OULU BUSINESS SCHOOL

UNIVERSITY OF OULU

**Sampo Niittyviita**

# ACQUIRED FIRM'S PRE-MERGER PERFORMANCE AND ACQUIRER'S LONG-TERM ACCOUNTING PERFORMANCE: THE CASE OF SOFTWARE AND HARDWARE INDUSTRIES

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| **Author** | | **Supervisor** | |
| Sampo Olavi Niittyviita | | Prof. Elias Oikarinen | |
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Abstract

The IT-industry has become ever more central in the world's economy. It has a considerable market share and impact on the economy, while mergers and acquisitions (M&A) in the IT-industry are also prevalent. There is limited research specifically focusing on the IT sector M&A. The IT-sector has a number of peculiar characteristics and different business models which affect how business is conducted within the sector. This thesis attempts to study whether these differences manifest themselves by studying M&A performance by dividing the IT sector into software and hardware industries. No prior research was found that has studied the impact of this division – to software and hardware industries – on long-term M&A performance. There is, however, some research focusing specifically on software M&A.

This thesis delves into the intricacies of the IT industry, examining the distinctions within mergers and acquisitions (M&A), encompassing both software and hardware industries. Through empirical analysis, this study aims to ascertain whether there is a difference in the long-term accounting performance of M&A activities between software and hardware industries, particularly when factoring in the pre-acquisition performance of the acquired firms. The research question in the study is: do software and hardware industry M&A long-term accounting performance, as measured by return on equity (ROE), differ when considering the acquired firm's pre-acquisition performance measured by ROE? The long-term study period in the study is four years after the acquisition. This study employs multiple linear regression and Mann-Whitney U test, utilizing data sourced from Refinitiv's databases. The dataset includes publicly listed U.S. firms' M&A activities between 2004 to 2016.

The results of the Mann-Whitney U test indicate disparities between the software and hardware industries in terms of M&A outcomes measured by change in ROE. While the multiple linear regression model also includes control variables, particularly acquirer size, which seems to negate the statistical significance of the target industry group. The results suggest no statistically significant correlation with the target industry group or the acquisition's target firm pre-acquisition performance with the long-term accounting performance of M&A, as measured by ROE. This is in contrast to prior research on target firm pre-acquisition performance which suggests that lower performance leads to better M&A outcomes. The study highlights the importance of having proper controls: without acquirer size as a control factor, it would seem that the target industry group impacts the M&A outcome. This is in line with previous M&A research which suggests that acquirer size is a relevant control factor.

Keywords
ex-ante performance, prior performance, pre-acquisition performance, return on equity, IT-sector, IT sector, IT industry, high-technology industry

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# 1 INTRODUCTION

Mergers and acquisitions (M&A) are conducted frequently in the corporate world: between 1992 and 2009 in the U.S., as many as 91.4% of public firms conducted one or more merger or acquisition (Netter, Stegemoller & Wintoki 2011). In this business environment, the computer software, supplies and services -industry point out as the most frequent industry in which M&A are conducted, both in the U.S. and Europe in 2009. In addition to that, the total cumulative transaction volume for these is also very high, second highest in the U.S. and the fifth highest place in the Europe. (Mergerstat Free Reports, 2009 via Buxmann, Diefenbach & Hess, 2013, p. 67, 68.) According to Ocieszak and Wnuk (2021) article, in which they looked at the number of software business M&A transactions between 1981 and 2018, the number of deals has been declining, while at the same time, the transaction valuations have been increasing for the deals. The IT-industry and more specifically software industry may very well be evolving in other aspects of M&A as well, e.g., what is the relevance of the acquired company's pre-acquisition performance.

One of the review articles covering M&A target's pre-acquisition performance is by Haleblian, Devers, McNamara, Carpenter and Davison (2009) which covers the timeframe of 1992-2009. It indicates that low pre-acquisition (ex-ante) performance is preferable of the acquisition target. However, the research looking specifically software companies on the effect of the acquired firm's ex-ante performance is showing inconsistent results (Schief, Buxmann & Schiereck, 2013). Leger and Quach (2009) show positive impact to ROA and ROE from target firm's ex-ante performance (measured in EPS) in a one-year timeframe of the merger/acquisition measured. While research has been conducted looking at short-term impact showing a negative impact to the cumulative abnormal return (CAR) from high target firm's ex-ante performance (Izci & Schierek, 2010 via Schief et. al., 2013). These results are in line with meta-analysis conducted by King, Wang, Samimi and Cortes (2021) for mergers and acquisitions in general in which the short-term effect is negative (CAR) and long-term effect is significantly positive for aggregated accounting measures and ROA for timeframes longer than one year.

The IT-sector includes, in addition to computer software, supplies and services, also, other hardware related industries such as: computer hardware and electronic components and communications equipment (Koh & Venkatraman, 1991; Lee & Lim, 2006; Canace & Mann, 2014). In other words, the IT sector has industries which focus on software and those focusing on hardware. Within the IT-sector, there are similarities in its subsectors, yet the characteristics of the software and hardware industries differ in many aspects. For example, the software industry requires little physical infrastructure compared to the hardware industry. There also exists business models which are characteristic to the software industry especially such as software as a service (SaaS) (Turner, Budgen & Brereton, 2003). Network and virtual network effects often occur in the IT-sector industries (Economides, 2001). These characteristic differences may have an impact on the success of mergers and acquisitions (M&A). For example, Zhu, Xia and Makino (2015) results suggest that cross-border acquisitions between IT-service firms (which includes software firms) are more likely to produce value compared to IT-manufacturing firms (i.e., hardware industries).

Two issues can be pointed out from the existing literature focusing on IT-sector M&A: there are differences within the software and hardware industries which may affect M&A performance and that there is little M&A research focusing on software and IT firms' target firm's pre-acquisition performance. Namely, research by Zhu et. al. (2015) and Schief et. al. (2013) supports these insights. Thus, this thesis sets out to answers the research question: do software and hardware industry M&A long-term accounting performance, as measured by return on equity (ROE), differ when considering the acquired firm's pre-acquisition performance measured by ROE?

The long-term accounting performance as well as pre-acquisition performance are measured by using ROE and the long-term time period is the four years after the acquisition in this study. To answer the research question, multiple linear regression and Mann-Whitney U test are conducted. The data for the analyses is collected from Refinitiv's databases (Refinitiv, n.d.-a; Refinitiv, n.d.-b).

The Mann-Whitney U test results suggest that software and hardware differ in their distributions on the outcome of the M&A measured in change in ROE. Additionally, they show that software and hardware firm acquirers exhibit different size distributions. However, when using the multiple linear regression model which has multiple independent variables including control variables, the difference in the distribution of long-term accounting performance disappears when controlling for acquirer size. Multiple linear regression results indicate that there is no statistically significant relationship between target industry group. It also implies that target pre-acquisition performance does not statistically significantly impact the four-year long-term accounting M&A performance as measured by ROE. Hence, the initial difference in distribution observed in the Mann-Whitney U test results seems to be attributed to the tendency of software firm acquirers to be larger firms compared to hardware firm counterparts which also predicts long-term M&A performance in the models.

The thesis proceeds to chapter two which delves into mergers and acquisitions beginning with M&A in a more general level and then following with M&A in the IT-sector. The next chapter covers the distinctive characteristics of IT-sector and its business environment and models. A detailed examination of the software and hardware industries of software and hardware industries which comprise the IT-sector is provided, explaining how they differ. The chapter also covers the specific features and phenomena within the IT-sector which could lead to differences in M&A between software and hardware industries. Chapter four then outlines the empirical methodology while chapter five presents the empirical findings. Finally, the last chapter gives the thesis a conclusion.

# 2 MERGERS AND ACQUISITIONS AND THE IT SECTOR

The topic of mergers and acquisitions covers many different research avenues. The broader set of corporate activities which M&A belongs to are called operational restructuring activities. Operational restructuring gives M&A a frame. The main focus of this thesis is on IT-sector M&A, thus, this section focuses on both: M&A in general and M&A in the IT-sector.

## 2.1 Operational restructuring

Mergers and acquisitions are operational restructuring activities of corporate restructuring. Corporate restructuring itself is a much broader concept which encompasses different kinds of activities, some of which are related to M&A. Corporate restructuring is typically divided into operational restructuring and financial restructuring. Financial restructuring includes activities such as repurchasing own shares or taking debt, while operational restructuring cover activities including changes in firm’s asset structure by acquisitions, sales of firm’s assets, spin-offs of companies or product lines and downsizing of firm’s business. (DePamphilis, 2019, p.13.) Figure 1 shows a summary of forms of operational restructuring.

Mergers are combinations of multiple firms, where either one or multiple companies ceases to exist and become part of another company. As a result of a merger, the merging companies may cease to exist and also form a new company entity often with a new name. A characteristic of mergers is that the merging firms are often of similar size. A merger can be either a statutory or a subsidiary merger. In a statutory merger, the acquiring company assumes the assets and liabilities of the merger target which ceases to exist as an entity. Whereas in a subsidiary merger, the merging company becomes a subsidiary company of the acquiring company, where the old brand name may continue its existence. (Depamphilis, 2019, p. 13-14.)

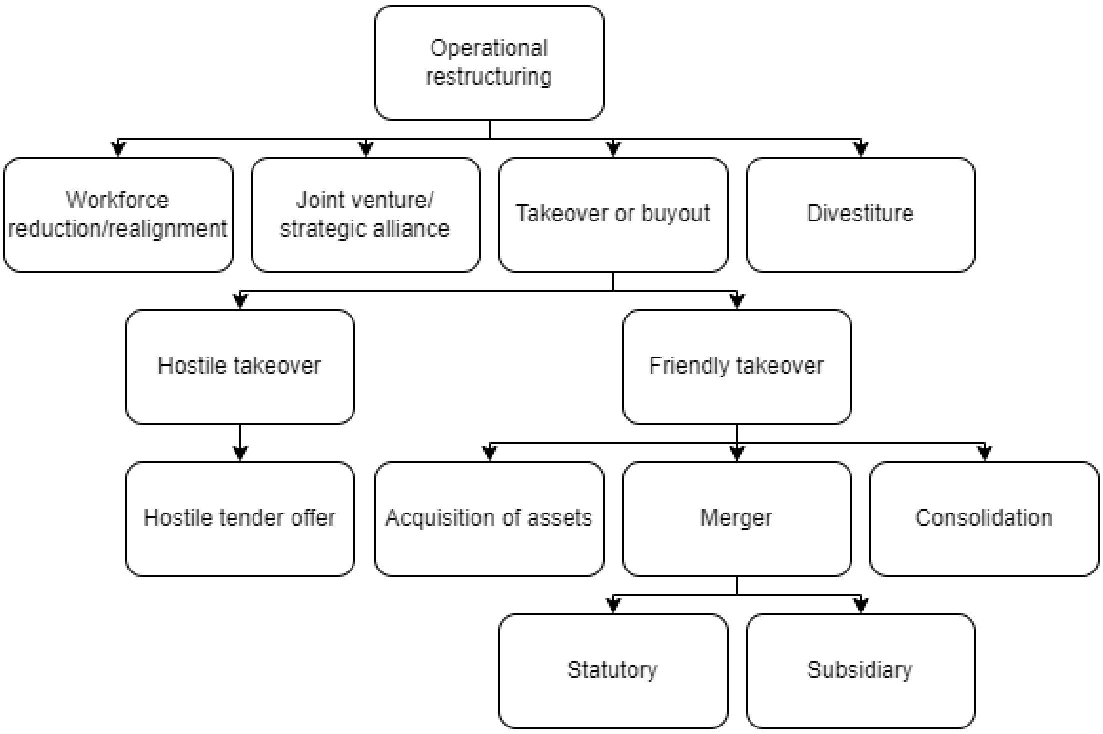


**Figure 1. Summary of forms of operational restructuring (adapted from DePamphilis, 2019, p. 15).**

Acquisition refers to the phenomenon when a company takes control of a subsidiary of another company, its assets, or a part of them. The acquisition may involve acquiring either stocks or assets of the acquisition target. The acquisition target may be a divestment of another company, e.g., a certain manufacturing plant of a company which the divesting company is selling. (DePamphilis, 2019, p. 14.) On the relevance of acquisition target type: see section 2.4.1.

Other operational restructuring activities are spin-offs, split-offs, and equity carve-outs. Spin-off occurs when the parent company creates a new legal subsidiary and distributes the new entity's shares to the owners of the parent company to create a new independent company. The split-off is similar, however, instead of distributing the shares to parent company's owners, the parent company offers to exchange parent stocks for stocks of the new subsidiary firm. In an equity carve-out, the parent company offers the subsidiary's stocks for the public to purchase. (DePamphilis, 2019, p. 14.)

The proposal which an acquiring company makes directly to the shareholders of the target company is called a tender offer. When the acquirer and the target company management negotiate with each other, yet the target firm's management do not wish to complete the acquisition, the tender offer made to the shareholders is called a hostile tender offer. If this hostile tender offer is accepted by the shareholders, while the management disagreed with the transaction, then a so-called hostile takeover has taken place. Most of the takeovers are friendly, and they are also preferred over hostile takeovers as hostile takeovers tend to be more expensive for the acquirer. (DePamphilis, 2019, p. 15.)

## 2.2 Motives for mergers and acquisitions

Business growth can be either organic or inorganic. The pace at which a company can grow organically is limited, and mergers and acquisitions are common activities that companies use to boost their overall growth. (Bruner & Perella, 2004, p. 123.) In many cases organic growth is not a feasible alternative for the company given its goals or the company simply wishes to boost its growth via inorganic acquisitions or mergers. For example, reinvesting in the firm's own business may not be a viable option for a firm if the firm operates under regulatory constraints. Then in this case the company could instead make inorganic investments via, for example an acquisition and, thus, diversify its business. (Bruner & Perella, 2004, p. 141.) There are various other reasons as well for why a company would conduct a merger or an acquisition. Many reasons have been proposed such as (DePamphilis, 2011, p. 3; DePamphilis, 2019, p. 6):

- diversification (gain access to new markets, patents, or products),
- strategic realignment e.g., expansion of R&D capabilities,
- tax benefits,
- gain operational or financial synergies (economies of scale and scope),
- managerial hubris (pride),
- mismanagement (agency problems) and managerialism,
- buying undervalued assets,
- overvaluation of acquirer stock price, or
- increasing market power.

There can also be motivations for acquisitions which may not lead to improved performance, e.g., blocking a rival's access to resources (King, Bauer & Schriber, 2018, p. 64).

There are also motives which affect certain industries specifically. For example, Hanelt, Firk, Hildebrandt and Kolbe (2021) have shown that industrial-age firms performance improves after digital M&A which might incentivize to conduct digital M&A. Also, there is a particular motive for M&A activities mostly affecting IT-firms which has been documented and researched called *acqui-hiring*. This term has been used when a company is acquired for its human resources and talents. Fantasia (2016) phrased the definition of acqui-hiring as "an operation where a company acquires a small firm, aiming at the quality of its people and how the team members interact with each other as a cohesive group, who has proven cultural fit as well as technical prowess." This phenomenon appears to be mostly affecting IT firms where skilled employees and teams who can innovate are in high demand (Mäkinen, Haber & Raymundo, 2012; Fantasia, 2016). While not much research has focused on this phenomenon, there is recent research by Kim (2018) and Ng and Stuart (2019) which indicates that it may not be a very effective method to achieve its goals. Nevertheless, this M&A motive may have some impact on the overall success rate of M&A related to IT firms or a subset of IT firms e.g., software firms.

### 2.3 Mergers and acquisitions research topics

The issue that M&A often fail is generally accepted in the M&A literature (Bauer & Matzler, 2014; Homburg & Bucerius, 2005; King, Dalton, Daily & Covin, 2004). Managers also tend to agree with this issue as well: as many as approximately one-third of managers regret that they proceeded with the mergers and acquisitions which they performed (Cullinan, Roux & Weddigen, 2004). How then are these successes and failures demonstrated?

There are many factors which have been studied related to mergers and acquisitions success. While not a comprehensive list, Renneboog and Vansteenkiste (2019) name some studied topics:

- “the bidder's and target's acquisitiveness (i.e., serial acquisitions and learning),
- managerial quality (including the effect of hubris, overconfidence, and narcissism of top management),
- the CEO's and board's social ties and networks and their incentives and compensation contracts,
- the structure of the board and the quality and busyness of its members,
- firm ownership structure (i.e., institutional, insider, or family ownership),
- geographical and cultural distance between bidder and target,
- bidder-target country differences in terms of corporate governance regulation and investor protection,
- political economics,
- industry and product market relatedness,
- the bidder's and target's historical financial performance,
- post-merger restructuring, and
- the characteristics of the transaction (i.e., means of payment, sources of financing, timing of the deal)”.

These factors which are studied in M&A research can be categorized into five groups:

- “acquirer characteristics;
- target characteristics;
- bid characteristics;
- industry and competition factors; and
- macro-environment characteristics” (Yaghoubi, Yaghoubi, Locke & Gibb, 2016).

Of these five groups, the focus of this thesis is first and foremost on target firm characteristics and industry factors.

## 2.4 Performance measures in mergers and acquisitions research

M&A performance is generally evaluated using three different approaches: accounting or financial measures, surveys, or alternatively by combining these three (King et. al., 2018, p. 64). Meta-analyses of M&A research have been conducted by King et. al. (2021), Homberg, Rost and Osterloh (2009); Stahl & Voigt (2008), and King et. al. (2004). The meta-analyses by King et. al. (2021) and King et. al. (2004) point out that acquisition performance is not significantly different from zero, albeit there is great variance in the performance of acquisitions. The King et. al. (2004) meta-analysis only studied four factors, while the newer article by King et. al. (2021) has as many as 19 factors. The newer study found 16 of the 19 factors to be significant predictors for various predictors of acquisition performance. The significant predictors were method of payment (cash), method of payment (stock), acquirer debt, acquisition premium, relatedness, acquisition experience, alliance experience, acquirer firm size, target firm size, acquirer prior performance, target prior performance, acquirer R&D, national cultural distance, geographic distance, relative size, and integration depth. However, it is worth noting that the meta-analysis only studied factors which were used in at least three articles of the 220 studies included in the analysis.

### 2.4.1 Issues with performance measures

There are a few issues in the studies in M&A research literature: the study periods often have a short time span, they narrowly focus only on a few factors simultaneously, and the studies mainly target large publics firms.

There is a great multitude of factors affecting M&A performance. At the same time, many of the papers studying M&A performance only focus on a few factors simultaneously (Renneboog & Vansteenkiste, 2019). This can have problems such as a lack of proper control of factors and that it does not provide a comprehensive view on the subject (also see Section 4.5.3 for further discussion related with M&A research control groups). In addition to factors affecting the M&A performance, there are factors which are completely unrelated which contribute to the performance simultaneously, for example, mergers and acquisitions tend to occur in waves in the market (DePamphilis, 2019, p. 12). There are also potentially issues with using industry averages – Gormley and Matsa (2014) show that simple industry averages as controls are insufficient and suggest that industry by year is better for controlling industry specific shocks.

While M&A performance is generally evaluated with accounting measures, financial measures or surveys (King et. al., 2018, p. 64). Of these three, M&A performance research is dominantly targeted at short-term financial performance which means a shorter time period than 21 days (King et. al., 2018, p. 46; Meglio & Risberg, 2010; King et. al., 2004). This can be a problem since it may be insufficient to only look at short-term performance, especially when looking at factors such as the acquired firm's per-merger performance. To illustrate this, for example, meta-analysis conducted by King et. al. (2021) for mergers and acquisitions in general shows that the short-term effect is negative (cumulative abnormal return) and long-term effect is significantly positive for aggregated accounting measures and ROA for timeframes longer than one year.

Another problem with M&A research is that the research typically only looks at large publicly traded firms which may skew the results (Conn, Cosh, Guest & Hughes, 2005; Capron & Shen, 2007; Netter et. al., 2011). The relevance of this issue is also emphasized by the research of Laamanen, Brauer and Junna (2014) which suggests that divested assets outperform privately held companies and privately held companies outperform publicly traded companies in acquisitions. Laamanen et. al. (2014) focused on software companies in their research which is part of the IT-sector, and as such it is relevant to the IT-sector at large. There are also other considerations to be taken regarding IT M&A.

### 2.4.2 Financial and accounting-based performance measures

Financial and accounting-based measures can be used to evaluate the M&A performance of a firm. There are advantages and disadvantages with both of these assessment measures which are shown in table 1. Accounting based measures can be e.g., return on assets (ROA), return on equity (ROE) or return on sales (ROS). There is also Tobin's q which is a combination of both financial and accounting measures. (King et. al., 2018, p. 44 & 64) Financial measures are e.g., CAR, CTAR or BHAR and they can be measured in either short- or long-term (Renneboog & Vansteenkiste, 2019).

**Table 1. Performance measures comparison (King et. al., 2018, p. 44).**

| | Advantage | Disadvantage |
|---|---|---|
| Accounting (e.g., ROA; ROS; ROE) | • Covers performance after acquisition<br>• Widely available<br>• Does not change due to measurement (repeatable) | • Accounting standards differ across nations<br>• Limited to public firms<br>• Can be manipulated by managers<br>• Influenced by industry<br>• Does not consider risk<br>• Confounding events |
| Stock (short) | • Measures market reaction to announcement (efficient market)<br>• Widely available<br>• Does not change due to measurement (repeatable) | • Better predictor than measure of performance<br>• Information asymmetry surrounds acquisitions<br>• Limited to public firms |
| Stock (long) | • Measures impact of having invested in firm after acquisition<br>• Widely available<br>• Does not change due to measurement (repeatable) | • Confounding events<br>• Limited to public firms<br>• Difficult to compare across nations |
| Tobin's q | • Hybrid of stock and accounting measures<br>• Widely available | • Accounting component based on historical versus replacement costs |

The accounting performance measures which are commonly used include return on assets, cash flows, growth in sales, growth in profits, growth in assets, return on sales, return on investment, return on equity and return on capital employed (Thanos & Papadakis, 2012). Of the measures of accounting performance, ROA is the most commonly used (King et. al., 2004). For example, in a review of M&A accounting performance measure studies by Thanos and Papadakis (2012), 47 % of the included studies had used ROA as an accounting performance measure. However, King et. al. (2021) also suggest that ROE and ROS should be used instead of ROA since acquisitions have an impact on the assets of the acquirer company. This has also been demonstrated by prior research (Ravenscraft & Scherer 1987; Sirower 1997). These are also backed up by the results of the meta-analysis which show that acquired firm's relative size has the largest relative weight in explaining ROA while it also has a negative impact on the M&A performance (King et. al., 2021).

Short-term and long-term M&A performance measure results are often conflicting as shown by meta-analysis conducted by King et. al. (2021) and, e.g., within the results of an IT M&A focused study by Canace and Mann (2014). A problem with long-term and short-term studies is that in both cases, the study periods vary between categories and within both categories. Another problem is that the performance is measured in a wide range of different methods which makes it more difficult to compare different studies to each other (Tuch & O'Sullivan, 2007).

The time frames of accounting measures in the studies focusing on M&A accounting performance vary significantly. As shown by Thanos and Papadikis (2012), the post-merger time frames in the studies can be anything from one year to seven years after the merger, whereas the pre-merger time frame can be from up to five years before the merger or only at the time of the merger. In many studies the time frame used in them is not clearly stated. The time frame is not explicitly reported in many studies which use accounting-based performance measures (Thanos & Papadakis, 2012; Meglio, 2009).

There looms the issue that as the time period of a long-term study becomes longer, even more external factors may be introduced to complicate studying the subject by looking at the long-term performance of a company after an acquisition. Also, when studying long-term performance, it is difficult to isolate the performance contribution caused by the M&A since more external factors come into the mix as time passes by which impact the overall performance of the firm (also section 4.5.3 is related to this). Short-term measurements do not have the problem since external factors do not have the time to be introduced in the same extent.

It has been shown by Malmendier, Moretti and Peters (2018) that short-term announcement gains or losses in stock market prices do not predict the long-term successfulness of an acquisition. While the contrary assumption is made in the M&A performance research that investors can predict the successfulness of the integration process, i.e., the short-term financial performance of a firm can be used to predict the long-term M&A successfulness (King et. al., 2018, p. 47). Malmendier et. al. (2018) studied both the winners and the losers of mergers. They show that losers of bidding contests for acquiring a company overperform the winner of a bid by 24 % after the first three years of the merger. As a resolution to the issues which they point out by their research, they suggest that researchers of M&A should go forward by developing the suggestions made by Lyon, Barber and Tsai (1999) further. However, in the context of studying industry specific phenomena, the solution may not be appropriate. As Lyon et. al. (1999) state, their suggested methods are not necessarily good for non-random samples, i.e., in samples concentrated in one industry which would suggest that alternative methods would be more beneficial in an industry specific context. Thus, it can be stated that the research using short-term and the long-term financial performance each have their benefits and downsides.

### 2.4.3 Target firm's prior performance

As stated in the previous section, there are a few alternatives looking at acquired firm's prior performance predating the acquisition – prior performance of target company can be either based on accounting performance, financial performance, or a combination of both (King et. al., 2018, p. 64). See table 1 for different accounting and financial performance measures. For example, Leger and Quach (2009) used earnings per share (EPS) as the measure of target firm pre-acquisition performance. Tobin's q has also been used as target firm's prior performance measurement (Lang, Stulz & Walkling, 1989; Servaes, 1991). According to Lang et. al. (1989) and Servaes (1991), when target firms have low Tobin's q and acquirers high Tobin's q measures, the total acquisition returns are larger.

As King et. al. (2021) article shows: the short-term returns may not be indicative of the long-term returns of an acquisition. Morck, Shleifer and Vishny (1990) study finds that short-run abnormal returns are negatively associated with higher target firm prior performance. Whereas Krishnan, Miller and Judge (1997) show that the prior performance before an acquisition of the target firm is associated with the post-acquisition performance of the new combined firm.

Even though there is research supporting the positive impact of target firm prior performance, it is typically not controlled in M&A research (King et. al., 2018). In a review article by Thanos & Papadikis (2012), only 16,2% of the reviewed studies assessed the financial performance of the target firm. Assessing the financial performance of the target is not always easy to include in studies due to data availability (Thanos & Papadikis, 2012). Also, looking at the target firm prior performance is not straightforward since it can influence the decision to make the acquisition decision in the first place (Park, 2003). In addition to the positive association of acquisition targets prior performance with the combined firm's post-acquisition performance, prior positive performance can be expected to increase the value of the target firm's assets. It may also influence the acquisition price which again may negate the potential combined firms' positive post-acquisition performance effect with a higher acquisition price. This relation is illustrated in figure 2. According to M&A meta-analysis, target firm's prior stock market performance is not significantly correlated with future performance, while the prior accounting performance is significantly correlated with the combined firms' future performance (King et. al., 2018).

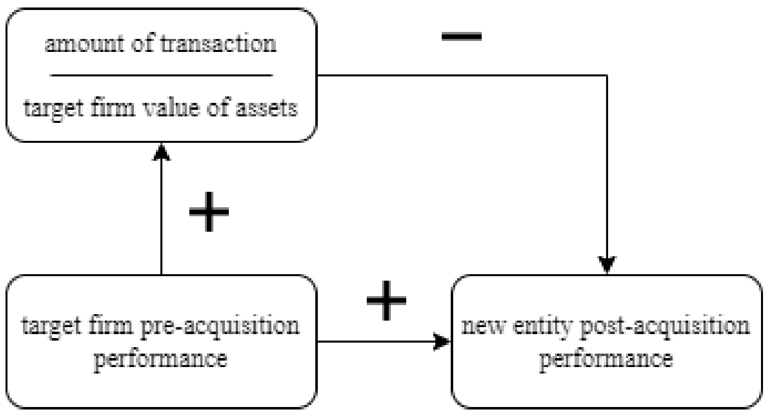


**Figure 2. The relationship with target firm's pre-acquisition performance and acquired and acquirors combined firm post acquisition performance (adapted from Leger & Quach, 2009).**

In this thesis' review of articles, no studies specifically focusing on IT M&A which looked at target firm's pre-acquisition performance were found. However, two articles studied software M&A (which partially overlaps with IT M&A) and looked at target firm's pre-acquisition performance: Leger and Quach (2009) and Izci and Schiereck (2010). The Izci and Schiereck (2010) article is written in German, thus, it was only covered as far as it was discussed in the article by Schief et. al. (2013). According to Schief et. al. (2013), Izci and Schiereck (2010) results indicated that high target company's ex-ante performance has negative impact on the short-term cumulative abnormal return (CAR). Whereas the article by Leger and Quach (2009) showed that target firm pre-acquisition performance (earnings per share, EPS) had non-significant impact on the cumulative abnormal return (CAR) and sales growth. Looking at accounting-based measures, the article's results showed that the target firm EPS had a significant positive impact on one-year ROE, yet the two-year impact was non-significant and negative. Similarly, the impact on profit margins was significantly positive in one-year timeframe and significantly negative after two years, yet with less significance in the two-year timeframe than one. However, the impact on ROA was significantly positive both for one- and two-year time period.

When studying target firm pre-acquisition performance for IT M&A, it should be taken into consideration that the characteristic of IT M&A is that they are often conducted for the sake of target firm R&D, innovative capabilities or existing technologies (see section 3.6). This can influence the relevance of pre-acquisition performance.

## 2.5 Differences between IT and non-IT mergers and acquisitions

Studies which focus specifically on IT M&A are rather scarce, while there is more research available which touches on the subject via e.g., high-technology or technology acquisition M&A research, for example, Ragozzino (2006). There is also research focusing on the software industry which is a large part of the IT-sector (e.g., Leger & Quach, 2009; Izci & Schiereck, 2010). While there is overlap with IT M&A with these kinds of studies, however, they do not focus on IT M&A per se, and because of that they may not fully encapsulate the characteristics of IT M&A. At least three studies can be distinguished as clearly focusing on IT M&A, where comparison is conducted between either IT to non-IT firms or within IT industries: Lee and Lim (2006), Canace and Mann (2014) and Zhu et. al, (2015).

The underlying reason for the lack of research targeting IT industry as a whole, rather than part of the IT industry e.g., software industry may be that the firms conducting their business in the IT industry are too diverse, whereas, studying e.g., software industry is a narrower research domain. At the same time, software industry shares many features which are peculiar to it while the IT-industry also includes manufacturing which likely shares more business model characteristics with traditional industrial manufacturing businesses.

Two studies have been conducted focusing on M&A and joint venture impact on the value of IT firms and non-IT firms – first by Lee and Lim (2006) and following in their footsteps with a similar research setup: Canace and Mann (2014). In comparison of their study setups, the first study by Lee and Lim (2006) had a smaller sample size (170 vs. 365 firm events) and shorter time period (January of 2000 to August of 2002 vs. January of 1995 to December of 2003). Canace and Mann (2014) included technology motivation in M&A and joint ventures as part of their study which Lee and Lim (2006) did not study. While Canace and Mann (2014) incorporated both long-term and short-term impacts in the research setup, Lee and Lim (2006) only studied short-term cumulative abnormal return (CAR).

Both studies by Lee and Lim (2006) and Canace and Mann (2014) find support that there is no significant short-term return for joint ventures. Yet, non-IT firms have negative short-term returns for joint venture announcements, contrary to Lee and Lim (2006), while the results also suggest that the positive joint venture performance is mainly driven by non-IT firms. While Lee and Lim (2006) did not find positive return for M&A announcements, Canace and Mann (2014) did find it. In the study by Canace and Mann (2014), the short-term valuation changes in the studied firms did not reflect the long-term effects of the M&A transactions. They showed that Long-term measures; accrual and cash-based performance measures (ROA, OROA, OCFROA), show distinctly better results for non-IT firms, while the short-term valuation is either neutral IT-firms or slightly positive for both M&A and joint ventures (Canace & Mann, 2014).

The relative firm sizes in a strategic alliance influences the short-term performance according to the results of Lee and Lim (2006). They suggest that the technology of the smaller IT firm in a strategic alliance gives the smaller participant a negotiation premium, lack of alternatives and competition for the small firm's innovativeness. Canace and Mann (2014) studied the technology motivation in their study with a similar setup as Lee and Lim (2006). Canace and Mann (2014) show that technology motivated M&A long-term performance declines and that the decline is mostly influenced by the IT firms in their sample.

The results of the study by Lee and Lim (2006) suggest that the smaller IT firm perform better than the larger IT firm in a strategic alliance. As a potential reason behind this, the authors point out that there are certain unique characteristics in the IT M&A related to the acquired technologies in M&A, namely, the competition for smaller IT firms which have certain technologies and/or software products. The authors also suggest that a lack of alternative firms for a small firm’s valuable IT product gives the smaller company ability to get better premiums for their firm in the alliance. Lee and Lim (2006) also state that it is typically the larger firm in a strategic alliance to initiate the deal for it to gain access to the innovativeness of the smaller firm and to their technologies.

It is noteworthy that all three studies (Zhu et. al., 2015; Lee & Lim, 2006; Canace & Mann, 2014) which specifically focus on differences within the IT-sector M&A or M&A between IT-sector and in general have data which fully or partially overlaps with the time period of the dot-com bubble. There is a lack of research which data is from time periods after the dot-com bubble in the body of literature focusing on the special characteristics of the IT-sector M&A. Newer data would be required to establish stronger support on the results so that the results would be more generalizable.

# 3 IT-SECTOR CHARACTERISTICS

In order to study in an industry-specific setting it is relevant for the researcher to have deep knowledge on an industry to make conclusions (Schief, Pussep & Buxmann, 2013). Thus, this chapter focuses on the IT industry and what makes it a relevant research context for M&A research. The IT industries can be considered as industrial business model layers and business models tend to share certain common characteristics (Wirtz, 2020, p 57-58). This way, the IT-sector also includes software and hardware industries which both have their own distinctive characteristics which may have an impact to M&A performance. Some key characteristics of the IT-sector which may impact M&A are covered in this chapter: importance of technology, prevalence of M&A activities, heavy market consolidation and often winner-take-all market conditions, high-technology industrial conditions, prevalence of autonomous approach to M&A, and network and virtual network effects. These kinds of factors could impact the profitability of mergers and acquisitions for IT firms.

## 3.1 Business models

King et. al. (2004) highlight the relevance of the research context in which M&A is studied. Research can focus on for example the industry where the business is conducting its business. Industry as a research context shares certain environmental conditions and external factors and also relevant to it are for example supplier and customer power, potential market entrance, and substitutes (Wirtz, 2020, p. 57-58). For example, the IT industry could be taken as a specific study context which shed light on certain studied factors which may not apply for M&A in general but apply for IT firms specifically. The industry is a business model layer which can be studied, yet there are also other business model layers in addition to industry.

### 3.1.1 Business model layers

A business model is a simplified and aggregated representation of a firm’s business activities (Wirtz, 2020, p. 57). How to form these representations is not necessarily simple however, since there does not exist a theoretical consensus regarding business models amongst researchers (Burkhart, Krumeich, Werth, & Loos, 2011). A widely cited book by Wirtz (2020) categorizes the business models of a firm in four levels: industry, corporate, business units and product level. These four levels are illustrated in figure 3. The industry level analyses environmental conditions, composition of services and goods and the way they are produced within an industry. The next level describes the company's business model in the level of the company, i.e., via characteristics such as market position and activities. However, the corporate level does not describe the firm's business activities sufficiently for large companies with diverse business activities. Whereas, in the case of smaller firms, the industry level is more likely to describe the firm's business more accurately. (Susman, 2007.) To describe these larger firm's business models, the firm's different activities of the firm can be divided into multiple business units which each one of them consist of one or more business units or products. The product level describes the particular product's characteristics which a company is producing, e.g., Apple's iPhone production consists of hardware and software which are produced different departments within the company. (Wirtz, 2020, p. 58-59.)

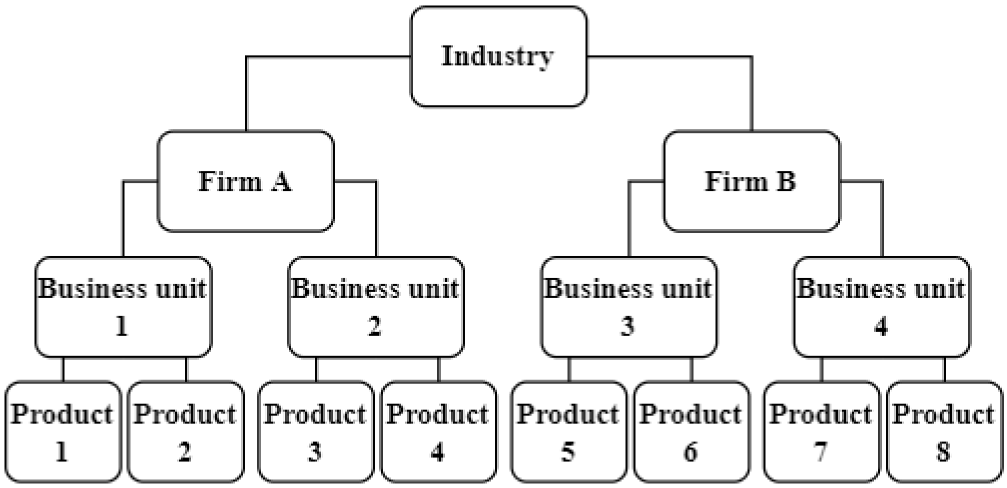


**Figure 3. Business model layers (adapted from Wirtz, 2020, p. 58).**

In the four layers shown in figure 3, the precision increases as the level of analysis moves closer to the product level, however, attaining data at these higher precision levels may become more difficult and complex. For example, the product portfolios of a company can be vast and, thus, the contribution of a product level to the whole can be difficult to estimate. In contrast, industry level classifications are available from e.g., Refinitiv databases. However, using industry level classifications have their own issues in that firms often conduct business under multiple industry levels (see section 3.3).

As shown in figure 3, there are many layers of analysis for using business models in analyzing in e.g., M&A performance. It does not compass all levels of business models to only use industry level as there may be quite a bit of differences within an industry in their business models. Many levels with greater precision are left out in the analysis of the level of industry. The firm's business activities may also span across many industries which can be an issue especially for larger firms when analyzing firms at the industry level. Therefore, the industry level classification used for a company may not be sufficient in describing the totality of a firm's business models.

### 3.1.2 Business models in IT

Studies have been conducted which focus on specifically IT business models (Redis, 2009), specific to the software industry (Engelhardt 2004) and software industry business model M&A performance (Schief, 2013). In a research of IT start-ups business models' performance by Redis (2009), positioning closer to the end-customer had a significant positive impact on the firms' turnover in 5-years' time, while also becoming profitable faster. The four levels of positioning Redis (2009) used were:

1. producer (component or hardware),
2. software developer,
3. service provider, and
4. e-business operator.

In these four levels the producer is the furthest away from the end-customer, while e-business operator is the closest. Additionally, the article shows that IT start-ups with business-to-customer (BtoC) become profitable faster and attain higher turnovers than IT start-ups with business-to-business (BtoB) business model. As for the potential reason behind the positive impact of this proximity to end-customer, the article suggested that when a company is positioned further away from the end customer in the industry's value chain, it could suffer from longer R&D timeframe and longer time to setup production, whereas a company closer to the end customer (e-commerce or service) these times would be shorter.

While the study did not use industrial classifications such as SIC to determine the position in the value chain, in the four-level positioning, the furthest in the value chain: 1. producer (component or hardware) represent hardware industries, while the other positions (software developer, service provider and e-business operator) correspond more with the SIC classification of software industries (although not necessarily completely). These should not however be equated with each other since the study by Redis (2009) used start-ups which can be expected to focus on a narrower area of business or fewer products, thus, better represent their classification than larger firms which may have expanded their businesses to different areas of business.

Peculiar to the software industry, software-as-a-service (SaaS) is a business model which characterizes the industry (Turner et.al., 2003). Characteristics such as this may impact the M&A performance of software firms compared to hardware industries. While Redis (2009) targeted his research both on the hardware and software industries, Engelhardt (2004) focused on the software industry business models. Engelhardt (2004) categorized software firms to four business model classes; 1) business software, 2) general software and services, 3) internet software and 4) specialized software, and showed significant differences in performance of sales and productivity growth between these software business model classes. Also, in the research conducted by Schief (2013), the study finds that the following firms' business model factors which have impact M&A performance: software stack layer, target customer and target industry.

## 3.2 The hardware and software industries distinction

The IT-sector can be divided by its business model to firms which business revolves around either hardware or software, e.g., Redis (2009). Alternatively, a similar division has been made into IT-service industries and IT-manufacturing which partially overlaps with this hardware and software division (Zhu et. al., 2015). Also, research has focused on the software industry which has certain characteristics that are peculiar to the industry, for example, software can be distributed via the internet which enables higher competition and internationalization of the competition (Schief, 2013). Capability of internet distribution also suggests that the software industry may have less importance on the firm's physical location and its employees who develop the software since the physical location has less relevance for the distribution of the software firm's product. Sections 3.1.2, 3.5, 3.6 cover additional characteristics of software firms and characteristic common to both hardware and software firms, i.e., the IT-sector.

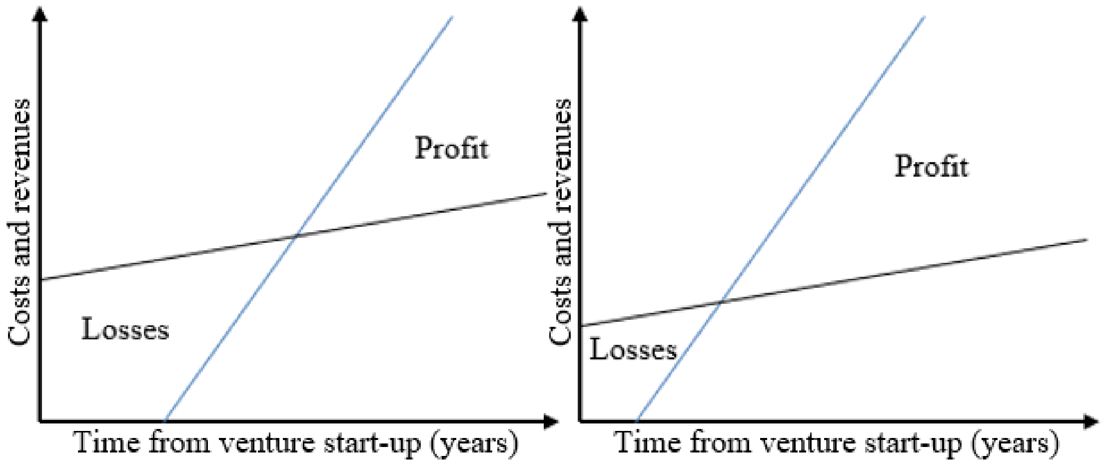


**Figure 4. Software and hardware-based new ventures revenues and costs (blue line represents revenue and black costs) (adapted from Tidd and Bessant, 2020, p. 454).**

There are differences between the hardware and software industries. One such difference between software and hardware firms is illustrated in figure 4. The left graph in the figure displays the time taken for a development-based venture, e.g., electronics manufacturer (hardware) and the right graph, a production-based venture, e.g., a software firm to become profitable. When acquiring IT-businesses at different stages of their development, e.g., early in start-up phase of the company or later when the company has become more established, it may have an impact to the value of acquisition price. This is demonstrated by (Tidd & Bessant, 2020, p. 453) – depending on whether a firm develops software or hardware, it has an impact on the time taken for a start-up to become cash-flow positive (figure 4). This can be potentially explained by characteristics as, for example, that fast innovation rates and short product cycles are peculiar to software firms (Klosterberg 2010, p. 258 via Schief, 2013 p. 1). Also, according to Oakey (2012), it takes three years for three-quarters of venture start-up software companies to become profitable. Results by Redis (2009) also support this that software companies become profitable faster than hardware companies.

Research by Graebner, Eisenhardt, and Roundy (2010) and Puranam, Singh, and Zollo (2006) show that industry classification can be used as a proxy whether the firms in the industry tend to use integrative or autonomous approach in M&A. Using this research as their basis, Zhu et. al. (2015) suggests that in cross-border mergers and acquisitions in the IT-sector, IT-service businesses outperform the IT-manufacturing businesses. They equated these industry classifications with whether the firms in the industry use predominantly autonomous or integrative approach in M&A. Thus, they interpret their results as that autonomous approach in acquiring businesses is more likely to produce value compared to integration approach of acquired companies.

It should be noted that there may be other factors as well related to industry other than autonomous or integrative approaches to M&A, e.g., the different underlying business models themselves which may impact the difference between industries in the study conducted by Zhu et. al. (2015), thus, it may be an overstatement to say that the results on the differences between IT service businesses and IT manufacturing indicate differences on autonomous and integrative approaches per se, especially when using only the two-digit SIC classifications rather than three or four to denote this difference which is likely too inaccurate. This – how to interpret SIC classifications – and industrial classification in general is covered in the next chapter.

### 3.3 Industrial classification systems

A common approach in classifying industries is to use industry classification systems such as SIC (Standard Industrial Classification) (e.g., Canace & Mann, 2014; Lee and Lim, 2006; Koh and Vernakatraman, 1991). There are other alternatives to it as well. Globally, there is the ISIC (International Standard Industrial Classification of All Economic Activities) which can be used to as a basis for comparing firms internationally (United Nations Statistics Division, n.d.). There are two commonly used industry classification systems in the U.S.: SIC (Standard Industrial Classification) and NAICS (North American Industry Classification System). NAICS codes are a 6-digit system which allows the identification of 1170 industries. (United

States Department of Labor, n.d.-a.) Whereas, the older classification system, SIC uses 4-digits and, thus, contains only 1004 industries (United States Department of Labor, n.d.-b). From both the NAICS and the SIC codes, as well as from ISIC to NAICS and vice versa conversions from one system to the other can be made.

The SIC codes can be divided into groups of two-, three-, or four-digits (United States Department of Labor, n.d.). For example, the four-digit code 7371: Computer Programming Services represents a single industry which contains both the two-digit major group code 73: Business Services and three-digit industry group code 737: Computer Programming, Data Processing, And Other Computer Related Services.

SIC classification has been used as the basis to study differences between firms in different industries, for example, high-technology firms and IT firms (e.g., Zhu et. al., 2015; Schief et. al., 2013; Ragozzino, 2006; Gao & Lyer, 2006). Zhu et. al. (2015) divided the IT-sector to IT manufacturing with SIC codes 35 and 36 and to IT services with SIC code 73. However, the issue with this is that there are many industries under these three codes (35, 36 and 73) which are not necessarily related to IT, especially in the case of 73. For example, 3553 refers to woodworking machinery industry and 7311 refers to advertising agencies (United States Department of Labor, n.d.-b).

An issue with describing a firm's business with a single industry classification is that firms often conduct business under multiple different industry classifications. For example, a bank could also have software development as part of its business where the software development part is not covered in the commercial banking classification, or to give another example, a firm could be participating both in software industrial type of activities as well as in computer hardware manufacturing (Apple's iPhone for example). Thus, it may not be sufficient to describe a firm comprehensively using only a single industry classification.

Alternative approach to using SIC or NAICS classifications for industries would be to categorize firms for example based on their websites, press releases, trade register, and news articles as was done by Redis (2009). This kind of approach would also allow a more detailed categorization such as the four levels of positioning in the value chain used by Redis (2009): 1) producer (component or hardware), 2) software developer, 3) service provider, and 4) e-business operator.

### 3.4 The big tech

The IT markets are often dominated by a few big players, where network effects and virtual network effects make a significant impact to the markets of the firms operating in the IT-sector (see section 3.5 on network effects). The dominant players in their own niche markets in the IT-sector make considerably influence to their corresponding market environments by acquiring smaller competitors and influencing the entry costs by their presence and market share (Ferrary, 2003). The rise to prominence of large tech companies known as the “Big Tech” has also been a striking feature of the markets of 2010s (Katz, 2021; Motta & Peitz, 2021). The Big Tech companies typically include Meta (previously Facebook[1]), Alphabet (previously Google[2]), Apple, Microsoft and Amazon (Katz, 2021; Motta & Peitz, 2021).

The key characteristic of the Big Tech is that their market dominance appears very monopolistic in their own area of business, and their businesses tend to appear as winner-takes-all markets in the markets in which they reside in.[3] To illustrate this, figure 5 displays the top 10 largest companies by market capital in the world in 2021 – 7 out of these 10 are IT companies (Murphy, Haverstock, Gara, Helman & Vardi, 2021). Furthermore, for example, Google, Meta and Amazon controlled 64.1% market share of the U.S. digital ad revenues in the year 2020 (Lebow, 2021), while Amazon’s market share in the U.S. of online retail sales was approximately 40% in 2020 (Davis, 2020). At the same time, Apple’s macOS and Microsoft’s Windows combined market shares were approximately 90% of desktop PC operating systems worldwide (Statcounter, 2022).

[1] Facebook announced on October 28th of 2021 that its name will be Meta from then onwards (Facebook, 2021).
[2] Alphabet Inc. changed its name from Google to Alphabet in 2015 (Google, 2015)
[3] The dominant position of these companies has received attention from policy makers who have been recently advocating for a tightening control for these kinds of digital businesses (Furman et. al, 2019; Crémer, de Montjoye & Schweitzer, 2019; Scott-Morton et. al., 2019).

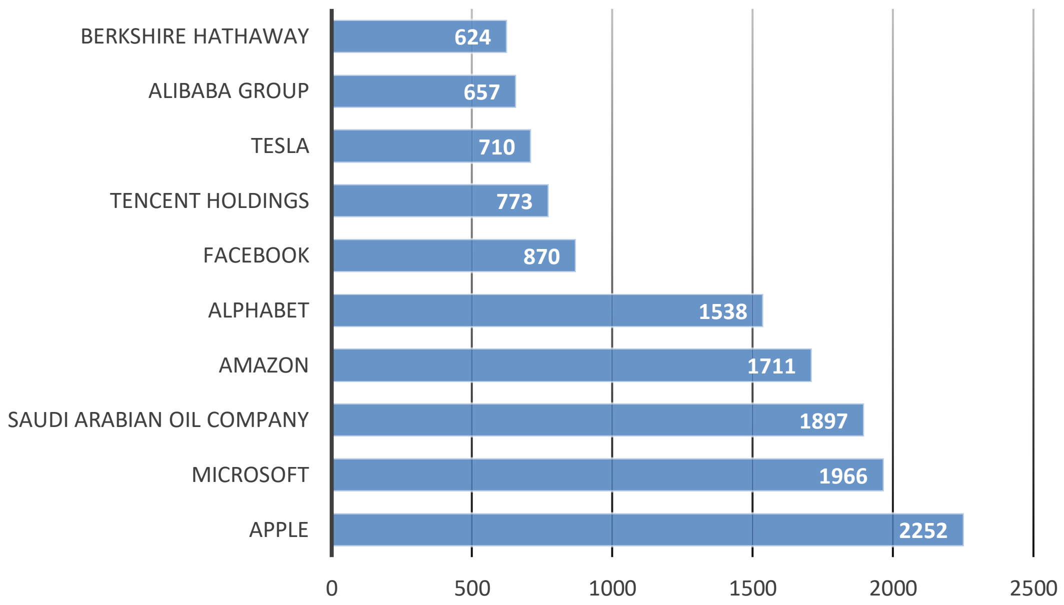


**Figure 5. The top 10 largest companies in the world by market capital in May 2021 (adapted from Murphy et. al., 2021).**

These Big Tech firms can be expected to make a considerable impact on the whole IT-sector. Not only do they comprise a large portion of the IT-sector, but they also alter the business environment with their presence. Newcomers to the market must compete with these giants in an environment where fixed costs are high and marginal costs are low (Katz, 2021). Access to technology and large numbers of customers can be seen as the keys to success. Due to the high fixed costs of developing software (i.e., access to technology) it is more difficult to enter the markets which may promote industry concentration. This kind of situation in the IT-sector was described by Bessen (2020) as: "Concentration appears to be rising because of "barriers to technology" if not actually barriers to entry".

The entry to the markets may become even more difficult in the future due to higher technology requirements and the costs associated with the entry to the markets as the time passes. Not only it is difficult for competitors to enter the markets of the Big Tech, but these companies are also active acquirers. Between 2015 and 2017, the Big Tech companies made 175 acquisitions in total, of which Amazon made 30, Apple 33, Alphabet 52, Microsoft 40 and Facebook 20 acquisitions (Gautier & Lamesch, 2021). The potential competitors for the Big Tech firms may have already been acquired in their start-up phases by them.

## 3.5 Network and virtual network effects

A closely related concept to the prominent role of the large tech companies is that of the network effects. Dominant market positions in IT-sector (especially in the software industry) are strengthened by network and virtual network effects (Economides, 2001). The large customer bases of many IT firms may strengthen network effects in their businesses.

The network effects refer to the phenomenon when the value of a good is increased by a network of the same goods (Katz & Shapiro, 1985). For example, telegraph machines are not worth anything by themselves unless there exists a network of users of telegraph machines as they were commonly used in the 19$^{th}$ century – the more there are telegraph users, the more valuable the individual telegraph machine is for its users. Similarly, in this way, network effects have been suggested to be the cause of increasing returns in software businesses (Buxmann et. al., 2013, p. 20; Van den Ende & Wijnberg, 2003).

Virtual network effects refer to the same phenomenon as that of network effects, yet in the context of a technological system, where the network effect is manifested by complementary and compatible components, for example, the coding of applications for Microsoft Windows increases the value of the Windows operating system which in turn further increases the value of the applications for Windows (Economides, 2001). This positive feedback loop is the key difference between traditional network effects and virtual network effects (Economides, 2001). Examples of acquisitions where virtual network effects may exist are the acquisitions of WhatsApp by Facebook in 2014 or Youtube by Google in 2006 (Facebook, 2014; Google, 2006).

Leger and Quach (2009) studied the network effects of software firm mergers by studying whether the software product portfolio combinations had an impact on merger performance. Their results showed that the markets ignored software product portfolio combinations (short-term performance), while the product portfolio combinations had a positive impact in the long-term performance. These results support the hypothesis that there may indeed exist virtual network effects in the software product portfolio combinations of the companies of a merger. However, their study setup has the limitation that it relies on press releases which are operationalized qualitative variables based on secondary data.

Gao and Lyer (2006) studied complementarity of acquirer and acquired firms in different layers of software stack (service, application software, middleware services, systems software and hardware). They showed that when the acquirer and acquired firms operated their businesses in adjacent software stack layers, then M&A earned higher abnormal returns compared to firms of M&A in the same or further apart software stack layer.

A related concept to network effects is that of the switching costs. Switching costs refer to the costs associated with changing a product which can further strengthen the market positions of established actors in the IT markets, while also enabling higher network effects (Shapiro & Varian, 1999). For example, changing your PC operating system would cost you to lose your access to many of the software which you are used to using and you would have to learn to use the new operating system in addition to many other disadvantages associated with that change.

## 3.6 High-technology industries

Information technology firms are considered to be high-technology firms – studies which focus on high-technology often focus on the IT-industry specifically, e.g., Zhu et. al., (2015) and Canace and Mann (2014), or the studies overlap in large part with the IT-industry, e.g., Dessyllas and Hughes (2005) and Kallunki, Pyykkö and Laamanen (2009). Dessyllas and Hughes (2005) and Kallunki et. al. (2009) used industries with SIC codes of 28, 35, 36, 37, 38, 48, 73 and 87. Within these SIC major groups, the industry groups 357, 366, 367, 382, 386, and 737 have been used by Koh and Venkatraman (1991), Lee and Lim (2006) and Canace and Mann (2014) to define the IT-sector. Table 2 lists these major groups which include IT industries (United States Department of Labor, n.d.). This makes it plausible that many of the research which is conducted for high-technology industries may also apply for the IT-sector specifically as well.

**Table 2. Technology firms SIC code classifications.**

| Major group | Contains IT industries | Name |
|---|---|---|
| 28 | NO | Chemicals and Allied Products |
| 35 | YES | Industrial and Commercial Machinery and Computer Equipment |
| 36 | YES | Electronic and Other Electrical Equipment and Components, Except Computer Equipment |
| 37 | NO | Transportation Equipment |
| 38 | NO | Measuring, Analysing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks |
| 48 | NO | Communications |
| 73 | YES | Business Services |
| 87 | NO | Engineering, Accounting, Research, Management, and Related Services |

Technology development and acquisitions are characteristic to the IT-sector (Ferrary, 2003). Thus, technology acquisitions can be expected to affect the IT-industry as well as mergers and acquisitions in the IT-industry. For example, it has been shown that when a technology firm acquires another technology firm, it positively impacts the M&A performance (Kallunki, et. al., 2009). High-tech companies also get premiums in M&A for their R&D investments and growth rates (Laamanen, 2007). Laamanen (2007) also shows that R&D investment-to-market ratios and R&D growth rates of target firms get positive premia when a firm is acquired. This on the other hand increases price-to-book (P/B) ratio of the acquisition target, and, thus, the P/B ratio do not fully indicate their value when the firm has a high-level of R&D. Yet, the markets react in the short-term to the P/B ratio of M&A. The market will react negatively to an acquisition which has a high P/B ratio and more positive when the P/B ratio is more favorable according to Laamanen (2007).

IT M&A are often conducted for the sake of target firm R&D, innovative capabilities or existing technologies (see section 2.2). These kinds of characteristics can be expected to have a negative impact on the profitability of a firm in the short-term since they are expenses which can be expected to initially have low profitability before the innovations and technological investments pay off (especially relevant for start-up companies). This has been demonstrated by Eberhart, Maxwell and Siddique (2004) by showing that increases in R&D spending result in significant positive long-term abnormal operating performance following the increase. Thus, R&D spending can distort the standard accounting measures such as price-to-earnings (P/E) or price-to-book (P/B) (Chan, Lakonishok & Sougiannis, 2001). However, the acquired firm which is integrated may lose some of its innovativeness in the process (Kapoor & Lim, 2007). This can be caused by the integration via e.g., employees leaving the company or due to changes in the company culture.

Motivations for M&A which stem from the need to acquire new technologies or innovativeness can also be relevant in relation to the private or public status of the acquired firm. Looking from the acquirer's perspective, whose goal is to attain technologies or boost its innovativeness, it should be more profitable for the company to acquire firms at a stage when they are still relatively small and young rather than when they are more established. As the firm becomes more established and becomes more profitable, the acquisition price to attain the innovativeness or technologies would increase. This would also imply that the privately held software companies are more feasible targets for many acquisitions than public companies. (Schief et. al., 2013.) However, not all software company (or similarly for IT companies) acquisitions can be expected to be acquisitions for the purpose of attaining technologies or innovativeness. For example, if a large IT service company acquires another IT service company which is specialized in developing software for other companies, i.e., a firm which does not have technologies or products of its own, rather it only develops software for other companies. You would expect that for this kind of a firm, the profitability and performance is more relevant than for a firm which is acquired for its technologies or innovativeness, thus, in the aforementioned example, to conduct an acquisition at relatively early stages of the firm's life cycle may not be as relevant.

# 4 EMPIRICAL RESEARCH APPROACH

The first section of this chapter covers the research question and its' hypotheses. The second section contains explanation for the choice of the variables used in the study. The third section continues with the data collection of U.S. mergers and acquisitions from the database and what kind of data preprocessing was conducted. The fourth section focuses on the statistical tests and their assumptions used in the study which are multiple linear regression and Mann-Whitney U test. The last section discusses the study limitations such as sample selection and composition, external events and influences, effects of multiple acquisitions, and challenges of group selection.

## 4.1 Research question

The research question of the study is the following: *do software and hardware industry M&A long-term accounting performance, as measured by return on equity (ROE), differ when considering the acquired firm's pre-acquisition performance measured by ROE?* The long-term effects are measured as the difference between the fourth year after acquisition and the year prior to it. To answer this research question, a null hypothesis and a single alternative hypothesis are formulated:

$H_0$: There is no significant difference in the long-term accounting performance, as measured by acquirer's change in ROE, between software and hardware industries when taking the acquired firm's pre-acquisition performance into account.
$H_1$: Software industries exhibit a significantly different relationship between their long-term accounting performance (acquirer's change in ROE) and the acquired firm's pre-acquisition performance compared to hardware industries.

The hypotheses of the research question are tested by conducting multiple linear regression and Mann-Whitney U test. The data for the analyses are collected from Refinitiv's databases (Refinitiv, n.d.-a; Refinitiv, n.d.-b).

Based on the literature review conducted as part of this thesis, it is postulated that the software industry exhibits distinct characteristics that diminish the influence of pre-acquisition performance in shaping the outcomes of acquisitions. It is expected that the software industry will achieve more favorable outcomes in acquisitions, even in cases where the pre-acquisition performance of the target firm may not meet the expectations that would be otherwise required of an acquisition target. This hypothesis is grounded in the understanding that when software firms are acquired other factors such as technologies, intellectual property, and intangible assets generate value in the M&A, which can outweigh the significance of pre-acquisition performance in determining overall success. Thus, the software industry is anticipated to surpass the expected outcomes based solely on the pre-acquisition performance of the target firms.

### 4.2 Variables in the study

Initially, it was planned to use EPS (earnings per share) as the factor for measuring target firm pre-merger business performance similarly as Leger and Quach (2009). However, it was determined that financial ratios return on equity (ROE) and return on sales (ROS) would be more appropriate indicators of business performance. Financial ratios offer better comparability between companies rather than EPS where the number of shares influences the measure. If you only use EPS as the measure of performance, issues may arise such as that the earnings may not necessarily come from operating activities, for example, they could come from divestments, i.e., the target firm could be performing badly if only looking at the EPS.

Accounting based measurement of ROE is used to measure the long-term impacts. ROA will not be included as suggested by King et. al. (2021). In M&A literature, scholars often compare the pre-acquisition ROA with the post-acquisition ROA (Thanos & Papadikis, 2012). Along similar lines ROE is used in this study. The long-term effects are measured in the fourth year after the time of the M&A occurrence.

This study incorporates control variables along the lines suggested by the meta-analysis of King et. al. (2021). King et. al. (2021) highlights the importance for future M&A research to control for three variables:

- method of payment,
- acquiring firm size, and

- acquiring firm debt.

Of these variables, King et. al. (2021) found that acquiring firm size and acquiring firm debt were significant predictors of all measures of acquisition performance. For the method of payment, the meta-analysis shows a consistent negative impact on method of payment (stock), while at the same time showing a significant positive impact on method of payment (cash) on the acquisition performance (King et. al., 2021).

King et. al. (2021) also show that measures like ROE or ROS should be used instead of ROA, since acquisitions have an impact on the assets of the acquirer company which then is impacted especially by firm's relative size. This study takes these considerations into account and applies them by controlling for method of payment, acquiring firm size and acquiring firm debt while also using ROE as the measure of business performance both for target firm pre-merger business performance and acquirer firm long-term business performance.

This study adheres to the recommended control variables as outlined by King et. al. (2021), specifically, the method of payment, acquiring firm size, and acquiring firm debt. However, it is important to note that while these variables are incorporated into the research framework, the method of payment is not employed as a variable for analysis per se, but rather controlled by focusing the study exclusively on M&A transactions where cash was the only method of payment.

In regard to the method of payment, this study focuses solely on M&A transactions where cash was used as the exclusive method of payment across all involved securities. This also includes transactions where multiple types of securities, such as ordinary shares, options, and restricted shares, were all purchased with cash. Transactions involving other forms of payment, such as stock or debt, thus, have been excluded from the analysis.

In this study to represent the acquiring firm debt, total debt-to-equity was used as the variable. This is the most common way to measure firm debt according to Bergh (1997) and King et. al. (2021). The control variable for the acquirer's firm size was measured by the number of employees in this study. Although the number of employees may not capture all aspects of firm size, it has been used previously in studies such as that of Bebenroth and Hemmert (2015).

Acquirer's firm size is used as an independent variable in the study. It is measured by the number of employees in this study. However, using the number of employees as a proxy for the firm size can present challenges, particularly in the context of software firms. In such firms, a relatively small number of employees could potentially generate significant revenue due to factors such as network effects (as discussed in section 3.5).

While the number of employees may not capture all aspects of firm size, it has been used previously in studies such as that of Bebenroth and Hemmert (2015). Other options for measuring firm size would be to use e.g., sales or total assets (King et. al., 2021). However, these alternatives also have limitations in fully measuring all aspects of a firm's size. Nevertheless, the number of employees was chosen as the most suitable option to represent firm size.

Following Koh and Venkatraman (1991), Lee and Lim (2006) and Canace and Mann (2014), the same industry groups were included to define the IT sector (table 3). In terms of SIC industry groups, this translates to 357, 366, 367, 382, 386 and 737. However, in the study to define the hardware and software sectors, not all of these were included.

**Table 3. Software and hardware major industry groups.**

| Code | Name |
|---|---|
| Hardware industry groups | |
| 357 | Computer and Office Equipment |
| 366 | Communications Equipment |
| 367 | Electronic Components and Accessories |
| 382 | Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling Instruments |
| 386 | Photographic Equipment and Supplies |
| Software industry Group 737: Computer Programming, Data Processing, and Other Computer Related Services | |
| 7371 | Computer Programming Services |
| 7372 | Prepackaged Software |
| 7373 | Computer Integrated Systems Design |
| 7374 | Computer Processing and Data Preparation and Processing Services |

The IT sector industry groups were divided into two categories; hardware and software industries (more on SIC codes in section 3.3). This study expands the division to IT-manufacturing and IT-service industries of Zhu et. al. (2015). Instead of two-digit SIC codes, four-digit SIC codes (i.e., industries) are used since not all firms under the major of groups 73, 35 and 36 fall within hardware and software industries (the insufficiency of this is division is explained in section 3.3). Also, two more industry groups are included in the study; 382 and 386, to match the SIC industry groups used by Koh and Venkatraman (1991), Lee and Lim (2006) and Canace and Mann (2014).

To represent the software industry, the SIC codes 7371-7374 were selected similarly as in previous studies (Schief et. al., 2013; Gao & Lyer, 2006). Thus, the codes 7375-7379 were excluded from the IT-sector defining industry groups. However, otherwise similarly as these previous studies, this study considers the rest of the IT-sector to be hardware industries. The hardware SIC codes used in this study were 357, 366, 367, 382 and 386. Hardware and software industry groups are listed in the table 3 (United States Department of Labor, n.d.-b). The full list of industries included in the study are shown in the appendix 1.

There exists also a newer alternative to SIC (Standard Industrial Classification) system called NAICS (North American Industry Classification System) which is newer and more extensive classification system (NAICS) (United States Department of Labor, n.d.-a). However, NAICS classification was not available on the Refinitiv M&A database (Refinitiv, n.d.-a).

## 4.3 Data collection and pre-processing

This section focuses on the details of the data used in the study, exploring its collection, preparation, and variables. The data collection process is outlined, highlighting the sources of data and specific criteria for selecting the dataset, and what kind of exclusion/inclusion criteria used, and data transformations were applied.

The data used in the study was collected from Refinitiv's databases. The acquirer long-term accounting performance data was collected from Refinitiv's Company fundamentals database, while the rest of the data was collected from Refinitiv's Deals

- Mergers and Acquisitions database (Refinitiv, n.d.-a; Refinitiv, n.d.-b). The data includes public firm mergers and acquisitions which were announced and effective between 2004 to 2016. Only the M&A which were effective within 183 days of the announcement were included in the study. The year 2004 is used as the starting point since the so-called IT bubble will be left out from the data set as it could heavily impact the results. The year 2016 for end time for acquisitions is used so that the three years period after the acquisition can be used to study the long-term accounting performance. To use at least a three-year time period after merger for a long-term study is suggested by e.g., King, Slotegraaf and Kesner (2008).

Another criterion for inclusion in the study were that both the acquirer and acquired firms must have been listed in the U.S. stock market. Only full transactions, where the acquiring firms acquired 100% ownership of the target firms in a single transaction, were included.

The M&A data used in the study is taken from Refinitiv's Deals - Mergers and Acquisitions database for publicly listed businesses based in the USA (Refinitiv, n.d.-a). Both the acquirer and the target are thus public firms in the USA. The reason for only looking at USA based companies is to get enough data and for firms which are properly comparable in terms of accounting data. Only public companies will be selected for the study for the same reasons as well.

Not all of the required data was available from the Refinitiv's Deals - Mergers and Acquisitions database, thus, the rest of the data was fetched from Refinitiv's Company Fundamentals database (Refinitiv, n.d.-a; Refinitiv, n.d.-b). Although most of the data related to target firms was available at the M&A database, the common equity from 1 year prior to the M&A event was not included. Consequently, this common equity 1 year prior had to be retrieved from the Refinitiv Company Fundamentals database for each target firm. This information was necessary to calculate the average common equity 12 months prior to the M&A which is needed for the return on equity.

Furthermore, acquirer long-term accounting data was not available in the M&A database. As a result, the accounting data for each of the acquirers of the M&A transactions had to be obtained from the Refinitiv Company fundamentals database.

The initial dataset which was fetched from Refinitiv's M&A database consisted of 161 M&A transactions. Of these transactions 63 target firms were hardware firms and 98 software firms. In total 7 acquisitions were removed from the data set based on not meeting this criterion of at least 181 days since announcement the transaction was not completed.

22 M&A transactions were excluded since the long-term performance was not observable since the acquiring firm delisted within the timeframe of the long-term performance period. Of these 22 firms, 7 were hardware firms and 15 were software firms. Three acquisitions were removed since the acquiring firm was clearly not an IT firm upon closer inspection.

A total of 13 target firms were excluded from the dataset due to their very low or negative equity at the time of the M&A. These values were deemed to be clearly incomparable with the normal range of return on equity. Firms which had negative common equity were excluded and those that had ROE value lower than -100%. Additionally, three acquiring firms were identified as having outlier values for ROE. One acquirer had negative long-term common equity, while the other two exhibited signs of financial distress, leading to low common equity. Specifically, one acquirer had an unusually high ROE of 234%, while the other had a significantly negative ROE of -167%. The range for the ROE values was between 90% to -30% for the acquirer in the dataset. The inclusion of such extreme values in the calculation of the ROE metric could lead to misleading interpretations, particularly in cases where the low common equity is indicative of past financial distress or poor firm performance. These values were excluded from the analysis due to their potential to distort the results.

This may impact the reliability of using ROE as a metric when common equity is negative or significantly low. Comparing the ROE of a firm with negative common equity to those with positive equity is not appropriate since the underlying financial situations differ greatly. Similarly, if the low common equity of a target firm is a result of recent financial distress, it may not be directly comparable to the ROE values of other firms. Whereas in other cases the very high ROE would indicate exceptional performance, when in reality the firm has had bad financial performance.

In this study, the number of employees was used as a control variable to measure the size of the acquirer's firm. To account for the potential non-linear relationship between firm size and the post-merger business performance, a natural logarithmic transformation was applied for the number of employees.

### 4.4 Statistical tests and models

This study employs two statistical analyses: multiple linear regression and Mann-Whitney U test to answer the research question of the study. Multiple linear regression is used for its ability to handle multiple independent (explanatory) variables while focusing on a single dependent variable. The Mann-Whitney U test serves as an alternative to ANOVA, as the dataset did not meet the assumptions required for ANOVA. The section 4.4.3 delves more deeply into the rationale for selecting these specific methods and also elaborates on the tests to affirm their assumptions. All the statistical analyses are performed using IBM SPSS Statistics 29.

#### 4.4.1 Multiple linear regression model

The regression model formulated to predict the change in return on equity (ΔROE) for the acquiring firm is expressed as:

$$acquirer\,\Delta ROE = \beta_0 + \beta_1 * target\,industry + \beta_2 * target\,firm\,pre\text{-}acquisition\,ROE + \beta_3 * acquirer\,size + \beta_4 * acquirer\,debt + \varepsilon$$

In these models, ‘acquirer ΔROE’ represents the change in the acquirer's ROE (long-term accounting performance) from the financial ratios calculated over the last 12 months prior to the merger announcement to the average long-term performance measured over a four-quarter period three years after the merger announcement. It is important to note that the quarter in which the merger announcement is released is excluded from this three-year timespan. For example, if the acquisition was announced in Q1 of 2010, then the last 12 months prior to the acquisition are Q1-Q4 of 2009 and the time period three years after the acquisition would be Q2 of 2013 to Q1 of 2014. Same logic applies to the independent variable of target firm pre-acquisition ROE. All of the variables are described in the table 4.

**Table 4. Variables and their descriptions used in the study.**

| Variable name | Variable description |
|---|---|
| **Target industry** | A categorical variable indicating the industry of the acquired firm. It takes on the values of 0 or 1, where 1 represents software firms and 0 represents hardware firms. |
| **Acquirer size** | The size of the acquiring firm measured as the number of employees (transformed using natural logarithm) at the time of the acquisition. |
| **Acquirer ΔROE** | Acquirer ΔROE represents the change in the acquirer's ROE (long-term accounting performance) from the financial ratios calculated over the four previous financial quarters prior to the merger announcement to the average long-term performance measured over a four-quarter period three years after the merger announcement. |
| **Acquirer debt** | The level of debt of the acquiring firm measured with the ratio of total debt to shareholder’s equity at the time of the acquisition. |
| **Target firm pre-acquisition ROE** | The ROE of the target firm in the 12-month period preceding the merger announcement. It is taken from the four previous financial quarters prior to the merger announcement. |

The target firm pre-acquisition ROE variable represents the performance of the target firms in the 12-month period preceding the merger announcement. Furthermore, the acquirer size and acquirer debt variables are included as independent variables to account for their potential impact on the acquiring firms’ performance. Similarly, as for the dependent variable of acquirer ΔROE, the target firm pre-acquisition ROE is measured as the average of four quarter prior to the announcement. For example, if the acquisition was announced in Q1 of 2010, then the last 12 months prior to the acquisition are Q1-Q4 of 2009.

The industry variable is a categorical variable which indicates the industry of the acquired firm. It takes on the values of 0 or 1, where 1 represents software firms and 0 represents hardware firms. The classification of the acquired firms into software and hardware industry categories is based on the SIC classification system. The detailed explanation of this categorization can be found in section 3.3.

For the acquirer debt variable, the total debt-to-equity from Refinitiv is used. In Refinitiv, it has the following description:

> ”Gearing: Total Debt divided by Shareholder's Equity as of the date of the most current financial information prior to the announcement of the

transaction. GEARING = (STRDEBT+ CVTDEBT + STD)/COMEQ+PFDEQ." (Refinitiv, n.d.-a)

In the regression model, the term ε represents the error term. It's important to note that the standard errors associated with ε have been adjusted to account for heteroscedasticity, specifically with White's heteroscedasticity-consistent standard errors. This was conducted using a SPSS macro created by Hayes and Cai (2007). The choice of using the standard errors is discussed further in the section 4.4.3 which focuses on statistical test assumptions.

### 4.4.2 Mann-Whitney U test model

The Mann-Whitney U test was employed as a non-parametric alternative to compare the distributions of key variables between the industry groups (software and hardware). The test uses the same variables as described in the previous section covering the multiple linear regression model which are acquirer ΔROE, acquirer size, target firm pre-acquisition ROE and acquirer debt. The choice of using the test was made due to the inability to meet the assumptions necessary for ANOVA which was initially considered to be used in the study. The rationale for opting for the Mann-Whitney U test is elaborated upon in section 4.4.3.

The Mann-Whitney U test tests whether the two groups come from the same population. In this study, two-tailed test is used. This means that if the null hypothesis of the test is rejected, then it indicates statistically significant difference between the medians of the two groups. However, it does not tell what the direction of the difference between the two groups is (i.e., whether one group has higher or lower median than the other). (Nachar, 2008) Thus, the Mann-Whitney U test is used with the following four hypotheses. For each of the null hypotheses, there are separate tests.

$H_0$: The distribution of target firm pre-acquisition ROE is the same whether the acquired firm is a software or a hardware industry firm.
$H_1$: The distribution of target firm pre-acquisition ROE is different between software and hardware industry firms.

$H_0$: The distribution of acquirer ΔROE is the same whether the acquired firm is a software or a hardware industry firm.
$H_1$: The distribution of acquirer ΔROE is different between software and hardware industry firms.

$H_0$: The distribution of acquirer size prior to acquisition announcement is the same whether the acquired firm is a software or a hardware industry firm.
$H_1$: The distribution of acquirer size prior to acquisition announcement is different between software and hardware industry firms.

$H_0$: The distribution of acquirer debt prior to acquisition announcement is the same whether the acquired firm is a software or a hardware industry firm.
$H_1$: The distribution of acquirer debt prior to acquisition announcement is different between software and hardware industry firms.

### 4.4.3 Assumption tests

Multiple linear regression has multiple assumptions which must be met so that the statistical method can be used. Also, the Mann-Whitney U test has a couple of assumptions as well. The Mann-Whitney U test requires that the two groups in the test (software and hardware industry groups) are independent of each other, and that the dependent variable must be ordinal or continuous. Multiple linear regression has the following assumptions:

- continuous dependent variable
- continuous or binary independent variables,
- linearity,
- independence of observations,
- residual independence,
- homoscedasticity of residuals,
- normality of residuals, and
- no multicollinearity (Tranmer, Murphy, Elliot & Pampaka, 2020).

This paragraph focuses on the *linearity* and *homoscedasticity* assumptions of linear regression. Figure 6 contains the Scatterplot of regression standardized residuals vs. standardized predicted values. However, there are only a few data points which deviate. There can also be seen a small downward trend as the predicted value increases. Based on this visual inspection, there is small non-linearity detectable in the dataset, however, this is rather small, and the tests are used, nevertheless. From the figure it can also be noted that there are fewer datapoints on the right tail of the scatterplot and they are slightly more dispersed than the rest of the values. Also, looking at the table 5 and table 6 on Breusch-Pagan test results, there appears to be heteroskedasticity in the model as can be seen from the significant F-value of 2.874 ($p = 0.026$). The independent variable "target ROE last 12 months" appears to be causing this ($t = -2.279$, $p = 0.025$). To address this issue White's heteroscedasticity-consistent standard errors were used. To be able to use these White's heteroscedasticity-consistent standard errors, a reasonable large sample size is required (Gujarati, 2014, p. 106-107). The sample size of 118 used in this study is sufficiently large to meet this criterion.

**Table 5. Regression coefficients for Breusch-Pagan test for heteroskedasticity.**

| | Unstandardized coefficients | | Standardized coefficients | | |
|---|---|---|---|---|---|
| | **B** | **Std. Error** | **Beta** | **t** | **Sig.** |
| **Constant** | -66.54 | 306.52 | | -0.217 | 0.829 |
| **Acquiror debt** | 199.95 | 150.09 | 0.120 | 1.332 | 0.185 |
| **Acquiror size** | 26.05 | 32.44 | 0.077 | 0.803 | 0.424 |
| **Target ROE last 12 months** | -6.56 | 2.88 | -0.205 | -2.279 | 0.025 |
| **Target industry** | 164.00 | 126.89 | 0.125 | 1.292 | 0.199 |

**Table 6. ANOVA results for Breusch-Pagan test for heteroskedasticity.**

| Predictor | Sum of squares | df | Mean square | F | Sig. |
|---|---|---|---|---|---|
| **Regression** | 4545333 | 4 | 1136333 | 2.874 | .026 |
| **Residual** | 44684442 | 113 | 395437 | | |
| **Total** | 49229775 | 117 | | | |

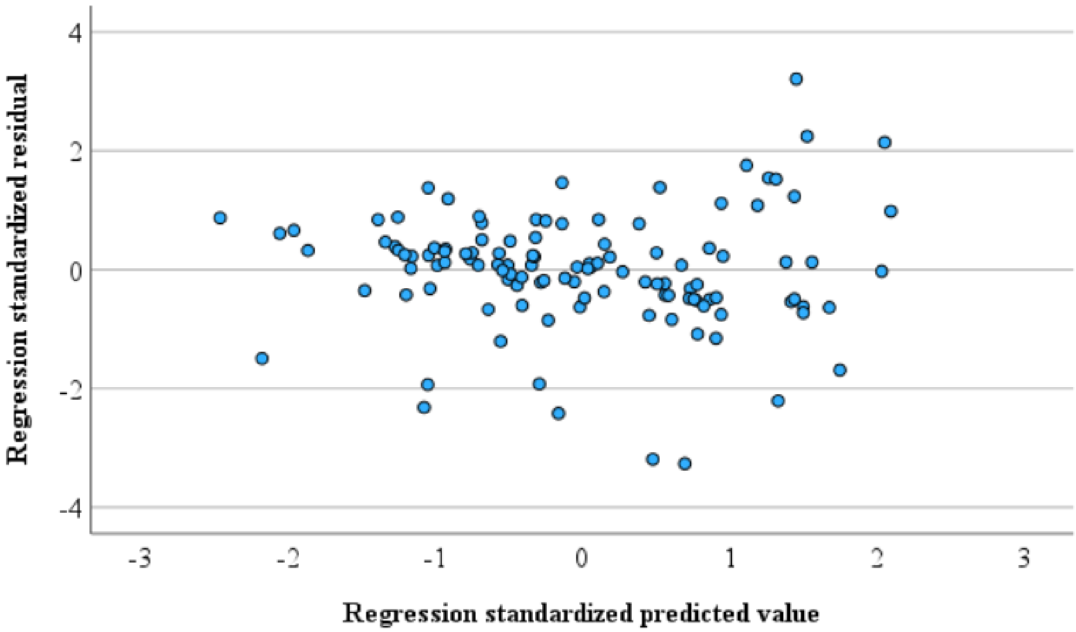


**Figure 6. Scatterplot of regression standardized residuals vs. standardized predicted values.**

The *normality* assumption is checked by using Jarque-Bera test of normality and by looking at the histogram in figure 7 and normal Q-Q plot of the dependent variable in figure 8. These graphs resemble a normal distribution when visually inspecting them, however, there can be seen some deviations from it. The data points in the histogram are more heavily centered at the middle of the distribution and it is slightly skewed to the right. The Q-Q plot follows the diagonal line quite closely, however, the same can be seen from the Q-Q plot that the left side of the distribution is less normally distributed.

Jarque-Bera test of normality is a commonly used method to test the normality assumption (Gujarati, 2014, p. 145-146). It is a large sample test and since the sample size in this study is 118, the test can be used. The critical chi-square value with 2 degrees of freedom is 5.991 at 0.05-significance level, while the Jarque-Bera value is 6,534 in this study. The value, however, is quite close to the 0.05-significance level.

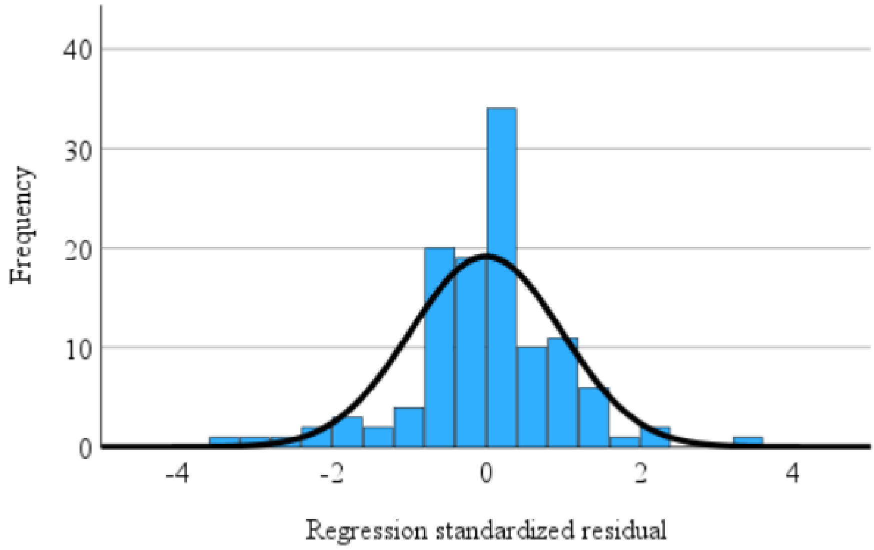


**Figure 7. Regression standardized residual histogram of acquirer ΔROE variable.**

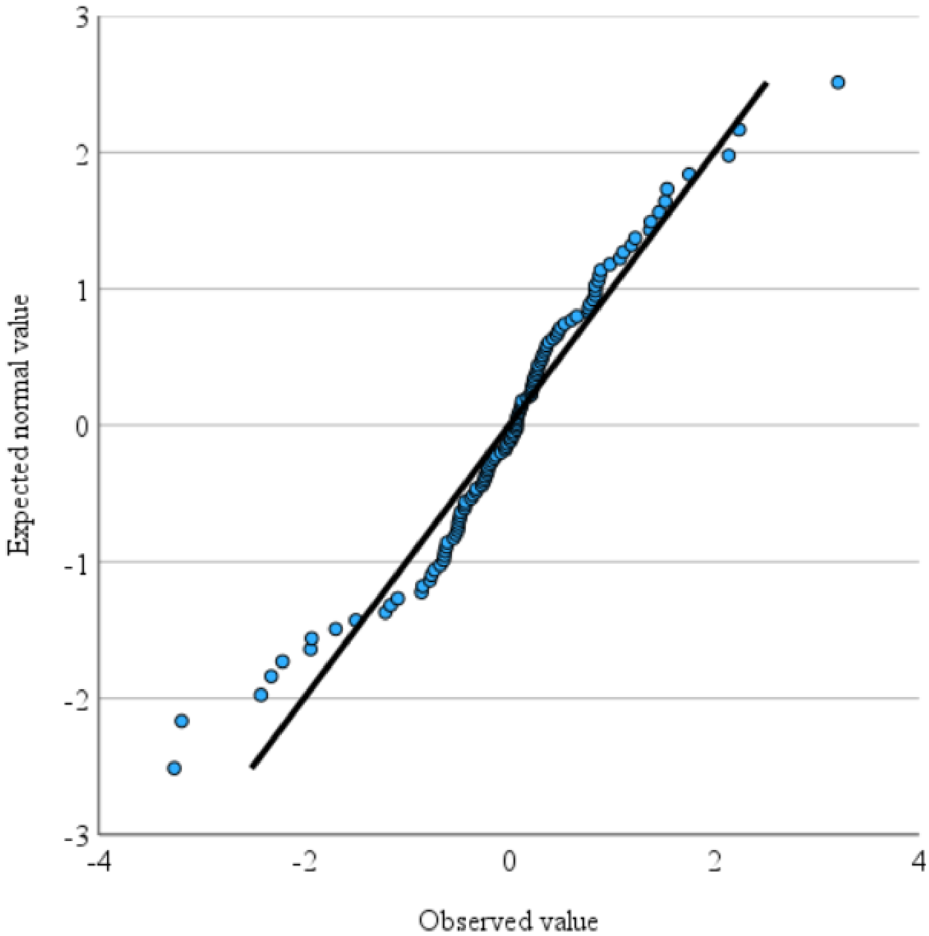


**Figure 8. Normal Q-Q plot of standardized residual.**

Based on the visual inspection and the Jarque-Bera tests in conjunction, it can be seen that the distribution is not normally distributed, however, there is only slight deviation from a normal distribution. This is not deemed as an issue in this study's context for using multiple linear regression. However, based on this slight deviation in addition to the issue of heteroscedasticity, ANOVA was not deemed an appropriate statistical method for this data set. Thus, Mann-Whitney U test is chosen instead since that test does not require the data to be normally distributed or homoscedasticity (Mann & Whitney, 1947). The assumptions which the Mann-Whitney U test requires that the two groups (software and hardware industry groups) are independent, and the dependent variable must be ordinal or continuous. The acquisitions between hardware and software industry groups do not overlap. Thus, the conditions for the Mann-Whitney U test are met for the data set used in the study.

*Independence of residuals* is also an assumption for linear regression. Durbin-Watson test is a commonly used test for detecting autocorrelation (testing independence of residuals) (Gujarati, 2014, p. 117). Based on the Durbin-Watson statistic of 1.815, as presented in table 7 the assumption of residual independence appears to be satisfied for the regression model. The statistic is close to the ideal value of 2, indicating that there is no significant evidence of autocorrelation in the residuals.

**Table 7. Multiple linear regression results for assumption tests.**

| Predictor | Coefficient | Robust SE (HC) | t-value | p-value |
|---|---|---|---|---|
| **Constant** | -26.224 | 8.892 | -2.949 | 0.004 |
| **Acquirer size** | 2.616 | 0.941 | 2.780 | 0.006376 |
| **Acquirer debt-to-equity** | -2.850 | 4.354 | -0.655 | 0.514093 |
| **Target industry** | 3.907 | 3.681 | 1.061 | 0.29075 |
| **Target firm pre-acquisition ROE** | -0.157 | 0.084 | -1.886 | 0.061917 |

R=0.361
$R^2$=0.130
adjusted $R^2$=0.099
std. error of the estimate=18.242
Durbin-Watson=1.815

While there appears to be independence of residuals, there are some potential issues with *independence of observations*. All of the data points could not be considered as

100% independent due to the fact that many of the acquisitions were completed by the same acquiring firms, for some of which the time periods partially overlapped. The acquisitions themselves are independent, however, the acquiring firm can be the same, which may lead to partial dependency. Overall, this may not have a very high impact on the independence of the events since these M&A events conducted by the same firms during the same long-term follow-up period is only a small portion of the total number of acquisitions. Also, after all the time period in which the acquirer change in ROE is measured is different for the acquisitions. This is not considered to be an issue to not use the multiple linear regression in this study.

The *multicollinearity assumption* is tested by evaluating VIF and tolerance values. In the regression model, the $R^2$ value is 0.130, indicating that 13% of the variance in the dependent variable (Acquirer delta ROE) is explained by the predictors in the model (table 7). Also, the highest pair-wise correlation observed among predictor variables was 0.361 (target industry and acquiror number of employees) (table 7). Looking at the tolerance and the variance inflation factor (VIF). A tolerance value below 0.1 or a VIF value exceeding 10 is typically considered indicative of problematic multicollinearity (Gujarati, 2014, p. 86). Specifically, the VIF values ranged from 1.004 to 1.167, and the tolerance values ranged from 0.857 to 0.996 (table 8). Based on these results, there does not appear to be multicollinearity among the tested variables.

**Table 8. Collinearity statistics.**

| | Tolerance | VIF |
|---|---|---|
| Acquiror size | 0.869 | 1.150 |
| Acquiror debt | 0.987 | 1.013 |
| Target ROE last 12 months | 0.996 | 1.004 |
| Target industry | 0.857 | 1.167 |

## 4.5 Limitations

In this section, the limitations of the study are discussed. These constraints and challenges should be taken into consideration since they may impact the interpretation of the results. Various aspects are discussed from sample selection and composition to external events and influences, effects of multiple acquisitions, and challenges of group selection.

### 4.5.1 Sample selection and composition

In order to be included in this study, both the acquirer and acquired firms had to meet the criterion of being listed on the U.S. stock market. Furthermore, only full transactions were considered, meaning that the acquisition involved the acquisition of a 100% stake in the target firm. It could be that the differences between hardware and software M&A manifest more prominently at an international level since due to, for example, physical location in developing software is less relevant since software can nevertheless be distributed via the internet.

It is worth noting that all the transactions included in the study were cash-only transactions. It may be the case that the firms which use cash as the only method of payment are in a better financial position to conduct the M&A, thus, reducing risk and the chance of a business failure leading to better business performance. It may also be the case then that for the acquirer debt variable being useful in a study like this, it would require that also the transactions, where stock was used as the method of payment also are included in the dataset. The low number of firms which had debt prior to the acquisition may also be too small of a dataset to estimate the effects of the level of acquirer debt in the study.

The data is not quite normal based on the Jarque-Bera test at 0.05-significance level. The critical chi-square value with 2 degrees of freedom is 5.991, while the Jarque-Bera test statistic is 6.534 in this study. This non-normal distribution poses limitations on the use of parametric statistical tests that assume normality. However, the difference is quite small, thus, multiple linear regression was used nevertheless (using White's heteroscedasticity-consistent standard errors).

### 4.5.2 External events and influences

The potential influence of confounding events was not taken into consideration in this study. One notable event during the study period was the occurrence of the 2008 financial crisis which may have had implications for the observed results. Furthermore, it is important to acknowledge that certain firms engaged in multiple M&A activities throughout the long-term study period, potentially introducing cumulative effects on their performance.

Within the dataset, it is observed that several acquiring firms engaged in multiple acquisitions, which could potentially influence the results. This pattern is also evident when examining the distribution of firm sizes (which have been transformed with natural logarithm). While the overall distribution follows a roughly normal pattern, there are a few large firms that have conducted a significant number of M&A transactions. Notably, Hewlett Packard completed 6 acquisitions, International Business Machines Corp completed 9, Oracle completed 11, and Cisco Systems completed 4. Collectively, these acquisitions account for 30 out of the total number of acquisitions, representing approximately 25% of the dataset. This may be related to the specific characteristics of the IT sector, as discussed in sections 3.4 and 3.5 which focus on the networks effects of IT sector and the so called “big tech”. In total there were 62 unique firms conducting acquisitions in the dataset which means 1.9 acquisitions per firm on average. For many of these acquisitions, the long-term study period overlapped with another M&A within the dataset. During the long-term accounting performance study period, there may also be other acquisitions to other markets outside the United States, acquisitions using also stock as the method of payment and also to non-IT firms which are not included in the dataset.

Many of the target firms appear to have been in some sort of financial distress either at the time of the acquisition or quite recently. This observation was based on comparing the common equity 1 year prior to the common equity in the quarter prior to the M&A announcement. Additionally, many of the target firms seemed to have relatively low common equity. This could reduce the usefulness of the ROE as a measure of business performance for some problem firms.

The results of this study should be interpreted while considering the potential impact of survivorship bias (Brown, Goetzmann, Ibbotson & Ross, 1992). Conducting a long-term study like this one introduces the possibility that some acquirers may have been delisted from the public stock market, which could influence the results. For instance, firms that have faced financial difficulties resulting from unsuccessful acquisitions may have been delisted due to various factors, such as being acquired by other firms. Conversely, it is also possible that successful performers were more likely to be acquired, as they may have been attractive targets for acquirers. The impact of the survivorship bias is unknown in this study's context.

Some firms were delisted during the observation period of long-term accounting performance, thus, these M&A had to be excluded from the dataset due to data unavailability. This exclusion could potentially impact the study. A total of 21 M&A transactions were excluded from the dataset because the acquiring firms were delisted before their long-term accounting performance could be observed. Among these excluded firms, 9 were classified as hardware firms, and 12 were classified as software firms.

It is noteworthy that a significant number of firms that conducted acquisitions in 2008 were delisted within four years after the M&A events. This coincides with the 2008 financial crisis. It is plausible that these firms experienced unfavorable outcomes from M&A activities during the crisis faced an increased risk of business failure, which led to their acquisition by other companies, bankruptcy, or a decision to delist from the public market to reduce costs.

In relation to the simultaneity problem, there likely do not arise issues with it. Since the target firm is incorporated into the acquiring firm, the target firm's business activities which generate the target firm's ROE become part of the acquiring firm which would support a one-way relationship. However, there may be some endogeneity arising from the acquiring firms' decisions on choosing acquisition targets partly based on their ROE, thus, the target ROE may influence the likelihood of being acquired while also at the same time the acquirer's desire to improve their ROE is influenced by the target firm's ROE.

The relative sizes of acquirer and the target to each other was not taken into consideration in the study. This may have some impact, for example, if acquirers tend to be relatively much larger firm compared to the target firms in software firm acquisitions, this may impact the acquisition performance in that the impact is much less negligible compared to hardware firm acquisitions.

There could also be an impact on whether the acquirer of the acquired firm is a software or a hardware firm. This was not taken into consideration in the study. For example, if there was a positive impact on the acquisition of a software firm compared to a hardware firm, it could be necessary that the acquirer was also a software firm. Alternatively, it could be necessary that the acquirer is within the IT sector. Within the dataset the acquirer can belong to any industry group, only the target firm industry group was looked at.

It should be noted that acquirer firm pre-acquisition performance was not included as an independent variable in the multiple linear regression model. The pre-acquisition performance was included as part of the model in the dependent variable (change in ROE), however, it could also be included as an independent variable as it could have an impact on the M&A performance as well. For example, it could impact firms which have lower ROE, there is greater potential in improving their ROE, however, for firms which have high ROE, these firms likely have less potential in improving ROE. In other words, if a firm's ROE is as high as it can get, it only can decrease.

### 4.5.3 Challenges of group selection

One of the challenges in M&A research is the lack of appropriate control groups M&A analysis. This study too has the same issue. The typical solution to get a good control group for M&A research is to get a large sample of average performances of similar companies, however, this solution is by no means ideal. For you to get a truly strong control group, you would need to have an alternative timeline of the same company. The reason behind this is that every single company's characteristic and how the company is situated is unique and, thus, the outcomes of the M&A are unique to that situation. This is illustrated by Bruner and Perella (2004) in a tripartition to classes of tests of M&A profitability: *weak, semi-strong and strong form* (table 9). He points out that the weak form is typically used by consultants and journalists. It relies on share price before and after the event, while the semi-strong form relies on a benchmark of similar companies. That on the other hand is used by many academics. The third, the strongest form, then would require the alternative timelines of the same company in the case that the merger or acquisition never took place. (Bruner & Perella, 2004, p. 32-33.) Obviously, from that you simply cannot get any data.

**Table 9. Classes of tests of M&A profitability (Bruner & Perella, 2004, p. 32).**

| Test | Structure: M&A pays if | Description and Comments |
|---|---|---|
| Weak form | $P_{after} > P_{before}$ | Is the share price after the deal better than before it? |
| Semistrong form | $\%R_{M\&A\ firm} > \%R_{benchmark}$ | Is the return of the firm greater than the benchmark? |
| Strong form | $\%R_{Firm\ with\ M\&A} > \%R_{firm\ without\ M\&A}$ | Is the return of the firm greater than what would have been without the deal? |

The problem with the weak form is that it does not control sufficiently for other firm events, market-wide events, market reactions to the M&A or other noise. These are better controlled with the semi-strong form, yet not completely. In the semi-strong form, when taking other companies as a benchmark, it allows to control at least to some extent market-wide effects and other industry related factors common to similar companies in the market. This does not, however, capture all the factors which affect a particular company's merger or acquisition which is being studied. (Bruner & Perella, 2004, p. 32-33.) These make studying M&A successfulness difficult.

# 5 RESULTS

The results of the empirical study of this thesis are described in this chapter. The tests conducted in this empirical study seek to answer the research question: *do software and hardware industry M&A long-term accounting performance, as measured by return on equity (ROE), differ when considering the acquired firm's pre-acquisition performance measured by ROE.* The statistical tests used in the study are multiple linear regression and the Mann-Whitney U test. The results of these tests are described in the first two sections. The last section of this chapter focuses on the analysis of the results and how they relate to previous research.

### 5.1.1 Multiple linear regression

To measure acquirer M&A success in terms of business performance, this study uses the acquirer's ΔROE as the measurement method. It represents the change in the acquirer's ROE (long-term accounting performance) from the financial ratios calculated over the four previous financial quarters prior to the merger announcement to the average long-term performance measured over a four-quarter period three years after the merger announcement. Table 10 reports the descriptive statistics of all the variables used in the study. The detailed descriptions for the variables used in the study are displayed in table 4.

**Table 10. Descriptive statistics.**

| | Range | Minimum | Maximum | Mean | Mean std. error | Std. deviation | Variance |
|---|---|---|---|---|---|---|---|
| **Acquirer size** | 8.264 | 4.700 | 12.964 | 9.840 | 0.177 | 1.922 | 3.694 |
| **Acquirer ΔROE** | 123.500 | -53.630 | 69.870 | 1.298 | 1.769 | 19.220 | 369.410 |
| **Acquirer debt-to-equity** | 2.298 | 0 | 2.298 | 0.169 | 0.0359 | 0.390 | 0.152 |
| **Target firm pre-acquisition ROE** | 124.120 | -84.449 | 39.673 | 0.116 | 1.863 | 20.233 | 409.365 |

Table 11 displays the multiple linear regression results, where heteroscedasticity-consistent standard errors are used to account for the violation of the homoscedasticity assumption of the regression. The independent variables of acquirer debt-to-equity, target pre-acquisition ROE, and target industry did not demonstrate statistical significance ($p < 0.05$) in their relationship with acquirer's ΔROE in the analyzed dataset. Thus, the results indicate that these variables do not appear to have a linear impact on the acquirer's ΔROE in the context of this study. Two independent variables which are of particular interest in relation to the research question of the study are the target industry and the acquired firm's pre-acquisition ROE. The acquired firm's pre-acquisition ROE four quarters prior to the acquisition announcement does not seem to impact the long-term accounting performance of the acquirer, as measured by acquirer's change of ROE ($p = 0.2879$, $\beta = -0.1575$). There does not appear to be a statistically significant difference in long-term accounting performance between software and hardware industries based on the target industry independent variable ($p = 0.2304$, $\beta = 3.9071$) or target firm pre-acquisition ROE ($p = 0.2879$, $\beta = -0.1575$). Thus, based on the regression analysis on the results of the analyzed dataset, we cannot reject the null hypothesis: "There is no significant difference in the long-term accounting performance, as measured by acquirer's change in ROE, between software and hardware industries when taking the acquired firm's pre-acquisition performance into account."

**Table 11. Heteroscedasticity-consistent regression coefficients for multiple linear regression.**

| Predictor | Coefficient | Robust SE (HC) | t-value | p-value |
|---|---|---|---|---|
| **Constant** | -26.224 | 9.687 | -2.707 | 0.008 |
| **Acquirer size** | 2.616 | 0.993 | 2.635 | 0.010 |
| **Acquirer debt-to-equity** | -2.850 | 6.146 | -0.464 | 0.643 |
| **Target industry** | 3.907 | 3.240 | 1.206 | 0.230 |
| **Target firm pre-acquisition ROE** | -0.158 | 0.148 | -1.068 | 0.288 |
| $R^2$=0.130, F(4, 113)=3.450, p-value=0.0106 | | | | |

There is no statistical significance in the regression model for the acquirer debt-to-equity (ratio of total debt to equity) independent variable ($p = 0.6437$, $\beta = -2.8498$). The debt variable in the dataset shows a significant concentration of values around 0 (see figure 9 and table 10). Among the 118 firms analyzed, approximately 61% of them have a debt-to-equity ratio of 0 or 1%, while around 27% have a ratio between 1% and 40%. Only a small portion, approximately 12%, have a ratio exceeding 40%.

Of the independent variables in the regression results table, only the acquirer size is statistically significant ($p = 0.010$ and $\beta = 2.62$). While holding all other variables constant, a one-unit increase in acquirer size (note that acquirer size is in natural logarithmic form) corresponds to a 2.62% absolute increase in the acquirer's ΔROE. While there is a linear relationship with acquirer size and the dependent variable in the regression model, while in reality this relationship is non-linear. This is due to the natural logarithmic transformation of acquirer size which is employed for the regression model. This transformation implies that a one-unit increase in the natural logarithm of acquirer size corresponds to a much larger change in acquirer size rather than a simple addition. For example, looking at the descriptive statistics in table 10, the range of acquirer size varies from 4.70 to 12.9 which equates to 110 employees and 426751 employees, and the mean is 9.84 which equates approximately to 18676 employees.

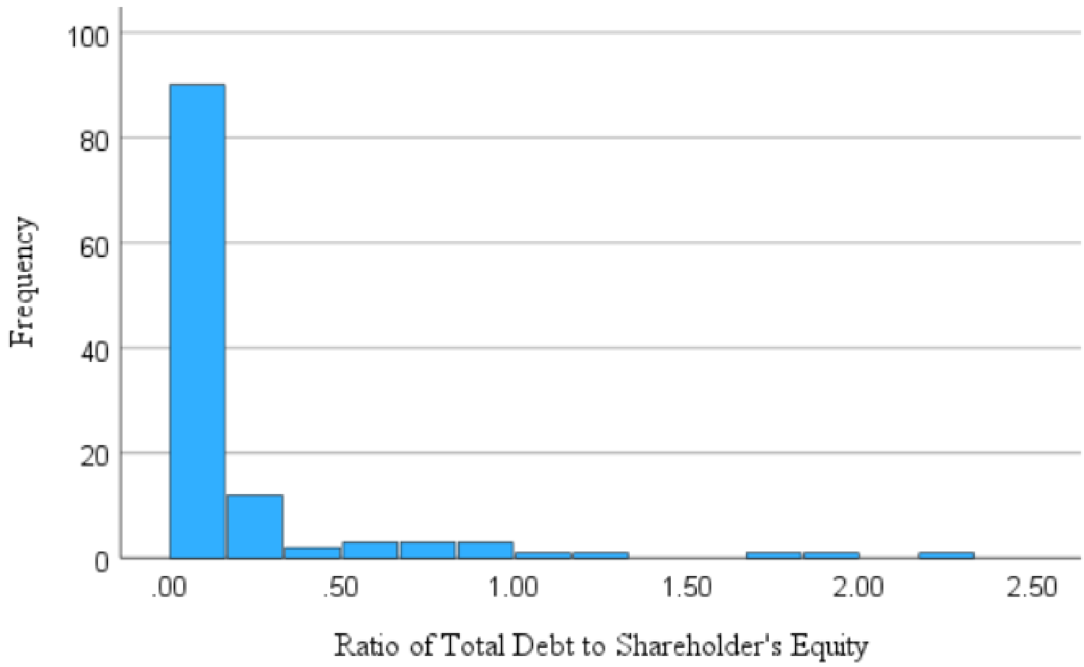


**Figure 9. Distribution of acquirer total debt-to-equity ratio.**

The model's overall explanatory power is shown in table 11. The F-statistic for the model is $F(4, 113) = 3.45$ with a corresponding p-value of 0.0106. This indicates that the regression model as a whole is statistically significant. The model used in the study, however, only explains a small part of the acquirer's change of ROE as demonstrated by the R-squared value of 0.13 of the regression model. This means that 13% of the variance of the dependent variable is explained by the independent variables of the regression model. Since this value is quite low, it implies that there are other factors influencing the acquirer's change of ROE which are not captured by the regression model used in the study.

### 5.1.2 Mann-Whitney U test

The Mann-Whitney U test was employed as a non-parametric alternative to compare the distributions of key variables between the industry groups (software and hardware). The test was conducted to gain supporting insights relating to the research question.

**Table 12. Mann-Whitney U test results**

| Null Hypothesis | Sig. | Decision |
|---|---|---|
| The distribution of target firm pre-acquisition ROE is the same whether the acquired firm is a software or a hardware industry firm. | .111 | Retain the null hypothesis. |
| The distribution of acquirer size prior to acquisition announcement is the same whether the acquired firm is a software or a hardware industry firm. | <.001 | Reject the null hypothesis. |
| The distribution of acquirer debt-to-equity prior to acquisition announcement is the same whether the acquired firm is a software or a hardware industry firm. | .375 | Retain the null hypothesis. |
| The distribution of acquirer ΔROE is the same whether the acquired firm is a software or a hardware industry firm. | .025 | Reject the null hypothesis. |

The Mann-Whitney U tests conducted on the variables of interest yielded p-values such that there are statistically significant differences on some of the distributions of the tested variables whether the target firm of an M&A was a software or hardware firm. Table 12 displays the null hypotheses of the Mann-Whitney U test and the results of the tests for each variable used in the study. There is a statistically significant difference in the *acquirer firm size* ($p < 0.001$) and *the long-term accounting performance measured as acquirer change of ROE* ($p < 0.05$) depending on whether the target firm was hardware or software firm. Consequently, we reject the following null hypotheses: *"the distribution of acquirer ΔROE is the same whether the acquired firm is a software or a hardware industry firm."*, and *"The distribution of acquirer size prior to acquisition announcement is the same whether the acquired firm is a software or a hardware industry firm."*

Instead, we retain the corresponding alternative hypotheses which suggest that there is a difference in the distributions of the variable of interest in the tests. By retaining these alternative hypotheses, we cannot yet tell what the direction of the difference is, i.e., whether software or hardware firms have larger values on the tested variable. The two-tailed Mann-Whitney U test does not provide this information. However, we can gain insights into the direction of these differences by examining the distribution of the variables in box plots. The distribution in figure 10 suggests that the acquirer's long-term accounting performance as measured by change in ROE tend to be better after the M&A for firms which acquire software firms. Figure 11 similarly indicates that the acquirers of software firms tend to be larger than the hardware firm acquirers.

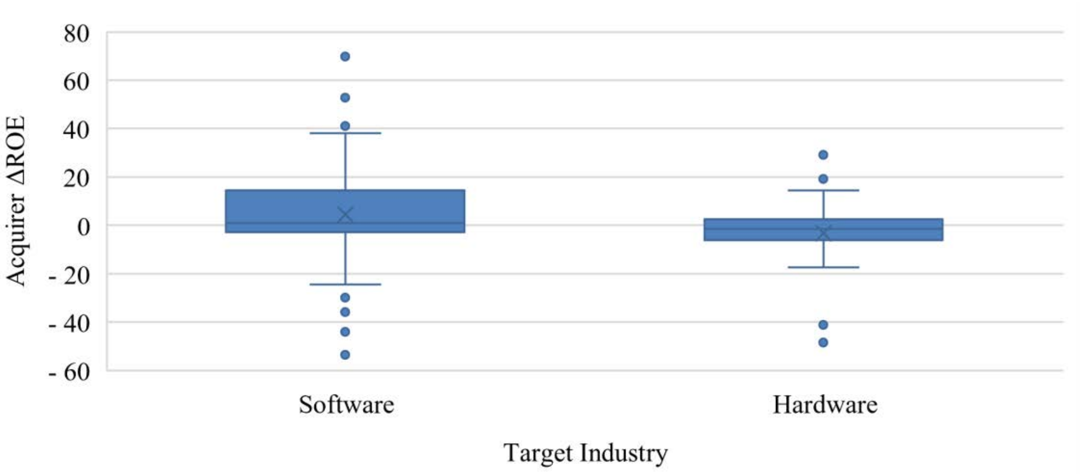


**Figure 10. The change of acquirer's ROE by acquisition target's industry group box plot.**

For the tested variables, *target firm pre-acquisition ROE* (p = 0.111) and the *acquirer debt-to-equity* (p = 0.375), there was no statistically significant difference between whether the target of M&A was a hardware or a software firm. Thus, we retain their corresponding null hypotheses (displayed in table 12). While no statistically significant difference between software and hardware firms on the *target firm pre-acquisition ROE* was detected, interestingly, the distribution of software and hardware firms on that variable looks considerably different. In figure 12, the box plot demonstrates greater data dispersion among software firms compared to hardware firms, as evidenced by the greater span between quartiles.

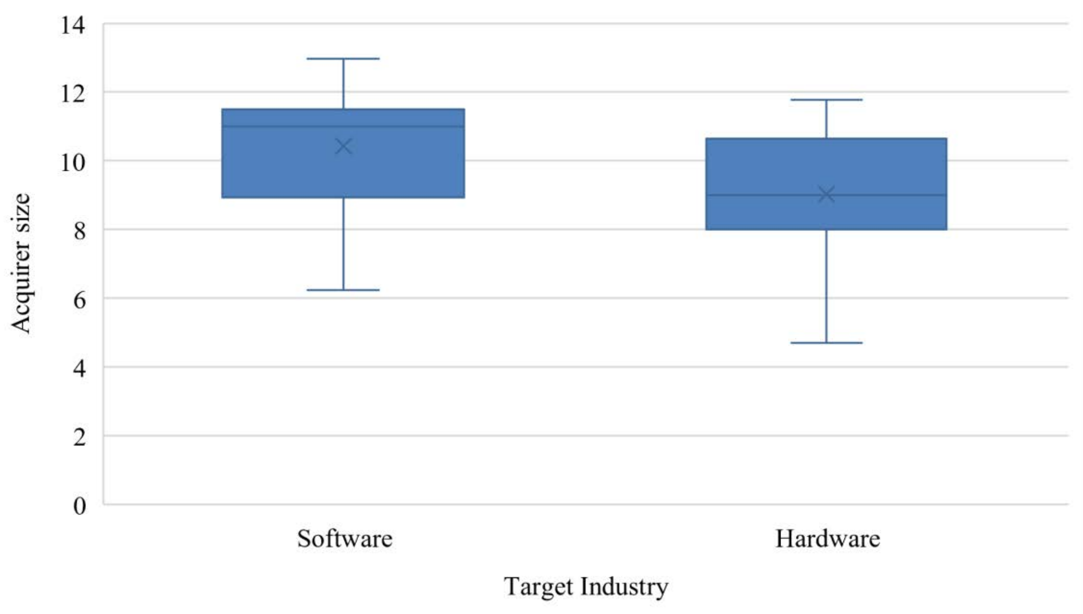


**Figure 11. Acquirer size by acquisition target industry box plot.**

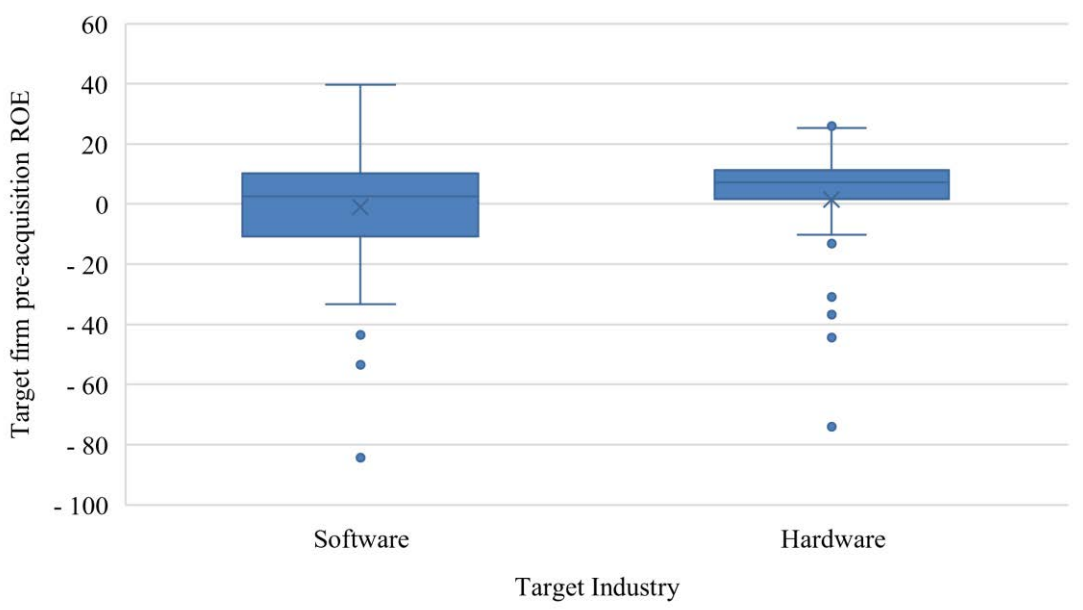


**Figure 12. Acquisition target firm pre-acquisition performance by target industry group box plot.**

### 5.1.3 Analysis

The main variables of interest in the study are the *target industry group*, *acquirer ΔROE, acquisition target pre-acquisition ROE*, these are the relevant variables to answer the research question. The research question can be answered solely with the multiple linear regression used in the study; however, the Mann-Whitney U test provides relevant additional insights on the individual variables relationships with the target industry group. Multiple linear regression results displayed in table 11 show that there is no linear relationship between *acquirer ΔROE* and *target firm pre-acquisition ROE* ($p = 0.2879$, $\beta = -0.1575$). There is also neither statistically significant difference on the distribution of target firm pre-acquisition ROE between software and hardware target firm industry groups ($p = 0.111$).

Based on the Mann-Whitney U test results on the *acquirer size* ($p < 0.001$) and *acquirer ΔROE* ($p < 0.05$), there appears to be a difference on the distribution between whether the target firm is a hardware or a software firm. The distribution in figure 10 suggests that the acquirer's long-term accounting performance as measured by change in ROE tends to be better after the M&A for firms which acquire software firms. By looking at the distributions of the number of employees in the firms as shown in figure 11, the software firms appear to be larger than hardware firms. However, looking at these results in conjunction with the multiple linear regression, the difference does not appear to be explained by the target firm industry group itself, but rather by other factors. In the multiple linear regression model, the size of the acquirer is a statistically significant predictor in the model ($p < 0.001$, $\beta = 2.62$). This appears to explain at least most of the difference behind the Mann-Whitney U test result on acquirer ΔROE. This highlights the crucial role of incorporating appropriate control variables. Without accounting for acquirer size as a control factor, acquiring software firms would appear to produce better long-term M&A outcomes for the acquiring firm as measured by ROE.

The results of this study are different compared to previous research regarding the target firm pre-acquisition performance. Previous research on target firm pre-acquisition performance in M&A suggests that low performance is preferred (Haleblian et. al., 2009). However, Leger and Quach (2009) is the only study specifically focusing on IT M&A (software in that case) which was found reviewing the related background literature. That study shows a positive impact to ROA and ROE from target firm's pre-acquisition performance (measured in EPS) in a one-year timeframe of the M&A. In that study, the two-years ROE was statistically non-significant and ROA was statistically significantly positive. Those are different study periods than which was used in this study, different measurement for measuring pre-acquisition performance (EPS) and also the study has a narrower focus (that is it focused only on software firms, while this study also includes hardware firms). Yet, Leger & Quach (2009) did not state in their study whether they used any control variables, for example, acquirer size in their study to get a positive impact on the pre-acquisition performance to long-term accounting performance.

There are many factors which you could expect that would lead to differences between hardware and software firms' M&A outcomes such as acqui-hiring (Fantasia, 2016), network and virtual network effects (Economides, 2001; Katz & Shapiro, 1985), and prevalence of technology acquisitions (Ferrary, 2003). Yet, at least in this research context, the hardware and software industries do not display a statistically significant difference between each other while considering the target firm's prior performance measured with ROE. This study does not, however, comprehensively answer the deeper underlying question whether there are differences between hardware and software industries M&A performance. Further studies would be necessary to measure both the acquirer's performance and the target firm's performance more comprehensively with the commonly used different methods of measuring the performance such as cash flows, sales growth, profit growth, asset growth, ROA, ROS, return on investment (ROI), and return on capital employed (ROCE) (Thanos & Papadikis, 2012).

As the study uses long-term study period of four years, it has some limitations as well. The problem with both long-term and short-term studies is that the study periods vary between categories and within both categories. Another problem is that the performance is measured in a wide range of different methods which makes it more difficult to compare different studies to each other (Tuch & O'Sullivan, 2007). This makes it so that when using only four-year long-term accounting performance with ROE as the method for measuring M&A successfulness. We cannot give a definitive answer to the question whether the software and hardware industries differ in this respect. We are also limited by the available data, and we cannot separate the M&A successfulness from the rest of the business performance of the acquirer, nor the influence of external events such as macroeconomic events. Optimally, both the short-term and long-term impacts would be beneficial to be studied at to answer the question.

Since the results of the multiple linear regression suggest that the target's pre-acquisition performance does not statistically significantly correlate with the acquirer's post-acquisition performance, a potential explanation for this could be that it is not the only determinant for the post-acquisition performance outcomes. For example, R&D has been shown to distort standard measures of accounting performance (Chan, Lakonishok & Sougiannis, 2001). Other factors, such as R&D spending can serve as an alternative motivation behind an acquisition and also contribute to the acquisition’s value and diminish the significance of target's pre-acquisition performance for its' impact on the acquirer post-acquisition performance. In acquisitions where pre-acquisition performance is lower, other value drivers might take precedence in making the acquisition decision and subsequently influencing the post-acquisition performance. Additionally, any positive or negative impact from the target’s pre-acquisition performance could be offset with a correspondingly higher or lower acquisition price.

The study attempted to control for three factors: acquirer size, acquirer debt and method of payment. The method of payment was controlled by only including a subset of available data where cash was the method of payment. The acquirer debt did not appear to be statistically significant while the acquirer size was. Since acquirer size was a statistically significant predictor in the multiple linear regression in the study, it supports previous research which suggests that it is an important control factor (e.g., King et. al, 2021). It has to be noted that the acquirer size was transformed using natural logarithm, thus, the relationship between acquirer size and acquirer M&A performance is not linear. The debt-to-equity did not appear to be a relevant control variable. This could be at least partially explained by the fact that the method of payment was controlled by only selecting firms which used cash as the method of payment. This could, for example, impact the debt-to-equity ratios in that those firms who acquire firms with cash only are in a better financial position and more likely have little to no debt.

To distinguish between hardware and software firms, SIC classification was used. Yet, the SIC classification may not be precise enough to make distinction from software and hardware firms which was aimed at in the study. It has been used in previous research (e.g., Zhu et. al., 2015; Schief et. al., 2013; Ragozzino, 2006; Gao & Lyer, 2006). The same division was not found in the previous literature at least in the context of M&A research, however, Zhu et. al. (2015) used a very similar approach in dividing the IT-sector to IT manufacturing and to IT services with SIC codes. This study used quite similar division, however, changes to the one used by Zhu et. al. (2015) was made. There are problems with using the SIC as is used in this study though. Many software firms are not just software firms, they can also be hardware firms simultaneously despite the main industry classification being a software industry industry group. The same applies for hardware industries. It may be relevant for the positive drivers supporting M&A to manifest that a software firm acquires another software firm. Some alternatives to using SIC codes could be investigated to categorize the target industry to one or even multiple simultaneous categories to overcome the limitations of the classification, for example, something similar which Redis (2009) have used.

There are other problems with simply using the target industry as an independent variable. We do not know whether the acquirers of software and hardware firms are software or hardware firms in this study (this was omitted to produce less complex model). You would expect that software firms are more likely to acquire other software firms and the same for hardware firms, however, there can be much overlap between the two groups since, for example, the IT-industry firms may have a wide range of products and/or services for sale which extends beyond a single software or hardware industry classification, for example, in the case of “big tech” firms (more on big tech firms in section 3.4).

The debt-to-equity variable has some issues with it in this study’s context. The level of debt-to-equity of the acquirers was heavily concentrated close to 0 (see table 10 and figure 9). Out of 118 firms, 72 firms have less than 1% debt to equity ratio and 32 have more than 1%, but less than 40%. Only 14 have higher than 40% debt to equity ratio. A potential reason for this is that since cash was the method of payment for these firms, they likely had better financial status when performing the M&A, for example, the reason why they paid with cash was that they had the option to pay the transaction with cash.

The model fit for the multiple linear regression can also be analysed. Firstly, this model fit can be assessed through the independent variables of the study. To a large extent, this can be expected in a long-term study like this. The follow-up period of the study (the fourth year after M&A) is quite long after the actual event. The long-term accounting performance of M&A is relevant, however, studying it is difficult due to issues such as confounding events, it does not measure risk and it is susceptible to manipulation by managers (King et. al, 2018). The number of independent variables is limited, and only the most important control factors based on earlier research are used in the model, as suggested by King et. al (2021). Secondly, the dependent variable used in the study likely impacts the model fit as well. The dependent variable (acquirer ΔROE) used in the study does not comprehensively correspond to acquirers M&A success. There are other accounting measures that can be used as well (e.g., ROA and ROS), and financial measures and surveys (King et. al. 2018). Table 1 displays these measures in greater detail. ROE, ROA, and ROS all portray different aspects of business performance, and thus, it is likely a single variable does not comprehensively describe business performance or M&A performance for that matter (Thanos & Papadikis, 2012). It only corresponds to an aspect of M&A success while also at the same time measuring the general business performance of the acquiror firm, where the performed acquisition is only a part of the whole picture.

The result of the analyses that, the software firm acquirers were larger, and they also had better long-term accounting performance outcomes as measured by ROE is also supported by previous literature on M&A. Previous literature suggests that the acquirer firm size has a positive impact on the M&A success (King et. al., 2021). A question raises, however; why do the acquirers of software firms tend to be larger than those of hardware firms? This could be attributed to a range of industry-related factors that not only lead to larger acquirers but also leading to software firm acquisitions, ultimately resulting in more favorable M&A outcomes, measured through metrics such as the change in ROE or using other metrics of M&A success.

# 6 CONCLUSIONS

The topic of this thesis focuses on the characteristics of the IT-industry and differences of mergers and acquisitions (M&A) within the IT-sector (software and hardware industries). Empirical analysis conducted as part of the thesis seeks to find out whether software and hardware industry M&A long-term accounting performance differ when acquired firm's pre-acquisition performance is taken into consideration. Return on equity (ROE) is used in the study as the method for measuring both target firm's pre-acquisition performance and the acquirer's post-acquisition long-term accounting performance. The long-term time frame is the difference of the prior year before the acquisition to the fourth year after the acquisition. The study employs multiple linear regression and Mann-Whitney U test, utilizing data sourced from Refinitiv's databases on publicly listed U.S. firms M&A between 2004 to 2016.

The results of the multiple linear regression indicate that there is no statistically significant difference between acquired software and hardware firms on their distribution ROE prior to the M&A announcement. These results suggest that only acquirer size was statistically significant predictor used in the model. Consequently, neither the industry of the target of the acquisition nor the target's pre-acquisition ROE statistically significantly impact the long-term accounting performance measured in change in ROE. There is, however, statistically significant difference on the size of the acquirer and the positive outcome of the M&A measured in change in ROE when looking these variables independently using Mann-Whitney U test. The Mann-Whitney U test results and observation of the associated box plots suggest that acquirers of software firms tend to have better M&A long-term accounting performance. This could be simply explained by that the acquirers of software firms tend to be larger in size. This is the implication since the multiple linear regression results do not exhibit better software firm performance unlike the Mann-Whitney U test results. The results on acquirer size lead to the question: why do software and hardware firm acquirers differ in size? While speculation, some industry-related factors could lead to both larger acquirer sizes and ultimately to better M&A outcomes.

No previous studies which focused specifically on the software and hardware differences on M&A performance was discovered during the literature review conducted as part of this thesis. There have been similar prior studies, however, which focus specifically on IT business models, the software industry and software industry business model M&A performance. The studies focusing on specifically target firm pre-acquisition performance suggest that a low performance is preferable, while this study did not find pre-acquisition performance statistically significantly impact long-term accounting performance. Prior research also suggests that acquirer size predicts M&A performance similarly as this study’s results suggest.

Using exclusively long-term accounting performance, measured by ROE, to evaluate M&A successfulness presents certain limitations. These include availability of data, the influence of external events such as macroeconomic events, and the challenge of disentangling M&A success from the overall business performance of the acquiring firm.

Considering the thesis findings, suggestions for further research can be made. Optimally, a more comprehensive assessment of the research question would benefit from using both short-term and long-term models which would employ different or more refined models. The long-term accounting performance study period used here (four years) could be varied. The regression model’s fit for the model used in this study is rather low which suggests that there is room for improvement. While the extent to which the model fit can be enhanced is not clear based on the literature review conducted as part of the thesis. Having additional independent variables and dependent variables in the model, could contribute to a better model fit. It would be worthwhile to conduct research looking at the research question from different angles by using different dependent variables or using a combination of multiple other commonly used metrics as dependent variables, such as cash flows, sales growth, profit growth, asset growth, ROA, ROS, ROI, and ROCE. These could establish a more comprehensive outlook on the issue.

There are other considerations to be taken for future research as well. Other acquisitions than just U.S. public firms could be studied since there can be differences between countries and between-country acquisitions. Especially in the light of previous research which suggests that M&A which targets private firms perform better compared to public firms. The SIC classification used in the study may lack the precision required to differentiate between software and hardware firms sufficiently. Other methods of creating this division could be investigated. Additionally, considering the industry of the acquirer in conjunction with the target's, there could unique characteristics inherent in different acquirer-target combinations (software and software, and hardware and software etc.) with distinct impacts on M&A performance.

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**APPENDICES**

# Appendix 1

## SOFTWARE AND HARDWARE SIC INDUSTRY GROUPS

**Table 13. Software and hardware SIC industry groups (United States Department of Labor, n.d.-b).**

| Code | Name |
|---|---|
| **Software industry** | |
| Industry Group 737: Computer Programming, Data Processing, and Other Computer Related Services | |
| 7371 | Computer Programming Services |
| 7372 | Prepackaged Software |
| 7373 | Computer Integrated Systems Design |
| 7374 | Computer Processing and Data Preparation and Processing Services |
| **Hardware industry** | |
| Industry Group 357: Computer and Office Equipment | |
| 3571 | Electronic Computers |
| 3572 | Computer Storage Devices |
| 3575 | Computer Terminals |
| 3577 | Computer Peripheral Equipment, Not Elsewhere Classified |
| 3578 | Calculating and Accounting Machines, Except Electronic Computers |
| 3579 | Office Machines, Not Elsewhere Classified |
| Industry Group 366: Communications Equipment | |
| 3661 | Telephone and Telegraph Apparatus |
| 3663 | Radio and Television Broadcasting and Communications Equipment |
| 3669 | Communications Equipment, Not Elsewhere Classified |
| Industry Group 367: Electronic Components and Accessories | |
| 3671 | Electron Tubes |
| 3672 | Printed Circuit Boards |
| 3674 | Semiconductors and Related Devices |
| 3675 | Electronic Capacitors |
| 3676 | Electronic Resistors |
| 3677 | Electronic Coils, Transformers, and Other Inductors |
| 3678 | Electronic Connectors |
| 3679 | Electronic Components, Not Elsewhere Classified |
| Industry Group 382: Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling Instruments | |
| 3821 | Laboratory Apparatus and Furniture |
| 3822 | Automatic Controls for Regulating Residential and Commercial Environments and Appliances |
| 3823 | Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products |
| 3824 | Totalizing Fluid Meters and Counting Devices |
| 3825 | Instruments for Measuring and Testing of Electricity and Electrical Signals |
| 3826 | Laboratory Analytical Instruments |

| | |
|---|---|
| 3827 | Optical Instruments and Lenses |
| 3829 | Measuring and Controlling Devices, Not Elsewhere Classified |

| Industry Group 386: Photographic Equipment and Supplies | |
|---|---|
| 3861 | Photographic Equipment and Supplies |