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Financial Distress Risk of LBOs - Evidence from Nordic Countries

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By

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Abstract

In this master thesis, we study the financial distress risk and bankruptcy rate of leveraged buyout companies in the Nordic market between 2000 and 2020. Furthermore, we examine industry effects on financial distress risk using the same panel data sample. Our findings suggest that buyout firms experience a higher financial distress risk compared to comparable firms not subject to a leveraged buyout transaction. However, our results do not let us conclude that buyout companies experience a higher probability of bankruptcy than comparable non-buyout companies. Lastly, our analysis examining industry effects does not have statistical power to analyse a firm's financial distress post an LBO transaction by the industry they operate in.

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Contents

1. Introduction and Motivation

Private Equity (PE) and Leveraged Buyouts (LBOs) have received increasing attention since the 1970s when distressed companies started seeking out to PE firms to raise funds. Since then, PE has been a substantial part of our corporate ecosystem with LBO remaining the highest performing PE sub-asset class. Although PE and LBOs have gained extensive recognition the last decades, there is still limited research on the potential negative impacts of the financing method. Researchers, practitioners, and regulators have questioned whether LBOs sponsored by PE firms create value, or if it is just value transference disguised as value creation. PE firms have been blamed for debt overloading and asset stripping in addition to the quick flipping of their portfolio companies, rendering them distressed or even bankrupt. Tykvova and Borell (2012) found that financial distress risk increases significantly after an LBO transaction based on buyouts from EU-15 countries. Furthermore, research provided by Ayash & Rastad (2020) further confirmed the financial impacts of LBOs when researching bankruptcy rates of US firms as they discovered that firms acquired through LBOs are 18% more likely to go bankrupt compared to comparable firms.

We will build on the abovementioned findings by researching financial distress risk in LBOs post transaction based on Nordic countries while taking inspiration from the methodology provided by those of Tykvova and Borell (2012). We will additionally research the real default rate by comparing buyout companies to comparable firms to examine whether buyout firms end in bankruptcy more often. Moreover, McKinsey (2022) suggest that industry is a large determinant of company performance, where they emphasize that a company's playing field can both strengthen and worsen firm performance. We find that there is little recent research regarding the industry effect on company performance in the Nordics and additionally find that there is limited research on industry effect on financial distress risk. We will therefore additionally analyse whether the financial distress risk of Nordic companies post buyout is affected by the industry the companies operate in.

We contribute to research within the field of LBOs by investigating financial distress risk and bankruptcy rates of Nordic companies around their buyouts in the period 2000–2020. We begin by analysing whether the financial distress risk and bankruptcy rate of companies in the Nordics increase following a leveraged buyout. Thereafter, we investigate the potential changes in financial distress risk based on the industry the company is operating in. Through a thorough analysis, we aspire to add to the literature elucidating the real effects of LBOs in the Nordics by using methods cultivated throughout our master's degree.

2. Literature Review

In this chapter, we will provide an overview of various research topics which we consider to be of relevance to our thesis. The first topic includes thorough explanations of how private equity funds operate and further define what a leveraged buyout is and how they connect to financial distress risk. The second topic considers the history of the leveraged buyout market and how it entered in the Nordics. Thereafter we delve into the market trends regarding industries and how it affects a company's financial distress risk. Lastly, we will focus on approaches to measure companies' financial distress.

2.1 Private Equity

Private equity (PE) is equity capital provided to enterprises that are not quoted on a stock market. PE is an asset class that differs greatly from other asset classes we know of. One of the main differences is that, unlike other asset classes, the annual returns cannot be used as a valid performance measure. Furthermore, an investment in a PE fund represents an investment in a stream of cash flows. This definition can satisfy the definition of bonds, but unlike the latter you cannot calculate the redemption yield of private equity at any time. The calculation in respect of a private equity fund can only be made once the very last cash flow has occurred unlike with bonds where it can be done on the day of the purchase (Wiley, 2010).

2.1.1 Leveraged Buyout and Venture Capital

PE investing at both the fund and company level can be subdivided into two main categories being "Venture Capital" and "Buyout" or "Leveraged Buyout". A leveraged buyout (LBO) is a transaction where the buyout company is acquired using a significant amount of debt. An LBO can involve various layers of debt that range from senior debt secured on assets of the company to cash flow lending with mezzanine debt. The typical debt to equity ratios of an LBO is between 7:3 to 9:1 (Kaplan and Stromberg, 2008).

Moreover, the main difference between "Buyout" and "Venture Capital" is that the former focuses on established companies rather than start-up companies, and additionally uses debt as well as equity financing. A significant difference is the distinction between "control" and "non-control" investing, where the buyout category takes a more controlling role as the private equity manager owns majority of the shares or has control over most of the voting rights of the company.

A private equity firm raises its capital through private equity funds, and these are typically structured as institutional limited partnerships that consist of a Limited Partner (LP) for an investor and a General Partner (GP) for a manager. The primary distinction between these two partner categories is that the sole investment powers lie on the GP of the fund, whereas the LPs have no voice in the investment process (Wiley, 2010).

2.1.2 The Evolution of LBOs

The private equity industry has experienced remarkable growth in the last 30 years with the US leading the way, before the UK and the rest of Europe followed shortly after. However, the industry has been subject to several ups and downs since the origin of private equity in 1946 (Prakash, C., & Warade, S. 2013). The first boom and bust cycle of LBOs was between 1982 till 1989 before the following cycle which came soon after and lasted between 1989 to 2002 with the early 2000s being characterized as “the age of mega-buyouts". Nevertheless, the boom was short lived as the information technology bubble busted in March 2000 resulting in buyout funds taking a back seat (Singh, H. 2018). The third cycle during 2003-2007 was known as the “golden age of private equity”. This was due to the combination of decreasing interest rates and the loosening of lending regulations. However, this boom was also ephemeral as the massive downturn in the economy led by the global financial crisis of 2008 occurred. Many mega buyouts that transpired during this boom quickly collapsed as they incurred substantial financial distress costs which eventually resulted in several companies defaulting.

The aftermath of the financial crisis due to the failure of asset-backed securitization was still present in the years after 2008. There are several studies in academia that have focused their research on the recovery from the financial crisis of 2008, and it is recognized that recoveries from financial boom-bust episodes are weak and sluggish as over-leveraged balance sheets need time to adjust. One of the studies that have focused on exactly this is from Kose and Terrones (2011). Although the recovery speeds have varied, the European countries resumed their growth patterns, albeit at considerably lower levels than before the crisis (Antoshin, S. et al. 2017).

After the crisis, policymakers from different regions put forward different regulatory and supervisory strategies. Their objective was to aid and regulate the financial system of their country. The interest rates were kept at an all-time low at this point and financial institutions invested in government bonds and corporate bonds to increase capital available for investments and acquisition financing (Singh, H. 2018). The low interest rates in combination with the covenant-lite loans increased liquidity in the market and the leverage lending volume. As cash floated around and low interest rates prevailed with respect to PE transactions, the buyout funds also gained popularity again globally.

By looking at the extensive PE trend reports of PwC for the subsequent years of 2015-2020 and their detailed findings on LBOs and the credit availability, we can gather useful intel on the LBO market (PwC, 2020). These years were impacted by the uncertainties of Brexit, the US/China trade war, Syria crisis and finally the Covid-pandemic which made planning for corporates difficult. Nevertheless, the European lending market boomed in these years which made LBO an attractive option and the impact of Covid-19 only lasted for the first quarter of 2020. In fact, the disorientation following the Covid-19 crisis was short-lived as central banks in the US and Europe aggressively pumped trillions into the financial economy which alleviated the liquidity concerns many PE funds had. Although one cannot say for certain that the challenges of the global economies is over as its economic impact remains difficult to forecast, we can observe by the sheer number and size of the deals made in 2021 that LBOs are making its comeback (Bain, 2021).

2.1.3 The Nordic and European LBO Market

The first private equity firms in the Nordics were established in Sweden during the rise of the LBOs in the 1980s and the other countries in the Nordic region followed in the 1990s.

In the Nordic buyout segment in 2020, the Swedish companies were the all-time high fund managers both in the Nordic segment and the international segment. Swedish PE firms claimed 43% of all buyout deals and accounted for 54% of the invested amount in the buyout segment in the Nordics (Argentum, 2020). Moreover, Swedish fund managers were involved in 33% of transactions, with the second largest country being the US. American fund managers were involved in

14% of all transactions which is marginally higher than the three other Nordic countries (Argentum, 2020). Historically, the Nordics have outperformed the rest of Europe in terms of returns, which potentially can explain the relatively large size of the market (EVCA, 2010). In fact, its growth and total market capitalization shows that it is one of the largest markets in relative terms (Argentum, 2020). There are several reasons for the attractiveness of the Nordic market, with an apparent one being the political and economic stability in the Nordics.

Today, most private equity research is based on US empirical data or theories, and we find that there is a deficiency of peer-reviewed literature investigating the PE market in the Nordic region. The size and age of the market has made the research on Nordic private equity performance challenging. Spliid, R. (2013) compared the Nordic PE market with the US market and found that the apparent difference is the size of the investment universe, with the Nordics being smaller and less developed which leads to fundraising being more complicated. According to the same article, the Nordic private equity firms are more dependent on international investors from different jurisdictions compared to the private equity firms in the US.

2.1.4 Financial Distress Risk Within LBOs

When a company increases its level of debt relative to its equity, it entails an increase in distress risk. Financial distress is a commonly used term within corporate finance describing the inability of companies to meet their financial obligations due to insufficient income or revenue. The cost of financial distress concerns the cost that the firm faces apart from the business costs. We have found several studies investigating the cost of financial distress. For instance, a study executed by Andrade, G. and Kaplan, S. in 2002 examined how costly financial distress is using evidence from companies that had been subject to leveraged transactions. The sample included 136 buyouts taken from the highly leveraged transactions in Kaplan and Stein (1990, 1993a) between 1980 and 1989 with a total transaction value exceeding 100 million USD. The study found that 31 of the 136 firms had defaulted as of December 1995. Furthermore, eight firms had trouble making debt payments. The research concluded that financial distress costs are not trivial in magnitude (Andrade G, & Kaplan, S. 2002). Furthermore, Kaplan and Stein (1993) found that increases in debt levels could induce a higher risk of financial distress and bankruptcy which eventually leads to an impairment of shareholders and debtholders. However, there are challenges with these studies. The small sample size used alongside the fact that research suggest that investors choose firms expected to have low costs of financial distress makes it difficult to conclude both how costly financial distress is, and to which extend buyout firms induce higher risk of financial distress.

As financial distress risk is comprised of both company specific factors and outside factors such as economic downturns, finding the precise risk of financial distress on a specific company can be quite complicated. However, there are key factors that help determine the risk of financial distress. The probability of financial distress depends on the likelihood that a firm will be unable to meet its debt commitments and therefore default. This probability increases with the size of a firm's liabilities relative to its assets as well as it increases with the volatility of a firm's cash flows and asset values. Thus, firms with steady cash flows such as utility companies, can use high levels of debt and still have a low probability of default. Contrary to this, firms whose value and cash flows are volatile must have significantly lower levels of debt to avoid the risk of default (Santosuosso, 2015).

Furthermore, the magnitude of the financial distress costs is likely to vary depending on the industry. An example is firms, such as IT firms, whose value comes largely from human capital. These companies are likely to incur high costs when they are exposed to financial distress risk due to the potential for loss of customers and the need to hire and retain key personnel, as well as a lack of tangible assets that can be easily liquidated. In contrast, firms whose main assets are physical capital, such as real estate firms, are likely to have a lower cost of financial distress, because a greater portion of their value derives from assets that can be sold relatively easily. This is further discussed in section 2.2.

2.2 Industry Sector and Financial Distress Risk

Literature suggest that industrial sector is a consequential factor in the construction of failure prediction models (Appiah, 2015). As previously mentioned, McKinsey & Company (2022) found that the industry a company compete in is the largest determinant of company performance relative to peers. This implies that industry effects are substantial and can function as escalators for companies operating in industries moving up the power curve. Contrary to this, companies operating in declining industries, also known as “sunset industries”, might have trouble improving company performance as they are characterized by financial instability and uncertainty (Kurian, 2013).

Due to the substantial impact industry performance has on company characteristics, the screening process preceding a buyout can be long and complex. PE companies will, prior to obtaining companies, typically look for firms with a stable cash flow and high profit margins as the free cash flow of the business dictates the amount of leverage the firm is able to support without going bankrupt. Moreover, companies operating in established industries are typically more attractive to investors as the cash flows are predictable. Furthermore, acquiring companies with low capital expenditures will generally be favourable as these costs deplete the cash otherwise used to pay down the debt.

2.2.1 Historical Market Trends Within Industries

Market trends in industries evolve rapidly as the world is quickly evolving. Industries that were roaring ten years ago are not necessarily the industries that experience high returns today. Trends in industries fluctuate due to several factors such as market and consumer trends. An example is the textile industry which is highly exposed and affected by trends and consumer expectations. This sector is also subject to increasing competition from emerging players, making it difficult for new players to enter (The European Commission, 2022). Notwithstanding, the industry continues to experience growth internationally and consequently saw a rise in returns after the Covid-pandemic due to an increasing use of e-commerce (McKinsey, 2021).

Furthermore, the food manufacturing industry is also an industry with high profit margins. Its return on equity is among the highest across the 21 NACE-industries[1] and the total shipment value has rapidly been growing since 2000. Due to this, food manufacturers have been especially popular targets for buyouts.

Healthcare facilities and hospitals have also been popular targets of LBOs as this sector has experienced a massive growth in the two last decades. The healthcare

[1] NACE-codes are a standard classification system used to classify business activities.

industry in general has been blossoming, reaching historic highs yearly since 2010 and is continuing to thrive till this day. The intersection between healthcare and IT has especially seen an acceleration in the last few years with the Covid-pandemic functioning as a launching point for medical innovation. However, the IT business alone has been subject to fluctuating trends due to increasing competition and is therefore not considered as steady of a target compared to companies intertwining healthcare and IT (Buchbinder et al., 2018).

Trends in the Nordics have, consistent with the rest of the world, been evolving in the last 100 years. The Nordics were in the early industrialization exposed to an extensive amount of forest resources and therefore started exporting commodities such as paper which brought wealth in the early 1900s. However, there has been a major shift in trends within the LBO market in the Nordics since the 1990s. According to the British Private Equity & Venture Capital Association, Finland and Sweden has the last years relied heavily on telecom and IT, whereas Norway has been large within offshore and energy. Furthermore, Denmark has been dominating within the consumer and services sector.

2.2.2 Volatility in Industry Sectors

As mentioned in the previous section, industries are characterized by various components which ultimately affect company performance. Sector characteristics entail different levels of volatility as industries operate in markets with different regulations and laws which have an impact on variables such as debt and tax. The trade-off theory is a commonly accepted theory in academia which identifies an optimal level of debt for which the value of the firm is maximized. At this point, the tax savings that result from the increased leverage are offset by the increased probability of incurring the costs of financial distress (Caetano & Serrasquiero, 2012). Moreover, there are other economic characteristics within industries that also affect company performance as companies' capital structure is directly connected to their operations (Sayari, N. & Mugan, C, 2015).

Figure 1 illustrates volatility indexes based on total return amongst different industries. The figure suggests that the most volatile sector is the energy sector comprising of electricity, gas, steam and air conditioning supply as this industry is highly affected by the changes in oil prices (Matt Moran, 2020). Oil prices have fluctuated largely since the 20th century, much due to the change in supply and demand. In addition to this, the energy sector is highly influenced by world crises, such as the Gulf War which had a negative effect on oil supply in the Middle East. The last ten years have also been subject to a huge increase in climate change. Due to this, the ambiguity regarding the prospect of the industry has also been a contributing factor to its volatileness as renewables such as wind power and solar are being favored (The ONS foundation, 2022).

Further studies indicate that the financial and insurance industry, in addition to the real estate sector, is also considered highly volatile as it is largely affected by economic downturns. This was especially the case following the financial crisis in 2008 which caused tremendous damage to the banking industry resulting in a global recession in which many companies struggled to bounce back from. However, literature suggests the financial distress cost of firms such as real estate companies are likely to be lower, as their assets mostly consist of physical capital which can be sold in case of default (Elkamhi et al, 2014).

As Figure 1 illustrates, the technology sector is considered the third most volatile sector. One of the determining factors in this is the change in consumer needs and high industry concentration, which negatively affects the price of failure for newer entrants (Kurian, 2013). As mentioned in section 2.1.2, the financial distress costs for IT companies are also, in contrast to real estate companies, typically high as they mostly obtain tangible assets which cannot be liquidated in the case of bankruptcy.

Furthermore, we infer that the remaining sectors display differing volatility levels. The consumer discretionary sector and the communication services sectors have a higher level of volatility compared to the other sectors. The consumer discretionary sector comprises of textiles, household goods and automobiles and parts and the communication services sector includes media and entertainment in addition to telecommunication support services. Literature suggests that the consumer discretionary sector is considered volatile due to its sensitivity towards economic cycles as consumers purchasing power largely decreases in recessions (Fidelity, 2022). It is additionally a sector which is highly affected by consumer trends ultimately affecting returns (The European Commission, 2022). Moreover, we find that the communication services industry is also highly affected by consumer behavior, which ultimately affects the industry's performance. It is additionally a sector with high industry concentration, making it difficult for new players to enter (The European Commission, 2022).

Lastly, we derive from Figure 1 that the consumer staples selector sector has the lowest level of volatility of the portrayed sectors. This sector consists of both food and beverage in addition to tobacco and household healthcare. Literature emphasizes that this specific sector experiences lower volatility compared to other industries due to it comprising of basic necessities which every household needs (VettaFi, 2022). Due to its low cash flow volatility, the food and beverage industry in addition to healthcare biotech, are industries that have been popular LBO targets (Business Insider, 2011).

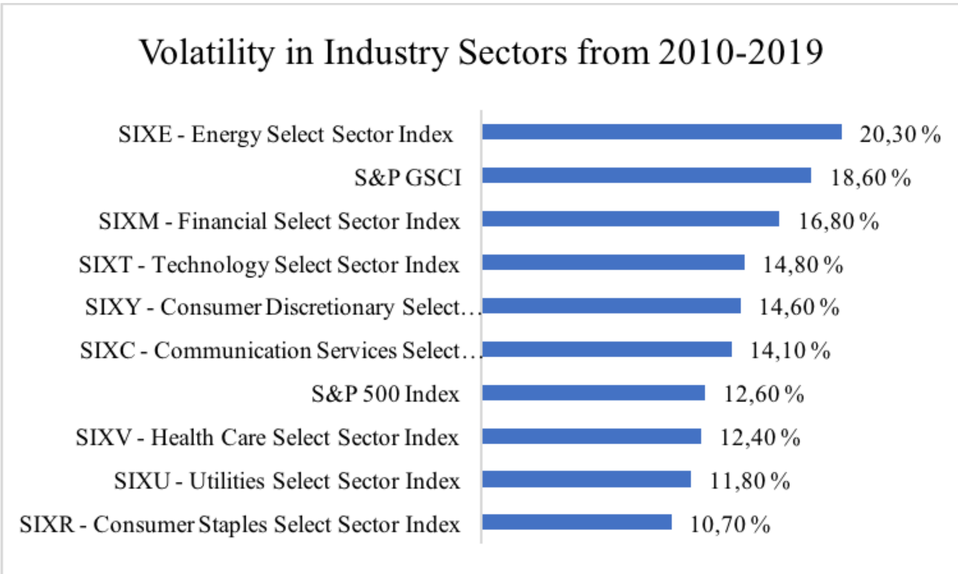

Figure 1 illustrate volatility indexes on total return (pre-tax) in different industry sectors.
Source: Bloomberg and Cboe Options Exchange

2.3 Financial Distress Measures

Financial statement analysis has been used to predict financial distress for a long time and was primarily used by creditors to evaluate creditworthiness of its borrowers (Beaver, Correia & McNichols, 2011). Initial studies used financial ratios, which is the relative relationship between two values derived from financial statements of a company. These ratios were used as predictors due to their availability in the financial statements of the firms, which are commonly available to the public (Rus & Waqas, 2018).

Several peer-reviewed analyses have implemented the Zmijewski score and Altman Z-score as measures to calculate the risk of financial distress. Ramdani (2020) used the Zmijewski method when determining financial distress on companies listed on the Indonesian stock exchange. Furthermore, Lord (2020) used the Altman Z-score to predict financial distress within the nursing home industry. The following sections will give a brief explanation of how these scores have been implemented in past studies on financial distress as well as how they measure financial distress.

2.3.1 Zmijewski-Score

The model proposed by Zmijewski (1984) uses accounting variables to conduct an analysis based on profitability, liquidity, and financial leverage in order to predict the financial condition of a company. This model can be applied to predict bankruptcies within two years and uses a probit regression. In the Zmijewski model, a high score indicates a higher level of financial distress. In fact, Zmijewski (1984) found that if the score is more than zero, the company is predicted to suffer from financial distress; in contrast, if the score is less than zero, the company is more likely to be free from financial distress. Zmijewski (1984) concludes by mentioning that the overall accuracy of his model is 95.25%.

The Zmijewski-score equals:

$$ZM = -4.336 - 4.513 * \frac{NI}{TA} + 5.679 * \frac{TL}{TA} + 0.004 * \frac{CA}{CL} \qquad (2.1)$$

where: NI = net income (profit/loss for period),
TA = total assets,
TL = total liabilities,
CA = current assets,
CL = current liabilities

Generally, a ZM-score of a healthy firm is negative whereas a high score indicates a higher financial distress risk.

2.3.2 Altman Z-score

Altman (1968) used a Multiple Discriminant Analysis (MDA) to study the likelihood of default of publicly traded manufacturing companies. In his research, he used 66 manufacturing firms in a period of 20 years (1946-1965) and Altman evaluated variables in a list consisting of 22 potential financial ratios, from which he ended up with five ratios that were the best predictors in terms of overall performance. By using financial ratios collected from the company's annual reports, he gave each company a Z-score which could be used to predict bankruptcy within two years. Altman's function gives a value of a so-called Z-score where high values indicate healthiness of a firm and low values suggest a higher probability of financial distress. Firms with a Z-score above 2.99 would be deemed relatively safe, whereas firms with Z-score below 1.81 are considered to have a high possibility of default. Scores between 1.81 and 2.99 are interpreted as the grey area, in which the model is not able to distinguish between healthy and bankrupt firms. There still exists a great possibility for default in said area, hence one should exercise caution. The five ratios are presented together with the final model in Equation 2.2.

$$Z = 0.717 * \frac{WC}{TA} + 0.847 * \frac{retE}{TA} + 3.107 * \frac{EBIT}{TA} + 0.42 * \frac{MV}{TL} + 0.998 * \frac{SAL}{TA} \tag{2.2}$$

where:
WC = working capital,
TA = total assets,
$retE$ = retained earnings,
$EBIT$ = earnings before interest and taxes,
MV = market value of equity,
TL = total liabilities,
SAL = sales

The zones of discrimination which we will use in our analysis, is defined by Altman as:

$$Z = \begin{cases} > 2.9, & \text{Safe Zone.} \\ 1.23 - 2.9, & \text{Gray Zone (Undefined).} \\ < 1.8, & \text{Distress Zone.} \end{cases} \tag{2.3}$$

3. Data

In this chapter, we will provide a synopsis of our data and how we collected it. We will introduce the chapter by giving a thorough explanation of how the data is obtained until we further explain how the dataset is cleaned and sorted. Thereafter, we describe how we created our control group and the criterion used before we explain how the accounting data is acquired. We end the chapter by illustrating how we accounted for outliers in our dataset. An overview of the collected data and the respective databases is illustrated in Appendix C.

In our thesis, we concentrate on companies of LBO transactions from Denmark, Finland, Norway and Sweden between 2000 and 2020. We choose to exclude Iceland due to a limited number of deals executed in this country during our timeframe of interest. All transactions are obtained from Zephyr and Nordic Knowledge Partners (NKP), which are database consisting of comprehensive information regarding M&A deals and has allowed us to obtain relevant information regarding the companies.

The accounting data is obtained from Orbis, and Centre for Corporate Governance Research (CCGR) based on companies' identification number which we obtained from Zephyr and NKP. In the case of the accounting data not being present on this database, we find data by using Proff or by finding annual reports online. This accounting data is thenceforth used to calculate the financial distress risk that will function as the pillar for our regression analysis.

3.1 Transactions

All LBO transaction data is collected from the global database Zephyr and Nordic Knowledge Partners (NKP). Here we limit the scope conducive to obtaining the relevant deals for our analysis. We customize our search and include deals categorized as *"Institutional Buy-Out"* and *"Private Equity"* under Deal Type. Moreover, we choose our countries of interest under the geography tab and restrict the search to only include target companies from these countries. Furthermore, we choose *"LBO"* under the subcategory *"Deal Financing"* to ensure that the transactions obtained indeed classifies as leveraged buyouts. Lastly, we choose to acquire deals from 01.01.2000-31.12.2020, which is the timeframe of significance to our analysis.

Once the search has been conducted, we omit deals assorted as *"Rumored"* to secure that the LBO transactions used in our analysis have been executed. Subsequently, we removed double entries, which leaves us with a total of 396 LBO transactions. Table 2 shows the number of transactions in the four countries of interest.

Table 2: Transactions

	Buyouts
Finland	78
Norway	80
Sweden	169
Denmark	69
Total	396

Transactions obtained from Zephyr and NKP

The table above illustrates a prevalence of Swedish LBO transactions. This is not surprising as Sweden is the largest economy in the Nordics and houses some of its most acclaimed PE companies. Moreover, we find that the number of deals between the remaining countries are largely analogous. Our sample size is substantially smaller compared to peer research on larger regions, such as the analysis provided by Tykvova & Borell which had a sample size of 1842 buyouts.

3.1.1 Industry Distribution

There are several industry classifications systems used to characterize productive activities. One which is widely used and accepted among peers is the FTSE classification system. This system is rapidly becoming the universal standard for industry classifications and is comprised of ten economic groups and 36 industrial sectors. We will apply these classification standards in our analysis. When referring to the industries in our analysis, we will use the economic groups as industry names.

After sorting our data, we found that we have companies operating in seven economic groups. Table 3 illustrates different economic groups and the FTSE sector within the groups.

Table 3: Industry Distribution

Economic Groups	**FTSE Sector**
Resources	Mining Oil & Gas
Cyclical Consumer Goods	Automobiles & Parts Household Goods Textiles
Non-Cyclical Consumer Goods	Beverages Food Producers&Processors Healthcare Personal care Pharmaceuticals&Biotech Tobacco
Cyclical Services	Leisure & Hotels Media & Entertainment Retailers Support Services Transport
Information Technology	IT Hardware Software & Services
Financials	Banks Insurance Investment Companies Investment Entities Life Assurance Real Estate Speciality & Other Finance
General	Aerospace and Defense Electronic & Electrical Engineering & Machinery Diversified Industries Construction & Building Materials Commercial Vehicles & Trucks Engineering Contractors & Fabricators

3.2 Control Group

Empirical studies suggest that PE investments are not considered random as they typically undergo a thorough screening process prior to investing, and usually prefer certain firm characteristics based on industry or region (Block, 2019).

Consequently, it is important to take these selection effects into account when forming the control group, as the non-random selection process regarding PE investments entail a systematic difference between companies being acquired and companies that have not been acquired. To measure the effect of an LBO on a firm’s financial distress risk and to ensure that the comparability is valid, we therefore employ a propensity score matching as suggested by Rosenbaum and Rubin (1983).

In order to eliminate selection bias, we firstly choose variables which we will use to match the firms. We choose to include the variables industry and country in addition to total assets and leverage ratio to identify comparable firms. Moreover, to ensure that the variables are not affected by the treatment, we choose to match the companies prior to the deal date of our buyout firms. Furthermore, we engage in exact matching regarding the industry groups, meaning that the control company must operate in the same industry to be characterised as a control company. We additionally choose to match with replacement based on Tykvova and Borell’s (2012) methodology, meaning that each comparable firm can be matched several times. By doing this, we increase the quality of the control companies (Caliendo & Kopeinig, 2008). When choosing the weight applied to the observations, we apply the nearest-neighbour method as peer reviewed research suggest that this is easy to interpret (Rosenbaum & Rubin, 1983). This method also eliminates bias and helps us identify firms that are similar. Once we have applied the propensity score matching method to identify control firms, we are left with a sample of 817 companies.

3.3 Accounting Data

Once all buyout firms and their respective matched control firms are identified, we find accounting data by using the global database Orbis and Corporate Governance Research (CCGR) in addition to Proff. The former database contains accounting data dating back to 1989 from all countries in addition to providing us with information regarding the firm's legal status. Whereas CCGR is a custom database which has complete data set of more than 3.5 million Norwegian companies in the buyout and venture market.

While the databases used consists of comprehensive data, it is still limited when it comes to available data in some markets, especially regarding the Danish market.

We therefore try to obtain the data using other methods, such as using the website Proff which contain accounting data for Norwegian, Danish and Swedish firms[2]. However, its data is limited, meaning that we will have to exclude the companies in which we do not find sufficient accounting data otherwise, such as by finding accounting data elsewhere online. Furthermore, we choose to only include unconsolidated accounting data, which from an accounting perspective only includes data from the specific subsidiary contrary to the parent company. This ensures that the accounting data regards our firms of interest and that possible parent companies do not influence the financial distress risk measures. By using unconsolidated accounting data for both buyout companies and control groups, we also establish a common ground for our further analysis and ensure that the data is comparable and commensurate.

To sufficiently measure the effect of the transaction on the firm's financial situation, we include accounting data for at least 3 years pre and post the transaction if the data is available. In the case of companies who have filed for bankruptcy, we collect accounting data up until the bankruptcy.

We find that there is a predominance of Swedish firms due to accounting data availability and it being a larger market. Once the accounting data is collected and examined, we are left with a dataset of 348 number of buyouts, which is a reduction of 48 due to missing data and 817 number comparable firms that were not subject to a buyout.

3.4 Treatment of Dataset

We calculate the FDR-scores as presented in Section 2.3; however, we see that our dataset suffers from outliers. Some of the accounting data acquired through Orbis and CCGR includes unreasonable values, i.e., the balance sheet does not add up or the numbers are arbitrarily high or low[3]. To mitigate the likelihood of falsification of our results, we chose to execute random sample tests by verifying the accounting by looking them up in Proff and removing the outliers.

[2] We use Proff.se, Proff.dk and Proff.no for acquiring accounting data for firms from Sweden, Denmark and Norway, respectively.
[3] Some of the accounting data we acquired breached the fundamental balance sheet equation: Assets = Liabilities + Equity.

3.4.1 Removing Outliers

Our initial number of observations as illustrated in table 2 was 396 transactions. However, as 48 of the buyout companies did not have available accounting data, our data sample was reduced to 348 buyout companies. Moreover, based on the abovementioned issues regarding obtaining sufficient accounting data, we engaged in a more detailed inspection of our accounting dataset. We find that some of the accounting numbers for both our buyout firms and comparable firms are disproportionately high and not consistent with the balance sheet of the firm, meaning the numbers are objectively incorrect. This ultimately affects the empirical results as it skews the distribution, creating an imprecise picture of our results. We therefore choose to remove the firms with inaccurate accounting numbers where we are not able to find the numbers of interest in other ways, such as by locating the annual report online. By removing the outliers, we are limiting the disruption of a potential relationship and can better depict a non-biased outcome. Once we have treated the dataset and removed the inaccurate numbers, we are left with 278 buyouts and 578 control companies. Table 4 illustrates the number of buyout firms and control firms before (untreated) and after (treated) removing outliers and faulty accounting data by country industry. We choose to keep the untreated dataset and apply our analysis on both the treated and untreated set to observe the difference between them.

Table 4: Number of buyouts by country and industry

	Untreated		Treated	
	Buyouts	Controls	Buyouts	Controls
Countries				
Finland	67	152	50	134
Norway	73	178	89	162
Sweden	148	365	102	210
Denmark	60	122	37	72
Total	**348**	**817**	**278**	**578**
Industries				
General	108	329	77	163
Resources	69	142	64	132
Financials	26	42	17	36
Information Technology	40	88	34	78
Cyclical Services	30	67	28	57
Non-Cyclical Consumer Goods	36	72	22	45
Cyclical Consumer Goods	39	77	34	68
Total	**348**	**817**	**278**	**578**

This table reports the composition of observations by country and industry for the untreated and treated data sample for the buyout and control firms, respectively.

3.4.2 Industry Distribution

As expected, we find that our sample group is heavily comprised of Swedish companies compared to companies from Norway, Finland and Denmark. This is, as previously mentioned, explained by the fact that Sweden is the largest economy in the Nordics. Moreover, we see that the *"General"* industry has the largest sample size, which is also expected as this industry distribution includes miscellaneous industries which do not fit into the other sectors. We also find that the *"Resources"* sector, which comprise of mining and oil & gas, has a larger sample size compared to the remaining five sectors. When looking at our sample data, we infer that a large portion of the firms in this sample are Norwegian, which is to be expected as mining, oil & gas has been popular industries in Norway and the CCGR database only has data for Norwegian companies as mentioned in section 3.3. Our sample also show that there is a predominance of Finnish and Swedish firms when analysing the companies performing in the *"Information Technology"* sector.

By looking at our data sample, we find that there is a slight change in industry trends as we find that the number of deals within the *"Information Technology"* and *"Cyclical Services"* sectors increases in the years following the financial crisis, whereas we find that activity within the *"Resources"* sector is higher before the financial crisis of 2007-2008. However, when looking at our whole sample of deals, we find that the number of deals from 2008-2012 is substantially lower compared to four years prior to the financial crisis. This is consistent with literature suggesting that investment activities decreased following the financial crisis (McKinsey, 2018).

3.5 Financial Distress Score Results

Table 5 illustrates descriptive statistics of the treated sample for the buyout and the control firms before and after the transaction. In the Z-score, the market value of equity is calculated by multiplying the current stock price by total outstanding shares. However, as we are examining private companies, we have decided to use book value of equity as an approximation of the firm's market value of equity.

Table 5: Descriptive data

	Pre		Post	
	(ZM)	(Z)	(ZM)	(Z)
Median				
Buyut firms	−1.88	2.38	−1.07	2.12
Control firms	−1.18	2.21	−1.18	2.21
Number of Observations				
Buyout firms	813	813	921	921
Control firms	4572	4572	4572	4572

This table reports medians of the financial distress scores Zmijewski-score and Altman Z-score for the firms who were involved in a leveraged buyout in 2000-2020 in the four Nordic countries of interest pre and post buyout compared to the matched control group. The data for Buyout firms and control firms correspond to the whole time period of 2000 to 2020. The control firms have note undergone a leveraged buyout and the medians for the financial distress scores are the same in the column pre and post.

From table 5 we infer that the median Z-score of neither group, buyout sample nor control firms, are placed in the "safe zone" as defined by Altman, please see equation 2.3. From the median Z-scores we can infer that only the control group is placed in the undefined zone, and that after the transaction they are placed in the distress zone. However, as we have a small sample and a big variation in the scores, we cannot infer any crucial findings from this description alone. We can however infer from the change in the median Zmijewski and Altman-Z score pre and post buyout for the buyout firm that it has increased and decreased, respectively, entailing a substantial change in the median towards a more distressed zone.

3.6 Bankruptcy Data

In this section, we have obtained information regarding our buyout firms and control companies' legal status which we have obtained through the database Orbis, CCGR and Proff. This information is obtained with the aim of investigating the distress risk not only based on accounting figures, but also by looking at the real distress. With this information we can analyse whether companies that have undergone a leveraged transaction more often end in bankruptcy compared to comparable companies that have not been subject to a buyout. The analysis will be further derived in section 5.2.

Table 6 depicts the bankruptcy rates of the buyout companies as well as the comparable companies that were not subject to a buyout. The bankruptcy rate illustrate the percentage of firms which have filed for bankruptcy or is no longer active. We assume that the classifications *"dissolved"*, *"inactive"* and *"bankrupt"* all illustrate that the companies have defaulted. Furthermore, we obtain the same information regarding the competitor firms and find a significant difference in the occurrence of defaulted companies illustrating an increase in bankruptcy rate among our control group. This contrasts with the findings provided by Ayash & Rastad (2020) mentioned in section 1. An explanation for this can be that Ayash & Rastad's sample size was larger, and their control sample was approximately the same size as their buyout sample. The sample size for the control group in our analysis is substantially larger than the sample size for the buyout group, which can influence the results. However, our results are comparable to those of Tykvova and Borell (2012) which concluded that although financial distress increases following an LBO, the bankruptcy rate amongst the buyout firms were not larger compared to their control group. In fact, their control group had a higher percentage of defaults compared to the buyout firms. They further concluded that a contributing factor to this is the fact that investors that acquire firms are typically better at handling financial distress compared to other investors as they are more experienced. Nonetheless, we cannot conclude from this table that buyout firms are subject to higher financial distress risk following a buyout compared to comparable firms and therefore choose to employ further analysis in section 5 regarding the real bankruptcy rates post LBO.

Table 6: Default Data

	Untreated		Treated	
	Buyouts	Controls	Buyouts	Controls
Active	348	817	278	578
Default	53	196	32	122
Default rate	15.23%	24%	11.51%	21.11%

This table reports the default data for the buyout and the matched control firms. We identify the following classifications; "dissolved", "inactive" and "bankrupt" as companies that have defaulted. All classifications are obtained from Orbis, CCGR and Proff.

4. Methodology

In this section, we will explain the statistical technique that we apply in chapter 5 for the empirical analysis of the findings. We run a dynamic multivariate panel regression to investigate the effect of an LBO transaction on a firm's financial distress risk in more detail. Tykvova and Borell (2012) found that LBO transactions lead to a significant increase in the financial distress risks of the buyout company. However, they found that buyout companies did not suffer higher bankruptcy rates compared to comparable non-buyout companies. We start by replicating Tykvova and Borell's approach on determining the effect of an LBO on a firm's financial distress risk, and then their approach on determining the real distress effect the buyout firm faces compared to the non-buyout firm. We replicate their approach with our dataset; thereby verifying if their conclusion still holds by expanding the time horizon to 2000−2020 and limit the market to include only companies from the Nordics. To do so, we formulate a dynamic multivariate panel regression analysis in section 4.1 and a binary model in section 4.2.

Due to the impact industry characteristics have on company performance, we will focus the remainder of the analysis on examining the relationship between a firm's financial distress and the industry they operate in. To do so we modify the regression model presented in section 4.1 and add interaction terms to investigate the possible differences.

The questions to be answered in the next sections will be whether Tykvova and Borell's findings are equally true for the Nordic market and whether certain industries drive the effect. Our hypotheses are derived from existing theories regarding the relationship between industry and financial distress as well as existing peer reviewed research on financial distress risk and default rate of buyout firms.

In our first analysis which we present in section 5.1 we aim to verify whether an LBO transaction has a significant effect on a firm's financial distress risk. Thus, we aim to verify whether our alternative hypothesis H_1 holds vs. our null hypothesis H_0:

H_0: There is no effect on the financial distress risk of buyout firm post an LBO transaction.

H_1: Buyout firms suffer from higher financial distress risk post an LBO transaction.

In our next analysis which we present in section 5.2, we aim to verify whether an LBO transaction has a significant effect on a firm's probability of bankruptcy. Thus, we aim to verify whether our alternative hypothesis H_2 holds vs. our null hypothesis H_01:

H_01: There is no effect on the probability of bankruptcy of buyout firm post an LBO transaction.

H_2: Buyout firms suffer from a higher probability of bankruptcy post an LBO transaction.

In our final analysis which we present in section 5.3, we aim to verify whether the industry the buyout firms operate in has a significant effect on the financial distress risk post an LBO transaction. Thus, we aim to verify whether our alternative hypothesis H_3 holds vs. our null hypothesis H_02:

H_02: There will be no significant prediction of a firm's financial distress risk post an LBO transaction by the industry they operate in.

H_3: The effect on the financial distress risk of a buyout firm post an LBO transaction will depend on the industry they operate in.

4.1 Multivariate Panel Regression Model

In order to examine our research question empirically and test our hypothesis, we need to operationalize it according to the characteristics of the panel dataset. As our data set includes different firms across different years, we must operate with regression models that fit an unbalanced panel data set. Thus, from the research question we derive an empirical question: To what extent does the leveraged buyout transaction explain the level of financial distress risk of a firm, after controlling for other relevant variables? We have chosen to run a dynamic multivariate panel regression where we control for the time invariant unobservable effects which are

country and industry. In addition to this, we use year dummy variables to account for time-varying conditions such as the
debt market situation.

In our regression model[4] we include all years for all buyout and control companies. Moreover, by using this model, we can include dummies to control for industry, country, and time meaning that we can capture the potential relationship between the predictor and outcome variables and analyse the variation over time. As we are operating with dummy variables, we must remove the first dummy variable from each categorical group; industry, country and year to not fall victim of the dummy variable trap. The dummy variable trap occurs if we include all binary variables as well as a common intercept. Foregoing this would create multicollinearity as the number of dummy variables would equal the number of values the categorical value can take on. The consequence of this would be incorrect calculations of regression coefficients and p-values (Brooks, C., 2008).

The regression model for our financial distress risk measures, Zmijewski-score and Altman Z-score, expresses that the financial distress risk that a particular firm faces in year t is explained by the lagged score, and lagged everage ratio in the prior year. The effect of the transaction is captured by the dummy variable LBO which takes the value 1 for observations after the transaction and 0 otherwise.

The regression model for the Zmijewski-score is presented by equation 4.1 and 4.2.

[4] Pooled Ordinary Least Squared model with dummy variables controlling for industry, country, and time.

$$ZM_{it} = \beta_0 + \beta_1 LBO_{it} + \beta_2 ZM_{i,t-1} + \beta_3 L_{i,t-1} + \gamma_2 I2_t + \gamma_n In_t + \\ ... + \delta_2 C2_t + \delta_n Cn_t + \lambda_2 T2_i + ... + \lambda_n Tn_i + \epsilon_{ict} \tag{4.1}$$

where: i = 1,2,...,n (i denotes the company),
t = 1,2,...,n (t denotes the year),
$ZM_{i,t-1}$ = vector of lagged ZM-scores for specific company
LBO_{it} = dummy variable having the value 1 if the observation was after the buyout, and 0 otherwise
$L_{i,t-1}$ = vector of observations of lagged leverage ratio
γ_t = an unobserved industry specific effect
δ_t = an unobserved country specific effect
λ_i = an unobserved year specific effect
ϵ_{it} = zero mean random disturbance with variance, σ^2_ϵ

$$ZM_{it} = \beta_0 + \beta_1 LBO_{it} + \beta_2 ZM_{i,t-1} + \beta_3 L_{i,t-1} + Industry_t \\ + Country_t + Year_i + \epsilon_{it} \tag{4.2}$$

The regression model for the Altman Z-score is presented by equation 4.3 and 4.4.

$$Z_{it} = \beta_0 + \beta_1 LBO_{it} + \beta_2 Z_{i,t-1} + \beta_3 L_{i,t-1} + \gamma_2 I2_t + \gamma_n In_t + \\ ... + \delta_2 C2_t + \delta_n Cn_t + \lambda_2 T2_i + ... + \lambda_n Tn_i + \epsilon_{ict} \tag{4.3}$$

where: i = 1,2,...,n (i denotes the company),
t = 1,2,...,n (t denotes the year),
$Z_{i,t-1}$ = vector of lagged Z-scores for specific company
LBO_{it} = dummy variable having the value 1 if the observation was after the buyout, and 0 otherwise
$L_{i,t-1}$ = vector of observations of lagged leverage ratio
γ_t = an unobserved industry specific effect
δ_t = an unobserved country specific effect
λ_i = an unobserved year specific effect
ϵ_{it} = zero mean random disturbance with variance, σ^2_ϵ

$$Z_{it} = \beta_0 + \beta_1 LBO_{it} + \beta_2 Z_{i,t-1} + \beta_3 L_{i,t-1} Industry_t \\ + Country_t + Year_i + \epsilon_{it} \tag{4.4}$$

We will from here on use equation 4.2 and 4.4 when referring to the regression model for the Zmijewski-score and the Altman Z-score respectively.

The implication of controlling for the fixed effects by using dummy variables is that the standard errors and test statistics are generally invalid because the model ignores the substantial serial correlation in the composite errors (Wooldridge, 2019). Thus, in order to compute standard errors and test statistics that are robust to arbitrary serial correlation (and heteroskedasticity) in the composite errors, we cluster the residuals by the company. The idea is that each cross-sectional unit is defined as a cluster of observations over time, and arbitrary correlation or serial correlation and changing variances are allowed within each cluster (Wooldridge, 2019). Furthermore, another implication of using a model of this nature with a lagged dependent variable is that the differenced residual in the model is necessarily correlated with the lagged dependent variable because both are a function of the residual (Joshua D. Angrist, and Jö-Steffen Pischke, 2009). By mistakenly using a model with these properties, the estimates of a positive treatment effect will tend to be too big. Thus, in order to check the robustness of the findings we estimate our model as portrayed in equation 4.2 and 4.4, and the model absent of the lagged dependent variable.

4.2 Bankruptcy Post LBO

As mentioned in section 3.6, we want to analyse whether companies end in bankruptcy more or less frequently after a buyout than comparable companies which have not been subject to a buyout transaction. To do so, we formulate a logistic regression model with a binary dependent variable which allows us to estimate the relationship between the effect of the LBO transaction and the probability of bankruptcy.

Our dependent variable BANKRUPTCY is a binary variable which takes a value of 1 if the firm goes bankrupt in the time period 2000–2020 and 0 otherwise. We obtained information on the bankruptcy of our buyout firms within this
period from the Orbis, CCGR and Proff databases as mentioned in section 3.3. A more detailed overview of the bankruptcy rates of our buyout firms and control group can be found in section 3.6. Axelson et al.'s (2013) results suggest that the size of the leverage increases in an LBO transaction during financial turmoil where companies are more likely to go bankrupt. We therefore control for both leverage ratio and total assets in our regression to test our hypothesis. Furthermore, analogous to the regression model explained in section 4.1, we control for year, country and industry fixed effects with dummy variables, and we follow the same procedure of removing the first dummy variable to account for the dummy variable trap. The vital variable of interest is the dummy variable BUYOUT, which equals 1 for buyouts and 0 otherwise. Both Axelson et al.'s (2013) and Tykvova and Borell's (2012) results indicate that higher distress risks are associated with higher

likelihood of bankruptcy. We therefore add the Zmijewski-score as an additional control variable to equation in order to verify the results.

The regression model expresses that the probability of bankruptcy that a particular firm faces in year t is explained by the leverage ratio, total assets, and their financial distress risk of that particular year. The effect of the transaction on a firm's bankruptcy probability is captured by the dummy variable BUYOUT.

The regression model for the bankruptcy rate is presented by equation 4.5.

$$\begin{aligned} BANKRUPTCY_{it} =& \beta_0 + \beta_1 BUYOUT_i + \beta_2 TA_{it} + \beta_3 L_{it} + \beta_4 ZM_{it} \\ &+ Industry_t + Country_t + Year_i + \epsilon_{it} \end{aligned} \tag{4.5}$$

4.3 Industry Effect Post LBO

We choose to use the regression models from section 4.1 as the pillar for our analysis and modify it in order to answer the question of whether industry specific differences can be observed by analysing the effect of each industry separately. This is done by adding the interaction term of the leveraged buyout variable, LBO, and the industry variable to be analysed successively.

The interaction term within itself will be a dummy variable taking the value 1 for all observation after the transaction within a respective industry and 0 otherwise. In practice this means that for the *"Financials"* industry, we add the term "Financials x LBO" to the base regression models presented in equation 4.2 and 4.4. By adding the interaction term, we can examine potential effects between industry sector and financial distress risk which ultimately allow us to derive our third hypothesis. Table 3 in section 3.1.1 shows that the "General" group is comprised of miscellaneous companies that do not fit into other categories, leaving us with a large sample of differing firms. We choose to remove the *"*General x LBO*"* dummy in our regression to account for the dummy variable trap as explained in section 4.1.

The new regression model, presented by equation 4.6 and 4.7, will still be accounting for the country and year effects, but as the interaction term controls for both the industry and the transaction, we have omitted the industry control variable in the new regression model. With this analysis we test whether the effect on the financial distress risk on a buyout firm will depend on the industry the firm operates in.

$$\begin{aligned} ZM_{it} = &\beta_0 + LBOxIndustry_{it} + \beta_2 ZM_{i,t-1} + \beta_3 L_{i,t-1} \\ &+ Country_t + Year_i + \epsilon_{it} \end{aligned} \tag{4.6}$$

$$\begin{aligned} Z_{it} = &\beta_0 + LBOxIndustry_{it} + \beta_2 Z_{i,t-1} + \beta_3 L_{i,t-1} \\ &+ Country_t + Year_i + \epsilon_{it} \end{aligned} \tag{4.7}$$

where: $LBOxIndustry_{it} = \gamma_2 I2_t * LBO_{it} + ... + \gamma_n In_t * LBO_{it}$

5. Results

In this section, we test our hypotheses and present our results from our analysis depicted in section 4. Hypothesis 1 is tested in 5.1 and aims to test if buyout firms suffer from higher financial distress risk post an LBO transaction. Hypothesis 2 is tested in 5.2 and seeks to test if buyout firms suffer from a higher probability of bankruptcy post an LBO transaction. Lastly, hypothesis 3 is tested in 5.3 and aims to test if the effect on the financial distress risk of a buyout firm post an LBO transaction will depend on the industry the firm operates in.

5.1 Financial Distress Risk of Buyout Companies

Table 7 gives an overview of our regression results of the two financial distress risk scores as shown in equation 2.2 and 2.3, whereby LBO captures the effect the transaction has on the financial distress risk of a company. Column (1) and (3) illustrate the results of the Zmijewski-score and Altman Z-score for the untreated data sample, respectively. Whereas column (2) and (4) illustrate the results of the Zmijewski-score and Altman Z-score for the untreated data sample, respectively. Subsequently, the tables illustrate the increased variability of our data sample before data treatment as the outliers were extreme values which thus disrupted the distribution by increasing the variability of the data. Due to this, our primary interest is the results from the analysis on our treated data sample, that is, columns (2) and (4). Nonetheless, we choose to include both data samples in the following sections to give a clear demonstration of the influence of outliers on the statistical significance of our analysis. The central variable of interest is the dummy variable LBO, which equals 1 for observations after the transaction and 0 otherwise.

As mentioned in section 2.3.1, a high Zmijewski score indicates a higher financial distress risk, whereas the Altman Z-score is generally positive indicating that the lower the value of the Z-score, the more financially distressed the company is. As depicted in the table, we can infer that the LBO transaction has a significant effect on a firm’s financial distress for the treated sample whereas the marginal effect of the LBO transaction is insignificant for the untreated sample which includes outliers. The outliers in the untreated sample have affected the relationship between an LBO transaction and the financial distress risk, as the outliers consisted of disproportionate values which ultimately skewed the distribution.

The results include both the buyout firms and their respective control firms. The table illustrates that the Zmijewski- and Altman Z-score, ceteris paribus, increases with 0.0748 and decreases with 0.0484 following the leveraged buyout transaction, respectively. These results illustrate that the financial distress risk of buyout firms increase post an LBO transaction. Moreover, by examining the t-stat value for our treated sample, which is found by dividing the coefficient with its standard deviation, we infer that the absolute value of the t-statistic for the ZM- and Z-score of 2.534 and 2.0526, respectively, is higher than the critical value at the 5% significance level of 1.96. This is not the case for our untreated sample as the absolute value of the t-statistics are lower than the critical value. This entails that we can reject the null hypothesis and accept hypothesis H_1, that buyout firms experience a higher financial distress risk after a buyout for our treated sample based on a significance level of 5%. The results are consistent with findings from scholars, such as Kaplan & Stein (1993) who found that increases in debt levels can result in an increase in financial distress risk. Furthermore, the results are consistent with the findings of Tykvova and Borell (2012), and this shows that the financial distress risk effect on a buyout firm post an LBO can be observed in the Nordics as well based on our sample.

Table 7: Panel regressions for buyouts and control firms

	ZM		Z	
	(1)	(2)	(3)	(4)
LBO	0.1055	0.0748**	−0.0874	−0.0484**
	(0.2067)	(0.0295)	(0.0965)	(0.0236)
Lagged Dep. Variable	Yes	Yes	Yes	Yes
Lagged Leverage Ratio	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	8595	6306	8595	6306
No. Entities	1165	855	1165	855
No. Target	348	276	348	276
No. control firms	817	579	817	579

This table reports the coefficients from our panel regressions with the financial distress risk measures, Zmijewski-score and Z-score, as the dependent variables. The respective standard deviations are reported in parenthesis. LBO is a dummy variable that takes a value of 1 for buyouts in the years after a buyout transaction and 0 otherwise. All the regressions include a constant as well as dummy variables to control for country, industry and year effects. The definition of the dependent and independent variables is provided in Appendix B. Furthermore ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

5.1.1 Robust Checks

Robustness checks can help test if the assumptions made in our analysis are true and if our results are robust. We therefore employ robust checks to investigate how certain our regression estimates are. We examine how our estimates behaves with certain modifications to see how they drive our results by altering our analysis (Klein, 2022).

5.1.1.1 Robustness check on Panel Regression Model

As mentioned in section 4.1, the regression model which we have applied introduces a limitation as we are using our model with a lagged dependent variable, and the differenced residual in the model is necessarily correlated with the lagged dependent variable because both are a function of the residual. We have therefore estimated our model with and without the lagged dependent variable for the treated sample to check the robustness of the findings. We have presented the results in table 8. Column (1) and (3) illustrate the results of the Zmijewski-score and Altman Z-score without the lagged score, respectively. Whereas column (2) and (4) illustrate the results of the Zmijewski-score and Altman Z-score with the lagged score, respectively.

Table 8: Robustness check: Panel regressions for buyouts and control firms

	ZM		Z	
	(1)	(2)	(3)	(4)
LBO	0.1298**	0.0748**	−0.0987**	−0.0484**
	(0.0524)	(0.0295)	(0.0398)	(0.0236)
Lagged Dep. Variable	No	Yes	No	Yes
Lagged Leverage Ratio	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	6306	6306	6306	6306
No. Entities	855	855	855	855
No. Target	276	276	276	276
No. control firms	579	579	579	579

This table reports the coefficients from our panel regressions with the financial distress risk measures, Zmijewski-score and Z-score, as the dependent variables. Column (1) and (3) have been estimated without the inclusion of the lagged dependent variable in order to check the robustness of the results. The respective standard deviations are reported in parenthesis. All the regressions include a constant as well as dummy variables to control for country, industry and year effects. The definition of the dependent and independent variables is provided in Appendix B. Furthermore ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Table 8 shows that omitting the lagged dependent variable from the regression will result in the LBO transaction having a higher effect on the financial distress risk of a company. However, by omitting the lagged risk score, we assume that a firm's overall healthiness of a particular year does not depend on its state the previous years. It seems unlikely since a firm's healthiness will depend on the state they are in, which is a result of prior events. Most firm's financial distress risk is highly correlated from one year to the next, and past financial risk scores are therefore an excellent predictor of future financial risk and financial risk growth.

5.1.1.2 Further Controlling for Country, Industry, and Time Effects

We investigate whether particular countries, industries or years drive our results. As explained in section 2.1.3, the Swedish companies were the all-time high fund managers both in the Nordic segment and the international segment. Moreover, the LBO market in Sweden is more developed compared to the other Nordic countries. In order to control whether the results are affected by the maturity of the market in a specific country we removed one country at a time and ran the regression to check for the robustness of the results.

In section 3.4, we presented table 4 which showed the aftermath of the treatment to the data sample. The table shows that the *"General"* industry makes up for 28% of our data sample. In our standard regression analysis presented in table 8 and table 9 we have removed this industry in order to account for the dummy variable trap. In our next robustness check we removed one industry at a time to control whether the results were affected by the size of the industry.

Lastly, as explained in section 2.1.2, there have been several major boom-and-bust cycles since the origin of the LBO market. In order to control whether these cycles affect the results we continued the abovementioned approach and removed one year at a time to analyse whether the results change.

Inclusively, the abovementioned robustness checks depicted in this section did not alter the results presented in our analysis in section 5.1.

5.2 Real Bankruptcy Rates Post LBO

Table 9 gives an overview of our regression results of the probability of bankruptcy as shown in equation 4.3, whereby BUYOUT captures the effect the transaction has on the bankruptcy probability of a company. As previously mentioned, column (1) shows the results from a logit estimation performed on the untreated sample and column (2) shows the results performed on the treated sample. The central variable of interest is the dummy variable BUYOUT, which equals 1 for buyouts and 0 otherwise.

Table 9: Probability of bankruptcy - Logit regressions for buyouts and control firms

	BANKRUPTCY	
	(1)	(2)
BUYOUT	0.0473	0.0177
	(0.0438)	(0.0134)
ZM-score	0.0089	0.0028***
	(0.0113)	(0.0011)
Total Assets	Yes	Yes
Leverage Ratio	Yes	Yes
Constant	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	8595	6306
No. Entities	1165	855
No. Target	348	276
No. control firms	817	579

This table presents the marginal effects from the logistic regression model in column (1) and (2), where the dependent variable BANKRUPTCY takes a value of 1 if the firm goes bankrupt in the time period of 2000–2020 and a value of 0 otherwise. Variable definitions are provided in Appendix B. All regressions include a constant as well as country, industry and year fixed effects. The standard errors are clustered by firm. Furthermore ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

The results from column (1) and (2) on the untreated and treated sample, respectively, shows that the marginal effect is insignificant. Comparable to the analysis in section 5.1, the outliers in the untreated sample have affected the results due to the increased variability in the data, which has decreased statistical power of the coefficients. We perform a two-sided hypothesis test to find out if the variable for the probability of bankruptcy is statistically different from zero with a 10% significance level. The critical value for a 10% significance is 1.645 and we reject the null hypothesis as the absolute value of the t-stat is lower than the critical value. Therefore, we cannot conclude that buyout companies experience a higher probability of bankruptcy than the matched comparable non-buyout group on any conventional significance level.

From an economical point of view, this can be explained by the fact that PE firms undergo extensive research on their target companies before acquiring them, and thus they control for the bankruptcy probabilities leading from the substantial leverage in the transaction.

Our results align with Tykvova and Borell's (2012) findings, as we do not find any support for the assumption that leveraged buyout transactions lead buyout companies into excessive financial distress ending in bankruptcy. Thus, we cannot reject hypothesis $H_0 1$ that there is no effect on the probability of bankruptcy of buyout firm post an LBO transaction.

5.2.1 Robust Checks

5.2.1.1 Logit Regression with Alternative Distress Risk Measures

To confirm our results, we run robust checks by employing Altman Z-score instead of the Zmijewski score as well as including both. In table 10, we present the results from the robustness check done on the treated sample. We add the Zmijewski-score, Altman Z-score and finally both scores in column (1), (2) and (3) respectively.

Table 10: Probability of bankruptcy - Robust check

	BANKRUPTCY		
	(1)	(2)	(3)
BUYOUT	0.0177	0.028	0.0033
	(0.0134)	(0.0229)	(0.0029)
ZM-score	0.0028***		0.0009***
	(0.0011)		(0.0004)
Z-score		−0.0011***	−0.0007***
		(0.0004)	(0.0003)
Total Assets	Yes	Yes	Yes
Leverage Ratio	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	6306	6306	6306
No. Entities	855	855	855
No. Target	276	276	276
No. control firms	579	579	579

This table presents the marginal effects from the logistic regression model in column (1) through (3), where the dependent variable BANKRUPTCY takes a value of 1 if the firm goes bankrupt in the time period of 2000–2020 and a value of 0 otherwise. Variable definitions are provided in Appendix B. All regressions include a constant as well as country, industry and year fixed effects. The standard errors are clustered by firm. Furthermore ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

The robustness check does not change the results. We can infer from the table that our rejection of $H_0 1$ is correct based on this robustness check.

5.2.1.2 Further Controlling for Country, Industry and Time Effects

We provide the same approach as depicted in section 5.1.1.2, and check if certain countries, industries or years drive our results. We firstly exclude the countries in our analysis before proceeding to exclude the industry and year coefficients one by one. This robust check is executed to examine if the exclusion of said variables will affect our results. After applying this robustness check, we find that our results are not changed by our modifications, indicating that our results are robust based on this test.

5.3 Industry Effect on Financial Distress Risk

As mentioned in section 2.2, the industry a company operates in is considered the largest determinant of the company's performance relative to peers (McKinsey, 2022), implying that industry and company performance is highly correlated. With the aim of expanding upon our results from section 5.1, we have performed an analysis examining the potential effects of industry on financial distress risk of buyout companies where the results are presented in table 11. Column (1) and (3) illustrate the results of the Zmijewski-score and Altman Z-score for the untreated data sample, respectively. Whereas column (2) and (4) illustrate the results of the Zmijewski-score and Altman Z-score for the untreated data sample, respectively. Our primary interest is the results from the analysis on our treated data sample, that is, columns (2) and (4). Nonetheless, we choose to include both data samples in the following sections to give a clear demonstration of the influence of outliers on the statistical significance of our analysis. The central variable of interest is the interaction dummy variable term industry x LBO, which equals 1 for all observation after the transaction within a respective industry and 0 elsewise. Henceforth we shall focus the examination of the results based on column (2) and (4) unless otherwise stated.

By looking at the coefficients for each interaction term dummy, we entail that there are some differences in the change in financial distress risk based on the sectors. We will therefore present our results industry wise, in which we comment on our results for each industry sector.

Table 11: Panel regressions for buyouts and control firms

	ZM		Z	
	(1)	(2)	(3)	(4)
Cyclical Services x LBO	0.0433	0.0167	−0.0028	−0.0609
	(0.0571)	(0.0531)	(0.0456)	(0.1042)
Cyclical Consumer Goods x LBO	0.0259	0.0078	−0.0012	−0.0739
	(0.0765)	(0.0853)	(0.0904)	(0.1074)
Information Technology x LBO	0.0208	0.0977**	−0.0578	−0.0891**
	(0.0287)	(0.0411)	(0.1192)	(0.0361)
Financials x LBO	0.0269	0.1443	−0.0139	−0.0437
	(0.1250)	(0.1755)	(0.0830)	(0.1038)
Non-Cyclical Consumer Goods x LBO	−0.0046	−0.0433	0.0412	0.0731
	(0.0444)	(0.0646)	(0.0712)	(0.0532)
Resources x LBO	0.0534	0.1415**	−0.1679	−0.1007**
	(0.0390)	(0.0618)	(0.1810)	(0.0448)
Lagged Dep. Variable	Yes	Yes	Yes	Yes
Lagged Leverage Ratio	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	8595	6306	8595	6306
No. Entities	1165	855	1165	855
No. Buyout	348	276	348	276
No. control firms	817	579	817	579

This table reports the coefficients from our panel regressions with the financial distress risk measures, Zmijewski-score and Z-score, as the dependent variables. The respective standard deviations are reported in parenthesis. The reported coefficients of the independent variables are interaction dummy variable terms that takes the value 1 for buyouts in the years after a buyout transaction within the respective industry and 0 otherwise. All the regressions include a constant as well as dummy variables to control for country and year effects. The definition of the dependent and independent variables is provided in Appendix B. Furthermore ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Cyclical Services

The Cyclical Services industry has, ceteris paribus, a positive effect and a negative effect on the Zmijewski- and Altman Z-score, respectively. The coefficient suggests that the financial distress risk of buyout firms in the Cyclical Services industry will increase following the buyout transaction compared to comparable firms in the same industry. Table 1 in section 2.2.2 illustrates that the Communication Services Sector, which encompasses some the industries in the *"Cyclical Services"*-sector has a lower sector volatility compared to the *"Resources", "Information Technology"* and *"Financials"*-sector which can explain why the increase in financial distress risk in this group is lower compared to said sectors. However, as we infer from the table, the variables are not statistically significant. We can therefore not infer whether the financial distress risk of buyout firms in the Cyclical Services industry post an LBO transaction have a higher financial distress risk compared to its comparable firms.

Cyclical Consumer Goods

The Cyclical Consumer Goods industry has, ceteris paribus, a positive- and a negative effect on the Zmijewski- and Altman Z-score, respectively. As with the Cyclical Services industry, this indicates a slight increase in financial distress risk post buyout transaction for the firms in this industry. The effect is consistent with the literature we reviewed in section 2.2.2, where literature suggests that this is highly exposed to both economic cycles and consumer trends (The European Commission, 2022). However, it is emphasised that although the industry experiences volatile returns, it continues to grow due to an increasing use of e-commerce (McKinsey, 2021). Nonetheless, as illustrated in table 11, the results are not statistically significant. This entails that we are unable to conclude that this industry has a marginal effect on financial distress risk of buyout companies on any conventual significance level.

Information Technology

The Information Technology industry has, ceteris paribus, the second most substantial positive and negative effect on the Zmijewski- and Altman Z-score, respectively. The result suggests that the financial distress risk of buyout firms in the Information Technology industry will increase following the transaction compared to comparable firms in the same industry. This is consistent with literature depicted in section 2.2.2, as the IT sector is considered to be highly volatile due to factors such as high industry concentration. We additionally infer from the table that the results are statistically significant at a 5% level. This entails that the Information Technology industry has a marginal effect on financial distress risk of buyout companies on a 5% significance level. Nevertheless, we cannot conclude that our results for certain depicts a factual relationship between the financial distress risk a buyout firm experiences post an LBO transaction and the industry they operate in. Our results are only significant based on our sample data depicted in table 4 which includes a limited number of buyout and control firms in each industry, and it influences the statistical power of our analysis.

Financials

The financial industry has, ceteris paribus, a positive- and a negative effect on the Zmijewski- and Altman Z-score, respectively. The coefficients suggests that the financial distress risk of buyout firms in the financial sector will increase following the transaction compared to comparable firms in the same industry. This result aligns with literature previously discussed, as the financial industry is considered highly volatile as it is largely affected by economic downturns as mentioned in section 2.2.2. Nevertheless, the marginal effect is insignificant based on all conventional significance levels. We can therefore not infer whether the financial distress risk of buyout firms post an LBO transaction are affected by being in the financial industry compared to its comparable firms.

Non-Cyclical Consumer Goods

The Non-Cyclical Consumer Goods industry has, ceteris paribus, a negative effect and a positive on the Zmijewski- and Altman Z-score, respectively. The coefficient suggests that the financial distress risk of buyout firms in the financial sector will decrease following the transaction compared to comparable firms in the same industry. This result could be expected as this sector comprises of both the food and beverage industry as well as healthcare biotech, which are two industries that have been popular targets of LBOs as firms in this industry have low cash flow volatility. However, the findings for this industry are also not statistically significant, which entails that we cannot certainly conclude that our results explain the effect in which we wish to capture.

Resources

The Resources industry has, ceteris paribus, the most substantial positive- and negative effect on the Zmijewski- and Altman Z-score, respectively. The coefficients suggests that the financial distress risk of buyout firms in this industry will increase following the transaction compared to comparable firms in the same industry. This finding is consistent with existing literature, as mentioned in section 2.2.2, suggesting that this industry sector is more volatile, resulting in the financial distress risk fluctuating more (PwC, 2020). An explanatory factor of the volatility in this sector is the fluctuations in the supply and demand for oil which has varied greatly since the 20th century. Moreover, the variable has a marginally significant effect on both the ZM- and Z-score based on a 5% significance level. Nevertheless, we cannot conclude that our results for certain depict a factual relationship between financial distress risk and companies operating in the Resources industry. Our results are only significant based on our sample data depicted in table 4 which includes a limited number of buyout and control firms in each industry, further influencing the statistical power of our analysis.

Based on the results discussed in this section, we infer that only two of the six industries, *"Information Technology"* and *"Resources"*, have statistically significant variables. As we are specifically researching how financial distress risk varies across industries by examining buyout firms in the Nordics, there are a limited number of deals executed in this market compared to peer research. This entails that we have a low number of buyout and control firms per industry group, which results in our analysis suffering from low statistical power which further influences our ability to draw conclusions. We can therefore not reject the null hypothesis $H_0 2$ that there will be no significant prediction of a firm's financial distress risk post an LBO transaction by the industry they operate in on any conventional significance level.

5.3.1 Robustness check on Panel Regression Model

We follow the same approach as in section 5.1.1.1 where we check the robustness of our results by estimating the model with and without the lagged dependent variable as the differenced residual in the model is necessarily correlated with the lagged dependent variable as both are a function of the residual. The results of this robustness check are presented in table 12.

Table 12: Robustness check: Panel regressions for buyouts and control firms

	ZM		Z	
	(1)	(2)	(3)	(4)
Cyclical Services x LBO	0.0208	0.0167	−0.1401	−0.0609
	(0.0287)	(0.0531)	(0.1539)	(0.1042)
Cyclical Consumer Goods x LBO	0.0111	0.0078	−0.1133	−0.0739
	(0.0361)	(0.0853)	(0.1906)	(0.1074)
Information Technology x LBO	0.1066*	0.0977**	−0.1009**	−0.0891**
	(0.0592)	(0.0411)	(0.0463)	(0.0361)
Financials x LBO	0.1770	0.1443	−0.0864	−0.0437
	(0.1341)	(0.1755)	(0.0961)	(0.1038)
Non-Cyclical Consumer Goods x LBO	−0.0232	−0.0433	0.0274	0.0731
	(0.1040)	(0.0646)	(0.0825)	(0.0532)
Resources x LBO	0.1928**	0.1415**	0.1242**	−0.1007**
	(0.0838)	(0.0618)	(0.0569)	(0.0448)
Lagged Dep. Variable	No	Yes	No	Yes
Lagged Leverage Ratio	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	6306	6306	6306	6306
No. Entities	855	855	855	855
No. Buyout	276	276	276	276
No. control firms	579	579	579	579

This table reports the coefficients from our panel regressions with the financial distress risk measures, Zmijewski-score and Z-score, as the dependent variables. Column (1) and (3) have been estimated without the inclusion of the lagged dependent variable in order to check the robustness of the results. The respective standard deviations are reported in parenthesis. All the regressions include a constant as well as dummy variables to control for country and year effects. The definition of the dependent and independent variables is provided in Appendix B. Furthermore ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

The results of the robustness check show the same pattern as in section 5.1.1.1, whereby the regression without the lagged dependent variable has led to an increased effect on the financial risk a firm suffers post an LBO transaction. However, due to the unlikelihood that these scores are independent of each other we do not deem the regression model which we used in our analysis in section 5.2 to be at fault.

Similar to our results discussed in 5.3 we find that the only significant variables are the "Resources x LBO" and "Information Technology x LBO". However, by excluding the lagged dependent variable we infer from the column (1) and (2) coefficient has increased and decreased for the Zmijewski- and Altman Z-score, respectively. However, as mentioned in section 5.1.1.1, it is unlikely that a firm's healthiness will be independent of the state they were in the previous year since most firm's financial distress risk is highly correlated from one year to the next. Furthermore, due to the consistency of the regression results we find the model where the lagged dependent variable is included to be a good predictor of future financial risk and financial risk growth. However, we instead deem the low number of observations per industry to be the reason for the low statistical power of the model.

Although we find that the implementation of the robustness checks in section 5.1.1, 5.2.1 and 5.3.1 indicate that our results are robust, there are pitfalls with the used checks as they do not necessarily provide satisfactory evidence for the validity of our analysis. However, by employing them we can limit the occurrence of potential misspecifications which ultimately strengthens the reliability of our analysis (Lu & White, 2014).

6. Limitations and Recommendations

Before presenting our conclusion, we will firstly discuss limitations of our analysis until we introduce potential recommendations for future research within the field of financial distress risk within LBOs. We will also discuss recommendations regarding our third analysis, related to industry effects on financial distress risk of buyout companies. The purpose with this thesis has been to extract meaningful information from the data sample collected in order to analyse the three hypotheses of interest and reach a purposeful conclusion. Nevertheless, we acknowledge that there are drawbacks with our thesis, ultimately influencing our results and the possibility to draw conclusions. We also identify several fields of research relevant for future research in which we find that there is a lack of studies.

A shortcoming of our thesis is related to the limitation of data availability regarding accounting data. As we experienced difficulties collecting sufficient and adequate data concerning private firms in the Nordics, our sample size was subject to a reduction. In addition to this, we experienced that our primary data sample included faulty outliers, which further decreased our sample size. This issue could possibly have been avoided if we had access to more databases, however, we have noticed a recurring trend in research within the PE field in which researchers struggle to find sufficient accounting data when dealing with private companies. Especially in the US is this seen as an impediment as private companies are not required to disclose financial information.

The abovementioned limitation ultimately affected the statistical power of our analyses. Although we eventually managed to collect sufficient data to perform the analyses illustrated in 5.1 and 5.2, we were unable to reject the null hypothesis in 5.3 as the number of buyout and control firms within each industry yielded a low number of observations which lowered the statistical power of the analysis. This issue could possibly have been countered if our sample size within the respective industries were larger.

An additional drawback which contributes to the limited number of buyout and control companies is the market in which our analysis is based upon. As the LBO market in the Nordics is, as previously stated, small in absolute terms compared to the EU and US, the number of deals is limited. Albeit we were subsequently able to collect a satisfactory amount of data to perform the first and second hypotheses, establishing causality could be easier if we had examined a larger market, such as Tykvova and Borell (2012) which analysed the EU-15 countries and had a dataset consisting of over 1842 buyouts.

There are additional limitations regarding our propensity score matching procedure. Firstly, the propensity scores matching procedure only account for observable variables, entailing that there might be factors affecting the assignment of the treatment which cannot be observed. Moreover, there is also a probability that we are including companies that are not similar to our buyout companies which results in a faulty comparison.

As we find that there is little research on the area of financial distress risk of buyout companies in general, we find that this is a relevant field for future studies. We additionally find that there is a limited number of studies examining the effects of leveraged buyouts in the Nordic countries. As LBOs is a much-discussed field within PE, we therefore believe that it could be interesting to make closer investigations within these fields.

As previously discussed, we additionally find differences when researching the sheer size of the Nordic countries compared to other markets. The Nordic market is small in absolute terms, but its returns continue to reach historic highs. We therefore believe it could be interesting to directly analyse the differences in how LBOs in the Nordic countries perform compared to other regions to observe a potential difference.

Lastly, we believe it could be interesting to further analyse the potential effects of industry performance on financial distress risk of companies both in general and regarding companies that have been subject to a leveraged buyout. Not only do we find that this is a field with limited research, however we also believe that this research area is highly interesting as peer literature emphasize the importance of industry performance on company performance (McKinsey, 2022). In addition to this, we believe it could be interesting to research industry effects on financial distress risk following the Covid-19 pandemic. Although literature illustrates that the disorientation following the pandemic was short-lived as central banks in both US and Europe quickly alleviated liquidity concerns by pumping trillions into the financial economy, it is still difficult to infer the economic impact of the pandemic on industries.

7. Conclusion

By taking inspiration from methods employed by those of Tykvova and Borell (2012), we analysed the financial distress risk of companies that have been subject to a leveraged buyout by examining deals executed in Norway, Sweden, Denmark and Finland ranging from 2000 to 2020. Furthermore, we additionally examined the default rates of buyouts and comparable companies to analyse whether buyout companies end in bankruptcy more often than comparable firms. Lastly, we analysed the potential industry effects on financial distress risk of buyouts following a transaction.

Our results portrayed in section 5.1 led us to reject the null hypothesis and accept hypothesis H_1, that firms subject to a buyout experience a higher financial distress risk after a buyout for our treated sample based on a significance level of 5%. These results are consistent with the findings provided by Tykvova and Borell (2012) in which they found an increase in financial distress risk in buyout companies based on samples from the EU-15 countries. Moreover, in 5.2, we did not find support for the assumption that LBO transactions lead buyout companies into excessive financial distress ending in bankruptcy. We were therefore not able to reject hypothesis H_01, that there is no effect on the probability of bankruptcy of buyout firms post an LBO transaction. From an economical point of view, this can be explained by the extensive research PE firms endure on target companies prior to acquisition, ultimately controlling for bankruptcy probabilities. These findings are additionally consistent with the findings of Tykvova and Borell (2012). Lastly, in 5.3, we analysed industry effects on financial distress risk of buyouts. In this analysis, we were unable to reject the null hypothesis H_02, that there will be no significant prediction of a firm's financial distress risk post an LBO transaction by the industry they operate in on any conventional significance level. A possible explanation for our empirical results in this analysis is the number of buyout and control companies in each industry group, which affected the statistical power of our analysis. As mentioned, we therefore recommend this field for future research.

Our research adds to an exceedingly relevant field which is highly discussed by academia and provide a framework for future studies. As there is little to no research on the area of financial distress risk of buyout companies in the Nordics in addition to there being limited data available, our research cannot alone conclude that the results illustrated in our analysis relates to all deals in the Nordics. We therefore suggest expanding upon this field and filling the research gap which exists in this area.

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9. Appendix

Appendix A – Financial Distress Risk Models

Formula		
Name	*Symbol*	*Model*
Zmijewski-score	ZM	$ZM = -4.336 - 4.513 * \frac{NI}{TA} + 5.679 * \frac{TL}{TA} + 0.004 * \frac{CA}{CL}$
Altman Z score	Z	$Z = 0.717 * \frac{WC}{TA} + 0.847 * \frac{retE}{TA} + 3.107 * \frac{EBIT}{TA} + 0.42 * \frac{MV}{TL} + 0.998 * \frac{SAL}{TA}$
Variable Description		
Name	*Symbol*	*Description*
Net Income	NI	The income less cost of goods sold, expenses, depreciation and amortization, interest, and taxes for the specific accounting period.
Total Assets	TA	The total amount of assets owned by the firm.
Total Liabilities	TL	The total amount of debt owned by the firm.
Current Assets	CA	The assets that a company expects to convert to cash within one year.
Current Liabilities	CL	The amount of debt that is due in a year or less.
Working Capital	WC	The amount of available capital which can be readily used by the firm in its day-to-day operations. It is the current assets less the current liabilities.
Retained Earnings	retE	The portion of a firms profit that is retained from net income at the end of a reporting period and saved for future use.
EBIT	EBIT	Earnings before interest and taxes.
Market Value of Equity	MV	The total value of a firm's equity calculated by multiplying the current stock price by total outstanding shares. As explained in section 3.5.
Sales	SAL	The income received by the firm from its sales of goods or the provision of services.

Appendix B – Regression Model: Variable description and source

Dependent Variable			
Name	*Symbol*	*Description*	*Source*
Zmijewski-score	ZM	Financial distress risk measure as presented in section 2.3.	Orbis, CCGR, Proff
Altman Z-score	Z	Financial distress risk measure as presented in section 2.3.	Orbis, CCGR, Proff
Real Distress	BANKRUPTCY	Binary variable which takes a value of 1 if the firm goes bankrupt in the time period 2000–2020 and 0 otherwise.	Orbis, CCGR and Proff
Independent Variable			
Name	*Symbol*	*Description*	*Source*
Leveraged Buyout	LBO	Dummy variable that takes a value of 1 for buyout firms in the years after a buyout transaction and 0 otherwise.	Zephyr and NKP
Leverage ratio	L	Total liabilities to total assets.	Orbis, CCGR, Proff
Industry	Industry	Industry of which the firm is in. The industry classification is defined in section 3.1.1.	Zephyr and NKP
Country	Country	Country of where the firm is domiciled in.	Zephyr and NKP
Year	Year	Reporting year of the accounting data.	Zephyr and NKP
Industry x Leveraged buyout	LBOxIndustry	An interactive dummy variable that takes a value of 1 for buyout firms in the year after a buyout transaction in a specific industry and 0 otherwise.	Zephyr and NKP
Buyout dummy variable	BUYOUT	Dummy variable that takes a value of 1 for buyout firms in the years after a buyout transaction and 0 for the years prior to the transaction and for control firms.	Zephyr and NKP

Appendix C – Data Collection