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Spinoffs in the Nordics

An Empirical Study of Value Creation in the Nordic Countries

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Abstract

This thesis investigates the long-term value creation of Nordic spinoffs from 1990 to 2022. First, we perform a *long-run event study* of spinoffs, parent firms, and proforma firms to conduct whether these firms create value in the long run. Moreover, we study the value creation factor *focus* to determine whether the value creation happens because of increased corporate focus. Additionally, we study the operating performance using a *difference-in-differences* model. In both models, we have compared spinoffs, parent firms, and proforma firms to matching firms using a *propensity score matching* model.

In our analysis, we find statistically significant evidence that spinoffs outperform the matching portfolio by 30% over a three-year event window. Parent firms outperform the matching portfolio by 8%. However, it is not significant at conventional levels. Moreover, we find evidence that *focus*-increasing firms outperform *non-focus*-increasing firms over a three-year window, indicating that some of the value creation is due to increased corporate *focus*.

Furthermore, our *difference-in-difference (DiD)* models indicate that the operating performance for spinoffs, parent firms, and proforma firms is better than their corresponding matching portfolios over the same three-year event window. We find statistically significant results for all performance metrics in the *DiD* model for the *DiD*-estimator, except for the first and second year of *ROA* and the third year of *current ratio*. Moreover, for the parent firms, we find no statistically significant results. For the proforma firms, we only find statistically significant results for *return on assets* and *leverage* in the first year. However, for spinoffs, the *DiD* results indicate reciprocal results between the event study models and the *DiD* models, meaning we can interpret the results economically.

To sum up, our findings indicate that spinoffs create shareholder value in the long term, while the results for parent and proforma firms are more ambiguous.

Keywords – Spinoff, Propensity Score Matching, Long-Run Event Study, Difference-in-differences

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1 Introduction

The concept of a personal glow-up after a breakup is well-known, but did you know that corporate breakups can also lead to a glow-up of the firms involved? In this thesis, we will explore the value creation associated with Nordic spinoffs, examining the firms that have emerged from corporate spinoffs in Nordic countries. Spinoffs, which are a form of corporate restructuring involving the separation of a subsidiary from its parent firm, have gained popularity in recent years as a way to increase corporate *focus* and improve efficiency. Previous research has shown that spinoffs can create value for firms in terms of both stock market performance and operating performance. However, these studies have primarily focused on the US market, and there has been little research on the spinoff landscape in Nordic countries.

In this study, we aim to investigate the value creation potential of spinoffs for firms in the Nordics. We analyze the long-term stock-market and operating performance of spinoffs, parent firms, and proforma firms over the 1990-2022 period. We implement various methodologies, such as *propensity score matching*, *long-run event study*, and *difference-in-differences*, to control for potential confounders and measure the causal effect of the spinoff event on firm performance.

Our findings show that Nordic spinoffs outperform their matching peers in the stock market over a three-year period, with statistically significant results. We also find that parent firms tend to outperform their peers, although this result is not statistically significant at conventional levels. Additionally, we find that cross-industry firms outperform intra-industry firms, indicating that increased corporate *focus* can play a role in the value creation potential of spinoff events. Our results are consistent with previous research on spinoffs in other countries, but our study is the first to investigate the spinoff landscape in the Nordics using a *difference-in-differences* model.

In our study of value creation in Nordic spinoffs, we build upon the work of Desai and Jain (1999) by conducting a comprehensive analysis of spinoffs, parent firms, and proforma firms in the Nordics. After collecting data on spinoff firms in Norway, Sweden, Denmark, and Finland, we carefully screened the data and removed firms that did not meet our criteria, leaving us with a sample of 81 spinoff firms and 74 parent firms. In this study, we explore the spinoff events that took place between 1990 and 2022.

In this analysis, we have employed three different methodologies: *propensity score matching*, *long-run event study*, and *difference-in-differences.* Our *propensity score matching* model creates a matching firm for each spinoff, parent firm, and proforma firm. The matching firms are selected based on the spinoff year (*Year*), industry code (*NAICS*), country identification number (*ISO*), and return on assets (*ROA*). For *Year*, *NAICS*, and *ISO*, we use exact matching. In the event of almost similar values for these variables, it could introduce bias and compromise the causal interpretation of our results. However, we use nearest-neighbor matching for *ROA*, which means we match with the closest value for *ROA*.

Once we have created matching firms for our spinoffs, parent firms, and proforma firms, we use these firms to study the stock market performance in a *long-run event study* and the operating performance in a *difference-in-differences* model. In the *long-run event study*, we calculate the mean *cumulative abnormal return (CAR)* and *buy-and-hold abnormal return (BHAR)* for both the treated firms (i.e., the spinoffs, parent firms, and proforma firms) and the control firms (i.e., the matching firms). These metrics allow us to evaluate the long-run stock market's reaction to the spinoff event.

In the *difference-in-difference* model, we compare the operating performance of treated and control firms before and after the spinoff event. This allows us to assess the effect of the spinoff on the firms' operational performance and determine whether spinoffs improve a firm's efficiency and profitability. By comparing the results from both the *long-run event study* and the *difference-in-differences* model, we can gain a comprehensive understanding of the value created by spinoffs in the Nordics.

Based on our *long-run event study*, we find that spinoff firms tend to outperform both the matching portfolio and the country index. Specifically, the *buy-and-hold abnormal return (BHAR)* figures for spinoff firms show a 30% and 11% improvement over the matching portfolio and the country index, respectively, over the three-year event window. On the other hand, parent firms outperform the matching portfolio by 8%, but underperform the country index by 2% over the same time period. These results suggest that spinoffs create value for shareholders, as they are associated with better stock market performance compared to both the matching portfolio and the country index.

Our *difference-in-differences* model shows that spinoff firms outperform the control group in terms of operating performance, as measured by *return on assets*, *current ratio*, and *leverage*. In particular, we find that spinoff firms experience a 12.8% increase in *return on assets*, a 263% increase in *current ratio*, and a 156% decrease in *leverage*, compared to the control group. These results are statistically significant at the 5% level for *return on assets* and *leverage*, and at the 10% level for the *current ratio*. On the other hand, the results for parent firms are not statistically significant, but they still outperform the control group with a 2.7% increase in *return on assets*, a 66% increase in *current ratio*, and a 25% increase in *leverage*. These findings suggest that spinoffs can improve a firm's operational performance, while the impact on parent firms is less clear.

This thesis contributes to the existing literature on spinoffs by introducing a new econometric method and a new geographical area to the study of value creation in spinoffs. To our knowledge, one of the methods we have used (i.e., the *difference-in-differences* model) has not yet been applied in previous spinoff studies. Additionally, our study focuses exclusively on the Nordic countries (Norway, Sweden, Denmark, and Finland), which have a different economic and cultural context as opposed to the US. These novel approaches and geographical focus allow us to provide new insights into the value created by spinoffs in the Nordics.

2 Literature Review and Hypotheses

In this section, we will provide a literature review on event study and value creation in spinoffs and present our hypotheses and contribution to existing research. We will focus on three main factors: information asymmetry, relative size, and corporate focus. Our research aims to provide insights into the determinants of value creation in spinoffs and contribute to the existing literature.

Spinoff event study

Spinoffs and their performance have been a topic of interest in the academic literature for decades. As a sub-group of initial public offerings (IPOs), spinoffs have often been studied using the *event study* methodology, which has been widely used to examine the stock market performance of IPOs (Aggarwal and Rivoli (1990); Ritter (1991)). Previous research has consistently found that spinoffs yield abnormal returns (Cusatis et al., 1993; Daley et al., 1997; Desai and Jain, 1999; Krishnaswami and Subramaniam, 1999; Feng et al., 2015; McConnell et al., 2001). And some of these studies find evidence that they outperform in the long run. Additionally, these studies show that spinoff firms tend to outperform their parent firms, contrary to the findings of Aggarwal and Rivoli (1990), and Ritter (1991). Given the contradictory evidence and the importance of corporate restructuring in the success of spinoffs, it is crucial to further investigate the factors contributing to value creation in spinoffs.

Information asymmetry

Information asymmetry is a key factor that drives firms to pursue spinoffs. Previous research on spinoffs has consistently identified information asymmetry as a primary motivation for firms to perform spinoffs (Chemmanur and Liu, 2011; Rose and Shekhar, 2018; Kriz et al., 2021). By pursuing a spinoff, the parent firm signals to the market that the spinoff has a higher intrinsic value than the market perceives. Additionally, the parent firm may believe that the market underestimates the potential synergy loss from the spinoff. Furthermore, these studies suggest that firms with valuable information are more likely to pursue a spinoff over other forms of corporate restructurings, such as an equity carveout, a stock issue, or an entity sale.

Relative size

According to previous research by Chemmanur and Yan (2004), and Krishnaswami and Subramaniam (1999), spinoffs tend to create excess value for both the parent firm and the spinoff itself. These researchers provide theoretical and empirical evidence that larger spinoffs relative to their parent firms are more likely to create higher excess value, likely due to the increased probability of a takeover. However, these findings are only sometimes accepted, as Ahn and Denis (2004) did not find this significant at the 5% level.

Corporate focus

Spinoffs can either take place within the same industry as the parent firm or in a different industry. Desai and Jain (1999) categorize spinoffs in different industries as *focus*-increasing, while spinoffs within the same industry are considered *non-focus*-increasing. Cross-industry spinoffs are expected to increase *focus* because they allow the parent firm to *focus* on its core competencies and divest non-core assets. Likewise, the spinoffs increase *focus* by allowing the subsidiary to be more efficiently managed by a dedicated entity. Desai and Jain (1999) find evidence that *focus*-increasing spinoffs create more value than *non-focus*-increasing spinoffs. There are several reasons for this. Firstly, it is generally believed that *focus*-increasing spinoffs are less likely to experience synergy loss than *non-focus*-increasing spinoffs. This is because the former type of spinoff is created with the specific intention of allowing the parent firm to *focus* on its core operations, while the latter type of spinoff is created for other reasons, such as to raise capital or to divest underperforming assets (Desai and Jain, 1999). Additionally, shareholder activism is often a driving factor behind spinoffs, and the expectation is that changes to governance and operational engineering will positively impact both stock market performance and accounting performance.

In this way, *focus*-increasing spinoffs can be seen as a result of shareholder activism. Therefore, we expect the increased corporate *focus* and shareholder activism to affect value creation significantly, and we will study this relationship in more detail in our analysis.

2.1 Hypotheses

Spinoff events have garnered significant interest among academics and practitioners alike. While much research has been conducted on the effects of spinoff events on firms in the US, the Nordics have been largely overlooked in this regard. Therefore, it is essential to develop and test hypotheses using multiple methodologies to gain a deeper understanding of the impact of the spinoff events on firms in the Nordics. This can provide valuable insights for regional investors and businesses and contribute to the existing body of literature on spinoff events.

There are multiple reasons why firms perform a spinoff event. First, the spinoff information may be harder to obtain than comparables, thus lowering its valuation. Additionally, it may be to forego the underinvestment problem or visualize the firm's underlying values (Chemmanur and Yan, 2004). Furthermore, according to information asymmetry and shareholder activism, pursuing a spinoff will be beneficial. Thus, our first hypothesis will be:

Hypothesis 1: Nordic firms create value in the stock markets by spinning off subsidiaries. Additionally, with an increased focus, in which a spinoff does not happen in the same industry as its parent firm, it will outperform the performance metrics compared to a spinoff that happens in the same industry as its parent.

Information asymmetry and shareholder activism suggest that spinoff events can be beneficial for firms. Therefore, our first hypothesis is that spinoff events create value for firms in the stock market, and spinoffs in different industries from the parent firm outperform spinoffs in the same industry. This hypothesis is considered necessary in light of information asymmetry and shareholder activism, and our study aims to understand whether firms that engage in spinoffs are better off than comparable firms and the country index in general.

Hypothesis 2: Nordic firms increase operating performance by spinning off subsidiaries.

To test hypothesis 2, we use performance metrics such as *return on assets*, *current ratio*, and *leverage*, which are intended to provide a broad view of a firm's operating performance. The hypothesis also notes that using pre-spinoff and post-spinoff data will make the results comparable. Additionally, the hypothesis raises the possibility that the lower stand-alone value of the parent and spinoff firms may provide incentives for managers to improve their operations, but it also notes that this may be offset by increased susceptibility to takeover.

2.2 Contribution to existing research

This thesis attempts to contribute to the existing literature in multiple ways. Firstly, it provides empirical evidence of how firms in the Nordics perform post-spinoff in the long run. The following is interesting as there have been multiple papers on the topics in the US, especially regarding the announcement return. Hence, we focus on the long-run performance. However, to our knowledge, there have not been any articles published regarding the Nordics. It also provides empirical evidence on how *focus* affects a firm post-spinoff-event. Additionally, it is exciting to comprehend why our results turn out the way they do, and compare it to existing spinoff theory.

Thirdly, we look at the development of the firm's performance metrics in a *DiD* model, to capture the causal effect of the spinoff event on operating performance. Besides, this will help assess why firms perform the way they do post-spinoff-event. Moreover, we contribute to existing research with new empirical evidence. We do so by 1) a comprehensive dataset with extensive use of sources. 2) various performance measures and metrics to capture as much of the effect as possible. Finally, 3) using several econometric approaches to make the results more robust.

3 Data Collection

This section will present our data collection process and the samples we obtained from it. First, we will present which data sources we use. Then, we will discuss our matching and sample construction process before providing summary statistics of our final data samples.

3.1 Data Sources

This section presents the methods and sources used in our Nordic spinoff analysis. The data used in our study has been collected from various sources, including *Refinitiv Eikon, Compustat Global's International Event Study* tool, *Compustat's Fundamental Annual* database, annual reports, and spinoff prospectuses. This diverse and comprehensive dataset allows us to analyze spinoff firms in the Nordic region thoroughly.

The present study utilizes a sample of spinoffs in the Nordic countries from 1990 to 2022, collected from Eikon Refinitiv. The sample includes 107 spinoffs and 86 corresponding parent firms, with each firm's distribution date recorded. This dataset is the foundation for our analysis of value creation in Nordic spinoffs. However, it is essential to note that the sample may be subject to any limitations or biases inherent in the data source.

To analyze the stock market performance of Nordic spinoffs, we have collected data from *Compustat Global's International Event Study* tool. This data includes daily stock market observations for each sample firm, starting from the spinoff distribution date and continuing for up to three years. The data includes total daily return, daily market return, and daily abnormal return. The market return is specific to the country where the firm is located. Because the data is collected on a daily basis, one year is assumed to have 252 trading days. This data will be used to assess the stock market performance of spinoff firms.

To analyze the operating performance of spinoff and parent firms, we have collected data from the spinoff prospectus and annual reports. We are interested in the firm's performance on a stand-alone basis, so we have gathered data from before the spinoff event. However, due to the large timespan covered by our study, we could not retrieve data for all firms. In addition, for some firms, old annual reports are not publicly available. The operating performance metrics we used – *return on assets*, *current ratio*, and *leverage* – were chosen because they are well-known financial metrics and are readily available in old annual reports. Additionally, we retrieved operating performance metrics from *Compustat's Fundamental Annual* database for the matching firms. To create matching portfolios for comparison, these firms were matched with each spinoff, parent firm, and proforma firm.

3.2 Sample Construction

We collected a dataset from Eikon Refinitiv containing a list of spinoffs completed in the Nordics from 1990 to 2022. The dataset includes information on 107 spinoffs and 86 parent firms, including the distribution date for each spinoff. However, we could only utilize some of these firms in our analysis for various reasons, which we will discuss in greater detail.

In order to improve the accuracy of our data, we conducted a thorough evaluation of each firm in our sample. We verified the accuracy of the identification number (ISIN), distribution date, and accounting data and also sought to match each sample firm with the corresponding matching firm. In this process, we encountered several issues with the data. Specifically, we identified 20 firms with incorrect identification codes, posing a challenge to accurately identifying the sample firms. We were able to manually correct the codes for only seven of these firms, ultimately leading to the exclusion of eight spinoffs and five parent firms from our study.

Additionally, our evaluation of the sample firms revealed that seven firms had misspecified distribution dates. The misspecified distribution dates result from inaccurate data from Eikon Refinitiv. Thus, we excluded an additional seven spinoffs from our data sample.

Through our matching procedure, we aimed to identify comparable firms by utilizing various factors such as *return on assets (ROA)*, *leverage ratio*, *NAICS-code*, *ISO-code*, and *spinoff year*. However, there were instances where fundamental data from *Compustat's Fundamental Annual* database was missing for five spinoffs and three parent firms, resulting in excluding these firms from our data sample. Moreover, in six spinoffs and four parent firms, we could not find firms that matched on our matching variables, which we will present below. This led us to omit them from the data sample.

After applying all the necessary quality checks and matching procedures, our final dataset includes information on 81 spinoffs and 74 parent firms. However, some of these firms have missing observations in operating accounting or stock market data in some event windows. As a result, there is variation in the number of observations available for different event windows and models. This may affect the accuracy and precision of our analysis.

3.3 Matching Criteria

To perform a *propensity score matching*, we match spinoffs and parent firms on a set of fundamentals. The fundamental characteristics we have used in the matching process are *ROA*, *leverage ratio*, *NAICS-code*, *ISO-code*, and *spinoff year*.

Return on Assets (ROA) is a metric showing the net income divided by total assets. It indicates the relative profitability compared to the firm's assets (Fama and Schwert, 1977). Hence, it is a good metric because it can tell investors how a firm convert its investments into net income. The interpretation of the *ROA* metric is that the higher the *ROA*, the better its asset profitability ratio is.

Leverage is a metric showing a firm's total liabilities given its total equity. Thus, the total liability is the combined debt that a firm owes. Total equity is a firm's total assets, given its total liabilities. Thus, it yields a *leverage ratio* for the firm. The higher a firm's *leverage*, the more debt they have compared to its total equity. *Leverage* can be both good and bad. For example, a firm with excessive *leverage* may imply that it is in financial distress, which is terrible. On the other hand, *leverage* may also be good if the firm employs its capital well, which implies higher returns net of fees than without it (Kosowski and Neftci, 2015).

We use *The North American Industry Classification System (NAICS)* to classify which industry a firm belongs to. The justification of the classification is related to collecting, analyzing, and publishing statistical data (Census Bureau, 2022). Hence, it serves as an excellent matching metric. Next, the *International Standard for country* codes and codes for their subdivisions *(ISO)* is used to classify countries (ISO, 2021). Its usage in our thesis is a matching criterion. The *ISO code* is to adhere to our preliminary thought on using countries within the Nordics as our origin of interest. Finally, we use the 2-digit *NAICS code* to match the firms in our data sample. The last matching criterion is the *spinoff year*. In our thesis, a year is considered a calendar year. Thus, we consider firms with a fiscal year-end in, for example, January 2021 through December 2021. This time consideration is due to validity reasons, as both the parent firm and the spinoff must be subject to matching firms in the same time interval to be comparable.

Table 3.1: Sample Construction

The table presents the rationale for the exclusion of spinoff and parent firms from the study. The identification code (ISIN) indicates the number of firms that were excluded due to inaccurate identification codes from Eikon Refinitiv. The misspecified distribution date shows the number of firms that were excluded due to incorrect distribution dates. The missing accounting data category shows the number of firms that lacked the necessary accounting data for the analysis. Lastly, the missing matching firms category indicates the number of observations that could not be matched with a corresponding firm and were therefore omitted.

Step	Description	Effect	Parents	Effect	Spinoffs
	Collected sample		86		107
1	Missing identification number	-5		-8	
2	Misspesificed distribution date	-		-7	
3	Missing accounting data	-3		-5	
4	Missing matching firms	-4		-6	
	Total	-12	74	-26	81

3.4 Summary Statistics

Table 3.2: Sector Distribution

The table reports the respective distribution of parent firm and spinoff firm industries. It also shows the individual share of each industry sector in percentage. The number of firms in a given industry is represented by the variable "n", and the percentage of the industry's total market share is represented by %.

Industry	**Parents**		**Spinoffs**	
	n	%	n	%
Agriculture and fishing	-	-	1	1.2
Mining	3	4.1	6	7.4
Utilities	2	2.7	1	1.2
Construction	6	8.1	3	2.7
Manufacturing	23	31.1	29	35.8
Wholesale Trade	6	8.1	6	7.4
Retail Trade	2	2.7	5	6.2
Transportion and Warehousing	1	1.4	-	-
Information	3	4.1	7	8.6
Finance and Insurance	10	13.5	10	13.5
Real Estate	5	6.8	9	11.1
Professional Services	6	8.1	6	7.4
Administrative and Support	6	8.1	4	4.9
Health Care	-	-	1	1.2
Entertainment and Recreation	1	1.4	1	1.2
Total	74	100	81	100

Table 3.2 shows the *NAICS* industry codes for 81 spinoffs and 74 parent firms in the Nordic countries. The tables show that *Manufacturing* is the most common industry for spinoffs and parent firms, accounting for 35.8% of spinoffs and 31.1% of parent firms. Moreover, *Finance and Insurance* is the second most common industry for spinoffs and parent firms. All in all, we observe a more comprehensive range of industries for spinoffs than parent firms.

Table 3.3: Spinoff Year Distribution

The table reports the respective distribution of spinoff firms taking place from 1990 to 2022. It shows whether the parent firms are focus-increasing, non-focus-increasing or if it is non-observable.

Year	**Spinoff**	***Focus-*** **increasing**	***Non-focus-*** **increasing**	**Non-observable (*focus*)**
1992	-	-	-	-
1996	3	1	-	2
1997	1	-	-	1
1998	6	3	1	2
1999	3	1	-	2
2000	3	1	2	-
2001	6	2	1	3
2002	1	-	1	-
2004	3	1	1	1
2005	4	3	-	1
2006	6	2	2	2
2007	7	4	1	2
2008	4	-	-	4
2010	3	-	1	2
2011	2	-	1	1
2012	2	-	2	-
2013	3	3	-	-
2014	2	-	1	1
2016	2	2	-	-
2017	5	1	3	1
2018	2	-	2	-
2019	5	2	3	-
2020	4	2	2	-
2021	4	1	3	-
2022	-	-	-	-
Total	81	29	27	25

Table 3.3 presents how the Nordic spinoffs are distributed over the sample period and whether the spinoff is increasing focus or not. As seen in the table, a total of 29 spinoffs were found to be *focus*-increasing, while 27 were *non-focus*-increasing. We also observe from the table that spinoffs occur more often when the economic times are good and the financial markets are liquid, which is consistent with the findings of Eckbo et al. (2013). However, it is essential to note that 25 of the observations in the sample did not have both spinoff and parent firm, making it impossible to determine whether the spinoff is increasing *focus* or not.

Table 3.4: Parent Year Distribution

The table reports the respective distribution of parent firms taking place from 1990 to 2022. It shows whether the parent firms are focus-increasing, non-focus-increasing or if it is non-observable.

Year	Parents	*Focus-* increasing	*Non-focus-* increasing	Non-observable (*focus*)
1992	1	-	-	1
1996	4	1	-	3
1997	-	-	-	-
1998	4	1	1	2
1999	2	1	-	1
2000	4	1	2	1
2001	3	2	1	-
2002	2	-	1	1
2004	3	1	1	1
2005	5	3	-	2
2006	4	2	2	-
2007	5	4	1	-
2008	4	-	4	-
2010	2	-	2	-
2011	1	-	1	-
2012	2	-	2	-
2013	3	3	-	-
2014	1	-	1	-
2016	2	2	-	-
2017	4	1	3	-
2018	2	-	2	-
2019	5	2	3	-
2020	5	2	2	1
2021	5	1	3	1
2022	1	-	-	1
Total	74	27	32	15

Table 3.4 presents the distribution of parent firms over the sample period and whether the firm is increasing *focus*. Out of the 74 parent firms, 27 firms are found to be increasing *focus*, while 32 are not. Additionally, 15 firms could not be classified due to a lack of information on their spinoff firms.

4 Methodology

In this section, we describe the methodology of our analysis. First, we introduce the *propensity score matching* model, which creates matching firms used in the *long-run event study* and the *difference-in-differences* model. We then present the *long-run event study*, which tests the long-term stock returns. Lastly, the implementation of operating metrics for the treated and control groups is discussed. The *difference-in-differences model* allows for the isolation and analysis of differences in operating metrics between the treated and control groups over time.

4.1 Propensity Score Matching

To accurately estimate the effect of a treatment, it is necessary to interpret its causal relationship. However, this is often challenging in observational studies due to potential issues such as self-selection bias (Dehejia and Wahba, 2002). From Table 3.3, we observe that spinoff activity tends to align with the stock market environment, particularly during bull markets such as the dot com bubble of the late 1990s and the years upon the global financial crisis in 2008. This finding is consistent with the work of Eckbo et al. (2013), who noted that many firms during the early 2000s sought to capitalize on higher valuation multiples in the technology and internet sectors by spinning off relevant divisions.

Additionally, Eckbo et al. (2013) found that spinoff activity increased in the years leading up to the global financial crisis, followed by a decrease in activity after the crisis. Hendershott (2004) also studied the impact of net value wealth creation and destruction during the internet boom and found that the timing of an initial public offering (IPO) had significant effects. These findings suggest that spinoff activity and firm characteristics are not random and that there may be a systematic difference between firms that spin off subsidiaries and those that do not. This difference could potentially lead to self-selection bias and should be considered when estimating treatment effects.

Propensity score matching is a statistical technique used to identify a control group similar to the treatment group regarding observable characteristics. By accounting for relevant differences between the treatment and control firms in observable covariates, we can obtain an unbiased estimate of the treatment effect (Dehejia and Wahba, 2002). However, it is essential to note that certain assumptions must hold for this method to be effective.

The use of *propensity score matching* is intended to reduce the selection bias of observational data, which may have different density weighting and lack distributional overlap (Heckman et al., 1997). As a result, several assumptions must be satisfied for this method to be effective. Firstly, balancing the propensity scores is essential to ensure that the treated and control groups with identical propensity scores have similar distributions of observed "x" (Rosenbaum and Rubin, 1983). Secondly, the assumption of conditional independence must hold, meaning that the sample of observed "x" should not be affected by the treatment, and the outcome should be independent in both samples for these covariates (Caliendo and Kopeinig, 2008). Thirdly, the assumption of common support must be satisfied, requiring that the probability of being a participant or non-participant is the same and that the functional attributes of a given unit share characteristics with both the treated group and the control group with a gradient probability (Garrido et al., 2014). These assumptions are crucial for obtaining valid results from *propensity score matching*.

However, several potential pitfalls are associated with *propensity score matching*. For example, if too many matching variables exist, the common support assumption may be violated, leading to substantially increased standard errors without significant bias reduction (Lechner, 2008). Similarly, the common support assumption may also be violated if there are too few matching variables. As a result, it is necessary to carefully select a finite set of matching variables to avoid these issues. Additionally, the matching estimator is based on a finite set of observable characteristics, which may lead to hidden bias in unobservable data. This is a common problem in applied studies, even though such characteristics may be important (Garrido et al., 2014).

Propensity score matching is based on the comparison of observable characteristics between a group that has received treatment and a group that has not. In our case, the treatment is a spinoff event (Webster-Clark et al., 2021). Using matching variables such as *NAICS*, *Year, ISO*, and *ROA*, we can analyze the effect of spinoff events on both stock market performance and operating performance metrics. However, as Caliendo and Kopeinig (2008) noted, there is a trade-off between efficiency and bias in the matching algorithm.

Efficiency refers to the precision of the estimated treatment effect, while bias refers to the distance of the estimated effect from the actual effect. In our study, the *NAICS, Year*, and *ISO* variables are subject to exact matching, while *ROA* is subject to nearest-neighbor matching (Caliendo and Kopeinig, 2008). By separating spinoffs, parent firms, and proforma firms into separate groups with their corresponding control groups, we can increase the precision of our estimates (Stuart, 2010).

In order to conduct a *propensity score matching*, we must choose between a binary treatment probit or logit model (Caliendo and Kopeinig, 2008). In this study, we use the logit model to analyze the event as a function of independent variables, which provides a better overview of our categorical variables data (Agresti, 2013). We use *Year, NAICS, ISO*, and *ROA* as independent variables.

Table 4.1: Difference in Means PSM

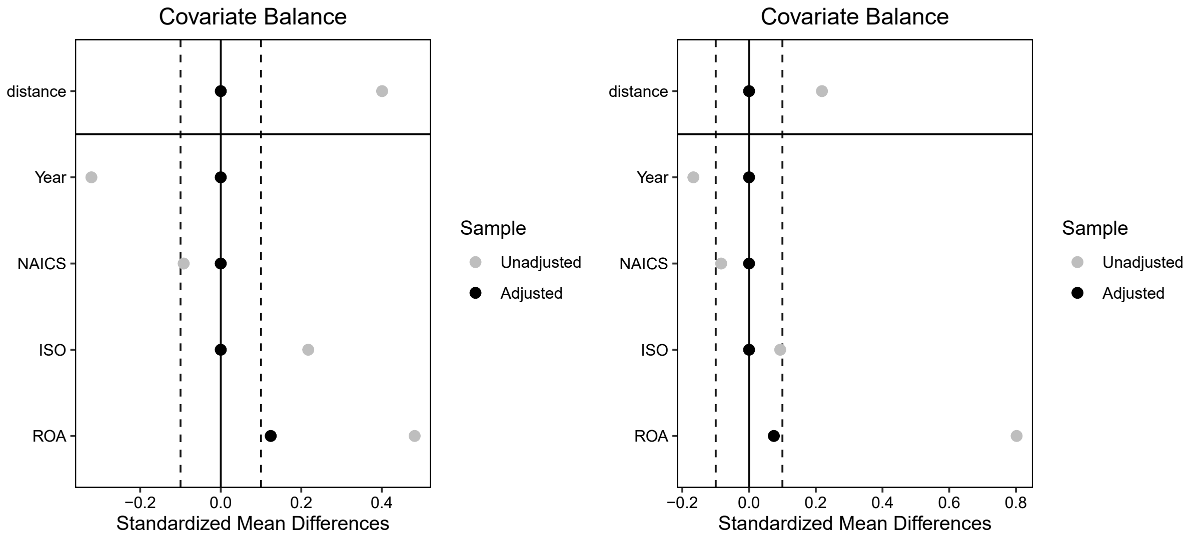
The tables present the difference in means for the covariates Year, NAICS, ISO, and ROA for the firms opposed to a treatment (Treat) and control firms (Control) regarding spinoffs and parents. Additionally, it presents the standardized mean differences (SMD) between the treatment (Treat) and control firms (Control).

	Spinoffs			**Parents**		
	Control	Treat	SMD	Control	Treat	SMD
	n=81	n=81		n=74	n=74	
Year (mean (SD))	2008.42 (7.76)	2008.42 (7.76)	<0.001	2008.12 (8.30)	2008.12 (8.30)	<0.001
NAICS (mean (SD))	40.57 (12.56)	40.57 (12.56)	<0.001	40.49 (12.43)	40.49 (12.43)	<0.001
ISO (mean (SD))	3.19 (1.18)	3.19 (1.18)	<0.001	3.04 (1.24)	3.04 (1.24)	<0.001
ROA (mean (SD))	0.00 (0.20)	0.01 (0.14)	0.100	0.02 (0.06)	0.02 (0.08)	0.082

Table 4.1 summarizes the results of the *propensity score matching* for spinoffs and parent firms. As previously mentioned, the matching covariates *Year, NAICS*, and *ISO* are subject to exact matching, resulting in zero standardized mean differences for these variables. We use 1:1 matching, which means we match each treatment firm with one control firm. The matched firms are selected based on the same year, industry, country, and *ROA*. *ROA* is matched using the nearest neighbor method, resulting in slightly larger standardized mean differences for each treated firm. However, due to the constraints of our data set, we could only identify one matching firm for each treated firm.

Figure 4.1: Covariance Balance

The figure presents the standardized mean differences for the covariates Year, NAICS, ISO, and ROA for treated and control firms. Additionally, the figure demonstrates the variation in balance between the adjusted and unadjusted samples, indicating the effect of propensity score matching in the analysis.



(a) *Spinoffs* ***(b)*** *Parents*

Figure 4.1 illustrates the covariate balance of the adjusted sample compared to the unadjusted sample. After adjusting for the matching covariates, we can see that the covariates with exact matching are fully balanced, with zero standardized mean differences between the treated and matching firms. The *ROA* covariate has higher standardized mean differences, but the matching firms are still much more balanced than the complete set of potential matching firms. Additionally, we observe that the matching firms for parents are more balanced than those for spinoffs, indicating that matching firms for spinoffs exhibit more variability in our sample.

4.2 Long-run Event Study

Event studies are econometric methods for analyzing the effects of specific events, such as spinoffs. This subsection describes the methodology for estimating spinoffs and their parent firm's long-run stock market performance. We also discuss the event study time period, the measurement of abnormal returns and benchmarks, and the statistical tests used in our event study.

When selecting the time period for an event study, two key considerations are the measurement period and the time regime. In *long-run event studies*, the event period is typically between one and five years (Collins et al., 2009; Danne et al., 2008). However, to capture the spinoff's full effect, we believe a more extended period is preferable. However, our data set is relatively small, so overextending the time period could result in omitting a significant number of observations. Therefore, we measure performance for three years post-spinoff distribution. In addition, the time period is consistent with other *long-run event studies* such as Ritter (1991). It allows us to focus on the post-event stock market performance without the pre-spinoff period.

There are two commonly used methods for estimating long-run stock market performance: the *buy-and-hold abnormal return* approach and the *calendar time* approach. The *buy-and-hold abnormal return* approach uses a benchmark to measure the abnormal *buy-and-hold return* for each event firm and tests the null hypothesis that the average abnormal return is zero. The *calendar time* approach, on the other hand, constructs a portfolio for each calendar month consisting of firms that have experienced an event within a specific time period prior to the month and test the null hypothesis that the intercept is zero in the regression of monthly *calendar time* portfolio returns against the factors in an asset-pricing model. The advantage of the *calendar time* approach is that it effectively controls for cross-sectional dependence among sample firms (Wharton Research Data Services, 2022).

In contrast, the *buy-and-hold abnormal return* approach reflects the actual returns of an investment strategy, such as a passive investment strategy in which investors maintain a relatively stable portfolio over the long term (Kerstens et al., 2022). In addition, the portfolio is not rebalanced throughout the study, and the use of a *buy-and-hold* strategy takes into account tax and commission effects (Rosenthal and Wang, 1993). In our event study, we use the *buy-and-hold* approach because it reflects the actual performance that an investor would receive by investing in these events.

When using a long-term *buy-and-hold* strategy and adjusting to a portfolio of matching firms, there may be a tendency towards right skewness. This is because the lower bound of returns is -100%, while there is no upper bound (Eckbo, 2006). However, the central limit theorem suggests that the distribution of returns will be approximately normal when the portfolio includes many independent random variables. Therefore, we use equally weighted *buy-and-hold returns* rather than value-weighted returns to reduce the potential for skewness. This approach provides a better overview of the overall returns of the portfolio.

In addition to reducing the potential for skewness in the distribution of returns, using equally weighted returns is also a common practice in empirical finance (Plyakha et al., 2021). For example, if a spinoff has a valuation of $1 billion and a portfolio of 100 spinoffs have a valuation of $1 million each, then the single spinoff would account for approximately 90% of the portfolio returns. While our data sample does not include such extreme cases, firms like Yara and Swedish Match could still significantly impact the *buy-and-hold returns* for spinoffs in the Nordics. By using equally weighted returns, we can avoid the potential bias introduced by such outliers.

We use two approaches to measure abnormal returns in the event window: *Cumulative abnormal return (CAR)* and *Buy-and-hold abnormal return (BHAR)*. While the differences between CAR and $BHAR$ are relatively small in the short term, they can diverge significantly in the long term. For example, Barber and Lyon (1997) found that $BHAR$ typically produces slightly lower returns than CAR. However, $BHAR$ outperforms CAR significantly when returns exceed 28% (Barber Lyon, 1997). The equations for calculating CAR and $BHAR$ are shown in equations 4.1 and 4.2 below.

Cumulative Abnormal Return (CAR):

$$CAR_{it} = \sum_{t=1}^{T} (R_{it} - E(R_{it})) \tag{4.1}$$

Buy-and-Hold Abnormal Return (BHAR):

$$BHAR_{it} = \prod (1 + R_{it}) - \prod_{t=1}^{T} (1 + E(R_{it})) \tag{4.2}$$

We use the respective country indexes as benchmarks for calculating abnormal returns for the treated firms. For example, we use the FT - Norway index for Norwegian firms, the FT – Denmark for Danish firms, the Helsinki General Index for Finnish firms, and the FT – Sweden index for Swedish firms. We use these country indexes to calculate abnormal returns, as this provides a better indication of each firm's performance. Furthermore, we calculate the abnormal returns for the matching firms as well, which is described in greater detail in subsection 4.1. We do not use the matching firms as benchmarks in the calculation of CAR and $BHAR$. Instead, we calculate CAR and $BHAR$ for the matching firms and compare their returns to those of the treated firms.

Parent firms experience a decrease in initial value due to the spinoff distribution. The value decrease in the parent firm equals the spinoff's market capitalization. However, since we only have return data from *Compustat*, we cannot include the spinoff market capitalization in the parent firm's data. As an alternative, we adjust the initial returns for parent firms by calculating normal returns for the first three days. This allows us to account for the value decrease resulting from the spinoff distribution in our analysis.

To test whether the mean CAR and $BHAR$ are statistically different in the treated and non-treated groups, we have implemented a standard t-test. We assume that the distribution of our observations is normal, which allows us to calculate p-values for the event study tables. This enables us to determine whether the observed differences between the treated and non-treated groups are statistically significant. By using a t-test, we can determine whether the mean CAR and $BHAR$ for treated and non-treated groups are significantly different, providing us with valuable insights into the effects of spinoffs on firm performance.

4.3 Difference-in-Differences

The *difference-in-differences (DiD)* methodology utilizes longitudinal data from both control and treatment groups to estimate a causal effect (Angrist and Pischke, 2008). This method is often used in cases where randomization on an individual level is impossible and exchangeability between the control and treatment groups cannot be assumed. In our case, we use *DiD* to estimate the effect of a spinoff event on the treated group. Our panel data will allow us to compare the changes in the treated and control groups over a limited time interval, potentially reducing bias caused by permanent differences between the groups and other factors that may affect the treated group over time (Angrist and Pischke, 2008). By using the *DiD* approach, we can improve the accuracy of our analysis and better estimate the effect of the spinoff event on the treated group.

For the *DiD* methodology to be valid, several assumptions must be met. These include the exchangeability assumption, which states that the control and treatment groups must be balanced with respect to their covariates. This assumption allows us to create exchangeable units in our observable data that are exogenous to the *DiD* analysis. Additionally, the positivity assumption must hold, meaning that the data must be valid and free from random and structural positivity violations. These assumptions are crucial for ensuring the validity of the *DiD* analysis and the accuracy of its results.

In addition to the exchangeability and positivity assumptions, the *DiD* methodology also relies on the consistency assumption, also known as the stable unit treatment value assumption. This assumption states that the observed exposure of interest must not differ from the counterfactual exposure of interest and that the causal effect of interest can only be obtained if the spinoff event does not occur. To satisfy this assumption, we can use our control group as a reference point to estimate the effects of the spinoff event. Another critical assumption of the *DiD* methodology is the parallel trend assumption, which states that any unmeasured determinants of the treatment must be equal across different regions and remain constant over time. This assumption is a subpart of the exchangeability assumption but is weaker due to a higher degree of uncertainty. As a result, unobserved counterfactual units may exist, and the baseline value for treated and control must be relatively similar but not necessarily identical.

To account for the *DiD* methodology's assumptions, we have implemented the *propensity score matching (PSM)* model, as described in subsection 4.1. As a result, we believe that the exchangeability, positivity, and consistency assumptions are satisfied because we have constructed control groups that are balanced on the covariates *Year, NAICS, ISO*, and *ROA*. However, we could not adequately test the parallel trend assumption because we needed observations from multiple years prior to the spinoff. As a result, this assumption may introduce bias into our results.

Moreover, we have applied the within-group fixed effects estimator, as suggested by Wooldridge (2015). This method is commonly employed to control for unobserved group-level heterogeneity in panel data. The estimator includes group-level variation in the dependent variables in the regression model, aiming to capture the group-level variation in the dependent variable that is not explained by other independent variables.

To address the potential issue of heteroscedasticity and autocorrelation in the residuals of the regression model, Wooldridge (2015) recommends using robust standard errors. Heteroscedasticity is defined as the presence of non-constant variance in the residuals, which can cause biased standard errors if not accounted for. Autocorrelation, referring to the correlation between residuals across time, can also lead to biased standard errors (Wooldridge, 2015). Pustejovsky and Tipton (2018) also advocate for the use of robust standard errors in small samples as they tend to be more accurate and less sensitive to certain types of model misspecification than standard errors typically used in larger samples.

In panel data, the cluster-robust-variance-covariance matrix is often utilized to calculate robust standard errors due to its ability to correct for the potential presence of both heteroscedasticity and autocorrelation within each group (Wooldridge, 2015). Therefore, by employing the within-estimator in *DID* models with a cluster-robust-variance-covariance matrix, we can reduce bias from potential heteroscedasticity and autocorrelation and obtain more accurate and robust standard errors.

Operating performance metrics

In order to implement a *DiD* methodology, we have chosen to use three operating performance metrics: *return on assets (ROA), current ratio*, and *leverage*. *ROA* measures a firm's profitability by dividing its net income by its total assets. Moreover, *leverage* is a measure of a firm's financial risk that is calculated by dividing its total liabilities by its total assets. Both of these metrics are discussed in greater detail in subsection 3.3. In addition to *ROA* and *leverage*, we have also chosen to use the *current ratio* as an operating performance metric. The *current ratio* is a liquidity ratio calculated by dividing a firm's current assets by its current liabilities. Current assets are cash and other liquid assets that are expected to be converted into cash within the next 12 months, while current liabilities are liabilities that are expected to be consumed within the next 12 months. The *current ratio* is often used to indicate a firm's working capital and cash flow, as a ratio greater than 1 indicates higher working capital and lower cash flow (Kumar, 2016). By using these three performance metrics, we aim to comprehensively evaluate the spinoff's impact on the firm's operating performance.

5 Analysis

In the following section, we present our findings throughout our analysis. We start by presenting our results. After that, we discuss the results obtained. Thirdly, we discuss the robustness of our results. Lastly, we discuss the limitations of the analysis and summarize the section.

5.1 Hypothesis 1

In hypothesis 1, we propose that Nordic firms create value in the stock market by spinning off subsidiaries. We analyze the stock market performance of spinoffs, parent firms and value-weighted proforma firms, and their respective matching firms. Moreover, we distinguish between *focus*-increasing and *non-focus*-increasing firms. The CAR and $BHAR$ are the metrics used for the stock market performance following one, two, and three years after the spinoff distribution. Hence, we are only measuring the post-event long-term stock market performance.

Table 5.1: Mean CAR and BHAR for Spinoffs

*The table report mean cumulative abnormal returns (CAR) and mean buy-and-hold abnormal returns (BHAR) for spinoff firms and matching firms for one ([0,1]), two ([0,2]), and three ([0,3]) years post spinoff distribution. The firms are structured as an equal-weighted portfolio. The figure in parentheses reveals the mean standard deviations. The returns are winsorized at the 2.5% tails. Observations are reported from January 1990 until October 2022. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Control	Spinoff	p-value
Panel A: [0, 1]			
	n=50	n=50	
CAR	-0.10*	0.03*	0.064
	(0.36)	(0.32)	
BHAR	-0.10**	0.02**	0.046
	(0.31)	(0.29)	
Panel B: [0, 2]			
	n=54	n=54	
CAR	-0.25**	-0.03**	0.019
	(0.54)	(0.43)	
BHAR	-0.20**	-0.04**	0.034
	(0.38)	(0.41)	
Panel C: [0, 3]			
	n=48	n=48	
CAR	-0.37***	0.08***	0.002
	(0.77)	(0.59)	
BHAR	-0.19**	0.11**	0.041
	(0.55)	(0.83)	

Table 5.1 reports the mean *cumulative abnormal return* (*CAR*) and mean *buy-and-hold abnormal return (BHAR)* for all spinoff and matching firms. The returns break down into three different event windows: one, two, and three years after the distribution date. The *buy-and-hold abnormal return* figures show an outperformance in the first and third years of 2% and 11% and a slight underperformance in the second year of 4% compared to the country index. However, spinoffs report a significant outperformance against the matching firms in all event windows. The p-value indicates that the outperformance is statistically significant at the 5% level. The *CAR* figures report to some extent the same

results as *BHAR* but with a slightly higher return in the first and second years, while the figure is slightly lower in the third year.

Figure 5.1: Spinoff Plot

The figure reports the cumulative total return (CTR) and cumulative abnormal return (CAR) for spinoffs and matching firms.

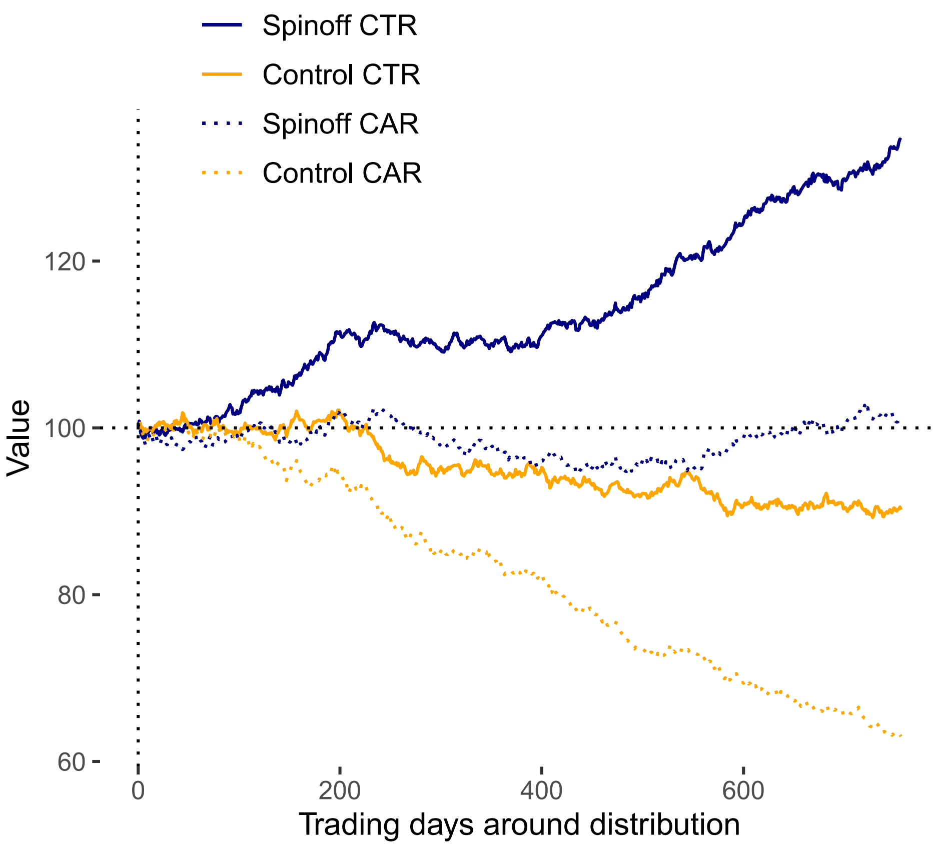


Figure 5.1 plots the *cumulative total return (CTR)* and *cumulative abnormal return (CAR)* for spinoffs and corresponding matching firms. The plot illustrates the substantial outperformance spinoffs have done during the first three years of trading as a stand-alone firm. Moreover, the matching portfolio reports a significant underperformance against both spinoffs and the market.

Table 5.2: Focus-increasing and non-focus-increasing Spinoffs

*The table reports the mean cumulative abnormal return (CAR) and mean buy-and-hold abnormal return (BHAR) for both focus-increasing and non-focus-increasing spinoffs and their respective matching firms. The time interval is one ([0,1]), two ([0,2]), and three ([0,3]) years post spinoff distribution. It is an equal-weighted portfolio where the numbers in parenthesis are the mean standard deviations. The returns are winsorized at the 2.5% tails. The observations are from January 1990 until October 2022. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Focus-increasing			**Non-focus-increasing**		
	Control	Spinoff	p-value	Control	Spinoff	p-value
Panel A: [0, 1]						
	n=16	n=16		n=21	n=21	
CAR	-0.12	0.07	0.216	-0.01	0.07	0.354
	(0.44)	(0.40)		(0.34)	(0.21)	
BHAR	-0.10	0.08	0.149	-0.03	0.05	0.398
	(0.57)	(0.37)		(0.33)	(0.21)	
Panel B: [0, 2]						
	n=16	n=16		n=22	n=22	
CAR	-0.25	0.04	0.154	-0.13	0.04	0.184
	(0.57)	(0.53)		(0.51)	(0.32)	
BHAR	-0.20	0.06	0.132	-0.11	0.00	0.345
	(0.34)	(0.58)		(0.44)	(0.28)	
Panel C: [0, 3]						
	n=17	n=17		n=19	n=19	
CAR	-0.43**	0.21**	0.014	-0.17	0.10	0.231
	(0.80)	(0.63)		(0.79)	(0.55)	
BHAR	-0.25*	0.30*	0.085	0.00	0.10	0.625
	(0.35)	(1.23)		(0.73)	(0.48)	

In Table 5.2, we distinguish between *focus*-increasing and *non-focus*-increasing spinoffs. As explained in section 2, we define *focus*-increasing firms as spinoffs that operate in a different industry than the parent firm. Hence, the subsidiary spins off to increase corporate *focus* for both the spinoff and the parent firm. *Non-focus*-increasing spinoffs operate in the same industry as the parent firm, meaning the subsidiary is not increasing *focus*. The overall interpretation from the table is that *focus*-increasing spinoffs outperform *non-focus*-increasing spinoffs. Over the three-year window, the *focus*-increasing spinoffs outperform *non-focus*-increasing spinoffs by 20% using the *BHAR* figures and 11% using the *CAR* figures. These returns are consistent with the findings of Desai and Jain (1999), who found that *focus*-increasing spinoffs outperform *non-focus*-increasing spinoffs by 33.36% over a three-year window. However, the p-values indicate non-significant results, except in the third year for *focus*-increasing spinoffs. Nevertheless, the results are still economically interpretable. According to Pearson (1931), statistical significance is not the same as economic significance. Hence, when results are purely logical but not statistically significant, they may deliver the truth despite a small sample size where one cannot reject the null hypotheses. In our instance, the results of both *focus*-increasing and *non-focus*-increasing deviate a lot from their respective control group. The indicated effect will thus be practically important.

Table 5.3: Mean CAR and BHAR for Parents

*The table report mean cumulative abnormal returns (CAR) and mean buy-and-hold abnormal returns (BHAR) for parent firms and matching firms for one ([0,1]), two ([0,2]), and three ([0,3]) years post spinoff distribution. The firms are structured as an equal-weighted portfolio. The figure in parentheses reveals the mean standard deviations. The returns are winsorized at the 2.5% tails. Observations are reported from January 1990 until October 2022. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Control	Parent	p-value
Panel A: [0, 1]			
	n=47	n=47	
CAR	-0.07	-0.09	0.770
	(0.37)	(0.35)	
BHAR	-0.03	-0.06	0.579
	(0.28)	(0.29)	
Panel B: [0, 2]			
	n=43	n=43	
CAR	-0.20	-0.11	0.501
	(0.65)	(0.59)	
BHAR	-0.10	-0.06	0.703
	(0.44)	(0.40)	
Panel C: [0, 3]			
	n=43	n=43	
CAR	-0.26	-0.11	0.416
	(0.91)	(0.77)	
BHAR	-0.10	-0.02	0.450
	(0.49)	(0.53)	

Table 5.3 reports the mean *CAR* and *BHAR* for all parent firms for one, two, and three years after the distribution of the spinoff. The parent firms report negative abnormal returns for every event window in the event study. In spite, the parent firms outperform the matching firms in the second and third years. The *BHAR* figures show that parent firms slightly underperform the matching portfolio by 3% in the first year. In the second and third years, parent firms outperform the matching firms by 4% and 8%, respectively. The high p-values reported indicates that the *BHAR* and *CAR* figures are insignificant at conventional significance levels. However, like the *focus*-increasing and *non-focus*-increasing samples above, it may have economically significance (Pearson, 1931).

Figure 5.2: Parents Plot

The figure reports the cumulative total return (CTR) and cumulative abnormal return (CAR) for parent firms and matching firms.

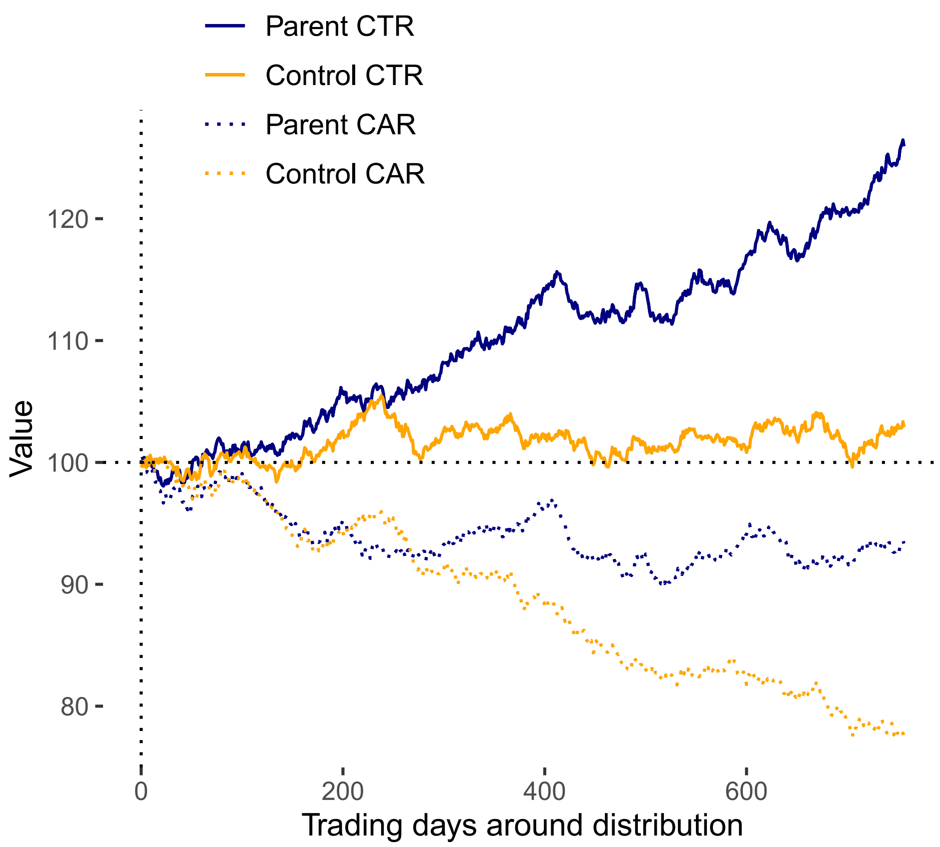


Figure 5.2 plots the *cumulative total return (CTR)* and *cumulative abnormal return (CAR)* for parent and matching firms from the distribution date until three years after the spinoff event. The plot strengthens our interpretation from the table above. The abnormal returns for parent and matching firms are negative in all event windows, even though the parent firms outperform the matching firms.

Table 5.4: Focus-increasing and non-focus-increasing Parents

*The table reports the mean cumulative abnormal return (CAR) and mean buy-and-hold abnormal return (BHAR) for both focus-increasing and non-focus-increasing parent firms and their respective matching firms. The time interval is one ([0,1]), two ([0,2]), and three ([0,3]) years post spinoff distribution. It is an equal-weighted portfolio where the numbers in parenthesis are the mean standard deviations. The returns are winsorized at the 2.5% tails. The observations are from January 1990 until October 2022. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Focus-increasing			**Non-focus-increasing**		
	Control	Parent	p-value	Control	Parent	p-value
Panel A: [0, 1]						
	n=20	n=20		n=23	n=23	
CAR	-0.07	-0.16	0.394	-0.13	-0.14	0.964
	(0.39)	(0.28)		(0.42)	(0.39)	
BHAR	-0.01	-0.14	0.160	-0.06	-0.08	0.752
	(0.32)	(0.23)		(0.28)	(0.22)	
Panel B: [0, 2]						
	n=18	n=18		n=22	n=22	
CAR	-0.16	-0.11	0.770	-0.28	-0.15	0.539
	(0.60)	(0.47)		(0.71)	(0.68)	
BHAR	-0.08	-0.08	1.000	-0.11	-0.05	0.655
	(0.40)	(0.45)		(0.50)	(0.36)	
Panel C: [0, 3]						
	n=18	n=18		n=22	n=22	
CAR	-0.21	-0.10	0.707	-0.38	-0.18	0.463
	(1.01)	(0.68)		(0.88)	(0.88)	
BHAR	-0.01	-0.01	0.982	-0.16	-0.02	0.338
	(0.53)	(0.61)		(0.49)	(0.48)	

In Table 5.4 we have distinguished between *focus*-increasing and *non-focus*-increasing parent firms. Both *focus*-increasing and *non-focus*-increasing parent firms are underperforming the country index, consistent with Table 5.3 (all parents). Moreover, looking at the $BHAR$ figures for the *focus*-increasing parent firms against the corresponding matching firms, they underperform the matching firms by 13% in the first year and produce the same abnormal returns in the second and third years. The CAR figures have larger standard deviations and report a 9% underperformance in the first year and an outperformance of 5% and 11% in the second and third years, respectively. Moreover, looking at $BHAR$ figures for the *non-focus*-increasing parent firms against the corresponding matching firms, they underperform in the first year by 2% and outperform in the second and third years by 6% and 14%, respectively. The CAR figures again report a significantly larger standard deviation in the abnormal returns, with the underperformance of 2% in the first year and outperformance in the second and third years of, respectively, 13% and 20%. Additionally, the larger standard deviations in the CAR figures are consistent with the findings of (Barber and Lyon, 1997). They argue that CAR figures produce larger returns than the $BHAR$ figures. Consequently, the standard deviations will also be larger.

Table 5.5: Mean CAR and BHAR for Proforma

*The table report mean cumulative abnormal returns (CAR) and mean buy-and-hold abnormal returns (BHAR) for proforma firms and matching firms for one ([0,1]), two ([0,2]), and three ([0,3]) years post spinoff distribution. The firms are structured as an equal-weighted portfolio. The figure in parentheses reveals the mean standard deviations. The returns are winsorized at the 2.5% tails. Observations are reported from January 1990 until October 2022. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Control	Proforma	p-value
Panel A: [0, 1]			
	n=34	n=34	
CAR	-0.05	-0.06	0.896
	(0.41)	(0.29)	
BHAR	-0.01	-0.05	0.553
	(0.30)	(0.18)	
Panel B: [0, 2]			
	n=33	n=33	
CAR	-0.25	-0.16	0.603
	(0.71)	(0.55)	
BHAR	-0.12	-0.11	0.923
	(0.48)	(0.29)	
Panel C: [0, 3]			
	n=32	n=32	
CAR	-0.33	-0.19	0.543
	(1.02)	(0.72)	
BHAR	-0.12	-0.10	0.904
	(0.55)	(0.37)	

The proforma firms used in this study do not exist in reality but serve as proxies for what the parent firms would look like if the spinoff had not occurred. These proforma firms are calculated by value-weighting the spinoff and parent firms by their market capitalization immediately after the spinoff distributions. Furthermore, we have not created specific matching firms for the proforma firms. Instead, we match the proforma firms with the same matching firms used for the parent firms. This is because the spinoffs are relatively small compared to the parent firms. Thus, the proforma firms share many of the same characteristics as the parent firms.

Table 5.5 presents the mean *CAR* and *BHAR* for the proforma firms over one, two, and three years following the distribution of spinoff shares. The proforma numbers in Table 5.5 are relatively similar to the ones of parent firms in Table 5.3. Thus, these results indicate that proforma firms consistently experience negative abnormal returns. However, the proforma firms outperform the matching firms in the second and third years. The BHAR figures show that proforma firms underperform the matching portfolio by 4% in the first year but outperform by 1% and 2% in the second and third years, respectively. However, the standard deviation is large, accompanied by high p-values for *CAR* and *BHAR*, implying uncertainty. Due to the large uncertainty, as previously noted in regard to parent firms, it is not feasible to interpret the results from an economic perspective.

5.2 Hypothesis 2

In this subsection, we present and discuss the result of our hypothesis revolving around whether firms in the Nordic increase operating performance by spinning off subsidiaries. Thus, our primary focus in the discussion will relate to the interest of *return on asset*, *current ratio*, and *leverage*.

The hypothesis aims to determine whether the spinoffs and parent firms have better operating performance metrics than their control peers. Whether it is better is subject to if the *return on asset* is higher, the *current ratio* is higher, or the *leverage* is lower. Using the mean return with a *DiD* methodology provides the result in Table 5.6, Table 5.7, and Table 5.8. In the following tables, variable T is denounced as 0, showing the differences from pre (*-1*) to, respectively, year one, two, and three post-spinoff event.

Table 5.6: Difference-in-differences for Spinoffs

*The table reports the development of the performance metrics for the independent variable post, treat, and treatpost regarding spinoffs. Thus, the variable post consists of spinoffs and their matching firms. The variable treat consists of spinoff firms. The variable treatpost is the difference-in-differences estimator. Variable "T" is one year pre-spinoff, whereas (T+1) is one year post-spinoff and (T+2) along with (T+3), respectively, two and three years post-spinoff. The observations are from January 1990 until October 2022. FE is entity fixed effects. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Dependent variable:								
	ROA			Current Ratio			Leverage		
	(T+1)	(T+2)	(T+3)	(T+1)	(T+2)	(T+3)	(T+1)	(T+2)	(T+3)
post	−0.037	−0.035	−0.067	−0.443	−1.264	−1.673	0.323	0.462	0.030
	t = −1.182	t = −1.230	t = −1.628	t = −0.899	t = −1.010	t = −1.197	t = 1.536	t = 1.056	t = 0.165
treat	−0.014	0.003	−0.032	−0.150	−0.258	−0.434	0.197	0.496	0.606
	t = −0.397	t = 0.158	t = −1.201	t = −0.195	t = −0.304	t = −0.450	t = 0.655	t = 0.956	t = 1.085
treatpost	0.069	0.063	0.128**	2.104**	2.288*	2.634*	−1.465**	−1.988***	−1.558**
	t = 1.357	t = 1.500	t = 1.961	t = 1.989	t = 1.669	t = 1.757	t = −2.523	t = −2.617	t = −2.404
Observations	208	183	164	204	177	159	214	187	169
R^2	0.018	0.026	0.051	0.049	0.033	0.043	0.074	0.087	0.118
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table shows that the *post* variable is in a negative trend regarding the *ROA* metric, where the coefficients decrease over the years. The t-values indicate an increased power over the years, with values of -1.182, -1.230, and -1.628, respectively. Furthermore, the *treat* variable is, additionally, in a negative trend regarding the *ROA* metric. The t-values indicate uncertainty, especially in year two. Moreover, the t-values are -0.397, 0.158, and -1.201, respectively. The *difference-in-differences* estimator *treatpost* indicates a relatively higher *ROA* for the *treat* variable than the *post* variable. The t-values are, respectively, 1.357, 1.500, and 1.961, implying an increased power over the years, whereas it is significant in the third year.

Forging ahead, the *post* variable is in a negative trend regarding the *current ratio metric*, where the coefficients decrease over the years. The t-values indicate an increased power over the years, with values of -0.899, -1.010, and -1.197, respectively. Additionally, the *treat* variable is in a negative trend regarding the *current ratio* metric. The t-values indicate uncertainty but an increased power over the years with the values -0.195, -0.304, and -0.450, respectively. Moreover, the *difference-in-differences* estimator *treatpost* indicates a relatively higher *current ratio* for the *treat* variable than the *post* variable. The t-values are, respectively, 1.989, 1.669, and 1.757, implying a decreased power over the years, whereas it is only significant at a 10% level in the third year.

Moving on, the *post* variable is in a negative trend regarding the *leverage* metric, where the coefficients decrease over the years. The t-values indicate a decreased power over the years, with values of 1.536, 1.056, and 0.165, respectively. Furthermore, the *treat* variable is in a positive trend regarding the *leverage* metric. The t-values indicate uncertainty but an increased power over the years with the values 0.655, 0.956, and 1.085, respectively. Moreover, the *DiD* estimator *treatpost* indicates a relatively lower *leverage* for the *treat* variable than the *post* variable. The t-values are, respectively, -2.523, -2.617, and -2.404, implying a decreased power over the years but still significant in the third year.

Table 5.7: Difference-in-differences for Parents

*The table reports the development of the performance metrics for the independent variable post, treat, and treatpost regarding parent firms. Thus, the variable post consists of parent firms and their matching firms. The variable treat consists of parent firms. The variable treatpost is the difference-in-differences estimator. Variable "T" is one year pre-event, whereas (T+1) is one-year post-event and (T+2) along with (T+3), respectively, two and three years post-event. The observations are from January 1990 until October 2022. FE is entity fixed effects. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Dependent variable:								
	ROA			Current Ratio			Leverage		
	(T+1)	(T+2)	(T+3)	(T+1)	(T+2)	(T+3)	(T+1)	(T+2)	(T+3)
post	−0.002	0.003	−0.008	−0.111	−0.046	−0.207	0.399	0.145	0.431
	t = −0.090	t = 0.142	t = −0.325	t = −0.529	t = −0.184	t = −0.626	t = 0.903	t = 0.434	t = 0.989
treat	−0.018	−0.028	−0.012	0.199	0.172	0.042	0.245	0.453	0.228
	t = −0.990	t = −1.305	t = −0.725	t = 0.611	t = 0.662	t = 0.194	t = 1.113	t = 1.383	t = 0.505
treatpost	0.034	0.011	0.027	0.620	0.494	0.655	−0.593	−0.288	0.249
	t = 1.209	t = 0.389	t = 1.027	t = 1.336	t = 1.042	t = 1.207	t = −1.477	t = −0.893	t = 0.327
Observations	160	149	134	163	150	134	166	153	137
R^2	0.035	0.015	0.020	0.045	0.031	0.038	0.030	0.024	0.036
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The results of Table 5.7 reveal a negative trend in the *post* variable with respect to the *return on assets* (*ROA*) metric, as indicated by the decreasing coefficients over the years. However, the t-values show increased power in this variable over the same period, with values of -0.090, 0.142, and -0.325. On the other hand, the *treat* variable exhibits a positive trend in regards to *ROA*, as indicated by the t-values that show some uncertainty and a decrease in power over the years (-0.990, -1.305, and -0.725). Moreover, the *difference-in-differences* estimator for *treatpost* suggests a relatively higher *ROA* for the *treat* variable compared to the *post* variable. The t-values for this estimator are 1.209, 0.389, and 1.027, indicating an increased power over the years, though the significance is not present in any years.

Moving forward, the results of the table show that the *post* variable is trending negatively concerning the *current ratio* metric, as indicated by the decreasing coefficients over the years. However, the t-values indicate an increased power in this variable over the same period, with values of -0.529, -0.184, and -0.626. In contrast, the *treat* variable exhibits a negative trend regarding the *current ratio* metric, as indicated by the t-values that show some uncertainty and a decrease in power over the years (0.611, 0.662, and 0.194). Furthermore, the *difference-in-differences* estimator for *treatpost* suggests a higher *current ratio* for the *treat* variable compared to the *post* variable. The t-values for this estimator are 1.336, 1.042, and 1.207, indicating a decrease in power over the years, though the significance is not present in any years.

Continuing, the table results reveal a positive trend in the *post* variable concerning the *leverage* metric, as indicated by the increasing coefficients over the years. In addition, the t-values show increased power in this variable over the same period, with values of 0.903, 0.434, and 0.989. In contrast, the *treat* variable exhibits a negative trend regarding *leverage*, as indicated by the t-values that show some uncertainty and a decrease in power over the years (1.113, 1.383, and 0.505). Furthermore, the *difference-in-differences* estimator indicates a higher *leverage* for the *treat* variable than the *post* variable. The t-values for this estimator are -1.477, -0.893, and 0.327, indicating a decrease in power over the years, though the significance is not present in any years.

Table 5.8: Difference-in-differences for Proforma

*The table reports the development of the performance metrics for the independent variable post, treat, and treatpost regarding proforma firms. Thus, the variable post consists of proforma firms and their matching firms. The variable treat consists of proforma firms. The variable treatpost is the difference-in-differences estimator. Variable "T" is one year pre-event, whereas (T+1) is one-year post-event and (T+2) along with (T+3), respectively, two and three years post-event. The observations are from January 1990 until October 2022. FE is entity fixed effects. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels.*

	Dependent variable:								
	ROA			Current Ratio			Leverage		
	(T+1)	(T+2)	(T+3)	(T+1)	(T+2)	(T+3)	(T+1)	(T+2)	(T+3)
post	−0.004	0.006	−0.011	−0.103	−0.046	−0.207	0.382	0.111	0.412
	t = −0.204	t = 0.332	t = −0.415	t = −0.497	t = −0.184	t = −0.626	t = 0.859	t = 0.332	t = 0.933
treat	−0.054**	−0.030**	−0.024	0.536	−0.030	−0.158	0.256	0.464	0.393
	t = −2.183	t = −2.009	t = −1.578	t = 0.361	t = −0.134	t = −0.888	t = 0.865	t = 1.142	t = 1.013
treatpost	0.082*	0.024	0.029	2.864	0.835	0.998	−0.985*	−0.823	−0.581
	t = 1.767	t = 1.016	t = 1.018	t = 1.552	t = 1.388	t = 1.538	t = −1.786	t = −1.498	t = −1.190
Observations	145	137	122	149	139	123	151	141	125
R^2	0.046	0.011	0.004	0.074	0.056	0.070	0.050	0.051	0.027
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5.8 shows that the *post* variable is in a negative trend regarding the *ROA* metric, where the coefficients decrease over the years. On the other hand, the t-values indicate uncertainty and increased power over the years, with values of -0.204, 0.332, and -0.415, respectively. However, the *treat* variable is in a positive trend regarding the *ROA* metric. The t-values indicate a decreased power over the years, with values of -2.183, -2.009, and -1.578, respectively. Moreover, the *difference-in-differences* estimator indicates a relatively higher *ROA* for the *treat* variable than the *post* variable. The t-values are, respectively, 1.767, 1.016, and 1.018, implying a decreased power over the years and is not significant in the third year.

Proceeding, the *post* variable is in a negative trend regarding the *current ratio* metric, where the coefficients decrease over the years. On the other hand, the t-values indicate an increased power over the years, with values of -0.497, -0.184, and -0.626, respectively. Additionally, the *treat* variable is in a negative trend regarding the *current ratio* metric. The t-values indicate uncertainty but an increased power over the years, with values of 0.361, -0.134, and -0.888, respectively. Moreover, the *difference-in-differences* estimator indicates a relatively higher *current ratio* for the *treat* variable than the *post* variable. The t-values are, respectively, 1.552, 1.388, and 1.538, implying a decreased power over the years and is not significant in the third year.

At first glance, the *post* variable is in a positive trend regarding the *leverage* metric, where the coefficients increase over the years. On the other hand, the t-values indicate uncertainty and increased power over the years, with values of 0.859, 0.332, and 0.933, respectively. Additionally, the *treat* variable is in a positive trend regarding the *leverage* metric. The t-values indicate uncertainty but an increased power over the years, with values of 0.865, 1.142, and 1.013, respectively. Moreover, the *difference-in-differences* estimator indicates a lower *leverage* for the *treat* variable than the *post* variable. The t-values are, respectively, -1.786, -1.498, and -1.190, implying a decreased power over the years and is not significant in the third year.

5.3 Discussion of results

In this subsection, we will synthesize the findings of our *long-run event study* and *difference-in-differences* model to better understand the direction and magnitude of their effect. We will also explore the connections between the findings of these two models and their relevance to existing empirical research.

In the *long-run event study*, our findings indicate that our *BHAR* figures for spinoff firms outperform the country indexes by 2% and 11% in the first- and third-years post-distribution but underperform by 4% in the second year. Additionally, spinoff firms demonstrate significant outperformance against matching firms in all event windows and are statistically significant at the 5% level. Furthermore, over the three-year event window, we find that *focus*-increasing spinoffs outperform *non-focus*-increasing spinoffs by 20% using BHAR figures and 11% using *CAR* figures. These results align with previous studies in the US, and despite not being statistically significant, the observed effect is of practical importance.

In the *DiD* model, the *DiD* estimator indicates that spinoff firms have a 12.8% higher *return on assets*, 263% higher *current ratio*, and 199% lower *leverage ratio* in the third year compared to the matching firms. Furthermore, both the *return on assets* and *leverage* are statistically significant at the 5% level, while *leverage ratio* is statistically significant at the 10% level. Therefore, the magnitude of the results suggests they also have economic significance.

Looking at the *long-run event study* for parent firms, we find that they consistently experience negative abnormal returns in all event windows. However, parent firms outperform their matching firms in the second and third years. Despite this observation, the results are not statistically significant at any conventional levels.

In the *DiD* model for parent firms, the *DiD* estimator indicates a 2.7% increase in their *return on assets*, as well as a 66% increase in their *current ratio* and a 25% increase in *leverage ratio* compared to matching firms in the third year. However, these results are not statistically significant in any of the event windows. Moreover, the increase in *ROA* may be influenced by the higher *leverage ratio*, thus raising questions about the economic significance of these results (Cai and Zhang, 2011).

After conducting a *long-run event study* on value-weighted proforma firms, we find that they outperform their matching firms in all event windows. However, not with statistically significant results at conventional levels. Similarly, the *DiD* model indicates that the proforma firms have a 2.9% higher *ROA*, a 100% higher *current ratio*, and a 58% lower *leverage ratio* in the third year. Nevertheless, these results are not statistically significant for any of the metrics analyzed in the third year, suggesting it is difficult to interpret the results economically.

The results of our analysis indicate a positive relationship between operating performance and stock market performance. In particular, we find that spinoffs outperform their matching portfolios in terms of operating metrics and stock market performance in all event windows. This is consistent with previous findings by Chemmanur and Yan (2004), who also found a positive relationship between these two measures. Furthermore, using the *DiD* model reveals a higher *current ratio* for spinoffs post distribution of shares, suggesting that these firms are more efficient in their use of assets to generate income. However, it is important to note that other factors may also contribute to this outcome, as highlighted by Hantono (2018).

5.4 Limitation of the models

Analyzing the relationship between both stock market performance and operating performance metrics is challenging. Despite having existing research that may resemble some parts of our *event study* models, the *difference-in-differences* models do not resemble any previous studies. Thus, examining and interpreting the relationship between stock performance and operating performance metrics is a challenging endeavor. Throughout our analysis, we utilize different methods, views, and structures from papers studying resembling topics. However, there are drawbacks to the methodologies we used.

Long-run event studies are known to suffer several biases. Barber and Lyon (1997) show that survivorship bias can result in poorly specified tests of long-run performance. For example, our sample sizes decreased quite a bit in the *long-run event study* from the first year until the third year. Hence, omitting these observations happens for several reasons, including incorrect data and delisting.

Moreover, our results have limitations due to the lack of robustness testing. However, by using multiple methodologies, we were able to increase the validity of our results and provide some level of robustness through the use of reciprocal results. Furthermore, we observe that our results are economically interpretable and in line with previous papers, which reduces the need for an external robustness test (Pearson, 1931). Additionally, we acknowledge that the sample sizes in our study differed across the different methodologies, which indicates less reliable results. However, we take this into account in our analysis and believe that our use of multiple methodologies and careful analysis still support the validity of our results.

6 Conclusion

The evidence of this thesis suggests six rules of thumb when considering investing in spinoffs. (1) The impact on the stock market performance for spinoffs contrary to the control group is observable and statistically significant in year one, and the impact increases with time. (2) The stock market performance for parent firms is more ambiguous. It starts poorly compared to its control group but performs better over time, although it is not statistically significant. (3) *Focus*-increasing spinoffs perform better than their control group in all event windows. However, the results are only significant at conventional levels in the third year regarding *CAR*. (4) *Non-focus*-increasing spinoffs perform worse than their control group in year one post-spinoff. However, they perform better than their control groups in years two and three, even though it is not significant and hard to interpret economically. (5) The operating metrics for spinoffs, namely, *ROA*, *current ratio*, and *leverage*, outperform its control group, where both *ROA* and *leverage* show a causal relationship to the spinoff event. However, *Current Ratio* is only significant at a 10% level but is still economically significant. (6) The operating metrics for parent firms relative to their control group show outperformance in *ROA* and *current ratio*. However, it shows an increase in *leverage*; hence it is unclear as it is not statistically significant. All in all, even though people do not consistently experience glow-ups post-breakup, it is certainly true for spinoffs.

6.1 Further research

We would find it interesting to do the same tests and include multiple matching firms per spinoff/parent firm with a larger dataset, perhaps from the stock market in the US or Europe. There are multiple reasons for this. Our data origins from the Nordics, as opposed to previous studies, using data from the US (Daley et al., 1997; Cusatis et al., 1993; Krishnaswami and Subramaniam, 1999; Desai and Jain, 1999). Our data has some limitations regarding sample size. Therefore, we would expect a more significant result with reduced bias in the control groups for the operating performance metrics by using data from either the US or Europe on the *difference-in-differences* models. However, we expect to see some of the same tendencies, ceteris paribus.

Additionally, it is interesting to subtract the total number of shares in the spinoff event study for parent firms rather than using the market return three days after the event. Mainly to observe if it would yield a different result but also as it may be more theoretically correct. However, due to the *Compustat* database's limitation, we could not exercise this.

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