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# The Secret SaaS to Valuation

*An empirical investigation into the applicability of relative valuation within the Software-as-a-Service industry*

by

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# Abstract

This thesis investigates the applicability and legitimacy of the relative valuation method within the Software-as-a-Service industry by comparing the implied enterprise values of SaaS companies in transactions to values estimated using peer group valuation multiples. To achieve this, a sample of 66 Nordic M&A and private placement transactions completed between 2020 and 2024 were selected for analysis. The main finding of the research is that the industry-specific multiple performs significantly better than traditional multiples for the studied companies. Another finding is that, in general, traditional valuation multiples have less explanatory power for SaaS companies compared to traditional companies, likely due to the unique subscription-based business model and recurring characteristic of revenue within the industry. These findings imply the need for a tailored approach in valuing SaaS companies, where traditional valuation multiples yield inadequate results. Instead, investors and valuation practitioners should consider the specific dynamics of the SaaS industry and select value drivers for relative valuation accordingly. Suggested future research includes exploring other multiples in the SaaS industry as well as other contexts, such as the large American SaaS market.

**Keywords**: Annual recurring revenue, relative valuation, software-as-a-service, value drivers

**Word count**: 18,231

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# 1 Introduction

The introduction provides an overview of the thesis and outlines the research question and delimitations. The focus of the research is on valuing Software-as-a-Service companies through relative valuation. This study explores the distinct business models and financial dynamics of SaaS companies, which are characterized by subscription-based revenue and high scalability. By examining both traditional and industry-specific valuation multiples, the thesis contributes to the existing knowledge on financial valuation. The aim is to determine the accuracy of relative valuation for such companies in the under-researched Nordic context.

## 1.1 Background

Although there exists a substantial body of literature on enterprise valuation and determinants of firm value, unresolved questions remain on the effectiveness of traditional valuation methods within young industries. Traditional views of valuation techniques rely heavily on financial accounting information reported in corporate filings. With the emergence of new types of industries, with unique characteristics and business models, investors and valuation practitioners have changed their views on valuation, focusing increasingly on industry-specific metrics (Japaridze, 2023). Despite the increasing societal importance of the technology sector, both financial and social, similar adaptation has not been seen in empirical research.

Towards the end of the Second World War in the 1940s, the Electronic Numerical Integrator and Computer (ENIAC) was developed as the world's first programmable computer. The emergence of the ENIAC and other computing devices laid the foundation for the Information Age, or IT revolution (Burks, 2002). Since its initiation, the IT revolution has resulted in major societal changes, one of the most influential being the introduction of the Internet in the late 20th century. The rise of the Internet served as an enabler of the transition from the hardware-centric approach of the early parts of the Information Age to the emergence of cloud computing. This revolutionized the global business environment as it removed the need for consumers to manage hardware themselves. By delivering computing services over the Internet with the need of active management by the user, consumers only had to pay for services used, which greatly increased the flexibility and cost-efficiency of the industry (Mills, 2021).

In contrast to on-premises data management, cloud-based alternatives provide a dynamic infrastructure for storage, process, and access to data over the cloud. The growth of data and its increasing importance for decision-making and innovation for organizations has influenced all societal players, with the emergence of cloud computing re-defining the ways in which information and digital assets are accessed and managed. At the most basic level, Infrastructure-as-a-Service (IaaS) is one of the three main delivery modes of cloud computing and removes the need for consumers to manage the hardware and virtualization, offering cloud-based storage and network solutions. In addition to the management of hardware and virtualization, Platform-as-a-Service (PaaS) providers, the second main service model, manages all software components required to develop applications over the Internet (Basit & Henry, 2024).

The third delivery model, Software-as-a-Service (SaaS), is the most outsourced-oriented form of cloud computing, offering minimal management by the consumer. With a market value of approximately 242 billion USD in 2022, the SaaS industry accounts for approximately 50 percent of the global cloud computing market (Grand View Research, n.d.). SaaS providers manage the hardware, virtualization, operating system, runtime, scaling and application code, thus providing consumers with ready to use applications. This broad offering, characterized by easy deployment and maintenance, is further expected to drive continued growth in the industry. The SaaS industry is expected to grow at a compounded annual growth rate (CAGR) of approximately 18.4 percent between 2024 and 2032, reaching a market value of 1,229 billion USD at the end of the forecasted period (Fortune Business Insights, 2024).

From a firm-level perspective, SaaS companies are further differentiated from other segments of the cloud computing industry in terms of the business model used. This is because SaaS providers often adopt a subscription-based approach, where customers are charged periodically for access to the software services, while PaaS and IaaS firms tend to adapt alternative revenue models (IBM, 2023). According to Japaridze (2023), such models are unique in their ability to create highly predictable and recurring revenues. Moreover, they can easily scale up or down to meet the demand of users without significant changes to the underlying infrastructure or software and at little to no cost. This unique combination of high growth possibilities and quality of revenue differentiate SaaS businesses from other industries. From an equity capital markets perspective, SaaS has received increased attention from investors, accounting for approximately 47 percent of all venture capital (VC) investments in 2023 (Dealroom, n.d.).

Cusumano (2004) argues that the increased interest in software companies can be attributable to their high scalability and predictable cash flows, rarely attainable in other industries. SaaS companies possess exceptional abilities to achieve high gross margins due to low marginal costs and economies of scale. Once the foundation for a software has been established, the cost of serving additional customers is relatively low, making SaaS companies highly profitable at scale (cf. Ali et al. 2010). High gross margins and operational efficiency constitute key metrics for venture capitalists in assessing the viability of an investment (Gompers & Lerner, 2004).

As investor interest in SaaS continues to surge, understanding the intricacies of valuation techniques in the industry becomes pivotal. Before an investment is made, both parties to the transaction must agree on the price. The price is in turn derived from the firm value, incorporating historical, current, and future prospects. Various valuation methods and models are used by investors attempting to derive the fair value of a firm. The theoretical emphasis has been focused primarily on discounted cash flow (DCF) valuation methods (Ross, 1995). The DCF approach, being highly susceptible to manipulation and requiring a wide range of assumptions, however, does not have the same superior status among practitioners. Instead, investment bankers and appraisers also tend to employ valuation models based on multiples (Lie & Lie, 2002). Relative valuation is a market-based approach to valuing business enterprises, where the firm’s financial metrics are compared to those of a peer group. Within the European finance industry, Bancel and Mittoo (2014) finds that relative valuation is the most commonly used method for valuing companies. In their survey of 424 European financial experts, approximately 80 percent of respondents report use of relative- and DCF valuation models, with relative valuation being slightly favored.

## 1.2 Problematization

Previous research in relative valuation has indicated high predictability and accuracy of the method. Liu et al. (2002) finds that multiples based on projected earnings are highly accurate in explaining market values of firms. Their research show that multiples based on two-years-ahead earnings estimates generate valuations within 20 percent of observed prices for approximately 60 percent of the firms. They further compare the relative explanatory power using multiples based on different value drivers. Historical earnings measures followed forward-looking drivers, in turn followed by cash flow measures and book value of equity. Berkman et al. (2000) investigate the accuracy of price-to-earnings (P/E) valuation compared to valuation methods based on discounted cash flow using a sample of 45 newly listed firms in New Zealand. They find high similarity in the predictability of DCF methods and price-to-earnings methods. For their best-performing P/E model, they report a median absolute error and mean absolute error of 19.7 percent and 31.9 percent, respectively. Using a selection of 592 European companies, Schreiner (2007) finds that the price-to-earnings before tax (P/EBT) ratio provide the most precise estimates for accrual flow multiples, with 47 percent of estimated values deviating from market values by less than 25 percent.

Common among these studies is the use of traditional multiples, including price-to-earnings, price-to-sales (P/S), and price-to-book value (P/B). Further, the selection of companies has not been limited to specific industries, which has resulted in a significant weight of companies in traditional industries. Traditional industries refer to those having been "established at least during the inter-war years (1918–1939) if not before" (Radicic, 2016, p. 1427). Less research has focused on the applicability of relative valuation and accuracy of specific multiples on newer industries. While the theoretical argument for using traditional multiples in valuation of traditional companies is strong, backed by solid empirical research, as described above, it is not necessarily the case for certain industries. Unlike investors interested in traditional industries, investors focused on the SaaS industry place great importance on the quality of revenue, with a key metric being annual recurring revenue (ARR) (Haley, 2021; Japaridze, 2023).

Previous research implies high accuracy of using sales multiples for valuation in general, suggesting it would be accurate in explaining the firm value of SaaS companies as well (Lie & Lie, 2002; Schreiner, 2007). SaaS investors' focused interest on recurring revenue, however, suggests that a modified sales multiple would perform better in explaining the firm value of SaaS companies (cf. Haley, 2018). Thus, by comparing enterprise value-to-sales (EV/SALES) to EV/ARR, the latter should depict higher explanatory power in valuing SaaS companies. Earnings multiples have also proven to have high explanatory power for the value of companies (Berkman et al. 2000; Liu et al. 2002; Schreiner, 2007). According to Cormier et al. (2017), using earnings before interest, tax, depreciation, and amortization (EBITDA) can improve assessment of earnings valuation and the predictive ability of future earnings. Utilizing EBITDA as an earnings measure instead of net income further removes the distortive nature of depreciation expenses on the information value of earnings (Lie & Lie, 2002). Depreciation schedules often vary across firms and do not necessarily reflect the actual deterioration of asset value, leading to distortion of net income. Using EV/EBITDA can overcome the issues of non-cash expenses inherently affecting earnings (Zaremba & Szczygielski, 2019). Considering that all these value drivers reflect an investment base including both debt and equity, enterprise value becomes the appropriate valuation measure.

This research will contribute to the current literature on the subject by investigating a multiple previously overlooked by empirical studies within the under-researched SaaS industry. The literature on firm valuations will benefit from insights within a new and distinct industry to expand the current knowledge base. While the dependent variable will be the same as with any research on valuations, that is the actual valuation in studied transactions, the effect of the independent variable EV/ARR has not been included in prior research. The other two independent variables, EV/EBITDA and EV/SALES will be studied for comparison. These will be compared both to previous research in other industries and to the SaaS-specific EV/ARR multiple.

## 1.3 Aim and Objectives

In response to the unprecedented growth of SaaS companies and the lack of empirical support in their valuations, particularly within the unexplored territory of unlisted Nordic SaaS enterprises, this study aims to dissect the efficacy of industry-specific and traditional valuation multiples. Traditional valuation metrics such as price-to-sales, price-to-earnings, and price-to-book value have long served as benchmarks for appraising businesses across sectors (Sharma & Prashar, 2013). However, given the unique business model of SaaS companies, most notably recurring revenue streams, the relevance and accuracy of these traditional metrics are called into question. This investigation sets out to determine whether an industry-specific multiple can provide more precise explanations of valuations for unlisted Nordic SaaS companies compared to its traditional counterparts. To attain the underlying goal of this investigation, the objectives are carefully structured into three parts:

1. An extensive review of existing literature to distinguish what separates SaaS from other industries, and the theoretical grounds for valuation multiples used in appraising SaaS companies,
2. A statistical analysis of unlisted Nordic SaaS companies based on empirical data where the accuracy of different multiples, both traditional and industry-specific, is examined, and,
3. A comparative statistical analysis between traditional and industry-specific multiples to ascertain the relative predictive accuracy and reliability of these multiples in reflecting the true value of unlisted Nordic SaaS companies.

## 1.4 Research Purpose

Building on the theoretical discussion of valuation methods, the purpose of this thesis is to broaden the knowledge surrounding relative valuation. Given the scarcity of focused research on the valuation of unlisted Nordic SaaS companies, this study aims to fill a significant void in the literature by examining the applicability and accuracy of these valuation metrics within a specific and underexplored context. The above objective is encapsulated by the following research question:

> *How does the choice between traditional multiples and industry-specific multiples influence the accuracy of relative valuation in the context of Software-as-a-Service?*

## 1.5 Delimitations

The delimitations of this study, focusing on the valuation of unlisted Nordic SaaS companies, are driven by the necessity to provide a focused and in-depth analysis within a specific sector and geographical region. Consequently, the following delimitations have been established to tailor the research scope and enhance the relevance and accuracy of the study's outcomes: (1) geographical focus, (2) unlisted companies, and (3) choice of multiples.

The research is geographically confined to the Nordic region, encompassing Sweden, Norway, Denmark, and Finland. This regional focus is motivated by the ease of finding data about Nordic companies. While this focus provides valuable localized insights, it also limits the generalizability of the findings to SaaS companies in other geographical contexts. Furthermore, this study specifically targets unlisted companies. The valuation of public companies involves different considerations, such as market sentiment and more readily available financial data which may affect the interchangeability between them. Lastly, while the thesis investigates both traditional and industry-specific valuation multiples, it is delimited by the selection of specific multiples for analysis: (1) EV/SALES, (2) EV/EBITDA, and (3) EV/ARR. These multiples are chosen partly based on their prevalent use in prior empirical research and partly based on the unique characteristics of the SaaS industry (Sharma & Prashar, 2013). Other potential value drivers are outside the scope of this study.

## 1.6 Disposition

This thesis is divided into 6 separate chapters. In Chapter 2, the theory behind and previous empirical research in relative valuation and fundamental distinction of the SaaS industry are described. Chapter 3 describes the methodology for the empirical research. The results from the research are presented in Chapter 4. In Chapter 5, the results are discussed and analyzed and lastly, Chapter 6 presents the conclusions of the research.

# 2 Literature review

This chapter examines the evolution and application of various firm valuation methods, building on the foundational concepts introduced earlier. Initially, it reviews traditional valuation approaches, emphasizing the transition from dividend to earnings yield that marked a significant shift in financial analysis practices. Subsequently, it discusses the adoption and refinement of modern valuation techniques, highlighting their relevance and application across different contexts. Additionally, the dynamic capabilities view is discussed as a distinguishing factor for SaaS companies. Finally, the efficient market hypothesis is presented, as its underlying assumptions are critical for the analysis. Throughout this literature review, the chapter aims to provide a thorough understanding of the complexities and dynamics of firm valuation, supporting a comprehensive assessment of the research question.

## 2.1 Valuation

Initially, shares were valued similarly to bonds, with a focus on the income they generated through dividends. The dividend yield, calculated as the dividend per share divided by the share price, was the dominant factor in share valuation. Investors also considered the book value of shares to ensure capital security, reflecting a perception of shares as quasi-bonds with uncertain dividends and maturity dates (Fisher, 1930; Keynes, 1925; Smith, 1925). In the 1920s, the focus began to shift toward earnings yield, especially in the U.S. This shift was influenced by the recognition that retained earnings could be reinvested to yield larger future earnings, diminishing the role of dividend yield in equity valuation. The concept of "growth stocks" emerged, emphasizing the potential for future growth over immediate dividend returns (Rutterford, 2004).

Because of this shift, the P/E ratio, which compares a company's market value per share to its earnings per share, became increasingly popular as a valuation metric (Graham et al. 1962). This shift was slower in the UK, where the market was more conservative in adopting new valuation techniques compared to the U.S. The emphasis on P/E ratios signified a broader acceptance of the importance of earnings over dividends in assessing a company's value (Rutterford, 2004). DCF methods, which estimate the value of an investment based on its expected future cash flows, began to gain prominence in the latter half of the 20th century. Initially devised for land investment, DCF techniques were adapted for equity valuation, offering a more comprehensive assessment of a company's potential value (Copeland, 1990).

Firm valuation has become an important process used to determine the economic value of businesses, important to a variety of stakeholders for different reasons. One group that widely uses valuation is investors and minority shareholders. They need to understand the value of the company that they are investing in to determine whether it is priced appropriately. Only by valuing the company can shareholders and investors assess the potential returns of their investments and make informed decisions based on said information (Srinivasan & Hanssens, 2008).

Pricer and Johnson (1997) further discuss that business owners and managers is another important group of stakeholders with vested interest in firm valuation. For business owners, unless a fair value of the firm can be derived, they will be unable to comprehend the value of their assets, causing financial uncertainty. The authors further declare that this is exceedingly relevant for the purpose of business sales, mergers, or acquisitions. A frequent use-case of firm valuation for business owners is to determine whether the offer they receive is reasonable. Understanding the economic value of the business is further important to the managers to make the right strategic decisions and long-term planning. By understanding the value, managers can better understand the value drivers and adjust their strategy accordingly (Pricer & Johnsson, 1997).

One of the most used methods for valuation is relative valuation, where assets are valued based on the valuation of comparable assets. Together with the discounted cash flow approach, relative valuation is the most popular method used by practitioners (Bancel & Mittoo, 2014). The fundamental argument for using relative valuation is intuitive. A wine collector interested in purchasing a case of vintage Bordeaux will make a judgement on how much to spend by examining transaction prices of similar wines from the same geographical area and production year. Similarly, investors interested in purchasing shares in a company will gauge a fair value by examining the market value of similar companies. Unlike alternative valuation methods, relative valuation does not analyze companies in isolation. With values derived from market values and financial metrics of comparable companies, a market-based approach is used. That is, the goal is to find the value of an asset by looking at how similar assets are priced by the market (Sharma & Prashar, 2013).

### 2.1.1 Different Valuation Methods

The dividend growth model (DGM) is a method for valuing a company's stock by assuming dividends grow at a constant rate in perpetuity. The model's main advantage is its simplicity since the only components required are the current dividend, projected dividend growth rate and a discount rate (Rutterford, 2004). It quickly gained popularity after its introduction in the 1960s. However, only about 20 percent of valuation experts use the model today (Bancel & Mittoo, 2014). This decreased attention can be attributed to its inherent limitations, one being that it is difficult to predict the future growth rate of dividends, an important input in the model. Moreover, the assumption of a constant growth rate rarely is true in practice (Ashton, 1995). In addition, with the rise of technology companies, focusing on growth rather than profitability in early stages, the model becomes redundant since such companies rarely distribute dividends (Ly Vath et al. 2008).

Another valuation method with similar usage as the DGM by experts is the net worth approach, also known as asset-based valuation (Bancel & Mittoo, 2014). The method fundamentally assesses the value of a company by summing up the value of its tangible and intangible assets and then subtracting its liabilities. Therefore, this method provides a clear snapshot of what a company is worth on its balance sheet at any given time. According to Fischer (1951), this approach is particularly useful for companies with significant physical assets, such as real estate or manufacturing firms. Further, Sullivan (2000) states that it is less applicable to companies whose value is predominantly based on intangible assets, like technology or service firms.

DCF models, used by roughly 80 percent of experts, is one of the most prevalent valuation methods, second only to relative valuation (Bancel & Mittoo, 2014). The core principle of DCF valuation is that the value of any asset is fundamentally based on the cash inflows and outflows it generates over its lifetime, discounted at a discount rate to derive the present value of said cash-flows. Unlike methods that rely solely on historical data, DCF analysis involves looking forward and forecasting future performance. In addition, DCF models are flexible in nature and can therefore be tailored to fit a wide variety of scenarios (Kumar, 2016). However, while DCF is a powerful tool for valuation, its accuracy is heavily dependent on the quality of the assumptions regarding future cash flows and the discount rate (Kumar, 2016). Furthermore, Ali et al. (2010) discuss the challenges of applying DCF models to internet companies due to their volatile and uncertain nature. They argue that the model has a limited use case in valuing internet companies since it is very difficult to determine their future cash-flows, the basis for conducting DCF valuation. Additionally, Chen et al. (2021) found significant discrepancies between DCF valuations and actual market prices in different industries due to the unique growth characteristics of tech companies.

### 2.1.2 Benefits and Disadvantages of Relative Valuation

Sharma and Prashar (2013) describe how relative valuation involves estimating the value of companies based on financial and valuation-related metrics of comparable firms. The simplicity of the method allows stakeholders to quickly estimate a company's value without the time-consuming and complex process of forecasting future cash flows. The data needed for relative valuation, such as price-to-earnings or enterprise value multiples, is commonly reported and easy to obtain. This accessibility enables valuations to be conducted even with limited information about the company's growth potential. However, the method typically focuses on current or historical metrics which may not adequately account for a company’s future growth prospects (Sharma & Prashar, 2013). Furthermore, the efficacy of relative valuation models is inherently dependent on the quality of information and comparability of peers, suggesting estimated valuations may not fully reflect a specific company’s characteristics, but rather those of its peers.

It does, however, provide an important consideration of current market perception and sentiment towards a company or sector, giving a strong reflection of what investors are willing to pay for similar assets. This is particularly useful in volatile markets where investor sentiment can significantly influence prices. Since relative valuation is based on current market multiples, it adapts quickly to changes in the market environment, providing a dynamic perspective on a company's valuation (Larsen et al. 2012). However, if the market is mispricing the peer group or if an incorrect peer group is selected, the relative valuation based on such comparable firms will be flawed. This can lead to significant errors in valuation if, for example, the entire market or sector is overvalued or undervalued. In addition, the method assumes that markets are efficient, and all securities are priced accurately, which may not be the case, especially in less liquid or highly volatile markets (Sharma & Prashar, 2013).

Moreover, Bhojraj and Lee (2002) argue that for companies with unique business models or those operating in niche industries, finding an accurate set of peers can be challenging. This can lead to inappropriate valuations if the chosen comparables differ significantly in metrics such as size, growth, or profitability. In industries with high variability in business models or financial structures, such as technology, using a straightforward relative valuation can lead to misleading results because the peers may not truly be comparable (Bhojraj & Lee, 2002). Despite these challenges, if done correctly, by comparing a firm to its peers, relative valuation provides a robust base for providing stakeholders with an accurate value for any given firm (Larsen et al. 2012).

### 2.1.3 Relative Valuation as a Four-Step Process

The relative valuation model is commonly deployed within a framework consisting of four sequential steps, regardless of the specific context (Damodaran, 2006; Schreiner, 2007). The structured approach facilitates a systematic assessment of each component determining the indicative valuation.

To derive an estimation of an enterprise's value using relative valuation, the first step is to determine appropriate value measures. A multiple is structured as a fraction with a price variable in the numerator and a value driver in the denominator. Equity value and enterprise value are the two most common price variables used by practitioners (Bancel & Mittoo, 2014). Despite the common use of the former, regardless of the value driver used in association, some value drivers advocate for use of the latter. Value drivers can be net profit, sales, cash flow or other financial accounting measures (Liu et al. 2002). Value drivers serve as the foundation on which a company's worth is determined, stressing their need to have value creating characteristics. This implies that the value drivers used in a relative valuation model should accurately align with the fundamentals of the industry in which the company operates. For some industries, where the most important value drivers are earnings and other metrics attributable to shareholders, the most suitable price variable is equity value. However, several value drivers, such as EBIT, EBITDA, and sales, represent value generated for other stakeholders as well, particularly lenders. By using total enterprise value, the value of the entire firm, including the stake of debt holders, is considered, resulting in a more accurate depiction (Damodaran, 2006). Despite the existence of empirical evidence supporting the relevance of alternative value drivers such as research and development (R&D) expenditure, valuation practitioners continue to favor more conventional valuation multiples, including EV/SALES, P/B, P/E, EV/EBIT, and EV/EBITDA (Bancel & Mittoo, 2014; Schreiner, 2007).

The second step in the valuation process involves compiling a list of comparable companies and constructing a peer group. Initially, this list should be extensive, encompassing a broad range of comparable firms. From this list, peers exhibiting characteristics similar to the target company are selected for further analysis (Sharma & Prashar, 2013). Ambiguity surrounds the recommended number of peers to be included in a peer group, with some variance among previous research methodologies. Bhojraj and Lee (2002) used four to six peers, Schreiner (2007) recommends a size of four to eight, and Cheng and McNamara (2000) employed a minimum number of six comparable firms. Shared operational and financial characteristics is essential as “[t]he greater the degree of similarity between the peer group of companies and the target company, the more accurate the valuation will be” (Nel, 2015, p. 30). Plenborg and Pimentel (2016) presents two selection frameworks with strong empirical support. First, the peer group should be selected with consideration on industry classification, based on the notion that companies operating in similar industries share similar risk profiles and growth prospects. Second, the peer group should consist of companies with similar financial profiles, including profitability, growth, and risk. While each selection method has strong empirical backing individually, combining industry and economic characteristics yields the most accurate valuations (Cheng & McNamara, 2000).

Once the peer group has been established and multiples for each peer have been computed, the third step involves aggregating the individual multiples to create a synthetic multiple (SM) that reflects the entire peer group. To determine the value representing the peer group, a choice must be made regarding the measure of central tendency, typically the arithmetic mean or the median. Although the arithmetic mean is commonly used among practitioners, it has been found to overestimate values due to the distortive effect of outliers (Damodaran, 2006; Herrmann and Richter, 2003). Consequently, most empirical studies favor the median value, as it is better suited to mitigate the effects of outliers and distributional skewness, finding that “[t]he median value is much more representative of the typical firm in the group, and any comparisons should be made to medians” (Damodaran, 2006, p. 241).

In the fourth and final step, the estimated valuation of the target company is computed. For enterprise value multiples, the estimated total enterprise value $\widehat{EV}_{i,t}$ for company i is calculated by multiplying the value driver $VD_{i,t}$ of company i by the corresponding synthetic peer group valuation $SM_{c,t}$. In Equation 1, $t$ denotes time, indicating that both the synthetic peer group valuation multiple and the value driver must reference the same point in time.

$$\widehat{EV}_{i,t} = VD_{i,t} \times SM_{c,t} \qquad \text{Eq. 1}$$

### 2.1.4 Multiples

Multiples are commonly categorized by the type of value driver used, which often varies across industries. Some of the most common groups of multiples include accrual flow multiples, book value multiples, forward-looking multiples, and cash flow multiples (Schreiner, 2007).

Sales-based multiples belong to the family of accrual flow multiples and are diligently used to compare a company’s value to its sales, with firm value measured as either equity value or enterprise value. Such multiples are particularly useful when traditional profitability-based metrics may not be applicable, such as with companies that have not yet achieved profitability. However, this is also one of their disadvantages, namely that they do not account for the profitability of a company, merely focusing on sales, which might not give the full picture of a company's financial health (Vruwink et al. 2011). Moreover, the ratio can vary significantly across different industries, making these multiples less reliable for cross-industry comparisons, as sales cycles and margins can differ widely (Nathan et al. 2001). For instance, it would be difficult to find a common multiple value for an industry with low profit margins such as the airline industry and one with high margins such as SaaS. While it may be difficult to compare different industries using the multiple, it is useful in comparing companies within the same industry or sector to gauge relative valuation levels (William et al. 1996).

In contrast, when comparing firms across industries, earnings-based multiples such as EV/EBITDA or P/E are commonly used (Nathan et al. 2001). These multiples compare a company's value to its earnings, offering a strong measure of a company's overall financial performance. There are advantages and disadvantages with both EV/EBITDA and P/E. One of the main advantages of the EV/EBITDA ratio is that it allows for better comparability across industries by eliminating the effects of different capital structures, tax rates, and depreciation policies (Zaremba & Szczygielski, 2019). However, the ratios do not account for capital expenditures, which can be significant, especially in capital-intensive industries (Bouwens et al. 2019). Further, unlike net income in the P/E ratio, EBITDA is less susceptible to manipulation through accounting policies and practices, providing a clearer picture of the operational efficiency of a company (Block, 2010).

Multiples can also be grouped based on their context-specificity, comparing general multiples and industry-specific multiples. Damodaran (2006) discusses two risks of using industry-specific multiples. First, since they are specific to the industry and cannot be applied to other sectors of the economy, there is a risk of under- or overvaluation of the industry relative to the market. Second, industry-specific multiples are less related to fundamentals, creating the risk of misinterpreting its financial ramifications. While the latter of the two risks may be applicable to situations in which non-financial value drivers are used, such as web traffic or number of customers, it is largely mitigated when employing industry-specific financial metrics (Liu et al. 2002).Therefore, the industry-specific EV/ARR is often used to value companies with subscription-based revenue models, most commonly in the SaaS industry (Japaridze, 2023). Annual recurring revenue serves as a modified revenue metric and has a clear connection to core business activities of SaaS firms. It could be argued that the fundamental importance of ARR is superior to that of revenue, considering that it removes such revenues that are not part of the company's core business model (Haley, 2018). The difference between ARR and sales metrics constitute non-recurring revenues, which should not be significant value drivers of SaaS firms considering that their business models revolve around subscriptions (Haley, 2018). With respect to the former risk, the ungeneralizable nature of industry-specific multiples would only constitute an issue if used to compare aggregated values of companies with that of other industries. The risk of distorting values on a market-level is inconsequential for industry-focused research.

### 2.1.5 Empirical Research

The literature on relative valuation and the determinants of enterprise value is extensive. Liu et al. (2002) make influential contributions through their study of approximately 20,000 observations from 1982 to 1999. They report that forward-looking multiples outperform other types of multiples in terms of relative performance. Specifically, they find that the two-year-ahead P/E ratio estimates values within 20 percent of actual values for approximately 60 percent of observations. Lie and Lie (2002) examine the relative accuracy of 10 commonly used valuation multiples using a sample of 8,621 companies. They find that the asset-based multiple (price-to-book value) yields less biased estimates compared to sales and earnings multiples. Furthermore, they observe that using EBITDA instead of EBIT improves valuation accuracy, except for companies in the pharmaceutical industry.

Schreiner (2007) presents a comprehensive study on the role of multiples in equity valuation. By investigating 497 U.S. companies and 592 European companies from 1996 to 2005, he demonstrates that multiples are reasonably accurate in approximating market values, thereby supporting the use of relative valuation. Two of his key findings are that forward-looking multiples generally outperform trailing multiples and that knowledge-related multiples, which include value drivers such as research and development, outperform traditional multiples in science-based industries. For the P/E multiple, he reports a median absolute error of 20.5 percent. Building on Schreiner's (2007) research, Larsson (2015) studies the valuation accuracy of three different equity value multiples for real estate and pharmaceutical companies. For real estate companies, the P/B multiple outperforms both the P/E and P/S multiples. He further reports that relative valuation performs better as a valuation model for the real estate industry compared to the pharmaceutical industry.

Studies by Berkman et al. (2000) and Kaplan and Ruback (1995) provide valuable insights into the relative accuracy of various valuation methods. Berkman et al. (2000) compares valuation estimates derived from traditional discounted cash flow models with those from price-to-earnings multiples. From their sample of 45 newly listed New Zealand companies, they find that the accuracy of each model is highly comparable. The best performing DCF model reports a median absolute valuation error of 20.1 percent, and the best performing P/E model reported a similar error of 19.7 percent. Kaplan and Ruback (1995) studies valuations within special situations, investigating the accuracy of various valuation methods within the context of highly leveraged transactions. Using a sample of 51 observations from 1983 to 1989, they report that both the DCF and relative valuation models are effective, with the relative valuation method showing that 37-58 percent of the valuations fell within 15 percent of actual transaction values when using the EV/EBITDA multiple.

Much of the literature on relative valuation has focused on the pricing of initial public offerings (IPOs). Since companies are valued as unlisted entities during the IPO process, this context provides interesting insights. Kim and Ritter (1999) examine the impact of comparable firm multiples on IPO valuations. Analyzing a sample of 190 IPOs from the years 1992 to 1993, they report a median absolute prediction error for the P/E ratio of 55.9 percent and find that valuation multiples based on forecasted one-year-ahead earnings are the most accurate. Aggarwal et al. (2009) extends this research by examining IPO valuations over three distinct time periods using a sample of 1,655 IPOs. They observe that non-profitable firms going public often receive higher valuations than those with positive earnings, suggesting that high growth prospects can distort earnings-based metrics such as P/E ratios. Bartov et al. (2002) further explores the differences in valuation fundamentals between internet and non-internet firms.

They find that for internet firms, earnings are not priced while negative cash flows are considered, indicating a significant deviation from traditional valuation practices.
Keun Yoo's research from 2006 analyzes a sample of 5,471 firms from 1981 to 1999 to investigate the efficacy of combining multiples. He finds that combining historical multiples improves the valuation accuracy compared to using single multiples alone. However, combining historical multiples with forward-looking metrics does not enhance valuation accuracy, suggesting that forward-looking multiples already encapsulate much of the information contained in historical metrics, and additional combinations do not provide incremental improvements.

## 2.2 Resource-Based View

Explaining competitive advantage has long been a topic of interest for researchers in the field of strategy. With the introduction of the resource-based view (RBV) of the firm, the focus shifted from external factors such as industry to internal factors, including resources and capabilities (Barney et al. 2021). Wernerfelt (1984) introduces the RBV and argues that to understand the competitive advantage of a firm, its resources and capabilities must be examined. He defines a resource as "anything which could be thought of as a strength or weakness of a given firm" (Wernerfelt, 1984, p. 172). Examples of resources include brand name, machinery, and personnel. Capabilities, on the other hand, are defined as "complex bundles of skills and accumulated knowledge, exercised through organizational processes, that enable firms to coordinate activities and make use of their assets" (Day, 1994, p. 38). Examples of capabilities include development expertise, customer support, and manufacturing capabilities. The RBV has a large focus on resources and capabilities, henceforth they will occasionally be jointly referred to as "RC".

Barney (1991) brings up the essential point that key resources and capabilities vary across industries. Because of this, understanding which RCs are key in certain industries can help understand their distinctions better. One paper examining the construction industry in Malaysia found that key resources and capabilities in that industry are largely tied to managerial skills (Jaafar & Abdul-Aziz, 2005). In contrast, another study, examining industries where product development is a major competitive factor, underscores other specific RCs as the most important value drivers. This research instead finds that capabilities such as innovation and integrating customer feedback are vital for long-term success (Verona, 1999). The key takeaway from this comparison is that value drivers tend to differ across industries.

Brandenburger and Stuart (1996) amend the RBV by introducing the value-based business strategy in which they suggest that firms can only appropriate as much value as they create. This suggests that for a company to be valuable, it must successfully add value to its customers. SaaS firms have an especially high need to consistently add value to their customers because of the subscription-based business model which gives the customers enhanced bargaining power (cf. Japaridze, 2023). The share of value that the company retains from its contributed value is determined by their relative bargaining power (Brandenburger & Stuart, 1996). Teece (2010) builds upon this and argues that creating and capturing value is not sufficient. He stresses that it is crucial that the firm can adapt in response to changing demands, technological advancements, and competitive pressures to maintain its advantage. Furthermore, the industries in which this is especially important are those largely dependent on technology and customer-centric business models, such as the SaaS industry.

### 2.2.1 Dynamic Capabilities View

The dynamic capabilities view (DCV) was introduced as an extension of the RBV with a focus on organizational agility and adaptation (Teece et al. 1997). Dynamic capabilities are described as a firm's "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al. 1997, p. 516). This theory addresses today's volatile and dynamic business environment and suggests that the best way to sustain competitive advantage is by developing dynamic capabilities.

To determine whether the dynamic capabilities view, or the more traditional resource-based view is more accurate in explaining the competitive advantage of firms, research was conducted on Taiwanese firms (Wu, 2010). He finds that the explanatory power of the two frameworks differ depending on the volatility of the industry in which they operate. The more volatile the industry, the more important dynamic capabilities are in explaining the competitive advantage. This suggests that when analyzing the competitive advantages in volatile industries, the DCV is superior to the RBV.

Another insightful study was conducted on the e-business industry, specifically to investigate the importance of dynamic capabilities (Daniel & Wilson, 2003). The research finds that e-businesses, that is companies whose operations are centered around the Internet, can no longer rely solely on their valuable resources but must also develop dynamic capabilities. They discover eight specific dynamic capabilities that are key for e-businesses, all of which are tied to either innovation or integration. The notion that dynamic capabilities are becoming increasingly important is strengthened by another empirical study, consisting of 120 internet-based companies (Liao et al. 2009). This study focused on innovation as a dynamic capability and finds that it is highly correlated to success.

While dynamic capabilities are becoming increasingly important for explaining value creation and competitive advantage of firms, especially internet firms, a new problem emerges. Pavlou and Sawy (2011) highlight the difficulty in measuring dynamic capabilities. This indicates that firms relying on dynamic capabilities to create economic value, such as internet firms, are difficult to assess in terms of valuation. Most previous research surrounding company valuation has been conducted on traditional firms, whose competitive advantage and economic value is better explained by the RBV (Wu, 2010). Since economic value in more volatile environments is better explained by the DCV than the RBV, this suggests that there is a research gap in valuing these volatile industries.

SaaS firms are a form of internet companies that are largely dependent on dynamic capabilities to keep their competitive advantage (Liao et al. 2009). This implies that the long-term value of SaaS firms is highly dependent on their ability to quickly adapt to the changing environment.

Moreover, since dynamic capabilities are difficult to measure, SaaS firms should be more difficult to value than traditional firms using traditional measures (cf. Pavlou & Sawy, 2011).

## 2.3 Efficient Market Hypothesis

The efficient market hypothesis (EMH), outlined by Euguene Fama (1970), posits that securities are priced accurately and fully reflect all available information at any given point in time. Moreover, there are three different forms of market efficiency based on the extent to which information is available to investors: weak, semi-strong and strong form. Weak form suggests that all historical pricing information is reflected in the securities' current prices, implying that past prices are insufficient in predicting future prices. Semi-strong form expands further and suggests that all public information is quickly incorporated and fully reflected in security pricing, and it is therefore impossible to earn abnormal profits through trading. Lastly, strong form implies that in addition to the prior, private information is also fully reflected in the price, hence, it is impossible to make abnormal profits through information of any kind. Fama (1970) concludes that with very few expectations, empirical evidence suggests that markets show weak and semi-strong form, while evidence for strong form is more limited.

In contrast, Malkiel (2003) reviews various statistical findings and behavioral explanations that suggest market predictability and inefficiency. He also discusses the role of "noise traders", the impact of psychological factors on trading, and the instances where markets seem to deviate from the predictions of the EMH. However, Malkiel states that many identified patterns do not provide reliable investment strategies that outperform the market once fees and risks are considered. Further, Bowman and Buchanan (1995) argue that individuals systematically underestimate the efficiency of markets which can be attributed to both market structure reasons and behavioral reasons. They discuss how the organization behind and regulation of markets as well as the nature of market participants and the flow of information can influence perceptions of market efficiency and accentuate bias. In addition, Marwala and Hurwitz (2017) propose that the implementation of AI in financial markets results in markets becoming increasingly efficient.

The EMH constitute an important basis for relative valuation, as it involves appraising the market's perception of a company's value. If market values of peers are priced inefficiently, the estimated value of the target company will be unreliable. However, the value of an asset is generally considered to equal the price someone is willing to pay for it. Therefore, it could be argued that understanding what the market is willing to pay for a financial asset is of importance regardless of whether the valuation is fundamentally accurate. Hence, relative valuation provides a good measure for company valuation (Larsen et al. 2012).

## 2.4 Hypotheses

Given the distinct characteristics of SaaS businesses, where annual recurring revenue is a critical metric reflecting stable and predictable cash flows (Danielson & Press, 2003), EV/ARR should better capture the ongoing value of these businesses compared to traditional EV/SALES metrics, which do not distinguish between recurring and non-recurring revenue. Sales can fluctuate significantly due to one-time charges and discounts, which can distort valuations (Nenkov, 2018). In contrast, ARR provides a smoother and more consistent basis for valuation by focusing solely on the recurring aspects of revenue, thereby reducing the impact of such volatility, and offering a more stable valuation metric. The predictability of ARR is highly valued, particularly in the volatile tech sector, as it provides a clear forecast of future cash flows (Cusumano, 2004). The ARR metric is tailor-made for subscription businesses like SaaS, where customer retention and lifetime value are more indicative of company performance than one-time sales (Dempsey & Kelliher, 2017).

Additionally, for unlisted and growth-oriented SaaS companies, profitability metrics such as EBITDA may not fully reflect the company's future potential since these companies often incur significant upfront costs (Ge et al. 2017). These costs can depress EBITDA in the short term while the company is still expanding (Markman & Gartner, 2002). The focus on ARR is particularly appropriate in industries like SaaS, where the business model is built around digital products and services that have relatively low marginal costs once developed (Dempsey & Kelliher, 2017). Furthermore, EV/ARR shares similar characteristics with forward-looking multiple which have proven to be more accurate in previous empirical research (Keun Yoo, 2006; Liu et al. 2002; Schreiner, 2007). Thus, the following hypotheses are formulated:

> H1: *The EV/ARR multiple provides a more accurate valuation of unlisted Nordic SaaS companies than the EV/SALES multiple.*

> H2: *The EV/ARR multiple provides a more accurate valuation of unlisted Nordic SaaS companies than the EV/EBITDA multiple.*

The median is known for its reduced sensitivity to extreme values, or outliers, within data sets. This is particularly important in the valuation of companies where a few outliers can significantly skew the results when using the arithmetic mean. In the context of unlisted SaaS companies, where the range of company sizes, growth rates, and profitability are broad (Benlian et al. 2009), using the median as the measure of central tendency can provide a more accurate reflection of the typical valuation multiple compared to using the arithmetic mean. Research supports the theoretical argument favoring the median, finding that valuations derived from peer group multiples estimated using the median are more accurate than those derived from multiples estimated based on the arithmetic mean (Baker & Ruback, 1999; Herrmann & Richter, 2003). Thus, the following hypothesis is formulated:

> H3: *Using median as the measure of central tendency for calculating multiples will yield superior performance of the valuation relative to that of using the arithmetic mean.*

As discussed above, SaaS companies are a special form of internet-companies that rely greatly on dynamic capabilities to create competitive advantage (Liao et al. 2009). Since dynamic capabilities are difficult to measure, this would indicate that it is challenging to assess the competitive advantages of SaaS firms and hence difficult to value them accurately (cf. Pavlou & Sawy, 2011). Because of the difficulty in assessing the competitive advantage of SaaS firms as well as the large share of intangible assets present (Sullivan, 2000), the fourth hypothesis is as follows:

> H4: *Valuation multiples have less explanatory power for SaaS companies than for traditional firms.*

# 3 Methodology

This chapter provides a comprehensive overview of the theoretical frameworks and methodological decisions implemented throughout this study. It starts with an outline of the research approach and design, establishing a foundational structure for examining the research question and enabling informed conclusions. Following this, it details the four-step valuation process, sample selection as well as the data collection of financial information. This is followed by a section where validity and reliability are addressed as well as limitations with the methodology.

## 3.1 Research Approach

The research approach aims to close the gap between theoretical frameworks and empirical study, as outlined by Bell et al. (2019). The subsequent section explores key elements within this framework, and based on the central research question, it explains and justifies the selection of a deductive approach for the study, along with the ontological and epistemological considerations involved.

Bell et al. (2019) establishes that both deductive and inductive approaches are fundamental in business research. These approaches are essentially the opposite of one another. Specifically, the deductive method involves examining existing theoretical frameworks about a phenomenon, formulating a hypothesis, and then empirically testing this hypothesis. This process implies that theory and hypothesis guide the data collection. Conversely, the inductive method starts with data collection, from which a theoretical proposition is then developed. According to Bell et al. (2019), it is common for elements of the inductive approach to appear in deductive research and vice versa.

The aim of this thesis is to investigate the efficacy of industry-specific and traditional multiples in valuing SaaS companies. This investigation is conducted utilizing statistical analysis of various multiples, focusing on exploring what distinguishes industry-specific from traditional valuation multiples in this sector. Given the nature of the research and the pre-existing theoretical frameworks relevant to company valuations, a deductive approach is deemed most suitable. This approach allows for hypotheses to be formulated based on established valuation theories, despite some deviations in existing literature regarding the applicability of said multiples. As highlighted in the literature review, while traditional multiples are widely recognized and utilized, their effectiveness compared to industry-specific multiples in valuing SaaS companies remains underexplored. Bell et al. (2019) suggest that a deductive approach may face challenges related to the selection and testing of theories. However, this concern is mitigated by the strong theoretical foundation presented in the literature review, which substantiates the use of both traditional and industry-specific multiples in the analysis. The alternative, being an inductive approach, would involve developing new theories based on observed data, which does not align with the objectives in this study. Thus, the decision to adopt a deductive method, grounded in established valuation frameworks, ensures a focused investigation into how these multiples perform in the valuation of unlisted Nordic SaaS companies, addressing the gap identified in current research.

In addition, Bell et al. (2019) propose that epistemological and ontological considerations must be defined in regard to research approach. For ontological considerations, constructionism is adopted as it aligns with the examination of how valuation methodologies may vary depending on the specific characteristics and industry context. This approach aligns with the notion that valuation practices are not universally fixed but rather shaped by the perceptions and insights of the evaluators, similar to the constructivist views described by Bell et al. (2019). The study is rooted in understanding how practitioners tend to perceive and apply relative valuation in the SaaS industry. This stance contrasts with an objectivist approach that would treat valuations as detached and uniform regardless of their context. The variability and subjectivity in applying these multiples, as seen in the findings, support the relevance of a constructionist approach, emphasizing the role of social actors in shaping valuation practices. (Bell et al. 2019).

Positivist approaches in the research are utilized to establish a clear, systematic framework for applying traditional and industry-specific valuation multiples. This aspect aligns with the positivist belief in observable, quantifiable data as a basis for drawing conclusions (Bell et al. 2019). Valuation multiples are treated as tools that, theoretically, should yield consistent results across different scenarios if the same conditions are met. The study employs statistical methods to analyze historical data and valuation outcomes, seeking patterns that can be generalized. Conversely, the study also incorporates interpretive methodologies, particularly when exploring the efficacy of industry-specific multiples. This approach is crucial because it acknowledges the subjective nature of valuation, which is influenced by rapid technological changes and varying business models that do not always align neatly with traditional valuation frameworks. The interpretative aspect is significant given the dynamic and innovative nature of the SaaS industry, where standard valuation models may not capture the unique value drivers of each company (cf. Bell et al. 2019).

## 3.2 Research Design

### 3.2.1 Quantitative Research

According to Bell et al. (2019), research can be conducted either quantitatively or qualitatively where the prior is employed in this particular study. The focus and outline of the different research methods differ from each other. The distinctions between the two may at times be unclear but quantitative research uses measurement and quantification while qualitative does not. The two research methods can be better understood by looking at their general orientation. Qualitative research puts an emphasis on the generation of theories with an inductive approach to the relationship between theory and research. It usually entails words and images rather than quantification. In quantitative research on the other hand, as the name suggests, there is an emphasis on quantification in the collection of data. The main goal of quantitative research is to test theories, as opposed to generate them, in line with the research objectives.

Bell et al. (2019) further describe that a distinction is made between the two research methods in how they view social reality. Social reality can be understood as “the part of reality that covers groups of agents and the social relationships therein, actions that are either collective or directed towards a social group, and the whole range of relevant resulting 'social entities', such as contracts or companies" (Borgo & Vieu, 2009, p.274). Quantitative research views social reality as an objective and external reality. Qualitative research on the other hand views social reality as constantly shifting. This is also the main critique of quantitative research from qualitative researchers, whereby they mean that the social world cannot be understood from a static point of view.

Quantitative research is characterized by having some central preoccupations, including measurement, causality, generalization, and replication. This type of research takes the point of view of the researcher and the researcher takes a distant position. In qualitative research on the other hand, the point of view is of the perspective of those being studied and the researcher takes an active role in the research in the sense that they seek close involvement with the studied people to get a genuine understanding (Bell et al. 2019).

### 3.2.2 Cross-sectional Research

To explain the relationship between the variables, cross-sectional research is conducted, utilizing secondary data. Cross-sectional research is a type of observational study where the outcome and the exposures are investigated simultaneously. The data for this research is collected at one point in time, making it cross-sectional as opposed to a longitudinal study, where data is collected repeatedly over a time period (Bell et al. 2019). To ensure that the dataset is robust enough to draw conclusions, samples are collected from observations over a five-year period, ranging from year 2020 to 2024[1]. The variables, however, are not examined over a time period and the changes are not investigated, instead multiple years are used to expand the sample size. The choice of conducting a cross-sectional study as opposed to a longitudinal study is largely due to the time and resource constraints of this research. Moreover, the research objectives are aligned with how variables change over time, but rather how the variables are linked to one another. The examination of relationships between variables therefore favors a cross-sectional study (Bell et al. 2019).

## 3.3 Data Collection

### 3.3.1 The Four-Step Valuation Process

For the relative valuation methodology, this study applies a four-step model similar to that used in previous research (Damodaran, 2006; Larsson, 2015; Schreiner, 2007). The four steps are as follows:

1. Determination of appropriate value measures
2. Construction of peer groups
3. Creation of synthetic peer group multiples
4. Application of synthetic multiples and valuation

**Step 1: Determination of appropriate value measures**

[1] For the year 2024, only the period between 1 January 2024 and 1 April 2024 was included in the study.

Determining which multiples to use in the valuation model necessitates the selections of appropriate value driver and a suitable price variable for each value driver. Commonly used value drivers encompass cash flow, earnings, sales, and other financial categories (Schreiner, 2007). In the selection of value drivers, emphasis is placed on the value relevance of the metric, i.e. the extent to which it contributes to value creation for the company's owners. A key metric in valuation of Software-as-a-Service companies is annual recurring revenue, which represents the total revenue generated through a subscription-based model over a 12-month period (Lamprecht et al. 2022). Compared to the traditional sales metric, ARR offers a more comprehensive and conclusive depiction of a company's financial health and growth prospects, enhancing its value relevance (Danielson & Press, 2003). Despite theoretical support for ARR as a value driver, empirical research predominately emphasizes total sales. This study uses both total sales and annual recurring revenue, facilitating insights into their explanatory power relative each other. In addition to sales multiples, earnings-based multiples are commonly used in both empirical studies and by practitioners (Bancel & Mittoo, 2014; Damodaran, 2006). In this study, earnings before interest, taxes, depreciation, and amortization serves as the earnings-related value driver. Unlike net income, EBITDA is (1) indifferent to variances in capital structure, enabling comparisons with sales multiples, (2) unaffected by the distorting effects of depreciation and amortization, and (3) more reflective of a business' core operations (Bouwens et al. 2019; Lie & Lie, 2002; Zaremba & Szczygielski, 2019).

Furthermore, total enterprise value, rather than equity value, is employed for all three multiples, as each value drivers reflect an investment base comprising both debt and equity. EV is calculated as the sum of the market value of equity and interest-bearing debt less cash. The multiples used in the study are computed according to Equations 2 through 4, with total enterprise value in the numerator and the value driver in the denominator.

$$\frac{EV}{ARR} \tag{Eq. 2}$$

$$\frac{EV}{SALES} \tag{Eq. 3}$$

$$\frac{EV}{EBITDA} \tag{Eq. 4}$$

**Step 2: Construction of Peer Groups**

To establish valuation estimates for companies using relative valuation, identifying comparable companies similar to the target company is essential. Following Cheng and McNamara (2000), peers were selected using a combination of industry classification and financial profiles. Since all transactions investigated in the study fall within the Software-as-a-Service industry, all peers are also active within SaaS, thereby satisfying the need for peers and target companies to operate in the same industry. Companies within the SaaS industry share distinct characteristics not found in companies operating in other industries. SaaS companies predominantly employ subscription-based revenue models, characterized by longer customer life cycles compared to traditional businesses (Japaridze, 2023). While categorizing companies within sub-industries may be logical in certain contexts, it is less applicable in the SaaS industry for two main reasons. First, sub-industries within SaaS are often ambiguous and difficult to define, with many companies operating in unique niches of the industry. Second, SaaS companies collectively face industry-wide risks and financial outlooks, suggesting that further segmentation would have inconsequential impact. The SaaS industry itself is very specific, constituting a segment of the cloud computing industry, which in turn is a component of the broader IT sector (Basit & Henry, 2024).

With all peers meeting the industry requirement, peers were grouped based on financial characteristics. Hence, it is possible to control for variations in variables that could influence valuations, including profitability, growth, industry, corporate maturity, and wider macroeconomic conditions, similar to that of a control variable. The transactions analyzed in the study included several companies with negative profitability. Using negative metrics from peers for estimating the value of a profitable company, or vice versa, produce meaningless results (Schreiner, 2007). Furthermore, empirical research shows that profitability plays a crucial role in valuation and must be considered (Novy-Marx, 2013). Consequently, the first financial categorization involved separating profitable peers from those with negative earnings. Within these two groups, peers were further divided based on growth rate, with the division set at a 20 percent year-over-year revenue growth rate. The resulting four peer groups (PG1, PG2, PG3, and PG4) are presented below.

| | **Growth ≥ 20%** | **Growth < 20%** |
|---|---|---|
| **EBITDA ≥ 0** | PG1 | PG2 |
| **EBITDA < 0** | PG3 | PG4 |

Investors place strong emphasis on growth rate and profit margin when assessing the financial health of a SaaS company. This emphasis is demonstrated by the widely adopted “rule of 40”, illustrated in Equation 5. The rule of 40 posits that SaaS companies are especially attractive if the sum of their growth rate and profit margin equals or exceeds 40 percent (Roche & Tandom, 2021). The rationale behind this metric is that it allows for intra-industry comparisons without the need for adjusting for differences in size. Depending on the stage of a company, the proportion of growth rate versus profit margin tends to vary, with profitability gaining importance as the company matures. Consequently, plotting growth rate against profitability should form an S-curve, illustrating the maturity of the firm (Roche & Tandom, 2021). Thus, grouping peers based on growth rate and profitability aligns with the principles underpinning the rule of 40.

$$Rule\ of\ 40: Growth\ rate + Profit\ margin\ \geq 40\% \qquad \text{Eq. 5}$$

**Step 3: Creation of Synthetic Peer Group Multiples**

Following the computation of multiples for all comparable companies, these multiples are aggregated to create synthetic multiples for each target company. Statistics provide several methods for summarizing many values with a single value, also known as measures of central tendency. The two most commonly used measures of central tendency for valuation purposes are the arithmetic mean and the median (Schreiner, 2007). Given their methodological differences, the choice of measure can significantly influence the results. Practitioners tend to prefer averages, such as the geometric mean and arithmetic mean, when deriving valuation multiples (Plenborg & Pimentel, 2016). However, previous research suggests that the median yields superior results due to its reduced sensitivity to outliers (Damodaran, 2006; Schreiner, 2007).

To evaluate the relative accuracy of both measures, this study employs two models that differ in their derivation of synthetic peer group multiples. Model 1 calculates the synthetic multiples by taking the arithmetic mean of all values within each target company's peer group, while Model 2 uses the median value. In Model 1, multiples for peers are aggregate into a synthetic peer group multiple $SM_{c,mean}$ using the arithmetic mean of the multiples $M_1$, $M_2$, ..., $M_n$ of all firms $j$ = 1, 2, ..., $n$ of the peer group $c$.

$$SM_{c,mean} = \frac{1}{n} \times \sum_{j}^{n} M_j \qquad \text{Eq. 6}$$

Given the potential for skewed distributions of peers' multiples, using the arithmetic mean can lead to overestimated values (Schreiner, 2007). To address this potential issue, Model 2 uses the median as the measure of central tendency in calculating synthetic multiples, thereby mitigating the distortive effects of outliers. The median represents the value that divides an ordered list of multiples into two equal halves. When sorting all multiples from smallest to largest, the median is the middle value. Depending on data availability and financial profile of the target company, the number of comparable companies varies across peer groups, but each consists of at least four observations, as recommended by Schreiner (2007). The calculation of synthetic multiples in Model 2 therefore differs slightly depending on whether there is an even or odd number of observations. In Model 2, the synthetic peer group multiple $SM_{c,median}$ is found by creating a size-dependent list of multiples $M_1$, $M_2$, ..., $M_n$ of all comparable firms $j$ = 1, 2, ..., $n$ of the peer group $c$ and applying the following formula:

$$SM_{c,median} = \begin{cases} M_{(n+1)/2} & if\ n\ is\ odd \\ \frac{1}{2} \times \left( M_{n/2} + M_{\frac{n}{2}+1} \right) & if\ n\ is\ even \end{cases} \qquad \text{Eq. 7}$$

Following the methodologies of Kim and Ritter (1999), Larsson (2015), Lie and Lie (2002), and Schreiner (2007), Model 2 allows for comparative inferences to be drawn both regarding the predictive power of multiples within the study, and in comparison, to the results of previous research.

**Step 4: Application of Synthetic Multiples and Valuation**
The final step in the valuation process involves applying the synthetic multiples from the two models to the associated value drivers of the target companies. The valuation estimates are derived following Equation 1. Utilizing two models and three valuation multiples results in each target company receiving six distinct estimated enterprise values.

| | ARR | EBITDA | SALES |
|---|---|---|---|
| **Model 1** | $EV^1$ | $EV^2$ | $EV^3$ |
| **Model 2** | $EV^4$ | $EV^5$ | $EV^6$ |

To evaluate the accuracy and predictive power of each valuation multiple, the estimated valuations are compared to the actual valuations observed in the transactions. The study includes two types of transactions: mergers and acquisitions (M&A) and private placements. In M&A transactions, target companies are acquired in their entirety, with the total consideration equaling the implied equity value. The total enterprise value is calculated by adding all interest-bearing debt and subtracting cash.

In private placements, or non-public offerings, only a partial ownership stake in the target company is acquired. Therefore, calculating the equity value is a prerequisite for determining the total enterprise value. The equity value of a target company in share issues can be either the pre- or post-money valuation. For consistency with M&A transactions, the pre-money valuation is used, reflecting the company's value before receiving funds from the capital raise. The pre-money valuation $PMV_{i,t}$ of company $i$ is calculated by multiplying the number of shares after the transaction $SA_{i,t}$ by the price per share $SP_{i,t}$, then subtracting the product of the number of shares issued $SI_{i,t}$ and the price per share. The total enterprise value for private placement transactions is then determined using the same method as for M&A transactions.

$$PMV_{i,t} = SA_{i,t} \times SP_{i,t} - SI_{i,t} \times SP_{i,t} \qquad \text{Eq. 8}$$

Valuation errors, or prediction errors, representing the deviation of the estimated EV from the actual EV used in a transaction, are used to compare the predictive power of the estimates. Using unadjusted differences between valuations can lead to inaccurate results considering that valuation errors are unlikely independent of the value, meaning that larger valuations will yield greater valuation errors. Following Kaplan and Ruback (1995), Kim and Ritter (1999), and Lie and Lie (2002), the valuation error $e_{i,t}$ for observation $i$ is calculated as the natural logarithm $ln$ of the ratio of the estimated value $\widehat{EV}_{i,t}$ to the actual value $EV_{i,t}$.

$$e_{i,t} = ln(\widehat{EV}_{i,t} - EV_{i,t}) \quad \text{Eq. 9}$$

The valuation error then becomes the fractional deviation of estimated values from actual values, where an error of zero implies no deviation. The key performance measures used are the mean and median absolute valuation error and the fraction of absolute valuation errors for multiples falling below 15 and 25 percent of observed actual values. By comparing the fraction of valuation errors falling within certain percentages from actual values associated with EV/ARR to those of EV/SALES and EV/EBITDA, conclusions can be drawn regarding the multiple's relative accuracy. Analyzing the mean and median absolute errors of Model 1 and Model 2 allows for identification of difference in accuracy between the models. By comparing the results of the study with those of previous studies, the overall applicability of relative valuation within Software-as-a-Service is determined. Metrics from Model 1 are compared with the results from Model 2 to evaluate the third hypothesis. To maintain consistency with previous research (Kim & Ritter, 1999; Larsson, 2015; Lie & Lie, 2002; Schreiner, 2007), only the results from Model 2 are used for hypotheses 1, 2, and 4.

To conclude whether differences between results are statistically significant, Z-tests are conducted to assess the difference in proportions of absolute valuation errors below certain thresholds. Z-tests consider both the number of observations of interest and the total sample size and are performed using the Microsoft Excel extension PHStat.

### 3.3.2 Sample Selection

In order to select the sample, the key criterion for including a company in our study was the availability of reliable ARR data. This criterion is essential as ARR is a significant indicator of performance and financial health in SaaS businesses, reflecting predictable and recurring revenue streams from customer subscriptions. The final sample comprise all Nordic unlisted SaaS companies for which we could verify and access ARR data.

In the sample collection process, Capital IQ was used to render a list of all M&A and private placement transactions for software companies between the years 2020 and 2024. This list consisted of 1,785 transactions. From that data set, 1,539 companies were removed since valuation information was not available for those transactions. From the 246 remaining transactions, 34 were removed because they involved listed firms. Out of the remaining 212 software companies, not all were classified as SaaS firms; each company was investigated individually to determine whether their business model was SaaS or another such as sales of on-premises software. This exclusion left the sample with 92 firms that all were using the SaaS business model and had undergone a transaction during the period. These SaaS companies were then investigated through annual reports and press releases to find their ARR. Out of the 92 SaaS companies identified, ARR was found for 66 of them, comprising the final sample used for data analysis.

Panel B of Table 1 presents descriptive statistics for 66 transactions from the 2020 to 2024 sample period. The median EV/ARR multiple using the predicted enterprise value is 6.2, the median EV/SALES multiple is 5.7, and the median EV/EBITDA is 8.6. The standard deviation of the EV/EBITDA multiple is significant (177), mainly due to outliers and a combination of large negative and positive values.

***Table 1.*** *Description of the Entire Sample*

***Panel A.*** *Sample selection criteria*

| | *N* |
|---|---|
| Nordic Software M&A and private placements | 1,785 |
| Exclusion of transactions when there is no information regarding implied valuations | 1,539 |
| Remaining | 246 |
| Exclusion of private placement transactions involving public companies | 34 |
| Remaining | 212 |
| Exclusion of non-SaaS transactions | 120 |
| Remaining | 92 |
| Exclusion of transactions when there is no information regarding ARR | 26 |
| Final sample | 66 |

***Panel B.*** *Descriptive statistics for the sample (n = 66)*

| | Mean | Minimum | Percentiles | | | Maximum | Standard deviation |
|---|---|---|---|---|---|---|---|
| | | | 25th | 50th | 75th | | |
| ARR (in MSEK) | 166.6 | 2.2 | 14.0 | 40.1 | 171.9 | 2,209.0 | 338.8 |
| Sales (in MSEK) | 197.7 | 2.9 | 17.2 | 51.0 | 234.3 | 2,556.0 | 394.4 |
| EBITDA (in MSEK) | 24.6 | -102.8 | -9.3 | 1.8 | 23.8 | 876.0 | 116.9 |
| Enterprise value (in MSEK) | 1,837.6 | 8.0 | 93.9 | 276.1 | 1,708.5 | 42,930.4 | 5,601.9 |
| EV/ARR | 9.6 | 2.2 | 4.0 | 6.2 | 10.4 | 88.7 | 12.7 |
| EV/SALES | 9.2 | 1.2 | 3.3 | 5.7 | 10.2 | 95.5 | 13.5 |
| EV/EBITDA | -9.3 | -1,047.9 | -24.1 | 8.6 | 35.4 | 594.4 | 177.0 |

The final sample of 66 transactions is unevenly distributed among the four peer groups from which comparable companies were selected. PG1, comprising transactions where the target companies exhibit both EBITDA-level profitability and a year-over-year growth rate exceeding 20 percent, is the smallest group with 5 observations. PG2, the largest group, contains more than half of the observations and includes companies that have grown at a rate below 20 percent but remain profitable, indicating business maturity.

| | **Growth ≥ 20%** | **Growth < 20%** |
|---|---|---|
| **EBITDA ≥ 0** | 5 | 34 |
| **EBITDA < 0** | 17 | 10 |

### 3.3.3 Collection of Valuation Multiples and Company Valuations

The collection of data was conducted through multiple sources, including the financial database Capital IQ, the Swedish Companies Registration Office, the financial database Valu8, corporate press releases, and various websites. This combination of sources facilitated the collection of both descriptive and numerical information pertaining to the observed transactions, thereby improving the validity and credibility of the thesis. Capital IQ, renowned for its rigorous quality control measures, is a widely recognized platform trusted by many financial institutions, including analyst firms, asset-management firms, and investment banks (Phillips, 2012). In instances where Capital IQ did not provide adequate data, the Trade and Industry Register from the Swedish Companies Registration Office, Valu8, and other sources were utilized. The Swedish Companies Registration Office, a government agency, is responsible for the registration of corporate information, thereby ensuring the accuracy of the data in accordance with legal requirements.

Data collection encompassed gathering all variables required for the paper, including both the implied valuations employed in transactions and the financial metrics used as value drivers. For all transactions, the latter entailed identifying and recording total sales, annual recurring revenue, and earnings before interest, tax, depreciation, and amortization for the year prior to the transaction. The requisite data for valuations varied depending on transaction type. In the case of M&A transactions, data pertaining to the total consideration paid, interest-bearing debt and cash were collected. Conversely, for private placement transactions, in addition to the balance sheet information, details on the share issuances, such as the total number of shares before and after, and share price, were collected. The final sample, consisting of 66 M&A and private placement SaaS transactions, was collected for specific points in time, holding true to the paper's cross-sectional method (Bell et al. 2019).

## 3.4 Validity and Reliability

Validity refers to whether a coded variable accurately captures the underlying theoretical concept (Bell et al. 2019). In this thesis, the challenges lie in accurately measuring the impact of the industry-specific multiple versus traditional valuation multiples on valuation accuracy. Validity is addressed using statistical analysis which is a widely recognized method in financial research and provides credible measures. While the potential differences between industry-specific and traditional multiples could be attributed to other factors, the methodology is designed to isolate the effects of these multiples through the application of peer groups. Peer groups are utilized with the ambition of controlling for variations in variables that could influence valuations, including profitability, growth, industry, corporate maturity, and wider macroeconomic conditions. By doing so, deviations in company valuations are primarily attributed to the multiple used. The research aims to determine the efficacy of each valuation multiple which ensures that the influence of external factors is minimized, and the primary variable of interest is effectively isolated.

Reliability, which refers to the consistency of a measurement, indicating that using an identical data collection process and analysis method will yield the same results when repeated under identical conditions, is of great importance (Bell et al. 2019). In this research paper, reliability is ensured using financial data from widely recognized sources such as Capital IQ, the Swedish Companies Registration Office, Valu8, and annual reports submitted by the companies themselves. These are used extensively within the area of financial analysis and supports the consistency of the data collected. Moreover, the selection process is largely standardized which ensures an objective response as opposed to less structured data collection methods such as surveys which could be subject to subjective bias. In addition, the statistical analysis is designed to be replicable. It has been based on established methodologies in previous empirical research within similar areas. The systematic approach to data collection and analysis ensures that the research is not only replicable but also minimizes bias, thereby strengthening the reliability of the results.

## 3.5 Limitations

The availability of ARR data posed limitations on the sample size. Some companies had to be excluded due to the lack of publicly accessible or reliable ARR figures. This somewhat restricts the sample size and potentially bias the result toward companies with more transparent reporting practices. However, valuing a company based on its ARR can only be done if they report ARR, which mitigates the problem in practice. Moreover, the selected sample represents a broad spectrum of Nordic SaaS companies with a wide array of financial profiles that have all reported ARR.

Another possible limitation of this research methodology is that it uses a cross-sectional study and does not consider how the multiples develop over time. A general critique against cross-sectional research is that the study might be misleading if the observations are not representative of current or future periods (Bell et al. 2019). However, this research is designed in a manner to minimize and perhaps even eliminate this issue. This is done by calculating the synthetic multiples from the peer groups in the exact point in time the transaction took place. Financial data from peer groups was collected for all transaction dates for which there were transactions associated with each peer. Since the study is conducted using relative valuation, the results are not affected by changes over time given that these changes affect the peers as well. Events that occurred during the period observed such as Covid-19, the war in Ukraine, and an economic downturn should therefore not affect the results since the results are merely relative among observations.

A third possible limitation of this study is the data reliability. Even though the data used in this study is taken from credible sources, the reliability of it should be questioned. The financials shown to the public may be somewhat modified to portray a more favorable picture of the company. This is, to larger extent, a problem when examining unlisted companies, as this study did because the reporting requirements and pressure from auditors is not as harsh as for listed companies. However, the probability that the financial reporting is faulty to such an extent across the entire sample that it affects the results is deemed low given the number of observations.

A final limitation of the study is the significant reliance on M&A transactions, mainly due to the limited availability of data for other transaction types. Therefore, most of the observations found in this study are based on mergers and acquisitions which could entail limitations. According to the theory of value creation, companies can unlock significant synergies by engaging in M&A activities, implying that the price acquirers are willing to pay can exceed that of non-strategic investors, namely a so-called premium. (Zhang, 2019).

# 4 Empirical Results

In the results section the findings from the data analysis are described and visualized. The results are then used to evaluate the previously stated hypotheses. Each proposition presented in the thesis is evaluated separately based on the results of the study and conclusions are drawn regarding whether the hypotheses are supported.

## 4.1 Data Analysis

Table 2 presents the statistical analysis of valuation errors across the entire sample. Mean and median statistics provide insight into the level of bias observed in the valuation estimates. Positive values indicate a tendency for actual values of the companies in the investigated transactions to fall below the values estimated using synthetic peer group multiples, while negative values indicated the opposite, with actual values exceeding estimated values. A value of zero signifies no bias, suggesting that valuation errors are evenly distributed without skewing towards either direction. A slight negative bias is observed across valuation multiples for both mean and median statistics. This implies that the estimated enterprise values are generally lower than the actual valuations used in transactions. All valuation multiples in Model 2 are negatively biased, while valuation errors Model 1 are slightly positively biased, signifying variations depending on the measure of central tendency used for calculation of peer group multiples. In the remainder of the analysis, emphasis will be placed on median as an indicator of bias, thereby mitigating the potential distortive influence of outliers and keeping consistency with previous research (Lie & Lie, 2002). The median absolute deviation statistics are smaller than the mean absolute deviation for five of the six multiples, indicating presence of outliers in valuation errors, influencing mean statistics. Comparing the results from Model 1 and Model 2, no constant superiority of either model is seen. EV/SALES and EV/EBITDA performs slightly better in Model 1, while EV/ARR has greater prediction power in Model 2.

Focusing on the results from Model 2, EV/ARR provides higher accuracy than both EV/SALES and EV/EBITDA. The EV/ARR multiple has the lowest median absolute error (0.284), meaning that the median value estimated using the multiple deviates from the actual values by approximately 28 percent. Conversely, the EV/EBITDA multiple stands out as the worst performer in terms of both median absolute error (1.084) and mean absolute error (1.276). EV/ARR yields a low median absolute deviation (0.189) compared with the corresponding statistics of EV/SALES (0.389) and EV/EBITDA (0.458), indicating more consistent and reliable valuation estimates from using EV/ARR.

***Table 2.*** *Valuation Errors for the Entire Sample*

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | EV/ ARR | EV/ SALES | EV/ EBITDA | EV/ ARR | EV/ SALES | EV/ EBITDA |
| Mean | 0.336 | -0.208 | 0.014 | -0.286 | -0.554 | -0.679 |
| Median | 0.311 | -0.174 | 0.061 | -0.131 | -0.370 | -0.642 |
| Mean Absolute Error | 0.813 | 0.648 | 1.046 | 0.517 | 0.783 | 1.276 |
| Median Absolute Error | 0.742 | 0.431 | 0.874 | 0.284 | 0.663 | 1.084 |
| Mean Absolute Deviation | 0.515 | 0.496 | 0.679 | 0.432 | 0.497 | 0.741 |
| Median Absolute Deviation | 0.644 | 0.312 | 0.589 | 0.189 | 0.389 | 0.458 |
| 25th percentile | -0.122 | -0.490 | -0.661 | -0.722 | -1.135 | -1.545 |
| 75th percentile | 1.172 | 0.257 | 1.086 | 0.134 | 0.004 | 0.350 |
| Number of observations | 66 | 66 | 66 | 66 | 66 | 66 |

The fraction of estimated values within various ranges from actual values for the different multiples are reported in Table 3. Fraction within a certain value refers to the fraction of absolute valuation errors that are lower than the corresponding threshold. Results from Model 1 are reported in Panel A and results from Model 2 in Panel B. Similar results to those presented in Table 2 can be seen regarding the relative valuation accuracy of the two models. The industry-specific EV/ARR performs better in Model 2 for all thresholds, with 30, 38, and 49 percent of absolute valuation errors falling below values of 15, 20, and 25 percent, respectively. However, as the performance measures show, the traditional multiples' group (EV/SALES and EV/EBITDA) demonstrate higher accuracy in Model 1. Because of the ambiguity and variations in performance, the third hypothesis is not accepted.

The empirical findings presented in Panel B of Table 3 provide strong support for the first two hypotheses. When comparing the accuracy of the EV/ARR multiple to that of the EV/EBITDA multiple, the differences in the fractions of absolute valuation errors below all three thresholds (15, 20, and 25 percent) are statistically significant at the 1 percent level. These findings support the second hypothesis, positing that the EV/ARR multiple is superior to the EV/EBITDA multiple in valuing SaaS companies. Similar conclusions can be drawn from the comparative analysis between the EV/ARR multiple and the EV/SALES multiple, with p-values remaining below 0.01 for thresholds of 20 and 25 percent. Even at the 15 percent threshold, the recognized discrepancy in proportions maintains statistical significance, albeit at the 5 percent level. These results show support for the first hypothesis, which contends that the EV/ARR multiple serves as a more reliable metric for estimating valuations within the SaaS industry compared to the EV/SALES multiple. Thus, the first two hypotheses are accepted.

***Table 3.*** *Relative Accuracy of Valuation Multiples*

| | Fraction within | | |
|---|---|---|---|
| | 15% | 20% | 25% |
| ***Panel A.*** *Prediction errors based on arithmetic means of peer groups (Model 1)* | | | |
| EV/ARR | 0.197 | 0.197 | 0.227 |
| EV/SALES | 0.197 | 0.227 | 0.333 |
| EV/EBITDA | 0.106 | 0.152 | 0.182 |
| ***Panel B.*** *Prediction errors based on medians of peer groups (Model 2)* | | | |
| EV/ARR | 0.303 | 0.379 | 0.485 |
| EV/SALES | 0.152** | 0.167*** | 0.197*** |
| EV/EBITDA | 0.091*** | 0.106*** | 0.136*** |

*Note*: */**/*** represent significance at the 10 percent/5 percent/1 percent level. The fraction of valuation errors whose absolute value is less than 15, 20, and 25 percent. A Z-test is conducted to ascertain the discrepancy in proportions, with p-values computed to compare the proportions of absolute valuation errors derived from EV/ARR below specified benchmark thresholds against those from EV/EBITDA and EV/SALES.

For added clarity, results are further categorized by separating the results from each of the four peer groups. The fractions of observations with absolute valuation errors below different thresholds for the peer groups are illustrated in Table 4. The results signify the proximity of the predicted values to actual values for each peer group. The predictive power of each multiple varies substantially across the peer groups. Using EV/ARR, 35 percent of estimated valuations for profitable, low growth companies (PG2) are found within 15 percent of actual valuations used in transactions. A significantly lower fraction is found in PG4, where only 10 percent of the absolute valuation errors is below 15 percent.

None of the absolute valuation errors for profitable, high-growth companies (PG1) using the EV/ARR multiple in Model 1 fall within the broadest threshold of 25 percent. While this group is significantly smaller than the other groups, consisting of only five transactions, the diminished relative accuracy suggest that predictive power can vary depending on financial characteristics of companies. Moreover, the comparison between the results of Model 1 and Model 2 reveals that Model 2 consistently offers better, or comparable prediction accuracy compared to Model 1. The best-performing statistics are highlighted in bold, indicating the most accurate financial metrics and calculation methods across the different settings. For instance, EV/ARR in Model 2 stands out for PG2, especially at higher accuracy thresholds, underscoring its effectiveness. However, unlike the aggregated results for the entire sample, EV/ARR is not superior across all peer groups uniformly.

***Table 4.*** *Valuation Accuracy for Each Peer Group*

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | EV/ ARR | EV/ SALES | EV/ EBITDA | EV/ ARR | EV/ SALES | EV/ EBITDA |
| ***Panel A.*** *Profitable, high growth companies (PG1)* | | | | | | |
| Fraction within 15% | 0.000 | 0.200 | 0.200 | 0.200 | 0.200 | **0.400** |
| Fraction within 20% | 0.000 | 0.200 | 0.200 | 0.400 | 0.200 | 0.400 |
| Fraction within 25% | 0.000 | 0.200 | 0.200 | 0.400 | 0.200 | 0.400 |
| Number of observations | 5 | 5 | 5 | 5 | 5 | 5 |
| ***Panel B.*** *Profitable, low growth companies (PG2)* | | | | | | |
| Fraction within 15% | 0.294 | 0.176 | 0.088 | **0.353** | 0.206 | 0.088 |
| Fraction within 20% | 0.294 | 0.235 | 0.147 | **0.471** | 0.206 | 0.118 |
| Fraction within 25% | 0.353 | 0.324 | 0.147 | **0.559** | 0.235 | 0.176 |
| Number of observations | 34 | 34 | 34 | 34 | 34 | 34 |
| ***Panel C.*** *Non-profitable, high growth companies (PG3)* | | | | | | |
| Fraction within 15% | 0.118 | 0.235 | 0.059 | **0.353** | 0.059 | 0.059 |
| Fraction within 20% | 0.118 | 0.235 | 0.059 | **0.353** | 0.118 | 0.059 |
| Fraction within 25% | 0.118 | 0.412 | 0.176 | 0.412 | 0.176 | 0.059 |
| Number of observations | 17 | 17 | 17 | 17 | 17 | 17 |
| ***Panel D.*** *Non-profitable, low growth companies (PG4)* | | | | | | |
| Fraction within 15% | 0.100 | 0.200 | 0.200 | 0.100 | 0.100 | 0.000 |
| Fraction within 20% | 0.100 | 0.200 | **0.300** | 0.100 | 0.100 | 0.000 |
| Fraction within 25% | 0.100 | 0.300 | 0.300 | **0.400** | 0.100 | 0.000 |
| Number of observations | 10 | 10 | 10 | 10 | 10 | 10 |

*Note*: The superior multiple in each peer group and fraction is marked in bold. If there is no superior multiple, meaning that two multiples showed the same accuracy, none is marked.

Figure 1 depicts the median and average valuation errors of Model 2, categorized by peer group and valuation multiple. Instead of presenting the errors in absolute terms, their actual values are displayed, facilitating assessment of the potential bias inherent in the multiples. For profitable companies with high growth (PG1), a definite positive bias is observed, demonstrating a tendency for overestimation of enterprise values relative to actual values. Conversely, valuation errors for non-profitable companies in PG3 and PG4 display a positive bias, suggesting that estimated valuations are generally lower than actual values. However, across the entire sample, valuation errors are evenly distributed without substantial bias toward either direction. These findings contribute to understanding how valuation multiples vary depending on financial metrics, controlling for potential impact of industry characteristics.

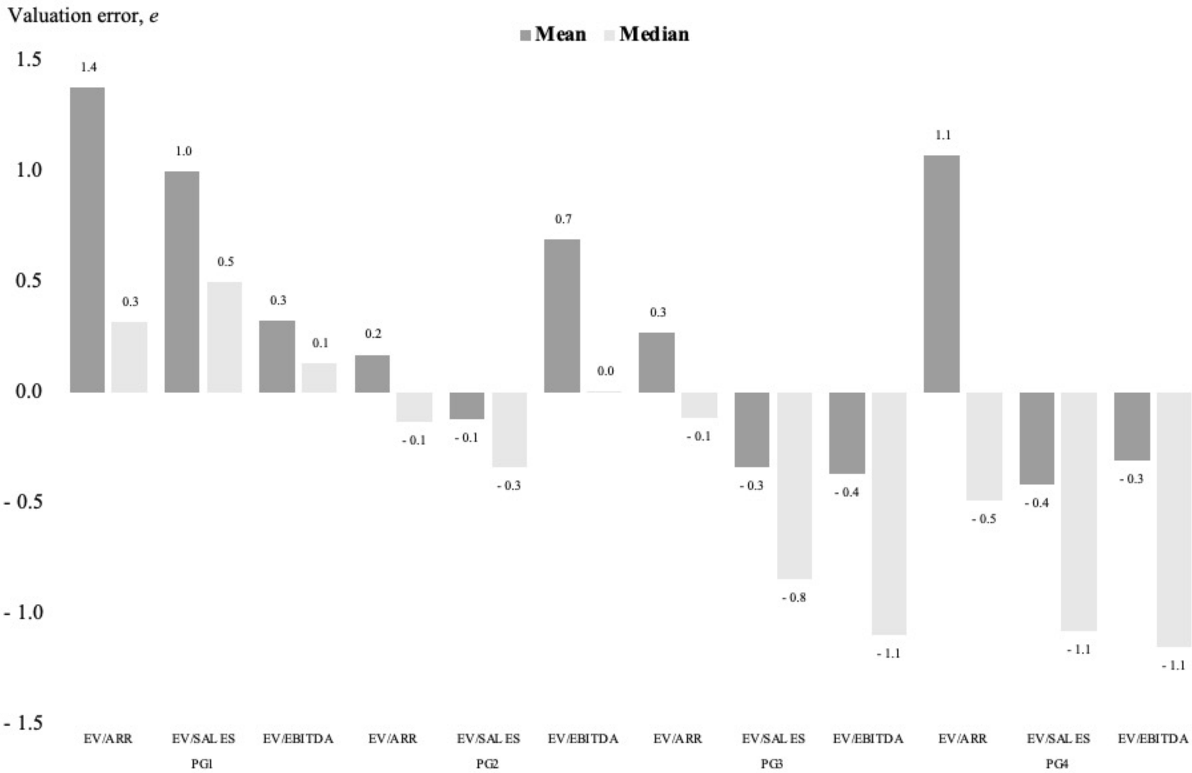


***Figure 1.*** *Distribution of Model 2 Valuation Errors Per Multiple and Peer Group*

Table 5 presents the findings regarding the valuation accuracy of traditional valuation multiples in relation to the findings of previous research. The table depicts the proportion of valuation errors within certain thresholds across the entire sample. For the earnings multiple, the study found that 9 percent of estimated valuations fell within 15 percent of actual valuations, and 14 percent within a 25 percent margin. The deviation from results in other studies are statistically significant for all but one study, which is the research conducted by Kim and Ritter (1999).

Strong support for hypothesis four is found in the context of the earnings multiple, where valuation accuracy is comparatively lower than all studies conducted on traditional industries, with the exception of Kim and Ritter (1999), where the result is lower but not statistically significant. The findings regarding the sales multiple are less substantial, with only the results of one of the comparable studies found to be significantly different. However, the significant difference in terms of earnings multiple, and the comparably low accuracy of the sales multiple motivates hypothesis four to be accepted.

***Table 5.*** *Results From Comparable Studies*

| | Earnings multiple | | Sales multiple | |
|---|---|---|---|---|
| Fraction within | 15% | 25% | 15% | 25% |
| This study | 0.091 | 0.136 | 0.152 | 0.197 |
| Larsson (2015)[1] | 0.330** | 0.580*** | 0.090 | 0.180 |
| Schreiner (2007)[1] | 0.312*** | 0.445*** | 0.229 | 0.340** |
| Keun Yoo (2006)[1] | 0.253*** | - | 0.168 | - |
| Lie & Lie (2002) | 0.285*** | - | 0.225 | - |
| Kim & Ritter (1999)[1] | 0.121 | - | 0.162 | - |

*Note*: */**/*** represent significance at the 10 percent/ 5 percent/ 1 percent level. A Z-test is conducted to ascertain the discrepancy in proportions, with computed p-values to compare the proportions of absolute valuation errors derived from this study below specified benchmark thresholds against those from other studies.
[1]For this study, the earnings multiple used is total enterprise value in relation to EBITDA and the sales multiple used is total enterprise value in relation to total sales. Some of the comparable studies use alternative earnings- and sales multiples, such as price-to-earnings and price-to-sales.

Interestingly, a comparison of the accuracy of the EV/ARR multiple, which essentially represents a sales-related metric, reveals its superiority not only to the EV/SALES multiple within this study but also in comparison to other studies. As seen in Panel B of Table 3, valuations estimated using the EV/ARR multiple demonstrate proportions of 30 and 49 percent for the 15 and 25 percent thresholds, respectively. These figures surpass the highest proportions observed in comparable studies, which stood at 23 and 34 percent, respectively.

# 5 Discussion

In this section the results are discussed in relation to the hypotheses presented previously. Each hypothesis is evaluated separately, and the results are interpreted and evaluated. The findings are put in relation to previous studies and theories to find probable explanations for the findings.

## 5.1 ARR's Superiority over Sales (H1)

The first hypothesis (H1) stated that the EV/ARR multiple would be superior to the EV/SALES multiple in generating valuation estimates. Examining Table 3, it can be observed that the EV/ARR multiple is significantly more accurate than the EV/SALES multiple for all fractions of valuation errors. Looking at the EV/ARR multiple, it has a larger fraction of companies within 15, 20 and 25 percent accuracy respectively compared to the EV/SALES multiple. For EV/ARR, 49 percent of observations fall within the 25 percent of the actual value as compared to 20 percent for the same threshold using EV/SALES. Furthermore, the EV/SALES multiple was not superior in any of the peer groups for any of the fractions, as can be seen in Table 4. However, since the peer groups have very few observations by themselves, the results per peer group cannot be used for drawing conclusions. Overall, it can be concluded that the first hypothesis is supported with statistical significance and that the EV/ARR multiple is indeed superior to the EV/SALES multiple in predicting an accurate valuation for unlisted Nordic SaaS companies.

This can be attributed to the fact that ARR is a metric specific to businesses like SaaS companies, where revenue is primarily generated through recurring subscriptions rather than one-time sales (Japaridze, 2023). The results of this study therefore suggest that since ARR is more representative of the business model that SaaS firms use, it is a more accurate representation of their ability to create long-term value. Since the research conducted in this study shows that EV/ARR is more accurate than EV/SALES, it indicates that investors indeed are more likely to favor recurring sales instead of total sales. The difference between ARR and sales for SaaS firms represents the one-time transactions. This distinction is crucial because ARR provides a more predictable and stable basis for valuation than sales, as shown by the statistically significant difference in the results of this study. For most SaaS companies, these one-time transactions that represent the difference between sales and ARR are tied to licenses or implementation of the software service (Tcholtchev, 2020).

Moreover, ARR not only represents current revenue but also implicitly accounts for future revenue that is likely to be generated, assuming that customer subscription agreements are maintained. This is particularly relevant in the SaaS industry where customer retention and subscription renewals are critical indicators of long-term viability and profitability (cf. Hochstein et al. 2023). According to Schreiner (2007), forward-looking multiples, which consider future revenue potential, tend to provide a more accurate valuation than those based solely on historical data. This is in line with findings by Liu et al. (2002) and Keun Yoo (2006), who noted that forward earnings measures, which include characteristics similar to those of ARR in their forward-looking nature, tend to produce more accurate valuations. Additionally, the use of ARR normalizes differences that might arise from varying business models within the tech sector, thereby making comparisons between companies more meaningful. As Keun Yoo (2006) suggests, valuation accuracy improves when using multiples that are closely aligned with the industry's revenue drivers. In the SaaS sector, ARR is the most effective metric, facilitating more accurate peer comparisons, as shown by this study. This aligns with the principle discussed by Damodaran (2006), where valuation should be based on fundamentals that are directly tied to the company's core business and growth prospects.

## 5.2 ARR's Superiority over EBITDA (H2)

Regarding hypothesis 2, an examination of Table 3 reveals that the EV/ARR multiple demonstrates greater accuracy across all valuation error categories compared to the EV/EBITDA multiple. A higher number of companies fall within the 15, 20, and 25 percent thresholds is seen when evaluated using the EV/ARR multiple. Furthermore, the results are statistically significant at the 1 percent level for all fractions within 15, 20 and 25 percent. Consequently, the findings confirm the second hypothesis, affirming that the EV/ARR multiple outperforms the EV/EBITDA multiple in accurately predicting valuations for unlisted Nordic SaaS companies.

Similarly to the first hypothesis, ARR is a revenue metric that specifically captures the essence of SaaS business models, which rely on recurring subscription revenues (Japaridze, 2023). Unlike EBITDA, influenced by short-term costs, ARR focuses solely on the revenue generation capability of the company. This focus is crucial in high growth industries where reinvestment and scaling are prioritized over current profitability (Damodaran, 2006). In addition, in contrast to EBITDA, ARR shares similar characteristics with forward-looking multiples which have proven more accurate in previous literature (Keun Yoo, 2006; Liu et al. 2002; Schreiner, 2007).

Moreover, SaaS companies are typically growth-oriented, investing heavily in customer acquisition and product development, which might suppress EBITDA in the short to medium term (Japaridze, 2023). This long-term focus makes ARR a more relevant metric for stakeholders who are interested in understanding the sustainable value creation potential of the company, rather than just its operational efficiency or profitability in the short run (Damodaran, 2006). Since EBITDA can be low or even negative in early stages, it may not accurately reflect the company's future growth potential (Bouwens et al. 2019). This is supported by Aggarwal et al. (2009), who, researching IPOs, finds that non-profitable companies are valued higher than profitable ones. He attributes this to variations in growth prospects, where investors prefer companies that use their capital towards growth rather than turning a profit. SaaS companies, often valuing growth above all else, may not want to impede their growth by focusing on profitability. Accordingly, investors are less likely to consider EBITDA to a similar extent when valuing SaaS firms. ARR, however, as a top-line metric, does not get distorted by these investment expenses and better represents the growth trajectory and the underlying health of the business (Liu et al., 2002; Schreiner, 2007).

Lastly, for SaaS companies, ARR is a comparable metric across the industry, making it easier to compare companies regardless of their specific cost structures or investment phases. In contrast, EBITDA can vary significantly based on management decisions, making it a less reliable metric for comparisons within this sector (Keun Yoo, 2006). Furthermore, investors often evaluate SaaS companies based on their ARR because it reflects the company's ability to generate consistent revenue over time. A growing ARR indicates a healthy, expanding customer base and can attract more investment (Japaridze, 2023).

## 5.3 Model 2's Superiority over Model 1 (H3)

The third hypothesis (H3) states that Model 2, using median from the peer group to derive the synthetic multiple, would be superior to Model 1, using the arithmetic mean, in generating accurate valuation multiples. Examining the results, outcomes vary greatly depending on whether Model 1 or 2 is employed. Looking at Table 3, it can be deduced that Model 2 is superior to Model 1 for the EV/ARR multiple for fractions within all three thresholds. Conversely, Model 1 provides more accurate predictions compared to Model 2 for both EV/SALES and EV/EBITDA. The variations in superiority between the models implies that neither model is superior to the other. This result in inconsistent with previous research, finding that using the median of peers yields greater accuracy in relative valuation (Baker & Ruback, 1999; Hermann & Richter, 2003).

Comparing the median absolute errors between Model 1 and Model 2 shows no clear or uniform superiority. As can be seen in Table 2, Model 1 produced the lowest median absolute error for both EV/SALES and EV/EBITDA, while Model 2 was superior in accuracy for the EV/ARR multiple. The by far largest difference between the models was in the EV/ARR, which showed a median absolute error of 0.284 in Model 2 and 0.742 in Model 1. This implies that if practitioners are to use EV/ARR for valuation, they should calculate the multiple using the median, as in Model 2. The performance difference between the two models suggests that the distribution of valuation multiples should guide the choice of measure of central tendency.

## 5.4 Difficulty Valuing SaaS Companies (H4)

The fourth hypothesis states that accurately valuing companies operating within Software-as-a-Service using relative valuation with traditional valuation multiples is more challenging compared to companies operating within alternative industries. Previous research within established industries, such as real estate, oil and gas, telecommunications, and banking, have found strong support for use of valuation multiples like price-to-sales and price-to-earnings (Larsson, 2015; Lie & Lie, 2002; Liu et al. 2002; Schreiner, 2007). By comparing the results of previous research to the results of this study, inferences can be drawn regarding the relative accuracy of traditional valuation multiples in the context of SaaS. While some previous studies used for comparison have employed slightly different multiples, such as price-to-earnings and price-to-sales ratios instead of enterprise value multiples, the fundamental principles underlying these metrics remain consistent in assessing the valuation of companies. P/E and P/S ratios, akin to EV/EBITDA and EV/SALES multiples, provide insights into a company's performance relative to its earnings and sales, respectively. Thus, the comparison with studies employing different multiples is justifiable, as the focus is evaluating the efficacy of earnings and sales.

Table 5 reveals significant variance in the accuracy of earnings and sales multiples across various studies. Kim and Ritter (1999) observed that only 12 percent of valuations estimated via the P/E ratio fell within a 15 percent margin of actual valuations. While their number of companies within 15 percent accuracy are lower compared to similar studies, they exceeded the accuracy found in this research. Their use of the P/E ratio as the earnings multiple, diverging from other studies, warrants consideration as a potential factor contributing to the reduced accuracy within the 15 percent threshold.

However, Larsson (2015) also employed the P/E ratio but achieved substantially higher accuracy, with 33 and 58 percent of estimated valuations falling within the 15 and 25 percent thresholds, respectively. His study demonstrated the most robust results across all examined studies for the earnings multiple. Conversely, the findings of this study revealed a mere 9 percent of estimate valuations within a 15 percent margin of actual values, indicating a significant deviation from the outcomes of previous research. For instance, Kim and Ritter (1999) reported a median absolute prediction error for the P/E ratio of 55.9 percent for the 190 IPOs used in their study, whereas this study yielded a notably higher figure of 108.4 percent, as detailed in Table 2.

Schreiner (2007) explores the accuracy of valuation multiples based on equity values of firms. Unlike this study, Schreiner's research employs equity value instead of total enterprise value as a proxy for firm value, utilizing price-to-EBITDA and price-to-sales as the earnings and sales multiples, respectively. He reported a median absolute valuation error of 29.5 percent for the earnings multiple, with 45 percent of estimated valuations falling within a 25 percent margin of actual valuations. In comparison, the reported proportion in this research is notably lower at 14 percent.

The rationale underpinning the fourth hypothesis posits that there are distinct and unique value drivers for companies operating within the SaaS industry, which should render traditional multiples less effective. Previous research on traditional industries often relies on common value drivers such as revenue and EBITDA. The SaaS industry deviates from other industries in several ways, notably in its increased reliance on dynamic capabilities. Dynamic capabilities pose challenges for measurement compared to the valuable and scarce resources typically analyzed within the resourced-based view (cf. Pavlou & Sawy, 2011). Given the divergence in fundamental value drivers and the SaaS industry's reliance on routines and capabilities to generate value, the relatively weaker accuracy of traditional earnings and sales multiples aligns with the theoretical framework presented in Chapter 2.

The findings presented in Table 5 aligns with the insights of the study from Bartov et al. (2002) concerning the valuation dynamics of internet firms. They report significant differences between internet firms and their traditional counterparts, noting that while traditional firms tend to prioritize earnings in valuation, negative cash flows are often disregarded. In contrast, for internet firms, earnings are not given similar importance, with revenue being the favored value driver. Their results help explain the diminishing explanatory power of the EV/EBITDA multiple within the SaaS industry compared to research done in more traditional industries. The de-emphasis on earnings in favor of revenue within the SaaS industry logically leads to an insignificant influence of EBITDA in determining the value of Software-as-a-Service companies. This is supported by the results, showing a significantly lower valuation accuracy for the earnings multiple compared to other research, underscoring the distinct valuation mechanisms employed for SaaS companies versus traditional industries.

In contrast to the comparable results of the earnings multiple, the efficacy of sales multiples in the SaaS industry is not necessarily inferior to that of alternative industries, as evidenced by the lack of statistically significant differences in Table 5. Although the explanatory power of sales multiples in the research may fall short in comparison to studies by Keun Yoo (2006), Kim and Ritter (1999), Lie and Lie (2002), and Schreiner (2007), the disparity is not statistically significant. Larsson (2015) reported the lowest proportion accurately predicted firm values, with only 9 percent falling within a 15 percent margin of actual values. Noteworthy, Larsson's study was heavily weighted to pharmaceutical companies, constituting 65 percent of his entire sample. According to Larsson (2015), the importance of sales in valuation is diminished within the pharmaceutical industry, where value creation is predominantly driven by R&D success. Thus, the observed weakness in the sales multiple's performance may be attributed to industry-specific characteristics, mirroring the findings for earnings multiples within the SaaS context.

The findings concluding that SaaS firms are more difficult to value using traditional metrics can, to a great extent, be attributed to the dynamic capabilities view. The DCV emphasizes the importance of dynamic capabilities in value creation, rather than valuable resources, as emphasized by the RBV (Teece et al., 1997). Research support the DCV over the RBV in the context of technology firms, suggesting that dynamic capabilities are the most important value driver (Daniel & Wilson, 2003; Liao et al. 2009). Since hypothesis four is supported by the results of this study, implications can be made regarding stakeholders interested in the value of SaaS firms. For instance, managers in the industry should focus on developing well-functioning dynamic capabilities such as effective innovation systems to maximize shareholder value. Furthermore, investors should put more weight in how a company has managed to handle change in the past and less weight in the company's tangible resources.

Furthermore, Fama's (1970) efficient market hypothesis posits that firms are accurately priced and that the value of traded assets is based on available information. Sharma and Prashar (2013) oppose this claim, arguing that there are several markets in which asset prices are not efficient. They further argue that this is especially the case for markets that are volatile and less liquid, like the private market. This research investigated unlisted SaaS firms and found that it is relatively harder to value them as compared to previous research, which has mostly looked at public companies (Ken Yoo, 2006; Larsson, 2015; Lie & Lie, 2002; Schreiner, 2007). The result of this study therefore supports the findings of Sharma & Prashar (2013), doubting the generalizability of the EMH to illiquid markets such as the private market. This is further in line with the research by Kim and Ritter (1999) who also investigated private firms and got less accurate results than the other studies investigated, which can be seen in Table 5.

Overall, the performance of traditional multiples, particularly EV/EBITDA and EV/SALES, in comparison to previous research, is notably inferior, corroborating the fourth hypothesis. This underscores a need for caution in using multiples by investors when evaluating SaaS firms for investment decisions. Consequently, for investors employing relative valuation models, it could be beneficial to prioritize industry-specific value drivers such as EV/ARR over traditional multiples like EV/SALES or EV/EBITDA.

# 6 Conclusion

The following chapter summarizes the main findings from this study derived from Chapter 4 and 5. Moreover, the research aim and objectives are assessed as well as implications, limitations and recommendations for future research are presented.

## 6.1 Main Findings

This research set out to investigate the SaaS industry and how well multiples perform in explaining the valuations of firms in the industry. The research gap identified is that previous research on relative valuation methods has been conducted almost exclusively on firms in traditional industries and no research has been conducted on the industry-specific variable EV/ARR. To investigate this problem, relative valuation within the SaaS industry was investigated, constituting the first official research on the EV/ARR multiple's accuracy in valuation.

This research contained four hypotheses in total which are based on theories such as the dynamic capabilities view as well as previous empirical research. These hypotheses were then tested through data analysis on a sample of 66 transactions involving Nordic SaaS firms between 2020 and 2024. The sample firms were then divided into four groups defined by profitability and growth. The results were gathered from synthetic multiples created using peer groups. The methodology and data analysis of this research is largely inspired by the methodology of well-established research papers on the same subject (Keun Yoo, 2006; Kim & Ritter, 1999; Lie & Lie, 2002; Schreiner, 2007). In line with these, the difference between the expected value and the actual value was used to determine the accuracy of each multiple.

For the valuation multiples investigated, the estimates exhibit a slight negative bias, as indicated by the median valuation errors being negative for the majority of the observations. This suggests that, in general, the actual enterprise values observed in real-world transactions exceed the enterprise values derived from peer group valuation multiples.

The first two hypotheses state that the EV/ARR multiple would perform better than the EV/EBITDA and EV/SALES multiples, respectively. These two hypotheses are supported by the statistically significant results of the study since the best-performing multiple for all fractions within 15, 20 and 25 percent accuracy, respectively, is the EV/ARR multiple. The results were predicted based on previous research on internet firms (Bartov et al. 2002; Liao et al. 2009) and industry-specific multiples (Aggarwal et al. 2009).

The third hypothesis stated that the median would be more accurate than the mean in predicting the firms' values. The findings from the data analysis did not support hypothesis 3 since the results were inconsistent in the accuracy of the multiples. Neither Model 1 nor Model 2 were superior overall. Thus, there was no clear pattern in their prediction accuracy, contradicting previous empirical evidence (Baker & Ruback, 1999; Hermann & Richter, 2003).

The fourth and final hypothesis of this paper, stating that the relative accuracy of traditional multiples would be lower for SaaS firms than for firms operating in traditional industries, was supported by the results. To determine this, the results of this study were compared to previous research on multiples in other, traditional, industries. The comparison showed that previous research had gotten a higher accuracy on their comparable synthetic multiples. This is likely due to the fact that SaaS firms are highly dependent on value drivers difficult to measure, such as their dynamic capabilities (Daniel & Wilson, 2003; Pavlou & Sawy, 2011).

## 6.2 Research Aim and Objectives

The aim and objectives of this study were to investigate whether the industry-specific multiple EV/ARR is more accurate in determining company value than its traditional counterparts, EV/SALES and EV/EBITDA. This was tested by looking at multiples to see how many of the predicted multiples were within the percentage fractions 15 percent and 25 percent of the actual value. The results show that EV/ARR is superior to its traditional counterparts as a value determinant, contributing to the existing literature on company valuation. The study has contributed by providing empirical evidence for justifying the usage of industry-specific multiples when valuing unlisted Nordic SaaS companies. The aim of this study is therefore regarded as having been accomplished.

## 6.3 Implications

The implications of this study primarily concern the future usage case for industry-specific multiples in the SaaS industry. Stakeholders involved with unlisted Nordic SaaS companies will find the greatest value in the results provided.

The main stakeholder is likely venture capital firms with presence in the Nordic region since they often invest in these types of companies. In this study they can find empirical evidence supporting the notion that industry-specific multiples, particularly EV/ARR, is in fact more accurate than traditional valuation multiples. This information is valuable when screening potential investments within the SaaS industry, ensuring accuracy of valuations. Specifically, VC firms are recommended to amend valuation models to include ARR as a value driver. For example, in M&A transactions, parties might rely to an increased extent on recurring revenue when negotiating deals, structuring buyouts and assessing synergies. Furthermore, ARR could become a more prevalent benchmark in M&A due diligence and valuation assessments for companies in the SaaS industry.

Another implication concerns SaaS companies and their management, for whom the result of this study indicates that more consistent reporting of ARR is beneficial for shareholders and investors. By doing so, companies can better communicate their value proposition to investors, highlighting ARR which may be a more relevant metric for understanding their future growth potential. This implies increased transparency and perhaps a more positive image towards the company from potential investors. Additionally, it is possible that future requirements of ARR reporting are imposed in industries where recurring revenue is important. There are also strategic implications, with the results of this study suggesting prioritization of strategies that increase ARR, such as increasing customer retention, developing more subscription-based offerings and focusing on long-term customer relationships.

Lastly, there are a few implications for academic research. First, it may be suitable for finance and accounting scholars to emphasize the importance of ARR in modern valuation practices, especially for SaaS companies. Second, future research can build upon these findings by comparing EV/ARR with other multiples and perhaps introduce new, industry-specific multiples as well as research different geographies. Third, researchers may explore different ways of incorporating ARR more effectively, potentially leading to more accurate valuation methods.

## 6.4 Limitations and Future Research

One limitation of this research is that it only investigated relative valuation and did not include other valuation methods such as those built on discounted cash flow. Future research should investigate whether other valuation models are relatively superior to relative valuation in determining the value of SaaS firms. There is a large need for valuing SaaS firms due to large investments into the industry and thus investors need a reliable valuation model considering this research has shown that traditional multiples are subpar. If there is a valuation method that is superior to the industry-specific EV/ARR, it would be highly interesting to know.

Building on this limitation and recommendations for further research, it would also be interesting to investigate other multiples, both traditional and SaaS-specific. This research specifically investigated three multiples out of which one was SaaS-specific. Other multiples could be compared against the ones researched in this study to determine whether other multiples are superior to the EV/ARR multiple which was superior in this research. Moreover, this research solely investigated so-called accrual flow multiples. Future research could therefore investigate other groups of multiples such as book value multiples, cash flow multiples, knowledge-related multiples, and forward-looking multiples (Schreiner, 2007). In addition, looking at equity value multiples considering all multiples in this research used enterprise value may produce different results.

The third and final limitation of this research is that it only investigated SaaS companies from the Nordic region, encompassing Sweden, Norway, Denmark, and Finland. This decision was made partly to ensure that the firms had similar geographical and institutional conditions to make the results as comparable as possible. The other reason for this distinction was that it is significantly easier to find financial information on companies in the Nordics due to legislation that requires limited liability companies to publicly disclose their annual reports. While there are advantages with looking exclusively at Nordic firms, it simultaneously limits the implications of the results. It cannot be stated with certainty that the results from this study are applicable to SaaS companies outside the Nordics which only represents a small part of the total SaaS industry. Future research could therefore investigate other geographical areas to see if the results remain the same. A concrete suggestion is to look at the U.S. SaaS market, containing more than half of the world's SaaS companies.

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# Appendix A

***Table A.*** *Absolute Valuation Errors for All Transactions*

| Transaction ID | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | EV/ ARR | EV/ SALES | EV/ EBITDA | EV/ ARR | EV/ SALES | EV/ EBITDA |
| PG12022T1 | 1.381 | 1.411 | 1.625 | 0.319 | 0.915 | 1.431 |
| PG12022T2 | 1.191 | 0.997 | 1.664 | 0.128 | 0.501 | 1.471 |
| PG12022T3 | 1.642 | 0.640 | 0.119 | 0.580 | 0.144 | 0.074 |
| PG12022T4 | 2.057 | 1.057 | 0.328 | 0.995 | 0.561 | 0.134 |
| PG12023T1 | 0.747 | 0.037 | 0.290 | 0.189 | 0.439 | 1.074 |
| PG22020T1 | 2.037 | 2.007 | 2.634 | 0.643 | 0.894 | 1.434 |
| PG22020T2 | 1.397 | 0.442 | 1.362 | 0.003 | 0.671 | 0.163 |
| PG22020T3 | 0.825 | 1.963 | 2.381 | 0.569 | 0.851 | 1.182 |
| PG22020T4 | 1.255 | 0.296 | 0.036 | 0.139 | 0.816 | 1.163 |
| PG22020T5 | 1.306 | 0.347 | 0.087 | 0.088 | 0.766 | 1.112 |
| PG22021T1 | 0.605 | 0.700 | 1.686 | 0.402 | 0.453 | 1.297 |
| PG22021T2 | 0.538 | 0.310 | 1.850 | 0.335 | 0.063 | 1.461 |
| PG22021T3 | 0.213 | 0.205 | 1.865 | 0.009 | 0.452 | 2.255 |
| PG22021T4 | 0.852 | 1.298 | 0.045 | 1.056 | 1.545 | 0.345 |
| PG22021T5 | 0.119 | 0.439 | 0.596 | 0.323 | 0.686 | 0.206 |
| PG22021T6 | 0.376 | 0.408 | 1.511 | 0.173 | 0.655 | 1.121 |
| PG22021T7 | 0.132 | 0.231 | 1.866 | 0.072 | 0.016 | 1.476 |
| PG22021T8 | 0.720 | 2.349 | 1.058 | 0.924 | 2.596 | 1.447 |
| PG22021T9 | 0.316 | 0.904 | 0.372 | 0.113 | 1.151 | 0.761 |
| PG22021T10 | 0.512 | 0.023 | 0.279 | 0.308 | 0.224 | 0.669 |
| PG22021T11 | 0.012 | 0.118 | 1.370 | 0.215 | 0.364 | 0.980 |
| PG22021T12 | 0.012 | 0.121 | 1.363 | 0.215 | 0.368 | 0.973 |
| PG22021T13 | 0.239 | 0.861 | 1.862 | 0.035 | 0.614 | 1.472 |
| PG22021T14 | 0.131 | 0.733 | 0.856 | 0.335 | 0.980 | 1.246 |
| PG22022T1 | 0.037 | 0.166 | 0.154 | 0.123 | 0.284 | 0.683 |
| PG22022T2 | 0.312 | 0.558 | 0.792 | 0.152 | 0.440 | 0.045 |
| PG22022T3 | 0.269 | 0.018 | 0.445 | 0.109 | 0.135 | 0.391 |
| PG22022T4 | 0.019 | 0.591 | 1.357 | 0.141 | 0.708 | 2.194 |
| PG22022T5 | 0.010 | 0.929 | 0.891 | 0.170 | 0.812 | 0.054 |
| PG22022T6 | 0.082 | 0.244 | 1.073 | 0.242 | 0.127 | 0.236 |
| PG22022T7 | 1.658 | 1.621 | 0.695 | 1.819 | 1.738 | 1.532 |
| PG22023T1 | 0.309 | 0.023 | 0.194 | 0.265 | 0.113 | 0.533 |
| PG22023T2 | 1.279 | 1.384 | 0.586 | 1.324 | 1.293 | 0.925 |
| PG22023T3 | 0.736 | 0.404 | 1.065 | 0.781 | 0.314 | 0.726 |
| PG22023T4 | 0.675 | 0.343 | 1.126 | 0.720 | 0.253 | 0.787 |
| PG22023T5 | 3.157 | 3.044 | 1.766 | 3.201 | 2.953 | 2.105 |
| PG22023T6 | 0.013 | 0.182 | 1.029 | 0.058 | 0.092 | 0.690 |
| PG22024T1 | 0.847 | 0.308 | 1.360 | 0.173 | 0.373 | 0.091 |
| PG22024T2 | 0.992 | 0.020 | 2.241 | 0.021 | 0.043 | 3.505 |
| PG32020T1 | 1.180 | 0.211 | 1.591 | 0.104 | 1.444 | 2.392 |
| PG32020T2 | 1.262 | 0.437 | 0.204 | 0.022 | 1.671 | 1.005 |

*Table A.* *Continued*

| Transaction ID | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | EV/ ARR | EV/ SALES | EV/ EBITDA | EV/ ARR | EV/ SALES | EV/ EBITDA |
| PG32020T3 | 1.262 | 0.437 | 0.204 | 0.022 | 1.671 | 1.005 |
| PG32020T4 | 1.734 | 0.035 | 0.269 | 0.450 | 1.198 | 0.533 |
| PG32021T1 | 0.598 | 0.062 | 0.355 | 0.085 | 0.283 | 0.015 |
| PG32021T2 | 1.028 | 1.111 | 0.831 | 1.541 | 1.456 | 1.170 |
| PG32021T3 | 0.274 | 0.020 | 0.366 | 0.239 | 0.365 | 0.705 |
| PG32021T4 | 1.735 | 2.341 | 1.662 | 2.249 | 2.686 | 2.001 |
| PG32022T1 | 0.093 | 0.230 | 1.931 | 0.141 | 0.192 | 3.213 |
| PG32022T2 | 0.859 | 0.205 | 0.382 | 0.625 | 0.243 | 0.900 |
| PG32022T3 | 1.056 | 0.662 | 0.485 | 0.823 | 0.700 | 0.797 |
| PG32022T4 | 0.119 | 0.339 | 3.314 | 0.114 | 0.301 | 4.596 |
| PG32023T1 | 0.876 | 0.056 | 0.467 | 0.440 | 0.129 | 0.471 |
| PG32023T2 | 0.828 | 1.133 | 0.649 | 1.264 | 1.060 | 1.587 |
| PG32023T3 | 0.605 | 0.917 | 1.264 | 1.041 | 0.844 | 2.202 |
| PG32024T1 | 0.294 | 0.457 | 0.078 | 0.415 | 0.365 | 1.094 |
| PG32024T2 | 0.969 | 1.157 | 2.344 | 1.091 | 1.065 | 3.515 |
| PG42020T1 | 2.154 | 0.305 | 1.852 | 0.231 | 0.798 | 3.405 |
| PG42020T2 | 1.193 | 0.403 | 0.614 | 0.731 | 1.507 | 2.167 |
| PG42020T3 | 1.170 | 0.425 | 0.637 | 0.753 | 1.529 | 2.189 |
| PG42020T4 | 1.678 | 0.082 | 0.129 | 0.246 | 1.022 | 1.682 |
| PG42022T1 | 0.637 | 0.456 | 4.168 | 0.238 | 0.546 | 4.326 |
| PG42022T2 | 1.177 | 0.001 | 1.420 | 0.302 | 0.091 | 1.261 |
| PG42022T3 | 0.975 | 0.203 | 1.218 | 0.100 | 0.293 | 1.059 |
| PG42022T4 | 0.457 | 1.040 | 0.115 | 1.332 | 1.130 | 0.273 |
| PG42022T5 | 0.386 | 1.340 | 0.448 | 1.261 | 1.430 | 0.607 |
| PG42023T1 | 0.060 | 0.962 | 0.161 | 0.823 | 1.264 | 0.615 |

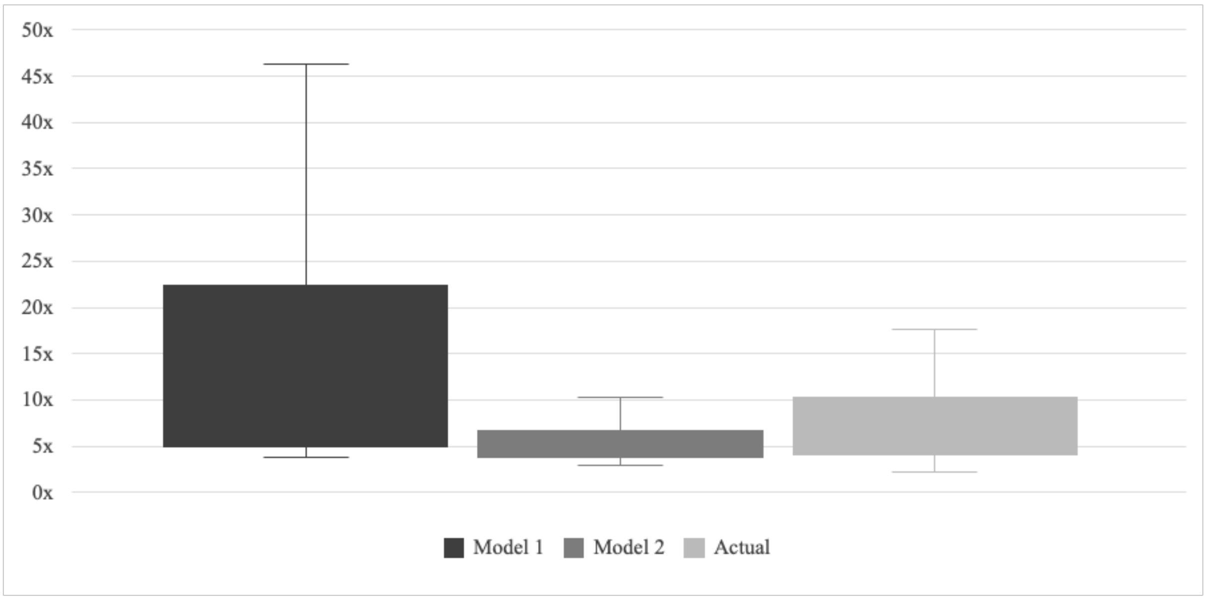


***Figure A.*** *Distribution of EV/ARR Multiples*

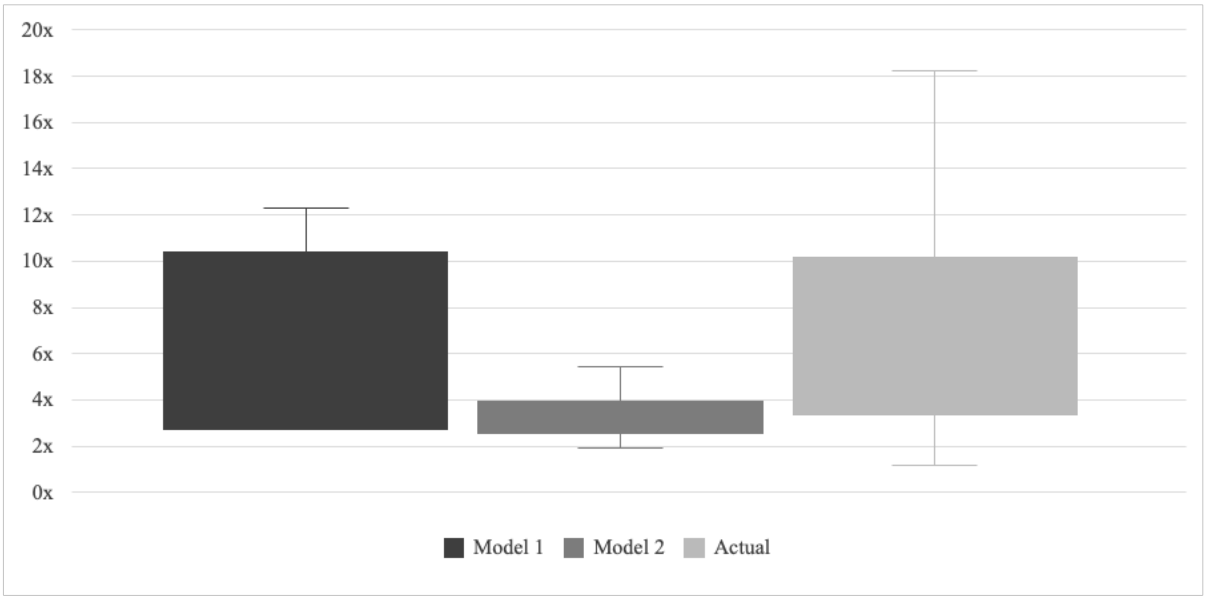


***Figure B.*** *Distribution of EV/SALES Multiples*

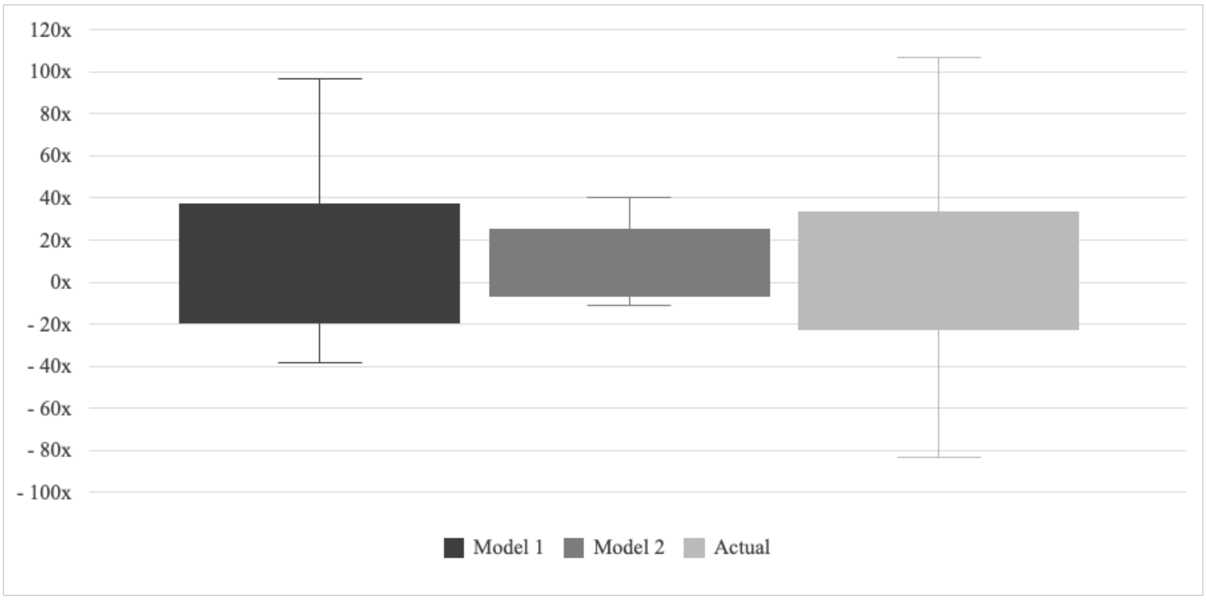


***Figure C.*** *Distribution of EV/EBITDA Multiples*

# Appendix B

## Statement of Authorship

We hereby declare that this bachelor thesis titled "The Secret SaaS to Valuation: An empirical investigation into the applicability of relative valuation within the Software-as-a-Service industry" is our original work and has not been submitted previously, in whole or in part, to any institution for assessment or award. We confirm that all work contained herein is entirely our own, except where explicitly stated otherwise in the form of references.

We have read and understand the university's policies on plagiarism and academic integrity, and we have applied these principles in producing this thesis. All sources of information and ideas have been acknowledged through proper referencing, and any assistance received during the project has been appropriately credited.

The text is ascribed to all authors throughout all sections of the thesis.

We have all contributed significantly to the planning, execution, and writing of this thesis, and we take full responsibility for the content presented herein.

Author 1: Axel Bäckström
Author 2: Erik Tångring
Author 3: Melker Winnerblad

# Appendix C

## Statements of AI usage

In the last two years, artificial intelligence (AI) has become increasingly normalized and used in all parts of society. Using generative AI (GAI) can both help and hinder your academic journey depending on how it is used. In this research, GAI has been used cautiously and only for specific tasks. The authors of this paper followed Lund University's guidelines on AI usage when writing this research. The usage of GAI was restricted to ChatGPT, and more specifically ChatGPT4. The authors of this paper used ChatGPT to generate ideas, get pointed in the right direction, and get recommendations on research to investigate. It was at no point used to generate content used in this text, instead it was used to ease writer's block, something that often occurs when writing a research paper of this scope. When GAI was used in any form, it was always viewed with a critical eye since the authors are aware that GAI sometimes blatantly lies or guesses its answers. In summary, GAI was used in this research but merely to get pointed in the right direction and it was always used with caution. Moreover, AI was used in some cases to rewrite certain sentences to get a better flow in the text. It was used in the following sections: Introduction, Literature Review.

Examples of prompts used:

> "Give me some general ideas on topics this section could be expanded on:
> [Insert section.]"
>
> "Rewrite the following sentence using language suitable for a bachelor thesis:
> [Insert sentence.]"