitable	.8	1	0	1	.4	118,070
Interest Rate	.011	.003	-.097	.737	.017	118,070
Max Ownership	.9	1	.5	1	.1	1180,70
Operating Margin	.055	.045	-.999	1	.119	118,070
Sector	4.6	5	0	9	3.3	118,070
Year	2,011.7	2012	2007	2016	2.86	118,070
Credit Score	2.2	2	1	6	.9	118,070
Region	3.8	4	1	6	1.4	118,070

Overview of descriptive statistics. All variables are previously defined in table 3.3. The columns present the variable name, mean, median, minimum value, maximum value, the standard deviation, and the number of observations. The control sample is displayed at the top part of the table (MA2 = 0), the treated sample is displayed in the middle part of the table (MA2 = 1), and the total sample at the bottom.

To further analyze the differences between the two groups, we perform a t-test with unequal variance to analyze whether the two groups are statistically different (Kim (2015)). The results are presented in table 3.5. The T-value for both variables indicates that the two groups are different. This is problematic when we want to isolate the causal effect on employee performance. We must limit the initial differences between the groups to interpret the effect as causal. Therefore, we perform a balancing prior to the matching process. This is outlined in the following methodology section.

Table 3.5: t-tests pre-matching

Variable	**Obs**	**Mean**	**Std. error**	**Std. dev**
EBITDA/Employees				
0	67,994	286.9	7.3	1907.5
1	937	159.6	12.0	366.7
T	9.07			
Ha: diff !=0	00.00***			
TI/Employees				
0	67,994	2878.6	26.2	6820.4
1	937	2404.6	121.7	3724.1
T	3.81			
Ha: diff !=0	0.00***			
ROA				
0	67,994	.075	.001	.143
1	937	.058	.007	.207
T	2.42			
Ha: diff !=0	0.02**			

The table presents a two-sample t-tests with unequal variance for our outcome variables. The control group are marked with 0, while the M&As group is marked with 1. The table presents total number of observations, mean, standard errors, and standard deviation. In the second section, the T-value and p-value for the null hypothesis that the two groups are not different.

4 Methodology

To analyze the causal effect on employees, we must isolate the effect of M&As on the target firm (Rubin (1974)) (Dehejia and Wahba (1999)). Therefore, we must limit performance differences between targets and other firms. The acquiring firm performs extensive research to find high-growth potential targets (Martin (2016)). This may lead to self-selection bias if only high-performing firms are chosen as targets. To specifically investigate the causal effects on a firm post-M&A and minimize self-selection bias, we use PSM (Caliendo and Kopeinig (2008)) (Rosenbaum and Rubin (1983)). Chari et al. (2009) and Szücs (2013) utilize PSM to identify the causal effect of M&As. PSM balances the differences pre-M&A between the acquired and non-acquired firms through propensity scores, which creates a suitable benchmark for comparison (Rosenbaum and Rubin (1983)). The two groups are then matched based on a NN matching of the propensity scores, which reduces the bias. Because of potential problems with the unconfoundedness assumption in PSM, we include a NN matching combined with a DD analysis as a robustness analysis. Combining these methods allows us to interpret the results as causal, with a relaxed unconfoundedness assumption. Then, we create a regression function which represents the production output of a firm. We base our analysis on the Cobb-Douglas production function to measure firm output. By controlling for capital and TFP, we isolate the effect on labor productivity. Lastly, we outline the selected variables for the production function.

4.1 Matching Methods

4.1.1 Propensity Score Matching

PSM estimates the effect of confounding variables (Rosenbaum and Rubin (1983)) (Angrist and Pischke (2009)). Firms are divided into two groups: a treated group and a control group. The treated group contains all firms marked as M&As by the identification algorithm. The control group includes all remaining firms. The matching of treated and control observations is conducted based on an assigned propensity score. The propensity score is the observation's likelihood of receiving the treatment. Treated observations are then matched with the control observations with the closest propensity score. The method aims to yield an unbiased estimate of the treatment effect. This is done by removing initial differences by matching firms based on pre-M&A data and exploring relevant differences post-M&A.

Bias is limited when outcomes are independent of assignment to the treatment conditions on pre-treatment covariates. To estimate the ATT, the outcome in the untreated state must be independent of the treatment assignment (Rosenbaum and Rubin (1983)). The ATT is defined as:

$$\tau_{ATT} = E[\tau \mid D = 1] = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1)] \tag{4.1}$$

The ATT is the estimated (E) treatment effect (τ) for an individual who received the treatment ($D = 1$) (Rosenbaum and Rubin (1983)) (Caliendo and Kopeinig (2008)). The treatment effect specifically looks at the estimated difference a treatment makes on individuals who received the treatment $[Y(1) \mid D = 1]$ compared to if they had not received the treatment $[Y(0) \mid D = 1]$. On the other hand, the average treatment effect (ATE) is defined as:

$$\tau_{ATE} = E(\tau) = E[Y(1) - Y(0)] \tag{4.2}$$

The ATE is the estimated (E) difference between if the treated state ($Y(1)$) and the non-treated state ($Y(0)$) (Rubin (1974)) (Caliendo and Kopeinig (2008)). The ATE only calculates the average treatment effect if the treatment was randomly assigned and does not specifically consider the effect of the treatment on those who received the treatment. If total randomness had existed in the data, $E(\tau|D = 1)$ would be equal to the $E(\tau)$. Then, firms involved in a M&As would be random. With randomized treatment assignments, the treated and the control groups can be directly compared. However, with non-randomized treatment assignments, the two groups differ systematically. Therefore, a direct comparison between the two groups may give skewed and biased results.

To compare the two groups, a balancing is required (Rosenbaum and Rubin (1983)). A balancing score, b(x), is a function of the covariates X. The conditional distribution of x given b(x) is the same for the treated ($D = 1$) and untreated ($D = 0$) groups. Creating propensity scores creates a basis for comparison of the two groups that control for the non-random treatment assignment.

A propensity score is the conditional probability of an individual receiving the treatment

(Rosenbaum and Rubin (1983)). Propensity scores are defined as:

$$P(X) = P(D = 1|X) \tag{4.3}$$

An individual's propensity score is the probability (P) of receiving the treatment, given the set of covariates X (Rosenbaum and Rubin (1983)) (Caliendo and Kopeinig (2008)). The method is based on two fundamental assumptions:

Assumption 1: Unconfoundedness:

$$Y(0), Y(1) \sqcup D|X \tag{4.4}$$

$\sqcup$ denotes independence between treatment and covariates (Caliendo and Kopeinig (2008)). The treatment does not influence a set of observable covariates X, and the potential outcomes of this set are independent of the treatment assignment (Rosenbaum and Rubin (1983)). Therefore, all variables affecting treatment assignment and potential outcomes need to be simultaneously observable.

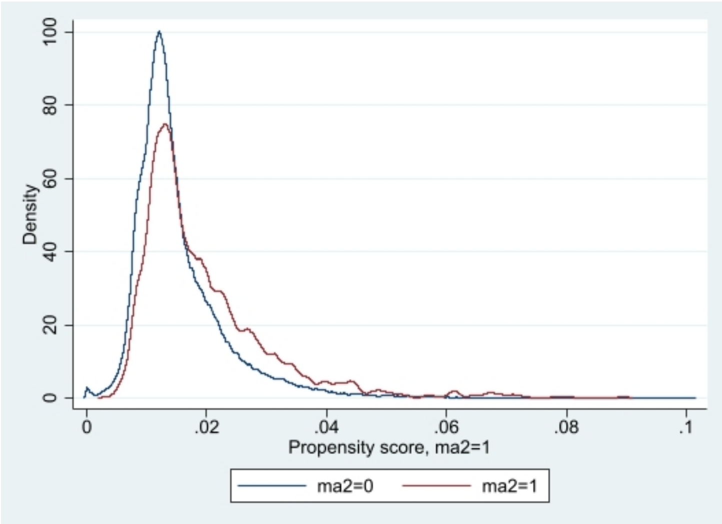
Assumption 2: Overlap:

$$0 < P(X) < 1 \tag{4.5}$$

The overlap assumption assures that an individual with the same covariates X has a positive probability of being in both groups (Rosenbaum and Rubin (1983)) (Caliendo and Kopeinig (2008)). This assumption is often referred to as common support. All individuals in the sample must be eligible to receive the treatment. No individual can be guaranteed to receive the treatment. Furthermore, the assumption demands an overlap in the distribution of propensity scores between the treated and the control group (Garrido et al. (2014)).

Figure 4.1 illustrates an overlap plot of the sample's propensity scores. A large overlap in propensity scores between the treated and the control groups indicate good matching (Caliendo and Kopeinig (2008)). There is a larger density of treated observations with propensity scores between 2% and 4%, which is relatively low for predicting the treatment. The basis for creating propensity scores is to achieve balance, which ultimately implies that low propensity scores do not present an obstacle if there is balance. The large degree of overlap indicates balance. The main challenge with the overlap assumption is a lack of control observations to compare to the treated observations. To control for this, a caliper is implemented in the main analysis.

Figure 4.1: Propensity Scores, Overlap



The figure visually presents the overlap plot for the propensity scores of the treated and control group. The treated are illustrated in red, and the control in blue. The Y-axis illustrates the density of the sample observations, and the x-axis the propensity score.

The caliper method imposes a maximum distance between matched observations to better fulfill the common support assumption (Caliendo and Kopeinig (2008)). This is often referred to as the propensity range. If there are no matches within the propensity range for a treated observation, the observation is dropped from the sample. Furthermore, control observations which are not within the propensity range of a treated observation are dropped. As treated observation with no clear match is no longer matched with possible outliers, bias is reduced. We will conduct analyses using mostly 0.25 times the SD to the propensity scores.

Previous research argue the strictness of Assumption 1 (Caliendo and Kopeinig (2008)). Heckman et al. (1998) demonstrate that the unconfoundedness assumption is overly strong. Per research, solely mean independency is needed in estimations of PSM (Caliendo and Kopeinig (2008)) (Heckman et al. (1998)). However, Lechner (2002) and Imbens (2004) argue why mean independency should not hold on its own, and violations of Assumption 1 might still be present in empirical research. Research implies different strictness on the assumptions. Therefore, to further control for bias, we conduct a NN matching combined with a DD analysis as a robustness test.

The calculation of the ATT is dependent on multiple decisions, both regarding the chosen model and variables. Based on Smith's (1997) findings, the probability model is disregarded due to the shortcomings of the model. A probit and a logit model present fitting characteristics for the thesis' binary treatment analysis and usually yield similar results. The logit distribution is the chosen model as it has more densely masses in the bounds(Caliendo and Kopeinig (2008)).

4.1.2 Nearest Neighbour

The NN method matches a treated observation with the most similar non-treated observation based on its covariates X (Imbens (2004)) (Caliendo and Kopeinig (2008)) . In comparison to PSM, NN matches solely on the similarity of the covariates, and does not calculate the probability of receiving the treatment (Rosenbaum and Rubin (1983)). Furthermore, matching can be conducted on exact values of covariates for stronger matches. The NN approach can be conducted in combination with a PSM analysis or a DD analysis. In PSM, NN matching matches treated and controls on propensity scores. In combination with a DD analysis, the NN approach creates a more comparable benchmark between the treated and controls. The NN approach can be used to match on exact covariates of treated and controls to create a matched sample, which the DD analysis is conducted on.

When increasing the number of control observations matched to each treated observation, you achieve "oversampling" (Caliendo and Kopeinig (2008)). Oversampling decreases the variance, while the bias in the analysis increases from average poorer matches (Smith (1997)) (Rassen et al. (2012)). We implement a 5:1 NN matching in one of the PSM analyses. This implies matching each treated observation to the five control observations with the most similar propensity scores. A caliper can be implemented in combination with oversampling. Then, each treated observation must have the desired number of matches within the caliper to be included in the analysis.

Matching processes are often divided between "with" and "without" replacement of matched observations (Austin (2014)). All of our NN-matching regressions are done using "with replacement". With replacement implies that a control observation can be matched with multiple treated observations. The method will increase the matching quality and decrease bias but will increase the variance in the analysis (Smith and Todd (2005)).

4.1.3 Difference-In-Difference

A DD analysis is conducted to control for potential problems with the unconfoundedness assumption in PSM.[16] This assumption is relaxed with the DD approach (Caliendo and Kopeinig (2008)). For M&As, several covariates may affect treatment assignment and outcome simultaneously, which are unobservable in accounting data. Examples of such covariates can be the technology and human capital within a company (Tcheng (2023)). Therefore, performing the combined NN and DD analysis may strengthen our analysis with a relaxed unconfoundedness assumption. When conducting the DD analysis this is done on a matched sample from the NN matching, and not the original sample to isolate the ATT. The NN matching tries to remove differences between the firms pre-treatment. Also, the NN tries to validate the parallel-trend assumption in DD.

The DD method identifies the causal effect of a binary treatment on panel data (Hopland (2017)). DD measures the difference in the change in outcomes between the treated and control observations post-treatment (Angrist and Pischke (2009)). The method assumes that the treated and controls would have had the same trends over time without the treatment. Thus, the differences in trends are caused by the treatment (Ryan et al. (2019)). This assumption is referred to as the Parallel Trend Assumption.

Our data consists of the same individuals observed over time, which can be characterized as longitudinal panel data (Lee and Kang (2006)). The data is divided into four groups based on two factors: treatment (MA2) and time (Post). The four groups are treated pre-treatment (1), treated post-treatment (2), control pre-treatment (3), and control post-treatment (4). The difference in outcomes for the two treatment groups is the difference between groups 2 and 1 (4.6) and between groups 4 and 3 (4.7). The differences in expected output pre- and post-treatment are defined as:

[16] The treatment does not influence a set of observable covariates X, and the potential outcomes of this set are independent of the treatment assignment (Rosenbaum and Rubin (1983)) (Caliendo and Kopeinig (2008)). Furthermore, all variables affecting treatment assignment and potential outcomes must be simultaneously observable.

$$E[Y_{ist} \mid s=1, t=1] - E[Y_{ist} \mid s=1, t=0] = \lambda_1 - \lambda_0 + \delta \tag{4.6}$$

$$E[Y_{ist} \mid s=0, t=1] - E[Y_{ist} \mid s=0, t=0] = \lambda_1 - \lambda_0 \tag{4.7}$$

where s denotes treatment, and t denotes time (Angrist and Pischke (2009)). λ_t describes the time specific effect. δ describes the DD-estimator, which reflects the causal effect of the treatment (Caliendo and Kopeinig (2008)). The DD-estimator is the difference between equations (4.6) and (4.7).

$$\begin{gathered}[E[Y_{ist} \mid s=1, t=1] - E[Y_{ist} \mid s=1, t=0]] - \\ [\mathrm{E}[\mathrm{Y}_{ist} \mid s=0, t=1] - E[Y_{ist} \mid s=0, t=1]] = \delta\end{gathered} \tag{4.8}$$

The calculation of the DD-estimator is derived from the following regression function (4.9) (Angrist and Pischke (2009)):

$$Y_{ist} = \alpha + \gamma_s * MA2 + \lambda_t * Post + \delta_{st} * MA2 * Post + \beta_X * X_{ist} + \varepsilon_{ist} \tag{4.9}$$

(4.9) describes the output Y_{ist}, which is a function of a constant (α), a treatment specific effect (γ_s), time specific effect (λ_t), a interaction effect between time and treatment (δ_{st}), a set of control variables X, and the residuals (ε) (Angrist and Pischke (2009)) . The DD-estimator describes the ATT and is denoted as (δ_{st}) in the regression function.

There are two sources of selection bias of concern with the DD method, across time and across groups (Stuart et al. (2014)). Selection bias across time implies that the groups change in composition over time. Selection bias across groups occurs when the two groups differ. This is especially of concern when they differ over time. In the current sample, the groups do not change across time as they consist of the same companies pre-and post-treatment.

Two statistical tests have been performed to assess our DD model's matching quality. Firstly, we have conducted a t-test with unequal variance to measure whether the means of the outcome variables are significantly different between the groups (Fagerland (2012)). Secondly, a two-sample Kolmogorov-Smirnov test (KS-test) is conducted to test for significant differences in the distribution of the three dependent variables between the groups (Dodge (2008)). KS-tests are superior to t-tests when comparing continuous variables because the test measures the distance between the distributions of observations instead of the means (Sekhon and Grieve (2012)). However, we perform both tests as ROA is not a continuous variable.

4.2 Productivity Function

This section will describe our productivity function, which is used to calculate labor productivity. The analysis is based on the Cobb-Douglas production function (4.10), as it is commonly used to calculate company outputs (Felipe and McCombie (2020)). In the Cobb-Douglas function, total output (Y) is a function of TFP (A), capital input (K), and labor input (L), with α and β being the output elasticity of K and L (Cobb and Douglas (1928)) (Solow (1957)).

$$Y = A * K^{\alpha} * L^{\beta} \tag{4.10}$$

The output elasticities represent the change in output given a 1% change in the input factor (Goolsbee et al. (2016)). Given constant returns to scale for the elasticity ratios $\alpha + \beta = 1 \Leftrightarrow \beta = 1 - \alpha$. Constant returns to scale imply an exact proportional change in output to the change in input factor.

The TFP is the calculated relationship of output per unit of cost (Felipe and McCombie (2020)). Therefore, TFP indicates how efficient a firm's production is in the transfer of labor and capital into output. Thus, we must control for TFP to limit omitted variable bias when measuring labor productivity. Rearranging the Cobb-Douglas function gives the formula for TFP:

$$A = \frac{Y}{K^{\alpha} * L^{1-\alpha}} \tag{4.11}$$

Furthermore, the thesis aims to examine labor productivity. This measure is the calculated added value per employee (Felipe and McCombie (2020)). It is a broader measure compared to TFP as it reflects the joint influence of changes in TFP and the capital-labor ratio:

$$\frac{Y}{L} = \frac{A * K^{\alpha} * L^{1-\alpha}}{L} = A * K^{\alpha} * L^{1-\alpha-1} \tag{4.12}$$

The labor productivity on logarithmic form is given by (Felipe and McCombie (2020)):

$$ln(\frac{Y}{L}) = ln(A) + \alpha ln(\frac{K}{L}) = ln(y) = ln(A) + \alpha ln(k) \tag{4.13}$$

Changes in TFP are directly linked to efficiency and, therefore, the effects of an acquisition on firm efficiency (Armagan and Ozden (2007)). Furthermore, the productivity function is derived from the residual from a production function of the logarithmic form:

$$y = \alpha + \theta^k k_i + \theta^l l_i + \varepsilon_i \tag{4.14}$$

y denotes the added value, k the physical capital input, and l the labor input (Beveren (2007)). The θ vectors are the average input elasticizes. Lastly, ε_{jst} is the error term of the regression function. Equation (4.14) is based on the assumption of constant returns to scale (Felipe and McCombie (2020)). If output increases more or less than proportional to the change in inputs, there are either increasing or decreasing returns to scale.

Our analysis is based on PSM and the productivity function to compute the ATT. Besides the defined variables from equation 4.14, we will control for a set of covariates X. Lastly, the binary *MA2* variable is included. This variable identifies the ATT. Ultimately, we end up with the following regression function for our analysis:

$$y_{i(t+n)} = \alpha + \tau_{ATT} * MA2 + \theta^k k_i + \theta^l l_i + \beta_x X_i + \varepsilon_{it} \tag{4.15}$$

The set of control variables *(X)* will be outlined in the following section.[17] Our model will analyze the effect of the treatment on different dependent variables in years *t-1, t, t+1, t+2* and *t+3*.

4.2.1 Variable Selection

In this section, we will outline the variables used in the analysis. Our initial variables include labor and capital from the Cobb-Douglass function (Solow (1957)). A set of covariates X is further included to control for TFP and sources of omitted variable bias.

In our analysis, M&As are determined as the treatment. To interpret the effect of the treatment as causal, we must satisfy both PSM assumptions. Therefore only variables unaffected by the M&A or the anticipation of a M&A should be included.[18] Furthermore, we match on pre-treatment variables to measure the causal effect post-treatment (Stuart

[17] Includes a size variable of the log(TA), Equity Ratio, Profitability, Interest Rate, Sector, Year, and Max Ownership.

[18] Unconfoundedness assumption.

(2010)). Additionally, no variables can violate the common support assumption. Lastly, perfect predictors are not allowed because of the overlap assumption.

Variable inclusion is based on statistical significance, importance to the labor productivity function, and general economic reasoning. See table 5.1 for Ordinary Least Square (OLS) regressions describing significant variables to MA2 and the three defined dependant variables. All variables relevant to one or more of the three dependent variables or MA2 are included. Employees and Physical Capital are parts of the Cobb-Douglas function. Log(TA) controls for firm size. Year, Credit Score, Region, and Sector are fixed effects. Max Ownership describes pre-M&As ownership structure. Equity Ratio, Profitable, Interest Rate, and Operating margin controls for economic performance.

5 Analysis

The analysis of this paper aims to measure the causal effect of M&A on employee performance. Firstly, we will conduct an OLS regression on MA2 and the three dependent variables in the matching year (Burton (2021)). An OLS analysis presents the effect of a M&A if we do not control for confounding variables and follows Healy et al. (1992). Secondly, we will present and discuss our main findings from the PSM analysis. Multiple PSM analyses have been conducted to explore different aspects and investigate possible instances of bias. Additionally, previous research indicated that both size and sector may affect post-M&A performance. Therefore, we conduct additional in-depth analyses to investigate these effects on employee performance. Lastly, we conduct a combined NN and DD analysis to strengthen the findings of the main PSM model. This is performed to control for sources of bias concerning the unconfoundedness assumption in PSM. We use a 5% p-value threshold for all statistical tests to determine statistical significance. Additionally, we discuss findings below a 10% value as indications.

5.1 OLS Regression

We have conducted an OLS analysis to display correlations and the effects of M&A without controlling for confounding. This implies that all significance is interpreted as correlations and thus not the causal effects of M&A (Burton (2021)). Such an analysis is similar to Healy et al. (1992), who found a positive effect on firm performance for the merged entity following an acquisition. The regression model analyses the three dependent variables in the matching year. Additionally, we present a regression with MA2 as the dependent variable.

The results are displayed in table 5.1. Most covariates have a statistically significant relationship to the three dependent variables. Equity Ratio, Operating Margin, and Max Ownership are the only covariates with a significant relationship to MA2. The results do not indicate any significant relationship between MA2 and our outcome variables beneath the 5% threshold. TI/Employees have a significant relationship to MA2 at a 10% level. This might indicate that the treated and untreated groups differ before the M&A. This is supported by the findings of the t-test conducted in table 3.4 which concluded that there were significant differences between the treated and the non-treated groups.

Table 5.1: OLS - Measuring in matching year

VARIABLE	(1) MA2	(2) $\frac{TI}{Employees}$	(3) $\frac{EBITDA}{Employees}$	(4) ROA
MA2		-52.2	-348.1*	-0.001
		(110.9)	(204.2)	(0.002)
Employees	-6.36e-08	-0.814***	-3.453***	3.66e-06***
	(1.35e-06)	(0.1)	(0.1)	(1.07e-06)
FA	-8.80e-11	8.28e-05***	0.0002***	8.30e-11
	(9.65e-11)	(3.68e-06)	(6.77e-06)	(7.63e-11)
log(TA)	0.0004	303.8***	1,566***	-0.01***
	(0.0003)	(10.0)	(18.4)	(0.0002)
Equity Ratio	-0.01**	-165.4**	-2,120***	0.003**
	(0.002)	(81.0)	(149.0)	(0.002)
Profitable	-0.0002	-521.6***	278.3***	0.133***
	(0.001)	(42.1)	(77.6)	(0.001)
Interest Rate	0.02	-14.3	-12,367***	-0.740***
	(0.02)	(855.6)	(1,575)	(0.018)
Max Ownership	-0.04***	21.7	-389.5**	-0.025***
	(0.003)	(98.4)	(181.2)	(0.002)
Operating Margin	-0.01**	6,672***	3,567***	0.575***
	(0.004)	(138.5)	(255.0)	(0.003)
Constant	0.05***	-2,810***	-12,665***	0.080***
	(0.004)	(153.2)	(282.1)	(0.003)
Observations	118,070	118,070	118,070	118,070
R-squared	0.004	0.045	0.111	0.588

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents a OLS regression measuring MA2 and the three dependant variables in the matching year. The regression have also controlled for Sector, Year, Credit Score, and Region which are not displayed in the regression. Coefficients are presented without parenthesis.

We have conducted the same OLS regression but included the three dependent variables two years after the M&A in table A.3.1. MA2 becomes negatively significant at a 10% p-value level for ROA. However, we can not interpret the OLS results as causal due to confounding. In the following sections, we conduct PSM and DD analyses to further analyze the causal effect on employees and control for possible confounding.

5.2 PSM Model

We have conducted multiple PSM analyses to interpret the effect on employees as causal. First, we will present our main findings from the PSM model. We have conducted three main analyses. All three PSM analyses are based on the labor productivity regression function and all previously defined control variables are included. PSM1 is a simple PSM analysis based on all selected variables. PSM2 introduces a caliper to improve the matching quality. PSM3 implements a 5:1 NN matching in addition to a caliper to remove outliers. Then, we will investigate how firm size and sector differences affect the PSM results.

5.2.1 PSM Results

We will first present and discuss the findings from PSM1. In the PSM1 analysis, we use a 1:1 NN matching without a caliper. The results are presented in table 5.2 and prove mostly insignificant. TI/Employees gives negative ATT in the matching year below the 10% level. There are indications of negative results for EBITDA/Employees in the first- and third-year post-M&A. Three years post-M&A the results indicate a negative ATT NOK 39,100 for EBITDA/Employee barely above the 5% p-value. The ATT for EBITDA/Employees has no significance in the other years but has negative effects in the first year at a 10% p-value level. The ATT on ROA is negatively significant in years one and indicate an effect in year two post-M&A. In year one, the treated sample has a ROA of 1.6 percentage points lower compared to if the firm had not been acquired. The ATT is insignificant and assumed to have no effect in year three post-M&A.

The results align with null hypothesis, which suggested no effect on employee performance. Furthermore, M&As negatively affect firm performance through ROA. Significant ATT in the treatment year for TI/Employees could indicate bias and skew results from a potentially incomplete balancing of treated and controls. This bias can be denoted to poor matching because of the statistical difference in year zero for TI/Employees. The purpose of PSM is to balance the two groups before the treatment. By these results, TI/Employees does not seem to be sufficiently matched. Overall, the initial PSM could not remove the initial differences between the two groups for TI/Employees. The effect on EBITDA/Employees supports our null hypothesis of M&As having no effect on employees post-M&A. However, EBITDA/Employees in year three is boarder line negatively significant. The ATT for ROA coincides with previous research and our expectations. EBITDA/Employees and ROA do not indicate poor matching in years zero and minus one. This provides extra validity to these results. In PSM2, a caliper restriction is introduced to better the matching and results. A caliper will also control for the lack of overlap in propensity scores in the tails.

Table 5.2: PSM1 - No caliper & 1:1 NN

Variable	$\tau_{\mathbf{ATT}}$	**Std. error**	**t**	**P>| z |**	**Obs.**
TI/Employees (-1)	-60.6	129.0	-0.47	0.639	118,070
TI/Employees	-231.0	136.1	-1.70	0.090*	118,070
TI/Employees (1)	-184.8	143.2	-1.29	0.197	118,070
TI/Employees (2)	-86.4	145.9	-0.59	0.554	118,070
TI/Employees (3)	-188.4	138.7	-1.36	0.174	118,070
EBITDA/Employees (-1)	-3.6	19.7	-0.18	0.855	118,070
EBITDA/Employees	-13.4	14.8	-0.90	0.366	118,070
EBITDA/Employees (1)	-31.2	17.6	-1.78	0.076*	118,070
EBITDA/Employees (2)	-19.7	18.1	-1.09	0.275	118,070
EBITDA/Employees (3)	-39.1	19.9	-1.96	0.050*	118,070
ROA (-1)	.062	.060	1.02	0.308	118,070
ROA	-.004	.006	-0.64	0.521	118,070
ROA (1)	-.016	.007	-2.26	0.024**	118,070
ROA (2)	-.012	.007	-1.82	0.069*	118,070
ROA (3)	-.067	.078	-0.86	0.390	118,070

τ_{ATT} is the coefficient for the ATT

*** p<0.01, ** p<0.05, * p<0.1

PSM1 analysis for time periods -1 to 3 for the three dependent variables. Analysis is based on PSM1 with 1:1 NN and no caliper. Each row presents variable name, the ATT (τ_{ATT}) for each variable in a given period, the standard errors (Std. error), t-value (t), p-value ($P >| z |$), and total number of observations (Obs.).

PSM2 is based on PSM1 and includes a caliper of 0.25 times the SD to the mean of the propensity scores. The caliper of 0.00193508 eliminates matched pairs with a larger difference in propensity scores from the sample. Implementing a caliper should thus improve matching and remove outliers. Results are presented in table 5.3. Close to 600 observations were removed. All performance measures become insignificant. These results differ from PSM1, which indicated significance in two outcome variables in multiple periods. Only ROA one-year post-M&A shows negative effects on a 10% p-value level and is thus not considered significant.

Pre-M&A ATT is eliminated, which indicates better balancing. Furthermore, this should indicate a larger overlap in propensity scores between the two groups. There is no indication of any significant ATT on employee performance. As outliers have been eliminated, so have the significant results. The negative performance effect could be caused by removed outliers or initial differences between the groups. The introduction of a caliper has increased the SD for most variables. This leads to increased p-values and less statistical significance. ROA in years two and three are insignificant, indicating no ATT. All pre-M&A dependent variables remain insignificant, indicating no causality issues. Because of the large differences between the two PSM models, we perform a third model to validate the results. In PSM3, we utilize the caliper of 0.25 times the SD to the mean of the propensity scores, but implement a 5:1 NN matching. This should improve the matching and remove outlier pairs with less than five matches within the caliper.

Table 5.3: PSM2 - Caliper (0.00193608) & 1:1 NN

Variable	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	-98.1	142.7	-0.69	0.492	117,436
TI/Employees	-153.0	137.6	-1.11	0.266	117,436
TI/Employees (1)	-135.1	151.3	-0.89	0.372	117,436
TI/Employees (2)	-150.4	162.2	-0.93	0.354	117,436
TI/Employees (3)	-235.8	148.9	-1.58	0.113	117,436
EBITDA/Employees (-1)	-4.2	17.3	-0.24	0.807	117,436
EBITDA/Employees	-5.1	16.5	-0.31	0.758	117,436
EBITDA/Employees (1)	-21.7	17.1	-1.27	0.204	117,436
EBITDA/Employees (2)	-20.3	18.9	-1.07	0.283	117,436
EBITDA/Employees (3)	-13.7	19.2	-0.71	0.475	117,436
ROA (-1)	.004	.006	0.60	0.546	117,436
ROA	.000	.006	0.02	0.986	117,436
ROA (1)	-.013	.007	-1.80	0.073*	117,436
ROA (2)	-.003	.007	-0.42	0.678	117,436
ROA (3)	-.079	.073	-1.08	0.282	117,436

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

PSM2 analyzes for different time periods on the three dependent variables. Used in the analysis is 1:1 NN matching and a caliper of 0.25 times the SD to the mean of the propensity scores. The caliper is 0.00193608. Each row presents the variable name, the ATT (τ_{ATT}) for each variable in a given period, the standard errors (Std. error), t-value (t), p-value ($P >| z |$), and total number of observations (Obs.)

PSM3 is based on PSM2 and includes a 5:1 NN matching, results are presented in table 5.4. The stricter matching requirement eliminates approximately 600 observations. The ATT for TI/Employees in the matching year and three years post-M&A is negatively significant, both at a 1% p-value level. The results suggest that M&As lead to a NOK 347,500 lower TI/Employees in year three. There are no significant pre-M&A ATT for EBITDA/Employees. However, results indicate that M&As affect EBITDA/Employees, and therefore employee performance, negatively three years post-M&A. The ATT of ROA indicates no pre-M&A issues. The ATT is mostly insignificant, but one-year post-M&A is negatively significant at a 1% p-value level. The negatively significant results for ROA in the acquisition year increase as the matching requirements become stricter. The ATT indicates two percentage points lower ROA one-year post-M&A and 1.1 percentage points lower two years after the M&A.

Similar to PSM1, there exists pre-M&A significance for TI/Employees. This indicates that the balancing does not remove the initial differences between the groups. Therefore, the ATT is not fully isolated. TI/Employees in the third year suggests significant negative ATT. However, these should be questioned due to poor matching. Larger nuances are discovered as the matched sample per treated observation increases. The increase to 5:1 NN matching results in a lower variance in the analysis, which decreases the p-values. This results in negatively significant results. Further elimination of outliers has partly provided evidence of the effects of M&As. The average distance in propensity scores increases from more matches per treated observation. This results in average poorer matches, which negatively affects the credibility of the results. Ultimately, PSM3 finds no effect of M&As on employee performance and a negative effect on firm performance.

Table 5.4: PSM3 - Caliper (0.00193608) & 5:1 NN

Measure	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	-147.8	118.9	-1.24	0.214	116,864
TI/Employees	-297.1	110.3	-2.69	0.007***	116,864
TI/Employees (1)	-229.5	117.8	-1.95	0.051*	116,864
TI/Employees (2)	-210.9	136.2	-1.55	0.121	116,864
TI/Employees (3)	-347.5	129.8	-2.68	0.007***	116,864
EBITDA/Employees (-1)	-.5	15.6	-0.03	0.975	116,864
EBITDA/Employees	-11.0	12.0	-0.92	0.359	116,864
EBITDA/Employees (1)	-23.8	14.6	-1.63	0.103	116,864
EBITDA/Employees (2)	-13.9	15.1	-0.92	0.357	116,864
EBITDA/Employees (3)	-32.0	19.3	-1.66	0.097*	116,864
ROA (-1)	-.001	.005	-0.10	0.918	116,864
ROA	-.002	.005	-0.44	0.658	116,864
ROA (1)	-.020	.005	-3.86	0.000***	116,864
ROA2	-.011	.006	-1.92	0.055*	116,864
ROA3	-.096	.076	-1.26	0.207	116,864

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table presents the PSM3 analysis for different time periods on the three dependent variables. PSM3 consists of a 5:1 NN matching combined with a caliper of 0.25 times the SD to the mean of the propensity scores. The propensity range is 0.00193608. Each row presents the variable name, the ATT (τ_{ATT}) for each variable in a given period, the standard errors (Std. error), t-value (t), p-value ($P >| z |$), and total number of observations (Obs.)

To assess the matching quality of the PSM analyses, we have performed a balancing summary of all three models. Table 5.5 below presents the SD of the covariates in the treatment and control group before and after matching for PSM3. A good match is indicated by post-matching differences close to zero. The table shows that SD decrease for nearly every covariate post-matching. This is indicated by the difference being close to zero for the post-matching group, while the pre-matching group still has large differences (Stata (2023)).. Additionally, the summary presents the variance ratio between the two groups, post-and pre-matching. A variance close to one indicates that the variances are very similar and thus a good match. The variance ratios also indicate good matching with most covariates close to one, except employees. These results indicate that PSM3 produced good matches and strengthened our findings' validity. However, there is still large difference in the variance of the employee variable between the treated and control group. Additionally, we performed the balance summary for the two other models and dummies, presented in table A4.1 to A4.3. However, these produced worse matches compared to PSM3. Therefore, we deem PSM3 as the most accurate of our models.

Table 5.5: Matching Quality - PSM3

Variables	Pre-Match	Post-Match	Pre-Var. Ratio	Post-Var. Ratio
Employees	-.0004	.004	.761	.80
FA	-.046	.0014	.59	.997
log(TA)	-.055	-.003	.876	.935
Equity Ratio	-.109	-.007	1.11	.999
Profitable	-.075	-.012	1.107	1.02
Interest Rate	.049	-.009	1.24	1.05
Max Ownership	-.278	.011	1.46	.945
Operating Margin	-.088	-.017	.946	1.02

The table shows a balance summary of PSM3. It presents pre- and post-matching standard difference of the treated group and the control group, as well as the variance ratios between them. Additionally, we have balanced for Year, Region and Credit Score. Full results is presented in table A4.6. The first column lists all the variables used in the matching. The second and third columns present the standard difference between the control and treated group pre- and post-matching. The two last columns present the variance ratio between the groups.

The three PSM models conclude that M&As mainly have no effects on employee performance. Furthermore, results indicate that M&As have negative effects on firm performance. The initial PSM model presented in table 5.2 provided strong evidence of negative effects on EBITDA/Employees. As a caliper is introduced in PSM2, both significant results and pre-M&A significance disappear, which indicate better matches. In PSM3, we introduced a 5:1 NN matching. The increased matches per treated observation resulted in reduced variances in the analysis. However, the bias increased from average poorer matches. In PSM3, pre-M&A significance reappeared for TI/Employees. Thereby, the TI/Employees results can be described as contradictory. As matching restrictions become stricter, results shift between insignificant and significantly negative. We contribute these shifts to the matching quality and regard it as the likely source of our contradictory results. The initial differences between the groups would therefore overestimate the treatment effect of M&As. In appendix A4.2, table A4.4, we have conducted an analysis with a 5:1 NN matching and a caliper of 0.05 times the SD to the means of the propensity scores. This analysis validates the findings of PSM1 and PSM3.[19]

Overall, the three PSM models mostly indicate no effect on employee performance. Even though PSM1 and PSM3 indicated negative effects on employee performance, these results indicated poor matching. Therefore there could be an overestimation of the treatment effect on these results. For firm performance, the balance summary and pre-treatment indicated good matching for the 5:1 NN model. Ultimately, the PSM model concludes that M&A do not affect employee performance and negatively affect firm performance.

5.2.2 Does the labor size matter?

Switzer (1996) and Schweizer and Patzelt (2012) argue that there exists a positive relationship between size and post-M&A firm performance. Even though size and the size of the labor force is not perfectly correlated, larger firms typically have larger labor force.[20] Additionally, employees is central in measuring labor productivity. A M&A could affect an employee's performance at a smaller firm differently than at a larger firm. The analysis is conducted to deepen our insight into how M&As affect employee performance. In this section, we analyze whether the size labor force affect employee and firm performance post-M&A.

Firms are divided into four groups based on the quarterlies of the distribution for employees. The composition of the four groups: (1) $10 > Employees$, (2) $10 \leq Employees < 17$, (3) $17 \leq Employees < 36$, (4) $Employees \geq 36$. The analysis is based on PSM2 as this model introduces a caliper to improve the matching quality. We do not introduce a 5:1

[19] In table A4.5 and A4.6 we have performed additional PSM analyses where we omitted control variables. Table A4.5 presents a replication of a Cobb-Douglas regression function, where we only control for Employees and FA. This analysis results in significant negative ATT for most years for EBITDA/Employees and ROA, both pre-and post-M&A. This would indicate large omitted variable bias. In table A4.6 we have omitted labor, which results in omitted variable bias. Overall, the analyses illustrate the importance of controlling for our control variables.

[20] 0.3 in positive correlation between log(TA) and Employees, see A3.2.

NN matching combined with the caliper as this was viewed as too strict of a matching requirement for the smaller samples the analyses is conducted on. Matching of treated and untreated observations could, in the previous analyses, have been done between observations which in this analysis are in different groups. This could make for poorer matches. Table 5.6 only presents results from the four complete tables in appendix A4.3 with a p-value lower than the 10% level.

Table 5.6: PSM analyses for labor size - Only significant results.

Variable	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
Group 1					
EBITDA/Employees	36.7	18.9	1.95	0.051*	27,145
EBITDA/Employees (3)	54.1	29.4	1.84	0.066*	27,145
Group 2					
TI/Employees	-320.1	193.6	-1.65	0.098*	29,079
ROA (2)	-.027	.014	-1.91	0.056*	29,079
Group 3					
EBITDA/Employees (1)	-33.0	17.9	-1.84	0.066*	30,954
ROA (1)	-.017	.010	-1.65	0.099*	30,954
Group 4					
EBITDA/Employees (1)	-71.9	42.2	-1.70	0.089*	29,175
ROA (1)	-.026	.012	-2.12	0.034**	29,175

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table present significant results from PSM analyses on the three sets of dependant variables for the four different groups of number of employees. Analyses have been conducted for time interval -1 to +3 for all three sets of outcome variables. Only significant results are presented. A caliper of 0.25 times the SD of propensity scores is used. See appendix A4.3 for in depth view. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), the p-value of the ATT ($P >\mid z \mid$), and the number of observations (Obs.).

The results only find significant results for ROA for group 4. Thus, the remaining results indicate no effect of M&As. Furthermore, all analyses which showed indications of effects are included in the table. For group one, EBITDA/Employees in the matching year and three years post-M&A indicate positive effects. The results strongly argue the collective results in the initial three PSM models. This indicates that for firms in group one, employees performance improve post-M&A. The ATT indicates an added value of NOK 54,100 on EBITDA/Employees. However, the results should be questioned due to pre-treatment significant ATT. Furthermore, the results are above the 5% threshold and can only be viewed as indications.

For the second group, TI/Employees in the matching year and ROA two years post-

M&A indicate negative performance effects. Results for the second group should also be questioned due to pre-M&A significant ATT for TI/Employees. Results for group three indicate negative effects on EBITDA/Employees and ROA in the first year post-M&A. For the last group, these two dependent variables indicate effects as well. Throughout the analysis, the ATT for ROA one year post-M&A is the only outcome variable which indicates statistically significant results. The ATT finds a negative effect of 2.6 percentage points on ROA for group four.

To conclude, the employee measures prove mostly insignificant. The results indicate pre-M&A effects for TI/Employees and EBITDA/Employees in the matching year. This could indicate bias and weaken the validity of these indications. Only the ATT for group four finds negative statistical significance for ROA. In total, these results confirm our main findings. M&As do not affect employee performance differently across labor size. M&As have no effect on firm performance for smaller firms. However, it seems that the negative effects on firm performance in the main findings are caused by the firms with the largest number of employees.

5.2.3 How Does Sector Affect Performance?

Several studies, such as Schiffbauer et al. (2017) and Siegel and Simons (2015), have suggested differences in labor productivity post-M&A between industries. Isolating the individual sector effects may widen our knowledge about how M&As affect employee performance. Therefore, we will isolate the effect of M&As on employee performance within the three largest sectors in our data set measured by number of observations. We use these groups because the other sectors have too few observations to create good matches. The three sector groups are manufacturing, construction, and retail. Furthermore, we include the remaining observations in a separate group in the analysis. The analysis is based on PSM2 as described in the labor section.

Table 5.7 below presents the results from PSM analyses with a p-value below 10% for each respective industry. The remaining results are presented in appendix A4.4. For the manufacturing industry, we find no significant effects. However, we find indications of a positive effect on EBITDA/Employees in the minus one year and the second year following the M&A. This is partly inconsistent with our PSM results, which identified no effect on employee performance. These results are also susceptible to poor matching due to the pre-treatment indication of ATT. However, for the manufacturing industry, our findings are consistent with the results of Schiffbauer et al. (2017) and Siegel and Simons (2015). Both papers found positively significant effects in the manufacturing industry. Our results only show indications of this effect. These findings are however weakened by the ATT in the minus one year, which might suggest self-selection bias. Ultimately, we find no significant effect for the manufacturing industry. However, we find indications of the positive effect found in previous research.

Table 5.7: Significant PSM Results Per Industry

Variable/Employees	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
Manufacturing					
EBITDA/Employees (-1)	60.34	34.51	1.75	0.08*	12,721
EBITDA/Employees (2)	67.73	35.18	1.93	0.05*	12,721
Retail					
TI/Employees	-1043.03	614.62	-1.70	0.09*	34,929
EBITDA/Employees	-55.92	25.72	-2.17	0.03**	34,929
EBITDA/Employees (1)	-60.14	27.77	-2.17	0.03**	34,929
EBITDA/Employees (2)	-71.67	26.60	-2.69	0.01***	34,929
EBITDA/Employees (3)	-43.32	23.55	-1.84	0.07*	34,929
ROA (2)	-0.021	0.009	-2.281	0.023**	34,929
Construction					
TI/Employees (2)	-315.04	162.81	-1.93	0.05*	18,065
Remaining Sectors					
ROA (1)	-0.028	0.012	-2.328	0.020**	46,537

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table presents significant covariates from the sector individual PSM models. The table is divided into the different sectors and resents the variable name, the ATT (τ_{ATT}) for each variable in a given period, the standard errors (Std. error), t-value (t), p-value ($P >| z |$), and total number of observations (Obs.). The remaining variables were the same as in the original PSM models, but those excluded were found insignificant. The entire outputs are presented in appendix A4.4. All PSM analyses are based on 1:1 NN with a caliper of 0,25 times the SD to the mean of the propensity scores.

The results for the retail industry indicate negative results for EBITDA/Employees in all years except minus one and three. This may indicate that employee performance in the retail industry decreases in terms of EBITDA/Employees following the M&A. However, we find significance in the matching year, which again indicates poor matching within the retail sector. Therefore, we do not consider these findings as causal. The findings might indicate self-selection bias where weaker retail companies are susceptible to M&As or poor matching. We further find indications of negative effects on TI/Employees in the matching year, which decreases our perception of the matching quality. Lastly, we find a negative effect on ROA in period two, which coincides with our previous findings in the main PSM models. Furthermore, ROA does not indicate poor matching, which strengthens the findings. Ultimately, we find indications of self-selection bias in the retail industry regarding TI/Employees and EBITDA/Employees. Results suggest a negatively significant ATT on ROA two years post-M&A.

We find less significant results for the construction and the remaining industries. The ATT indicates a negative effect on TI/Employees for the construction industry two periods after the M&A but is above the 5% threshold. In the remaining industries, we find a negatively significant effect on ROA one period after the M&A. This coincides well with our other PSM findings and suggests that the remaining industries experience lower firm productivity post-M&A.

Ultimately, the results on industry differences support our main findings of no effect on employee performance. We find indications of positive effects on EBITDA/Employees in the manufacturing industry, which coincide with previous research. Furthermore, our results suggest a significant negative effect on EBITDA/Employees in the retail industry. These results are, however, susceptible to poor matching or self-selection bias. Therefore, these are not interpreted as causal. Lastly, we find negative effects on firm performance following M&As in the retail and the remaining sectors.

5.3 DD Analysis

In this section, we outline a DD robustness analysis to assess potential violations of the unconfoundedness assumption in the PSM analysis. This assumption is relaxed in DD, and may thus validate our PSM findings if no bias is discovered (Caliendo and Kopeinig (2008)). First, we transform our initial horizontal data set to a vertical data set, this removed 72 occurrences of MA2.[21] Second, we perform a NN matching where we exact match on Year and Sector to improve matching quality, and match on the previously defined covariates controlled for in the PSM analyses. Each treated observation is matched with the most similar control within the same year and sector. We then create a new

[21]We had 1,820 MA2 occurrences in the initial data set, and are left with 1748 in the vertical data set. These are removed due to missing values.

matched sample based on the matched pairs. Then, we perform a DD analysis on this new sample. Lastly, we perform KS-tests and t-tests to assess the matching quality. Additionally, we visually interpret the trends of the outcome variables and employees to assess the parallel trend assumption.

After performing the NN matching procedure, we are left with 1,719 treated observations and an identical number of control observations.[22] Table 5.8 presents the findings of the three DD analyses conducted. Post*MA2 represents the DD-estimator, Post the post-treatment period, and MA2 the treatment variable. We find no significant results for the DD-estimator, the period effect, nor the treatment effect. However, we find indications of a positive DD-estimator on EBITDA/Employees in the third year. See appendix A5 for the full DD analyses.

The DD analysis was conducted as a robustness analysis regarding the unconfoundedness assumption in PSM. The findings of the DD analyses align with the findings of PSM2 which found no significant ATT on employee and firm performance. Furthermore, PSM1 and PSM3 found no effects on employee performance, which aligns with the DD results. However, the findings of PSM1 and PSM3 on firm performance concluded that M&As have a negative firm performance effect. The DD analyses do not find a negative effect on firm performance, which weakens the PSM findings. Therefore, we cannot relax concerns of variables with simultaneously influence treatment and ROA not being controlled for. The different results may originate from several sources. The NN matching does not control for the distance between the matches. Therefore, there might be large differences between certain pairs of treated and controls. Additionally, because we are exact matching on year and sector we are left with a somewhat different sample of treated observations compared to the PSM analyses.[23] Furthermore, the matching quality may affect the results and the validity of the DD results. Therefore, we perform perform KS-tests, t-tests, and a visual interpretation of the trends to asses the matching quality.

[22]As previously defined, all of our analyses are done using with replacement. Therefore, if multiple treated observations are matched to the same controls, this will generate duplicates of that control observation (Caliendo and Kopeinig (2008)). In our matched sample 1.06% of the control observations are matched to two treated observations, and 0.17% of the controls are matched to three treated observations.

[23]The original PSM sample consisted of 1820 treated observations. The DD analysis consists of 1719 treated observations.

Table 5.8: DD-Estimator Results, All Periods

VARIABLES	(1) $\frac{TI}{Employees}$	(2) $\frac{EBITDA}{Employees}$	(3) ROA
Period t=1			
Post*MA2	116.2	11.8	0.003
	(140.8)	(15.4)	(0.005)
Post	-9.8	-2.5	-0.001
	(102.9)	(11.3)	(0.004)
MA2	71.0	6.8	-0.001
	(99.7)	(10.9)	(0.004)
Period t=2			
Post*MA2	146.5	7.2	0.005
	(158.0)	(15.6)	(0.005)
Post	-43.3	-0.9	0.001
	(119.0)	(11.7)	(0.004)
MA2	71.0	6.7	-0.0004
	(111.7)	(11.1)	(0.003)
Period t=3			
Post*MA2	71.2	27.2*	0.001
	(144.5)	(15.4)	(0.005)
Post	-44.9	-13.9	-0.001
	(114.4)	(12.2)	(0.004)
MA2	70.9	6.0	-0.001
	(102.2)	(10.9)	(0.004)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents DD regression of the year before M&A against the three years after. Each column represents TI/Employees, EBITDA/Employees, and ROA. The DD-estimator (δ) is denoted as "MA2*Post". "Post" (λ) denotes the effect of being in the last period, and "MA" (γ) indicated whether the observation is in the treated group.

To assess the matching quality of the NN matching, we have performed KS-tests and t-tests. The tests are performed for the treatment group compared to the control group for period minus one and zero. Tables 5.9 and 5.10 present our findings for each period. Neither the KS-tests nor the t-tests find any significant differences. This suggest that the treated and the control groups have both statistically similar means and distributions for the pre-treatment period. However, there are indication of different distributions between the two groups for EBITDA/Employees in period minus one. Ultimately, the two groups seem to be accurately matched.

Even though the groups seem to be sufficiently matched, DD relies on the parallel trend assumption. Therefore, we visually interpret the trends in the means for the outcome variables and employees. Figure 5.13 illustrates graphically the means over time for the

Table 5.9: KS and T-test: Period -1

Variable	D-Value	p-value
TI/Emp.	0.0384	0.159
EBITDA/Emp.	0.0419	0.098*
ROA	0.0332	0.301

Variable	T-Value	p-value
TI/Emp.	-1.289	0.198
EBITDA/Emp.	-0.589	0.556
ROA	0.334	0.739

Table 5.10: KS and T-test: Period 0

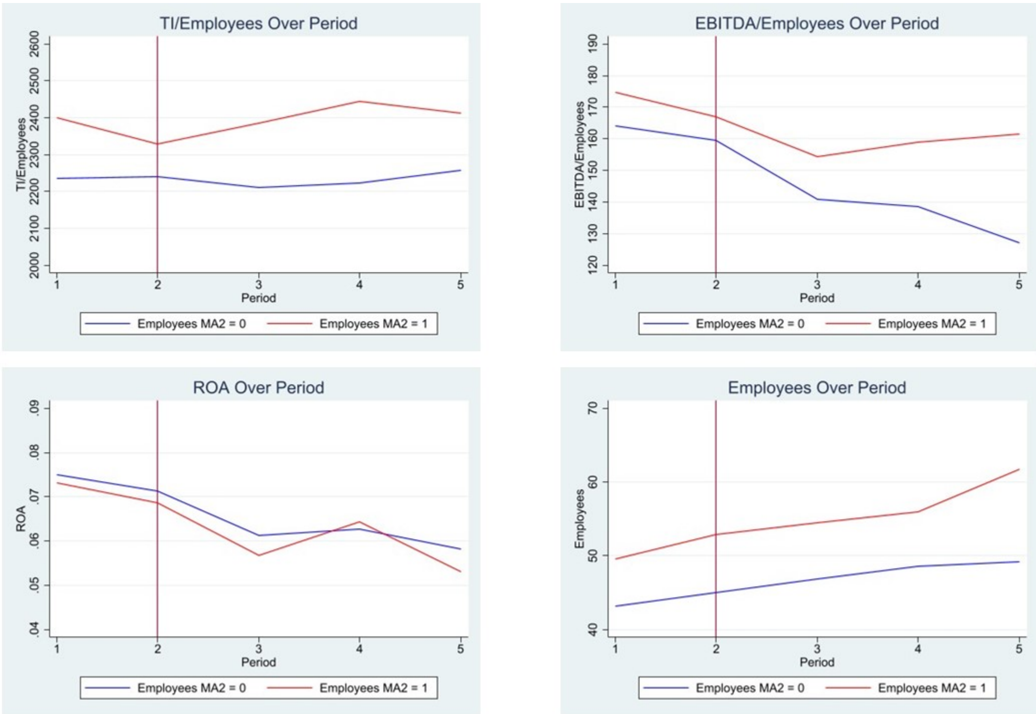
Variable	D-Value	p-value
TI/Emp.	0.0262	0.598
EBITDA/Emp.	0.0349	0.246
ROA	0.0407	0.116

Variable	T-Value	p-value
TI/Emp.	-0.797	0.427
EBITDA/Emp.	-0.555	0.580
ROA	0.468	0.640

The tables present KS test and t-test for period minus 1 and zero comparing the treated to the control group. The first three rows present KS-test for the dependent variables. D-value represents a metric for measuring distance between the distributions of the treatment group and the control group, and the p-value for the groups being equal. The fourth to sixth rows presents the t-test results for the dependent variables. The table presents T-value and P-value for all the outcome variables.

outcome variables and employees. The figure marks period two as the matching year, previously defined as the pre-acquisition year. Most of the variables seem to be following similar trends between period one and two. However, TI/Employees seems to have a negative trend compared to the control group. Furthermore, measuring trends between two periods is far from sufficient to confirm the parallel trend assumption because long-term trends are not accounted for. Therefore, our trends may appear more similar than they are long-term. Therefore, we cannot fully confirm that the parallel trend assumption holds, which weakens the robustness of the DD analysis. However, we note that the groups seem to follow similar trends post treatment as well. EBITDA/Employees is the only variable which experiences notable differences in the trends, where the means of the groups seem to diverge after period 3. Employees also experience some divergence in period five. In total, we deem the parallel trend assumption to hold, but note that the measured time frame is to small to account for long-term trends.

Figure 5.1: Employees means per period



The figure visually presents the means of the outcome variables and employees over period. The means are calculated pre-NN matching. The Y axis presents the mean value of the variable. The X axis presents period from one to five, where year two is the pre-M&A.

Overall, the DD results support the PSM results of no significant effects on employee performance. However, the DD model did not find the same effects on ROA, which weakened the findings of the PSM analyses. Additionally, EBITDA/Employees indicated a positive effect which contradict the PSM findings. However, EBITDA/Employees indicated differences in the distributions which weakens the indicated effect. The remaining outcomes indicated balanced groups. Furthermore, we find some weaknesses in the parallel trend assumption for TI/Employees, which weakens its causal interpretation.

Ultimately, the DD results suggest little concern regarding the unconfoundedness assumption for TI/Employees and EBITDA/Employees, as they support the PSM findings. This strengthens our findings that M&As do not affect employee performance as. However, the PSM findings of negative firm performance post-MA is weakened as the DD analysis found no effect. Therefore, we cannot interpret the effect on firm performance from PSM as causal without concerns of confounding.

6 Conclusion

6.1 Summary

This paper has analyzed how M&As affect employee performance. Our analysis is based on Norwegian accounting data for private firms between 2007 and 2016. We have created an algorithm which identifies M&As from accounting data. The algorithm is the first of its kind for Norwegian accounting data, and may create new possibilities for M&A research in Norway. Our main analysis utilized PSM to isolate the causal effect of M&As on employee performance. The PSM model matches target to control firms based on pre-M&A characteristics. Then, we developed a regression function based on the Cobb-Douglass production function to isolate labour productivity. Additionally, we performed separate PSM analyses to isolate the effect of labour size and sector. We have performed three PSM analyses based on caliper and NN matching. Additionally, a NN matching combined with a DD analysis was performed to control for potential violations of the unconfoundedness assumption in PSM.

We found that M&As do not affect employee performance. However, firm performance decreased post-M&A. The PSM model indicated poor matching for TI/Employees which weakened the validity of the results. The remaining outcome variables show mostly good matching, which strengthened the findings. To further asses employee performance we isolated the effect of the labor size and sector effects. We found no significant differences in the effect of M&As on employee performance between firm sizes. The negative firm performance post-M&A were found isolated to the largest firms. We neither find any trustworthy effect on employee performance in the sector differences. EBITDA/Employees did show negative employee performance, but these findings were accompanied with poor matching. However, the negative effects on ROA were isolated to the retail industry and the remaining sectors.

The DD analysis supported the findings of the PSM analysis. However, there are some contradictory findings regarding ROA, which does not remove concerns of confounding. However, the DD analysis consisted of a somewhat different sample than PSM, which may cause the difference. Therefore, we still interpret the ROA results of PSM as causal, but the interpretation is weakened due to possible confounding. Additionally, EBITDA/Employees indicated a positive effect, but were associated with poor matching. However, the parallel trend assumption seems to hold for all dependent variables, but TI/Employees show some difference in the trend. Ultimately, we deem our findings to be robust, but the validity of our findings on firm performance are reduced. We conclude that M&As do not affect employee performance and firm performance decrease post-M&A.

6.2 Limitations

There are multiple factors which limit our findings. In this section we discuss limitations regarding our analysis. The use of accounting data might limit our analysis. Accounting data does not explain all factors which affect the treatment assignment, and may be susceptible to confounding. There will exist factors, such as technological and human resources, which accounting data does not control for. Thereby, our analysis might be susceptible to confounding from factors we cannot control for.

Even though we have attempted to control for the unconfoundedness assumption with our DD analysis, it still limits our analysis. The DD analysis partly finds contradictory results to the main PSM analysis. Therefore, we cannot out-rule confounding in the PSM analysis of firm performance. Our interpretation of the negative effect on firm performance is therefore weakened.

Our paper is based on a self-created identification algorithm to detect M&As from accounting data. The algorithm has created 15% false positive M&As, which creates a inaccurate representation of the treated group. Thus, an improvement in the identification algorithm would improve the accuracy of our analysis.

We found errors regarding the share of M&As in the years of 2006 and 2017. Removing these years limits our analysis and reduced or researched time-frame. Additionally, our analysis might be susceptible to selection bias from these years. We have not been able to assess the root cause of these errors, and resolving them would improve the analysis.

PSM was implemented to balance the treated and controls. However, we were unable to fully balance some of our models, which reduced the trustworthiness their results. Future research can develop improved balancing models and other employee performance metrics which better balances the treated and controls.

We have only used a time-frame of five years per observation in our analysis. Thereby, we only measure the short-term effects of M&A. Our analysis is therefore only interpreted as short-term effects. The short time period also limits our ability to asses the parallel trend assumption in DD, which limits its validity.

6.3 Suggestions for Further Research

This thesis has several aspects that scholars may further research in the future. Our algorithm may create new possibilities for scholars to research private Norwegian M&As. Additionally, our analysis has several limitations which may be investigated by future research. Ultimately, we have multiple suggestions for further research which may utilize our algorithm or build on our analysis:

Firstly, researchers may improve our algorithm to create more accurate models for M&A research. This will create a more accurate interpretation of the causal effect of M&As. We suggest implementing a textual recognition algorithm to improve the detection of false positives. A machine learning model should be able to improve the detection rate. Secondly, because we found that M&As negatively impact firm performance, researchers may further research this effect for Norwegian firms and discover the causes. Thirdly, researchers may perform field experiments on Norwegian M&As and collect more direct performance measures for each individual employee. Doing so would provide a more detailed view of the individual effects of M&As on employees, not only on the labor force as a whole. Fourthly, we have only measured the employee performance three years post-M&A. Researchers may investigate the long term effects by expanding the time frame beyond three years. Lastly, researches may investigate whether the effect on employee performance is different outside of Norway.

References

André, P., Kooli, M., and L'Her, J.-F. (2004). The long-run performance of mergers and acquisitions: Evidence from the canadian stock market. *Financial Management*, 33(4):27–43.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics*. Princeton University Press.

Armagan, G. and Ozden, A. (2007). Determinations of total factor productivity with cobb-douglas production function in agriculture: The case of aydin-turkey. *Journal of Applied Sciences*, 7(4):499–502.

Austin, P. (2014). A comparison of 12 algorithms for matching on the propensity score. *Statistics in medicine*, 33.

Barber, B. 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.

Bekier, M. M., Bogardus, A. J., and Oldham, T. (2001). Why mergers fail. *McKinsey Quarterly*, (4):6 – 10.

Beveren, I. V. (2007). Total factor productivity estimation: A practical review. *LICOS Discussion Papers*, (18207).

Burton, A. (2021). Ols (linear) regression. pages 509 – 514.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.

Chari, A., Chen, W., and Dominguez, K. (2009). Foreign ownership and corporate restructuring: Direct investment by emerging-market firms in the united states. Working Papers 601, Research Seminar in International Economics, University of Michigan.

Christensen, C. M., Alton, R., Rising, C., and Walbeck, A. (2011). The big idea: The new m&a playbook. *Harvard Business Review*.

Cobb, C. W. and Douglas, P. H. (1928). A theory of production. *The American Economic Review*, 18(1):139–165.

Degbey, W. Y., Rodgers, P., Kromah, M. D., and Weber, Y. (2021). The impact of psychological ownership on employee retention in mergers and acquisitions. *Human Resource Management Review*, 31(3):100745. HRM Challenges In Cross-Cultural Collaborations.

Dehejia, R. H. and Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94(448):1053–1062.

Devos, E., Kadapakkam, P.-R., and Krishnamurthy, S. (2008). How Do Mergers Create Value? A Comparison of Taxes, Market Power, and Efficiency Improvements as Explanations for Synergies. *The Review of Financial Studies*, 22(3):1179–1211.

Dickerson, A. P., Gibson, H. D., and Tsakalotos, E. (1997). The impact of acquisitions on company performance: Evidence from a large panel of uk firms. *Oxford Economic Papers*, 49(3):344–361.

Dimopoulos, T. and Sacchetto, S. (2017). Merger activity in industry equilibrium. *Journal of Financial Economics*, 126(1):200–226.

Dodge, Y. (2008). *Kolmogorov–Smirnov Test*, pages 283–287. Springer New York, New York, NY.

Dun and Bradstreet (2022). Our scores and ratings. *Retrived from https://www.dnb.co.uk/about-us/our-analytics/predictors-scores-ratings/scores-ratings.*

Fagerland, M. W. (2012). t-tests, non-parametric tests, and large studies—a paradox of statistical practice? *BMC Medical Research Methodology*, 12(78).

Feldman, E. R. and Hernandez, E. (2022). Synergy in mergers and acquisitions: Typology, life cycles, and value. *Academy of Management Review*, 47(4):549 – 578.

Felipe, J. and McCombie, J. (2020). The illusions of calculating total factor productivity and testing growth models: from cobb-douglas to solow and romer. *Journal of Post Keynesian Economics*, 43(3):470–513.

Fisher, F. M. and McGowan, J. J. (1983). On the misuse of accounting rates of return to infer monopoly profits. *American Economic Review*, 73(1):82–97.

Garrido, M. M., Kelley, A. S., Paris, J., Roza, K., Meier, D. E., Morrison, R. S., and Aldridge, M. D. (2014). Methods for constructing and assessing propensity scores. *Health services research*, 49(5):1701–1720.

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

Golubov, A. and Xiong, N. (2020). Post-acquisition performance of private acquirers. *Journal of Corporate Finance*, 60:101545.

Goolsbee, A., Levitt, S., and Syverson, C. (2016). Microeconomics. *Worth Publishers*, 2.

Grant, R. M., Jammine, A. P., and Thomas, H. (1988). Diversity, diversification, and profitability among british manufacturing companies, 1972-84. *The Academy of Management Journal*, 31(4):771–801.

Grigorieva, S. and Petrunina, T. (2015). he performance of mergers and acquisitions in emerging capital markets: new angle. *Journal of Management Control*, (26):377–403.

Healy, P. M., Palepu, K. G., and Ruback, R. S. (1992). Does corporate performance improve after mergers? *Journal of Financial Economics*, 31(2):135–175.

Heckman, J. J., Ichimura, H., and Todd, P. (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies*, 65(2):261–294.

Hitt, M., Harrison, J., Ireland, R., and Best, A. (2002). Attributes of successful and unsuccessful acquisitions of us firms. *British Journal of Management*, 9:91 – 114.

Homberg, F., Rost, K., and OSterloh, M. (2009). Do synergies exist in related acquisitions? A meta-analysis of acquisition studies. *Review of Managerial Science*, 3:75–116.

Hopland, A. O. (2017). Econometrics for business research. *Norwegian School of Economics (NHH), Department of Business and Management Science.*

Imbens, G. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics*, 86(1):4–29.

Jemison, D. B. and Sitkin, S. B. (1986). Corporate acquisitions: A process perspective. *The Academy of Management Review*, 11(1):145–163.

Kaetzler, B., Kordestani, K., O'Loughlin, E., and Oostende, M. V. (2019). Managing and supporting emplyees through cultural change in mergers. *McKinsey & Company*.

Kansal, S. and Chandani, A. (2014). Effective management of change during merger and acquisition. *Procedia Economics and Finance*, 11:208–217.

Kim, T. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology*, 68:540.

King, D., Dalton, D., Daily, C., and Covin, J. (2004). Meta-analyses of post-acquisition performance: Indications of unidentified moderators. *Management Faculty Research and Publications*, 25.

Krishnan, H., Hitt, M., and Park, D. (2007). Acquisition premiums, subsequent workforce reductions and post-acquisition performance. *Journal of Management Studies*, 44:709–732.

Lechner, M. (2002). Some practical issues in the evaluation of heterogeneous labour market programmes by matching methods. *Journal of the Royal Statistical Society Series A*, 165(1):59–82.

Lee, M.-J. and Kang, C. (2006). Identification for difference in differences with cross-section and panel data. *Economics Letters*, 92(2):270–276.

Linn, S. and Switzer, J. A. (2001). Are cash acquisitions associated with better postcombination operating performance than stock acquisitions? *Journal of Banking Finance*, 25(6):1113–1138.

Loughran, T. and Ritter, J. (1997). The operating performance of firms conducting seasoned equity offerings. *Journal of Finance*, 52(5):1823–50.

Martin, R. L. (2016). M&a: The one thing you need to get right. *Harvard Business Review*.

Martynova, M., Oosting, S., and Renneboog, L. (2007). 4 - the long-term operating performance in european mergers and acquisitions. pages 79–116.

Meckl, R. and Röhrle, F. (2016). Do ma deals create or destroy value? a meta-analysis. *European Journal of Business and Economics*, 11.

Miller, K. (2020). 5 critical steps in the change management process. *Harvard Business School Online*.

Mjøs, A. and Selle, S. (2022). Regnskapsdatabasen - norwegian corporate accounts. *Center for Applied Reseach at NHH (SNF)*, (4).

Moe, D. and Bloch, V. V. H. (2020). Regionale inndelinger 2020 - en oversikt over standarder i norsk offisiell statistikk. *Statistics Norway*.

Nyberg, A. J. and Trevor, C. O. (2009). After layoffs, help survivers be more effective. *Harvard Business Review*.

Pereiro, L. E. (2016). The misvaluation curse in mergers and acquisitions. *Journal of Corporate Accounting Finance (Wiley)*, 27(2):11 – 15.

Powell, R. and Stark, A. W. (2005). Does operating performance increase post-takeover for uk takeovers? a comparison of performance measures and benchmarks. *Journal of Corporate Finance*, 11(1-2):293–317.

Rassen, J. A., Shelat, A. A., Myers, J., Glynn, R. J., J.Rothman, K., and Schneeweiss, S. (2012). One-to-many propensity score matching in cohort studies. *Pharmacoepidemiology and Drug Safety*, 21(S2):69–80.

Recardo, R. J. and Toterhi, T. (2015). Strategic integration: How to realize the value of an acquisition. *Global Business Organizational Excellence*, 35(1):6 – 22.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66:688–701.

Ryan, A. M., Kontopantelis, E., Linden, A., and James F Burgess, J. (2019). Now trending: Coping with non-parallel trends in difference-in-differences analysis. *Statistical Methods in Medical Research*, 28(12):3697–3711.

Schiffbauer, M., Siedschlag, I., and Ruane, F. (2017). Do foreign mergers and acquisitions boost firm productivity? *International Business Review*, 26(6):1124–1140.

Schweizer, L. and Patzelt, H. (2012). Employee commitment in the post-acquisition integration process: The effect of integration speed and leadership. *Scandinavian Journal of Management*, 28(4):298–310.

Sekhon, J. S. and Grieve, R. D. (2012). A matching method for improving covariate balance in cost-effectiveness analyses. *Health Economics*, 21(6):695–714.

Siegel, D. S. and Simons, K. (2015). Assessing the effects of mergers and acquisitions on firm performance, plant productivity, and workers: new evidence from matched employer-employee data. *Strategic Management Journal*, 31(8):903–916.

Smith, H. L. (1997). Matching with multiple controls to estimate treatment effects in observational studies. *Sociological Methodology*, 27:325–353.

Smith, J. A. and Todd, P. E. (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1-2):305–353.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3):312–320.

Stata (2023). tebalance summarize — covariate-balance summary statistics. *Retrived from: https://www.stata.com/manuals/tetebalancesummarize.pdf.*

Stuart, E., Huskamp, H., Duckworth, K., Simmons, J., Song, Z., Chernew, M., and Barry, C. (2014). Using propensity scores in difference-in-differences models to estimate the effects of a policy change. *Health services & outcomes research methodology*, 14:166–182.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, 25(1):1–21.

Switzer, J. A. (1996). Evidence on real gains in corporate acquisitions. *Journal of Economics and Business*, 48(5):443–460.

Szücs, F. (2013). Ma and rd: Asymmetric effects on acquirers and targets? DIW Discussion Papers 1331, Berlin.

Tantalo, C. and Priem, R. (2014). Value creation through stakeholder synergy. *Strategic Management Journal*, 37.

Tcheng, H. (2023). Tech due diligence: the new pillar of ma activity. *Retrived from BearingPoint.com 09.01.2023*.

Thanos, I. and Papadakis, V. (2012). The use of accounting-based measures in measuring ma performance: A review of five decades of research. *Advances in Mergers and Acquisitions*, 10:103–120.

Tuch, C. and O'Sullivan, N. (2007). The impact of acquisitions on firm performance: A review of the evidence. *International Journal of Management Reviews*, 9(2):141–170.

Williams, B. K. (2011). Passive and active adaptive management: Approaches and an example. *Journal of Environmental Management*, 92(5):1371–1378. Adaptive management for Natural Resources.

Wilms, R., Mäthner, E., Winnen, L., and Lanwehr, R. (2021). Omitted variable bias: A threat to estimating causal relationships. *Methods in Psychology*, 5:100075.

Zhang, C. (2019). The review of factors affecting merger premium. *Journal of Service Science and Management*, 12:200–213.

Appendix

A1 The M&A Identification Algorithm

The algorithm has been published on GitHub to enable others to use it in the future. It can be accessed at this GitHub page:

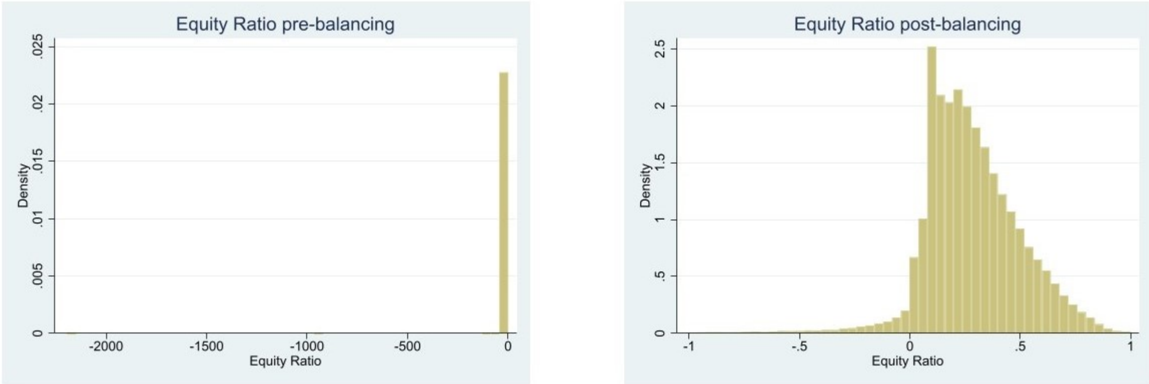
https://github.com/Taxmaster1/M-A-Identification-Algorithm-for-Norwegian-Accounting-Data

The algorithm is coded in a simplistic way to promote usability for others. We have therefore sacrificed efficiency in terms of processing time and length of the file. It is however clear to the user what the conditions are and where to change the parameters. Also, people with minimal coding experience should be able to understand the structure and execution of the algorithm.

The algorithm can be further improved in several ways to either improve accuracy, efficiency, and usability. By applying textual recognition modules one may improve the accuracy of the algorithm. This may decrease the share of false positives if the algorithm can identify similarities which are obvious to the human eye. One can do this by creating a manual training data-set with identified and false M&As and apply a machine learning model. Furthermore, one can improve the efficiency by applying object oriented programming and reduce the amount of nested loops within the algorithm. Lastly, the usability may be improved by creating a user-interface or a run-file where the user can easily change the parameters without interacting with the actual algorithm.

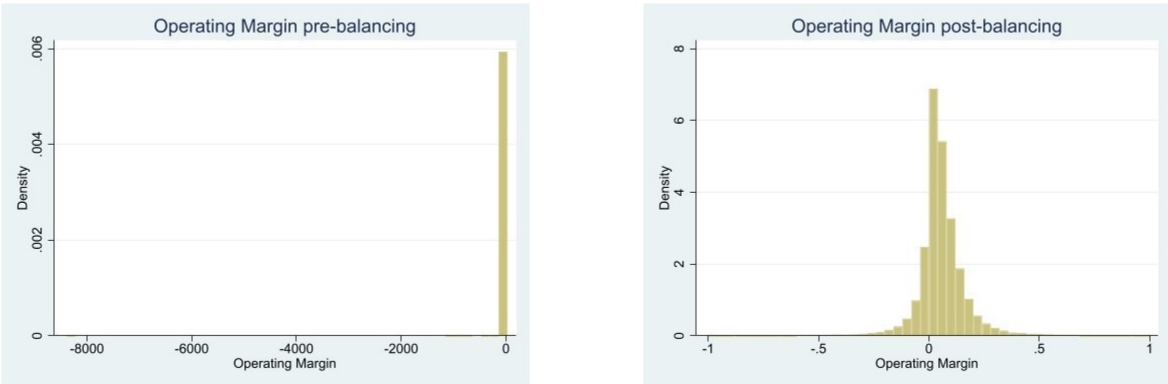
A2 Descriptive

Figure A2.1: Histogram of Equity Ratio pre- and post-balancing



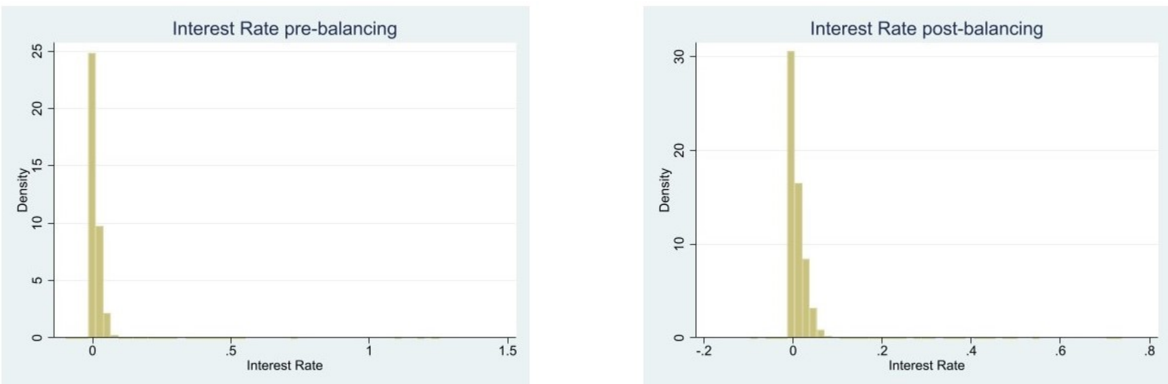
The figure visually presents the histogram for Equity Ratio pre-balancing on the left, and post-balancing on the right. The balancing removed any value outside the range of -1 and 1.

Figure A2.2: Histogram of Operating Margin pre- and post-balancing



The figure visually presents the histogram for Operating Margin pre-balancing on the left, and post-balancing on the right. The balancing removed any value outside the range of -1 and 1.

Figure A2.3: Histogram of Interest Rate pre- and post-balancing



The figure visually presents the histogram for Interest Rate pre-balancing on the left, and post-balancing on the right. The balancing removed any value outside the range of -1 and 1.

Table A2.1: MA2 means for each year before filtering

	Mean	Sum	N
2006			
MA2	.0204	358	17,550
2007			
MA2	.007	144	19,692
2008			
MA2	.009	156	17,270
2009			
MA2	.006	114	18,506
2010			
MA2	.008	166	19,815
2011			
MA2	.009	178	20,912
2012			
MA2	.011	220	19,420
2013			
MA2	.008	182	22,902
2014			
MA2	.016	317	20,213
2015			
MA2	.008	215	27,993
2016			
MA2	.009	258	28,253
2017			
MA2	.001	22	27,185
Total			
MA2	.007	2,331	343,091

Mean and count of MA2 per year from our data. Please note that MA2 require a -1 and +3 time-frame, and therefore there are no observations before 2006 and after 2017.

Table A2.2: Sector Dummy

Dummy	**Sector**
1	Agriculture
2	Offshore/Shipping
3	Transport
4	Manufacturing
5	Telecom/IT/Tech
6	Electricity
7	Construction
8	Wholesale/Retail
9	Finance
10	Other Services

Table presents description of Sector. Sectors are assigned by common industry group by Mjøs and Selle (2022).

Table A2.3: Credit Score Dummy

Dummy	**Credit Score**
1	AAA
2	AA
3	A
4	B
5	C
6	Not rated
7	Bankrupt/Discontinued

Table presents description of Credit Score. Scores are assigned by Mjøs and Selle (2022), who use Dun and Bradstreet (2022) rating system.

Table A2.4: Region Dummy

Dummy	**Region**
1	North-Norway
2	Trøndelag
3	Vestlandet
4	Agder & Southeast-Norway
5	Oslo & Viken
6	Innlandet

Table presents description of Region. Regions are assigned by Mjøs and Selle (2022) and are based on registered location for the organization. They use the areas presented by Moe and Blosch (2020) from Statistics Norway.

A3 OLS-regressions

OLS regression results for the three regressions of TI/Employees, EBITDA/Employees, and ROA. Additional to the variables displayed Sector, Year, Credit Score, and Region are controlled for.

Table A3.1: OLS - Measuring t+2

VARIABLES	(1) $\frac{TI}{Employees}(2)$	(2) $\frac{EBITDA}{Employees}(2)$	(3) ROA (2)
MA2	-288.4	-85.9	-0.008*
	(227.9)	(123.3)	(0.005)
Employees	-3.5***	-0.9***	-1.34e-06
	(0.1)	(0.1)	(2.08e-06)
FA	0.0002***	9.00e-05***	-0.0
	(7.56e-06)	(4.09e-06)	(1.49e-10)
log(TA)	1.6***	322.7***	-0.004***
	(20.5)	(11.1)	(0.0004)
Equity Ratio	-2.3***	-529.6***	-0.096***
	(165.7)	(89.7)	(0.003)
Profitable	547.7***	199.8***	0.091***
	(78.5)	(42.5)	(0.002)
Interest Rate	-12.9***	-260.5	-0.712***
	(1,8)	(951.3)	(0.035)
Max Ownership	-443.4**	-44.8	-0.047***
	(202.3)	(109.4)	(0.004)
Constant	-13.2***	-2.7***	0.137***
	(314.9)	(170.4)	(0.006)
Observations	118,070	118,070	118,070
R-squared	0.097	0.023	0.094

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents a OLS regression measuring the three sets of dependant variables for the second year after the M&A. Additional to the variables displayed Sector, Year, Credit Score, and Region are controlled for.

Table A3.2: Correlation matrix for independent variables and MA2

	MA2	Employees	FA	log(TA)	ER	Profitable	Interest Rate	Max Ownership
MA2	1.00							
Employees	-0.00	1.00						
FA	-0.00	0.20	1.00					
log(TA)	-0.01	0.31	0.18	1.00				
ER	-0.02	0.00	-0.01	0.17	1.00			
Profitable	-0.01	0.01	0.01	0.07	0.21	1.00		
Interest Rate	0.01	-0.04	-0.01	-0.05	-0.12	-0.12	1.00	
Max Ownership	-0.04	0.05	0.01	0.08	-0.06	-0.05	-0.04	1.00
N	118070							

The table presents the correlation between our independent variables. None of the correlations are unacceptably high. We do however note that Employees and log(TA) are somewhat high.

A4 Additional PSM analyses

A4.1 PSM Matching Quality

Table A4.1: Standard Difference of Matching Quality: PSM 1:1 NN - No Caliper

Variables	Pre-Match	Post-Match	Pre-Var. Ratio	Post-Var. Ratio
Employees	-.018	.024	.438	1.65
FA	-.044	-.007	.002	1.386
log(TA)	-.080	-.009	.810	.897
Equity Ratio	-.129	.012	1.152	.911
Profitable	-.092	-.018	1.129	1.022
Interest Rate	.058	-.016	1.239	.609
Max Ownership	-.301	-.004	1.506	.991
Operating Margin	-.116	-.002	.957	.960
Sector 1	-.052	.016	.661	1.156
Sector 2	-.019	-.033	.887	.813
Sector 3	.008	.042	1.038	1.246
Sector 4	-.001	.017	.997	1.040
Sector 5	-.015	.028	.928	1.155
Sector 6	-.087	-.009	.318	.858
Sector 7	-.091	-.024	.833	.950
Sector 8	.010	.005	1.009	1.004
Sector 9	-.046	0	.608	1
2008	-.035	.010	.902	1.033
2009	-.126	.005	.667	1.017
2010	-.041	-.023	.891	.934
2011	-.008	-.013	.979	.965
2012	.046	-.010	1.124	.976
2013	-.029	.013	.927	1.04
2014	.154	-.008	1.398	.986
2015	-.009	0	.978	1
2016	.044	.049	1.107	1.122
Credit Score 2	-.048	-.003	.995	1
Credit Score 3	.001	.015	1.002	1.021
Credit Score 4	.152	-.018	1.477	.963
Credit Score 5	.060	.009	1.66	1.066
Credit Score 6	-.031	.011	.594	1.249
Region 2	-.006	.0146	.982	1.049
Region 3	-.007	.0285	.994	1.030
Region 4	.036	.008	1.080	1.016
Region 5	-.048	-.028	.973	.984
Region 6	.040	-.034	1.159	.892

The table shows a balance summary for our initial PSM model with 1:1 NN matching. It presents pre- and post-matching standard difference of the treated group and the control group, as well as the variance ratios between them. The first column lists all the variables used in the matching. The second and third columns present the standard difference between the control and treated group pre- and post-matching. The two last columns present the variance ratio between the groups.

Table A4.2: Matching Quality PSM 1:1 NN - Caliper(0.00193608)

Variables	SD Pre-Match	SD Post-Match	Pre-Var. Ratio	Post-Var. Ratio
Employees	-.004	-.001	.622	1.37
FA	-.052	-.027	.508	.779
log(TA)	-.061	-.010	.874	.892
Equity Ratio	-.126	.024	1.153	1.008
Profitable	-.088	.062	1.123	.933
Interest Rate	.054	-.029	1.230	1.235
Max Ownership	-.297	-.017	1.495	.978
Operating Margin	-.107	.034	.999	.878
Sector 1	-.052	-.015	.659	.882
Sector 2	-.014	.016	.911	1.115
Sector 3	.008	.052	1.042	1.314
Sector 4	-.002	.008	.996	1.020
Sector 5	-.015	-.012	.930	.944
Sector 6	-.063	.010	.413	1.199
Sector 7	-.092	-.031	.832	.937
Sector 8	.008	-.008	1.007	.993
Sector 9	-.040	-.0192	.647	.801
2008	-.034	-.016	.903	.952
2009	-.124	-.025	.672	.915
2010	-.040	.008	.892	1.024
2011	-.008	.004	.980	1.011
2012	.046	.030	1.124	1.078
2013	-.028	.006	.928	1.016
2014	.152	-.031	1.393	.946
2015	-.009	0	.979	1
2016	.043	.0033	1.107	1.007
Credit Score 2	-.045	.038	.996	1.007
Credit Score 3	.0003	-.053	1.001	.933
Credit Score 4	.147	-.031	1.461	.937
Credit Score 5	.060	.013	1.666	1.102
Credit Score 6	-.021	-.043	.699	.501
Region 2	-.006	.030	.983	1.103
Region 3	-.009	-.021	.992	.980
Region 4	.034	.011	1.076	1.023
Region 5	-.046	.005	.975	1.003
Region 6	.040	-.032	1.159	.898

The table shows a balance summary for our second PSM model with 1:1 NN matching and a caliper restriction of .00193608. It presents pre- and post-matching standard difference of the treated group and the control group, as well as the variance ratios between them. The first column lists all the variables used in the matching. The second and third columns present the standard difference between the control and treated group pre- and post-matching. The two last columns present the variance ratio between the groups.

Table A4.3: Matching Quality PSM 5:1 NN - Caliper(0.00193608)

Variables	Pre-Match	Post-Match	Pre-Var. Ratio	Post-Var. Ratio
Employees	-.0004	.004	.761	.800
FA	-.045	.001	.591	.997
log(TA)	-.055	-.003	.876	.935
Equity Ratio	-.109	-.007	1.105	.999
Profitable	-.075	-.012	1.107	1.015
Interest Rate	.049	-.009	1.240	1.048
Max Ownership	-.278	.011	1.463	.945
Operating Margin	-.088	-.017	.946	1.022
Sector 1	-.051	.006	.667	1.057
Sector 2	-.012	.002	.927	1.016
Sector 3	.008	.014	1.041	1.070
Sector 4	.0004	.021	1.002	1.050
Sector 5	-.016	-.010	.927	.954
Sector 6	-.059	0	.435	1
Sector 7	-.088	.009	.841	1.019
Sector 8	.008	-.007	1.007	.995
Sector 9	-.039	.007	.655	1.090
2008	-.031	.003	.914	1.010
2009	-.121	-.013	.680	.953
2010	-.038	-.017	.898	.952
2011	-.009	.005	.976	1.015
2012	.039	-.013	1.106	.968
2013	-.026	-.020	.934	.948
2014	.150	.011	1.394	1.021
2015	-.004	.007	.991	1.017
2016	.040	.020	1.098	1.047
Credit Score 2	-.035	-.011	.997	.999
Credit Score 3	.005	.008	1.008	1.011
Credit Score 4	.1255	.011	1.398	1.027
Credit Score 5	.050	.009	1.546	1.076
Credit Score 6	-.020	.007	.710	1.136
Region 2	-.003	.011	.991	1.037
Region 3	-.010	-.007	.990	.993
Region 4	.035	0	1.078	1
Region 5	-.041	.003	.978	1.002
Region 6	.037	-.009	1.146	.971

The table shows a balance summary for our third PSM model with 5:1 NN matching and a caliper restriction of .00193608. It presents pre- and post-matching standard difference of the treated group and the control group, as well as the variance ratios between them. The first column lists all the variables used in the matching. The second and third columns present the standard difference between the control and treated group pre- and post-matching. The two last columns present the variance ratio between the groups.

A4.2 Alternative PSM analyses

Table A4.4: PSM - 5% caliper (0.000387216) and 5:1 NN

Measure	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
Tot-1/Employees	-226.1	127.1	-1.78	0.075*	112,819
Tot/Employees	-313.86	110.2	-2.85	0.004***	112,819
Tot1/Employees	-216.7	121.4	-1.79	0.074*	112,819
Tot2/Employees	-208.2	143.9	-1.45	0.148	112,819
Tot3/Employees	-332.2	132.3	-2.51	0.012**	112,819
EBITDA-1/Employees	-5.2	12.6	-0.41	0.682	112,819
EBITDA/Employees	-6.7	11.3	-0.60	0.552	112,819
EBITDA1/Employees	-13.1	13.9	-0.94	0.345	112,819
EBITDA2/Employees	-4.6	14.3	-0.33	0.745	112,819
EBITDA3/Employees	-17.3	15.3	-1.13	0.258	112,819
ROA-1	-.001	.004	-0.13	0.899	112,819
ROA	-.003	.004	-0.57	0.572	112,819
ROA1	-.017	.005	-3.05	0.002***	112,819
ROA2	-.006	.005	-1.18	0.239	112,819
ROA3	-.092	.080	-1.15	0.252	112,819

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

This PSM analysis implements a strict caliper of 5% of the SD to the propensity scores (0.000387216). In combination with the caliper, the matching is done with a 5:1 NN-matching. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >| z |$).

Table A4.5: PSM - Cobb-Douglas regression

Measure	τ_{ATT}	Std. error	t	P>| z |	Obs.
Tot-1/Employees	-85.7	126.1	-0.68	0.497	118,070
Tot/Employees	-88.4	102.1	-0.87	0.387	118,070
Tot1/Employees	-48.2	110.1	-0.44	0.661	118,070
Tot2/Employees	-62.3	131.3	-0.47	0.636	118,070
Tot3/Employees	-149.1	118.0	-1.26	0.206	118,070
EBITDA-1/Employees	-85.8	24.4	-3.51	0.000***	118,070
EBITDA/Employees	-71.5	18.8	-3.80	0.000***	118,070
EBITDA1/Employees	-87.1	20.1	-4.34	0.000***	118,070
EBITDA2/Employees	-90.7	27.4	-3.30	0.001***	118,070
EBITDA3/Employees	-79.2	21.1	-3.76	0.000***	118,070
ROA-1	-.018	.005	-3.42	0.001***	118,070
ROA	-.016	.006	-2.85	0.004***	118,070
ROA1	-.035	.007	-5.37	0.000***	118,070
ROA2	-.017	.006	-2.76	0.006***	118,070
ROA3	-.098	.076	-1.29	0.197	118,070

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

In this PSM analysis we only control for labor and physical capital. As a majority of variables become significant we conclude this is because of omitted variable bias (Wilms et al. (2021)). The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >\mid z \mid$).

Table A4.6: PSM- Controlling for everything except labor force

Measure	τ_{ATT}	Std. error	t	P>| z |	Obs.
Tot-1/Employees	-212.7	162.5	-1.31	0.191	118,070
Tot/Employees	-311.2	149.5	-2.08	0.037**	118,070
Tot1/Employees	-181.4	144.9	-1.25	0.211	118,070
Tot2/Employees	-141.4	172.2	-0.82	0.412	118,070
Tot3/Employees	-249.1	159.6	-1.56	0.119	118,070
EBITDA-1/Employees	-31.4	22.7	-1.38	0.166	118,070
EBITDA/Employees	-42.1	24.2	-1.74	0.081*	118,070
EBITDA1/Employees	-38.9	17.8	-2.19	0.029**	118,070
EBITDA2/Employees	-23.4	25.8	-0.91	0.364	118,070
EBITDA3/Employees	-36.1	25.8	-1.40	0.162	118,070
ROA-1	-.006	.006	-1.04	0.298	118,070
ROA	-.008	.005	-1.39	0.165	118,070
ROA1	-.020	.007	-2.90	0.004***	118,070
ROA2	-.004	.007	-0.59	0.556	118,070
ROA3	-.096	.075	-1.28	0.201	118,070

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

This PSM analysis controls for all factors except labour. There is no caliper and a 1:1 NN matching. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >\mid z \mid$).

A4.3 Labor size analyses

Table A4.7: PSM - Group 1, 25% caliper (0.00200588)

Measure	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	-66.3	229.8	-0.29	0.773	27,145
TI/Employees	-30.1	229.5	-0.13	0.896	27,145
TI/Employees (1)	-15.7	275.1	-0.06	0.955	27,145
TI/Employees (2)	123.4	259.5	0.48	0.635	27,145
TI/Employees (3)	-99.9	298.2	-0.33	0.738	27,145
EBITDA/Employees (-1)	8.8	28.1	0.31	0.754	27,145
EBITDA/Employees	36.7	18.9	1.95	0.051*	27,145
EBITDA/Employees (1)	43.9	31.3	1.40	0.161	27,145
EBITDA/Employees (2)	52.0	38.1	1.36	0.173	27,145
EBITDA/Employees (3)	54.1	29.4	1.84	0.066*	27,145
ROA (-1)	.005	.013	0.43	0.666	27,145
ROA	.003	.012	0.24	0.813	27,145
ROA (1)	-.009	.016	-0.58	0.562	27,145
ROA (2)	.002	.014	0.12	0.901	27,145
ROA (3)	-.002	.017	-0.11	0.911	27,145

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table shows a PSM analysis of the labor group1 with a 25% caliper to the SD to the mean of the propensity scores (0.00200588). This group contains firms with more than or equal to 17 employees, and less than 36 employees. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >| z |$).

Table A4.8: PSM - Group 2, 25% caliper (0.00184425)

Measure	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	-190.9	176.7	-1.08	0.280	29,079
TI/Employees	-320.1	193.6	-1.65	0.098*	29,079
TI/Employees (1)	-240.2	203.5	-1.18	0.238	29,079
TI/Employees (2)	-332.4	221.2	-1.50	0.133	29,079
TI/Employees (3)	-364.1	234.3	-1.55	0.120	29,079
EBITDA/Employees (-1)	-.5	38.5	-0.01	0.989	29,079
EBITDA/Employees	-13.0	33.0	-0.42	0.672	29,079
EBITDA/Employees (1)	1.2	28.3	0.04	0.967	29,079
EBITDA/Employees (2)	-21.4	37.7	-0.57	0.570	29,079
EBITDA/Employees (3)	-28.4	36.1	-0.79	0.432	29,079
ROA (-1)	-.010	.012	-0.82	0.414	29,079
ROA	-.003	.011	-0.24	0.812	29,079
ROA (1)	-.019	.013	-1.43	0.151	29,079
ROA (2)	-.027	.014	-1.91	0.056*	29,079
ROA (3)	-.0002	.032	-0.01	0.995	29,079

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table shows a PSM analysis of the labor group 2 with a 25% caliper to the SD to the mean of the propensity scores (0.00184425). This group contains firms with more than or equal to 10 employees, and less than 17 employees. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >| z |$).

Table A4.9: PSM - Group 3, 25% caliper (0.0027275)

Measure	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	-142.7	237.4	-0.60	0.548	30,954
TI/Employees	-232.5	203.3	-1.14	0.253	30,954
TI/Employees (1)	-221.5	240.8	-0.92	0.358	30,954
TI/Employees (2)	-271.3	222.9	-1.22	0.223	30,954
TI/Employees (3)	-416.9	318.5	-1.31	0.191	30,954
EBITDA/Employees (-1)	-1.1	17.1	-0.07	0.947	30,954
EBITDA/Employees	-5.7	19.5	-0.29	0.772	30,954
EBITDA/Employees (1)	-33.0	17.9	-1.84	0.066*	30,954
EBITDA/Employees (2)	-1.1	18.5	-0.06	0.954	30,954
EBITDA/Employees (3)	-23.5	18.8	-1.25	0.211	30,954
ROA (-1)	.005	.010	0.46	0.645	30,954
ROA	-.009	.012	-0.75	0.451	30,954
ROA (1)	-.017	.010	-1.65	0.099*	30,954
ROA (2)	-.001	.012	-0.09	0.928	30,954
ROA (3)	-.278	.255	-1.09	0.276	30,954

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table shows a PSM analysis of the labor group 3 with a 25% caliper to the SD to the mean of the propensity scores (0.0027275). This group contains firms with more than or equal to 17 employees, and less than 36 employees. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >| z |$).

Table A4.10: PSM - Group 4, 25% caliper (0.00206325)

Measure	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P**>| **z** |	**Obs.**
TI/Employees (-1)	-53.9	285.1	-0.19	0.850	29,175
TI/Employees	-202.2	231.2	-0.87	0.382	29,175
TI/Employees (1)	-233.3	254.3	-0.92	0.359	29,175
TI/Employees (2)	-136.6	296.1	-0.46	0.644	29,175
TI/Employees (3)	-162.1	294.7	-0.55	0.582	29,175
EBITDA/Employees (-1)	-51.0	56.2	-0.91	0.364	29,175
EBITDA/Employees (	-24.8	34.3	-0.72	0.470	29,175
EBITDA/Employees (1)	-71.9	42.2	-1.70	0.089*	29,175
EBITDA/Employees (2)	-50.4	40.0	-1.26	0.208	29,175
EBITDA/Employees (3)	-38.4	44.2	-0.87	0.385	29,175
ROA (-1)	.005	.008	0.60	0.549	29,175
ROA	.011	.008	1.39	0.164	29,175
ROA (1)	-.026	.012	-2.12	0.034**	29,175
ROA (2)	.004	.013	0.28	0.779	29,175
ROA (3)	.004	.010	0.34	0.735	29,175

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table shows a PSM analysis of the labor group 4 with a 25% caliper to the SD to the mean of the propensity scores (0.00206325). This group contains firms with 36 employees or more. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. Presented in the table is the ATT (τ_{ATT}), standard error of the ATT (Std. error), the t-value of the ATT (t), and the p-value of the ATT ($P >\mid z \mid$).

A4.4 Sector analyses

Table A4.11: PSM - Manufacturing, caliper(0.002078)

Variable	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	-449.5	621.6	-0.72	0.47	12,721
TI/Employees	-583.3	610.1	-0.96	0.34	12,721
TI/Employees (1)	-653.3	722.3	-0.90	0.37	12,721
TI/Employees (2)	-752.3	767.9	-0.98	0.33	12,721
TI/Employees (3)	-921.6	992.5	-0.93	0.35	12,721
EBITDA/Employees (-1)	60.3	34.5	1.75	0.08*	12,721
EBITDA/Employees	39.2	27.0	1.45	0.15	12,721
EBITDA/Employees (1)	43.2	31.4	1.38	0.17	12,721
EBITDA/Employees (2)	67.7	35.2	1.93	0.05**	12,721
EBITDA/Employees (3)	29.8	44.6	0.67	0.50	12,721
ROA (-1)	-0.016	0.015	-1.014	0.311	12,721
ROA	-0.006	0.013	-0.448	0.654	12,721
ROA (1)	-0.006	0.013	-0.452	0.652	12,721
ROA (2)	0.015	0.013	1.170	0.242	12,721
ROA (3)	-0.020	0.014	-1.406	0.160	12,721

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table presents the PSM results for the manufacturing industry. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. The matching is based on 1:1 NN with a caliper of 25% SD to the mean of the propensity scores, which was 0.002078. The table presents the ATT (τ_{ATT}), standard error (Std. error), t-value (t), p-value ($P >| z |$), and number of observations.

Table A4.12: PSM - Construction, caliper (0.001537)

Variable/Employees	$\tau_{\mathbf{ATT}}$	Std. error	t	P>| z |	Obs.
TI/Employees (-1)	-155.3	117.0	-1.33	0.18	18,065
TI/Employees	-242.1	175.7	-1.38	0.17	18,065
TI/Employees (1)	-228.7	169.7	-1.35	0.18	18,065
TI/Employees (2)	-315.0	162.8	-1.93	0.05**	18,065
TI/Employees (3)	-252.7	157.3	-1.61	0.11	18,065
EBITDA/Employees (-1)	-27.9	32.8	-0.85	0.39	18,065
EBITDA/Employees	-18.3	36.3	-0.50	0.61	18,065
EBITDA/Employees (1)	-37.8	35.6	-1.06	0.29	18,065
EBITDA/Employees (2)	-56.6	37.9	-1.49	0.14	18,065
EBITDA/Employees (3)	-75.1	57.7	-1.30	0.19	18,065
ROA/Employees (-1)	0.000	0.016	0.026	0.980	18,065
ROA/Employees	0.015	0.012	1.290	0.197	18,065
ROA/Employees (1)	-0.008	0.014	-0.551	0.582	18,065
ROA/Employees (2)	-0.004	0.021	-0.212	0.832	18,065
ROA/Employees (3)	-0.013	0.015	-0.900	0.368	18,065

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table presents the PSM results for the construction industry. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. The matching is based on 1:1 NN with a caliper of 25% SD to the mean of the propensity scores, which was 0.001537. The table presents the ATT (τ_{ATT}), standard error (Std. error), t-value (t), p-value ($P >| z |$), and number of observations.

Table A4.13: PSM - Retail, caliper (0.00192)

Variable/Employees	$\tau_{\mathbf{ATT}}$	Std. error	t	P>| z |	Obs.
TI/Employees (-1)	-997.9	655.4	-1.52	0.13	34,929
TI/Employees	-1,043.0	614.6	-1.70	0.09*	34,929
TI/Employees (1)	-1,015.4	699.2	-1.45	0.15	34,929
TI/Employees (2)	-938.8	858.5	-1.09	0.27	34,929
TI/Employees (3)	-1,000.3	670.7	-1.49	0.14	34,929
EBITDA/Employees (-1)	-38.4	28.5	-1.35	0.18	34,929
EBITDA/Employees	-55.9	25.7	-2.17	0.03**	34,929
EBITDA/Employees (1)	-60.1	27.8	-2.17	0.03**	34,929
EBITDA/Employees (2)	-71.7	26.6	-2.69	0.01***	34,929
EBITDA/Employees (3)	-43.3	23.6	-1.84	0.07*	34,929
ROA (-1)	-0.008	0.008	-0.964	0.335	34,929
ROA	-0.007	0.007	-0.994	0.320	34,929
ROA (1)	-0.004	0.010	-0.415	0.678	34,929
ROA (2)	-0.021	0.009	-2.281	0.023**	34,929
ROA (3)	-0.002	0.010	-0.196	0.844	34,929

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table presents the PSM results for the retail industry. The results are sorted by year minus one to plus three, where year zero is the year before the M&A, for each of the dependent variables. The matching is based on 1:1 NN with a caliper of 25% SD to the mean of the propensity scores which was 0.00192. It presents the ATT (τ_{ATT}), standard error (Std. error), t-value (t), p-value ($P >| z |$), and number of observations.

Table A4.14: PSM - Remaining sectors, caliper(0.002232)

Variable/Employees	$\tau_{\mathbf{ATT}}$	**Std. error**	t	**P>| z |**	**Obs.**
TI/Employees (-1)	4.0	172.0	0.02	0.98	46,537
TI/Employees	-122.3	140.7	-0.87	0.38	46,537
TI/Employees (1)	-147.2	150.7	-0.98	0.33	46,537
TI/Employees (2)	-119.7	163.3	-0.73	0.46	46,537
TI/Employees (3)	-166.6	178.8	-0.93	0.35	46,537
EBITDA/Employees (-1)	-37.2	33.7	-1.10	0.27	46,537
EBITDA/Employees	-21.4	30.8	-0.69	0.49	46,537
EBITDA/Employees (1)	-33.1	34.7	-0.96	0.34	46,537
EBITDA/Employees (2)	-27.6	43.1	-0.64	0.52	46,537
EBITDA/Employees (3)	-9.7	36.6	-0.26	0.79	46,537
ROA (-1)	-0.006	0.011	-0.521	0.602	46,537
ROA	-0.011	0.010	-1.043	0.297	46,537
ROA (1)	-0.028	0.012	-2.328	0.020**	46,537
ROA (2)	-0.004	0.013	-0.287	0.774	46,537
ROA (3)	-0.191	0.173	-1.101	0.271	46,537

τ_{ATT} is the coefficient for the ATT
*** p<0.01, ** p<0.05, * p<0.1

The table presents the PSM results for the remaining industries. The results are sorted by year minus one to plus three , where year zero is the year before the M&A, for each of the dependent variables. The matching is based on 1:1 NN with a caliper of 25% SD to the mean of the propensity scores, which was 0.002232. The table presents the ATT (τ_{ATT}), standard error (Std. error), t-value (t), p-value ($P >| z |$), and number of observations.

A5 DD Regressions

Table A5.1: DD Results - t=0 against t= 1

	(1)	(2)	(3)
VARIABLES	$\frac{TI}{Employees}$	$\frac{EBITDA}{Employees}$	ROA
Post*MA2	116.2	11.8	0.003
	(140.8)	(15.4)	(0.005)
Post	-9.8	-2.5	-0.001
	(102.9)	(11.3)	(0.004)
MA2	71.0	6.8	-0.001
	(99.7)	(10.9)	(0.004)
Employees	-3.8***	-0.3***	-1.63e-06
	(0.2)	(0.03)	(8.09e-06)
FA	0.001***	0.0001***	-5.31e-09
	(0.0002)	(1.65e-05)	(5.34e-09)
log(TA)	1,028***	73.2***	-0.005***
	(31.2)	(3.4)	(0.001)
Equity Ratio	-667.5***	-72.3***	0.053***
	(217.4)	(23.8)	(0.007)
Profitable	513.9***	-34.9***	0.111***
	(109.1)	(12.0)	(0.004)
Operating Margin	26.5	2,128***	0.979***
	(440.4)	(48.3)	(0.015)
Interest Rate	-4,528**	-41.9	-0.611***
	(2,024)	(221.8)	(0.072)
Max Ownership	-795.0***	37.2	-0.011
	(217.8)	(23.9)	(0.008)
Constant	-7,836***	-615.4***	-0.006
	(422.8)	(46.3)	(0.014)
Observations	6,876	6,876	6,876
R-squared	0.262	0.414	0.643

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The table presents DD regression of the year before M&A against the year after. Each column represents TI/Employees, EBITDA/Employees, and ROA. The DD-estimator (δ) is denoted as "MA2*Post". "Post" (λ) denotes the effect of being in the last period, and "MA2" (γ) indicated whether the observation is in the treated group. The regression controls for year, sector, and region in addition to the presented variables.

Table A5.2: DD Results - t=0 against t=2

VARIABLES	(1) $\frac{TI}{Employees}$	(2) $\frac{EBITDA}{Employees}$	(3) ROA
Post*MA2	146.5	7.2	0.005
	(158.0)	(15.6)	(0.005)
Post	-43.3	-0.9	0.001
	(119.0)	(11.7)	(0.004)
MA2	71.0	6.7	-0.0004
	(111.7)	(11.1)	(0.003)
Employees	-3.9***	-0.3***	2.28e-06
	(0.3)	(0.03)	(7.74e-06)
FA	0.001***	9.56e-05***	-8.97e-09*
	(0.0002)	(1.65e-05)	(5.10e-09)
log(TA)	1,047***	74.5***	-0.007***
	(34.9)	(3.5)	(0.001)
Equity Ratio	-793.0***	-69.3***	0.046***
	(241.4)	(23.9)	(0.006)
Profitable	619.5***	-44.6***	0.099***
	(123.5)	(12.2)	(0.004)
Operating Margin	-461.3	2,237***	1.005***
	(529.0)	(52.3)	(0.016)
Interest Rate	-7,836***	-17.2	-0.895***
	(2,629)	(260.1)	(0.080)
Max Ownership	-787.5***	34.3	-0.0035
	(248.9)	(24.6)	(0.008)
Constant	-7,910***	-624.7***	0.015
	(476.7)	(47.2)	(0.014)
Observations	6,876	6,876	6,876
R-squared	0.234	0.394	0.641

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Difference in difference regression of the year before M&A against two years after. Each column represents TI/Employees, EBITDA/Employees, and ROA. The DD-estimator (δ) is denoted as "MA2*Post". "Post" (λ) denotes the effect of being in the last period, and "MA2" (γ) indicated whether the observation is in the treated group. The regression controls for year, sector, and region in addition to the presented variables.

Table A5.3: DD Results - t=0 against t=3

VARIABLES	(1) $\frac{TI}{Employees}$	(2) $\frac{EBITDA}{Employees}$	(3) ROA
Post*MA2	71.2	27.2*	0.001
	(144.5)	(15.4)	(0.005)
Post	-44.9	-13.9	-0.001
	(114.4)	(12.2)	(0.004)
MA2	70.9	6.0	-0.001
	(102.2)	(10.9)	(0.004)
Employees	-3.521***	-0.253***	-1.16e-06
	(0.2)	(0.02)	(7.26e-06)
FA	0.001***	6.10e-05***	-5.55e-09
	(0.0002)	(1.56e-05)	(4.96e-09)
log(TA)	1,020***	76.6***	-0.006***
	(31.5)	(3.4)	(0.001)
Equity Ratio	-607.0***	-55.6**	0.059***
	(208.9)	(22.3)	(0.006)
Profitable	560.5***	-26.3**	0.110***
	(110.7)	(11.8)	(0.004)
Operating Margin	-212.2	2,077***	0.954***
	(455.4)	(48.6)	(0.015)
Interest Rate	-6,650***	1.3	-0.710***
	(2,386)	(254.6)	(0.080)
Max Ownership	-534.3**	24.4	-0.007
	(230.2)	(24.6)	(0.008)
Constant	-7,926***	-635.1***	-0.004
	(432.3)	(46.1)	(0.014)
Observations	6,876	6,876	6,876
R-squared	0.268	0.382	0.646

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Difference in difference regression of the year before M&A against three years after. Each column represents TI/Employees, EBITDA/Employees, and ROA. The DD-estimator (δ) is denoted as "MA2*Post". "Post" (λ) denotes the effect of being in the last period, and "MA2" (γ) indicated whether the observation is in the treated group. The regression controls for year, sector, and region in addition to the presented variables.

Table A5.4: T-tests post-NN 1:1 matching period -1

Variable	**Obs**	**Mean**	**Std. error**	**Std. dev**
TI/Employees				
0	1,719	2,236	69.8	2,895
1	1,719	2,399	105.4	4,371
T	–1.289			
Ha: diff !=0	0.198			
EBITDA/Employees				
0	1,719	164.1	14.6	605.4
1	1,719	174.8	10.7	442.2
T	-0.589			
Ha: diff !=0	0.556			
ROA				
0	1,719	.075	.004	.157
1	1,719	.073	.004	.157
T	0.334			
Ha: diff !=0	0.739			

The table presents a two-sample t-tests with unequal variance for our outcome variables in period 1 post 1:1 NN matching for the DD analysis. The control group are marked with 0, while the M&As group is marked with 1. The table presents total number of observations, mean, standard errors, and standard deviation. In the second section, the T-value and p-value for the null hypothesis that the two groups are not different.

Table A5.5: T-tests post-NN 1:1 matching period 0

Variable	**Obs**	**Mean**	**Std. error**	**Std. dev**
TI/Employees				
0	1,719	2,240	72.2	2,993
1	1,719	2,328	84.5	3,505
T	-0.797			
Ha: diff !=0	0.426			
EBITDA/Employees				
0	1,719	159.6	10.0	416.0
1	1,719	167.1	9.1	375.7
T	-0.555			
Ha: diff !=0	0.579			
ROA				
0	1,719	.071	.004	.144
1	1,719	.069	.005	.195
T	0.4678			
Ha: diff !=0	0.640			

The table presents a two-sample t-tests with unequal variance for our outcome variables for period 0 post 1:1 NN matching for the DD analysis. The control group are marked with 0, while the M&As group is marked with 1. The table presents total number of observations, mean, standard errors, and standard deviation. In the second section, the T-value and p-value for the null hypothesis that the two groups are not different.