Customers & Innovation as Share Price Determinants of The Cloud's New Cornerstone

---

A Panel Regression Study on US-listed SaaS Companies

Authors:
Carl Oscar Milebratt
Oscar Holmbergh

Supervisor:
Angelika Lindstrand

18 May 2021

Abstract

This paper examines the effect of revenue, customer acquisition cost, research and development expenses, and earnings per share on the share price movements of SaaS companies listed on the New York Stock Exchange or Nasdaq. Additionally, the report explores if the metrics explanatory power varies between large SaaS companies (market capitalization > 10 billion USD) and mid- and small-cap companies (market capitalization < 10 billion USD). Revenue has a significant impact on the share price movement of SaaS companies, as demonstrated by panel data regression analysis. This is almost certainly due to investors' appreciation for the SaaS business model's ability to retain and attract customers in a highly competitive environment. Customer acquisition cost ratio is a valuable metric for valuing SaaS businesses because it captures sales and marketing efficiency, critical in fast-growing markets like SaaS. EPS is not a good proxy for share price movements in large-cap SaaS companies, which is most likely because stable, mature businesses are simpler to value, and thus stock markets do not react as strongly to earnings releases as they do to mid- and small-cap SaaS companies. R&D has a sizable impact on the share prices of mid- and small-cap SaaS companies. This is probably because smaller firms are more reliant on innovation success than large firms, and investors appear to factor R&D into stock price valuations based on future profit expectations.

Keywords

Software-as-a-Service (SaaS), Subscription-based enterprises, Earnings per share (EPS), Research and development (R&D), Customer Acquisition Cost (CAC), Investor Sentiment, Sales & Marketing efficiency, Revenue, Valuation, Share price

Acknowledgments

We would like to express our gratitude to Angelika Lindstrand for her invaluable insights and assistance and Emelie Fröberg for guiding us through the regression jungle. A big thank you is directed to the faculty on the Center for Retailing for three rewarding years. Lastly, we would like to thank our friends and family for their unconditional support and love.

Bachelor Thesis
Bachelor Program in Retail Management
Stockholm School of Economics

1. Introduction

During the 19th-century gold rush, people traveled to San Francisco with dreams of enrichment. Today, San Francisco is undergoing another gold rush. The city is home to Software-as-a-Service, one of the fastest-growing industries on the planet. Salesforce Tower in downtown San Francisco, the tallest building west of Chicago, is a clear indication of the cloud computing paradigm shift. The 326-meter-tall structure not only houses the tech giant but also serves as a symbol of a new era in which recurring revenue is the new gold and SaaS vendors the gold miners. As of 31 December 2020, the software industry has a total market capitalization of $4,3 trillion, and Software-as-a-Service businesses recently eclipsed traditional application providers as the new industry standard for delivering and updating software (Fidelity Investments, 2021).

Global B2B SaaS adoption has surged during the past decade, and forecasts indicate that growth will not stagnate (Costello & Rimol, 2020). Valuates Reports (2020) project total SaaS spending to reach 307,3 billion USD by 2026 with a compound annual growth rate of 11,7% during 2020-2026. Moreover, converting to cloud-based SaaS from traditional application software is a top priority for 43 % of companies in 2020 - an escalation from 29 % in 2019. Some of the increased demand results from growing online usage due to Covid-19, and many organizations discover that public cloud services provide a more dependable alternative for business continuity.(Flexera, 2020). However, the advantages of SaaS have become widely recognized not only among businesses but also among investors.

The computer software and services industry is the second largest spender on research and development, trailing only the pharmaceutical and biotechnology industry. In 2018, US-based SaaS companies spent 63,1 billion USD on R&D, equating to a fifth of all R&D expenditures in the United States (Mikulic, 2020). Furthermore, revenue growth and marketing efficiency are viewed as critical success factors for SaaS businesses (Cohen & Neubert, 2019). This has sparked a movement from traditional valuation methods towards more customer-centric approaches in the pursuit to capture the value drivers of the SaaS business model. Nevertheless, few research reports have investigated its implications for stock market valuation (Newton & Schlecht, 2016; Cohen & Neubert, 2019). This study aims to contribute to the growing body of research concerning SaaS valuation and increase awareness of an industry whose market value has skyrocketed.

2. Background

2.1 SaaS - An Emerging Trend

As competition becomes more global and markets increasingly complex, higher demands are placed on companies' flexibility. To keep up with contemporary market challenges, most companies must implement expensive business systems that facilitate functions such as customer relationship management, enterprise research planning, and supply chain management (Mathrani & Viehland, 2005). Developing in-house information systems are costly, but the actual software purchase price usually corresponds to a small part of the total cost of ownership. In fact, between 50 and 80 percent of companies’ IT budgets are spent on implementation and maintenance (Waters, 2005). Therefore, seeking alternatives to reduce IT investments and resembling operational costs becomes a logical path to make a company more competitive in the market (Chou & Chou, 2008). Software-as-a-Service is a viable alternative to in-house information systems because it is a cost-effective solution that enables companies to focus on their core business (Lee et al., 2003).

SaaS architecture differs from traditional software, where multiple copies of the software, with different configurations, are installed across various customer sites (Hacigümüş et al., 2002). Within the SaaS model, all customers share a single configuration of hardware, operating system, and network while the vendor assumes responsibility for servers and software. Customers use only the applications as final products by accessing services with IT support, including customization, updating, and software maintenance (Chou & Chou, 2008). The result is a contract-based service where the customer receives the benefits of the software at a significantly lower cost than if they had developed the product themselves (Waters, 2005; Nerino, 2007). Several factors, such as the length of using time at the customer’s site and the number of users, determine how hefty the fee will be (Chou & Chou, 2008).

Companies' efforts to generate recurring revenues have increased significantly in recent decades. Because supplier-customer agreements are rarely time-bound, SaaS companies must aspire to retain customers through frequent maintenance and service updates (Nerino, 2007). The ultimate aim with subscription-based business models, such as SaaS, is to increase the predictability of revenue streams and consequently reduce firm-specific risk (McCarthy et al., 2017). Also, hosted applications can be accessed by multiple clients, and scale economies can easily be achieved by vendors (Chou & Chou, 2008). Consequently, the SaaS business model has attracted investors' attention, and the industry has seen stock market returns of approximately 512% since 2011 (S&P Global, 2021). Simultaneously, the market size has nearly thirtyfold since 2008, as illustrated in **Figure 1**. The trend has been accelerated by technological advancements and rising market expectations and has cast doubt on several traditional valuation techniques (Cohen & Neubert, 2019; Newton & Schlecht, 2016).

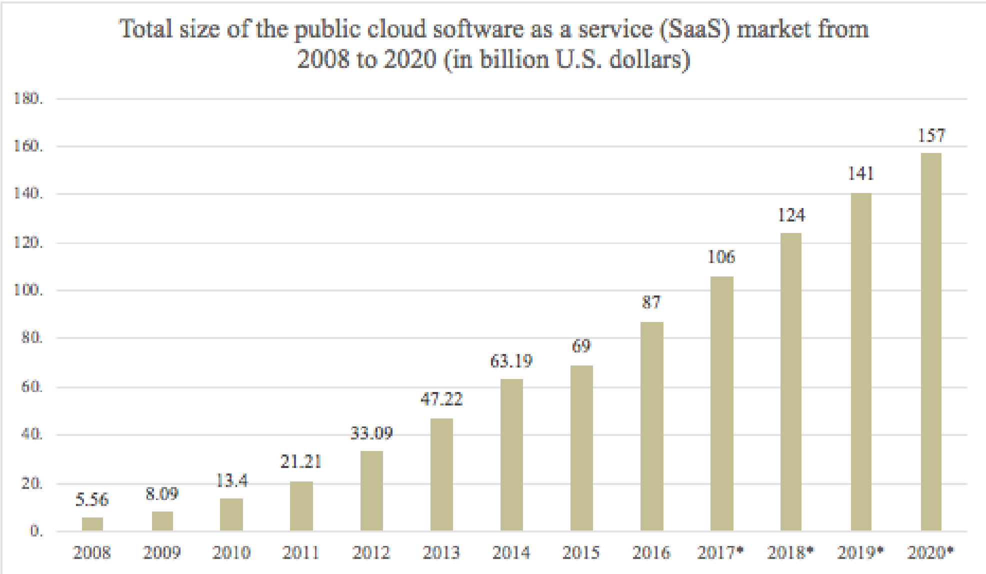

Figure 1: Total size of the public cloud software as a service (SaaS) market from 2008 to 2020 (Mlitz, 2021).

2.2 Purpose and Research Question

Many SaaS companies are on the rise, and the share price performance signals a huge investor interest (Cohen & Neubert, 2019). Most SaaS research discusses the business model's implications and the economies from a marketer's perspective (e.g., Chou & Chou, 2008; Bonacchi & Perego, 2012; Schulze et al., 2012). The research on drivers of share price movements is broad and extensive as of now. However, empirical research concerning the valuation of SaaS businesses is limited (Newton & Schlecht, 2016; Cohen & Neubert, 2019). This report seeks to evaluate the importance of certain financial fundamentals and SaaS-related key performance indicators. More precisely, the purpose is to fill the research gap by examining how revenue, customer acquisition costs, research and development expenses, and earnings per share affect the share price movements of listed SaaS companies in the U.S.

2.3 Scope and Delimitations

This study examines the impact of four performance metrics on the stock prices of 74 SaaS companies listed on the New York Stock Exchange or Nasdaq. The investigation spans the years 2010 to 2020 and focuses on companies with a market capitalization of more than $300 million that have disclosed subscription revenue data for at least four consecutive fiscal quarters. Additionally, SaaS companies that have been publicly traded for less than a year as of 31 December 2020 are omitted. Among other performance indicators, churn rates, customer lifetime value, and retention rates are critical when valuing subscription-based enterprises (McCarthy et al., 2017). However, these metrics are excluded due to existing discrepancies in calculation methods and insufficient reporting.

3. Literature Review

3.1 Theoretical Background

Valuation of high-growth companies is more complex than the valuation of mature companies with stable cash flow streams. Besides, historical financial information of technology-based firms in fast-changing industries is of little value to investors (Gupta et al., 2004). Thus, the SaaS business model renders some of the relative valuation methods and metrices inapplicable (Cohen & Neubert, 2019). Smale (2021) further demonstrates that most intrinsic corporate value lies within such firms' qualitative or intangible measures. This is especially true for service sectors (Livne et al., 2011). Thus, customer-related data, such as customer churn, customer lifetime value, customer acquisition cost, and recurring revenue, are essential to investors and financial analysts (McCarthy et al., 2017). Much of the existing research regarding customer-centric performance measures examine the importance of specific metrics on firm performance. For example, Gupta et al. (2004) discovered that customer retention has a more significant impact on customer value than customer acquisition and capital costs. In like manner, average revenue per customer and number of subscribers have a powerful predictive ability of future profitability (Simpson, 2010).

Amir & Lev (1996) were the first to conclude that investors primarily rely on non-GAAP customer-centric information when making investment decisions in the wireless communication industry. The authors further argue that there are several intangible-related deficiencies in financial statements and that a potential solution to this problem is additional disclosures or on-balance-sheet accounting. Since then, a significant portion of research on customer equity and company valuation has focused on the possibilities and challenges associated with disclosing internal customer data (e.g., Gleaves et al., 2008; Wiesel et al., 2008; Bonacchi & Perego, 2012; Lev, 2018). Other dimensions of the customer equity literature have been devoted to developing realistic customer retention and acquisition models and integrating them into standardized financial frameworks for corporate valuation (McCarthy et al., 2017; Gupta et al., 2004; Kumar & Shah, 2009; Hand, 2015).

Software-as-a-Service businesses have transcended traditional application providers as the new industry standard for delivering and updating software. The difference in software distribution engenders several fundamental benefits for SaaS providers and customers. Also, the increase in public disclosure of customer-centric metrics has come due to the increased popularity of subscription-based businesses (McCarthy et al., 2017). However, few research papers have examined the impact of customer-centric metrics and financial fundamentals on the share prices of SaaS companies (Newton & Schlecht, 2016; Cohen & Neubert, 2019).

3.2 Theoretical Framework

The subscription business model aims to generate recurring revenue and, thus, more predictable revenue streams. This is primarily why the model has become so appealing to software vendors in recent years. According to Bonacchi & Perego (2012), subscription-based enterprises follow a common strategy: acquire customers through marketing (CAC) , retain customers and minimize churn rate (Revenue), and finally, once the customer base has been established: seek new clients and modify the business to suit these new target groups (R&D). Hence, recurring revenue streams and how effectively new customers are attracted is essential for any company employing the subscription business model. The report will incorporate Earnings Per Share (EPS) and R&D expenditure in order to consider profitability and its impact on SaaS companies' share price movements and how investors evaluate research and development in their investment analysis. The following section will cover previous research on the focal performance metrics' impact on share price movements.

3.2.1 Revenue

Research suggests that the use of revenue and sales figures in firm valuation has increased over time and that earnings' capacity to summarize contemporaneous information affecting firm value has deteriorated in recent decades (Collins et al., 1997; Lev & Zarowin, 1999; Brown et al., 1999; Chandra & Ru, 2008). Revenue may be particularly relevant when valuing technology firms for at least three related reasons. First, such businesses operate in an uncertain and rapidly changing environment, for which the current accounting model is inadequate (Lev & Zarowin, 1999). Second, technology firms are likely to have more volatile earnings due to a mismatch between startup costs and future benefits (Amir & Lev, 1996). Technology firms typically incur high research and development costs, which are expensed in the income statement but are valued as assets by the market (Lev & Sougiannis, 1996). Third, because they typically operate in industries that were created as a result of recent technological advances, they are typically younger and have higher expected growth rates (Chandra et al., 2004; Chandra & Ru, 2008). Thus, revenue growth is more critical for young firms in emerging industries because it results in competitive advantages, the creation of barriers to entry for potential entrants, and greater future earnings (Chandler 2001; Spar 2001).

Stable revenue generation is required to succeed in developing long-term profitable business models. The subscription model results in a more predictable revenue stream that allows for more accurate business forecasting and, consequently, lower risk for investors (Singer, 2014). Newton & Schlecht (2016) found revenue to be twice as important as profits when determining the value of SaaS companies. Additionally, high retention rates reflect a firm's ability to retain revenue and have a strong association with long-term firm profitability and customer success (Livne et al., 2011; Trenz et al., 2019; Fornell et al., 2016). Hence, the performance of subscription businesses is contingent on their ability to attract and retain customers. For example, Reichheld & Sasser (1990) found that improving customer retention increases profitability. Furthermore, Gupta et al. (2004) found that an increase in retention leads to increased customer value, leading to an increase in shareholder value. Likewise, Schulze et al. (2012) suggest that a 10% increase in customer equity leads to an increase of 15.5% increase in shareholder value.

Customer equity considers both customer acquisition cost and retention rates, supporting the theories that increased retention rates affect firm values (Gupta et al., 2006). Taken together, research suggests that revenue is an essential measure for all businesses. This is also true in subscription-based industries where businesses rely heavily on customers continuing with their subscriptions. Therefore, recurring revenue streams could potentially provide valuable insights into the business model's success for SaaS companies and be of interest to investors. Since retention rates are directly linked to recurring revenue, it may be assumed that SaaS companies will be valued upon their ability to retain and grow the revenue base. Xu & Cai (2009) discovered evidence from the early 2000s that there is a strong correlation between revenue and valuation for high-technology loss-generating firms. In conclusion, it is hypothesized that the revenue stream in SaaS companies explains a sizable proportion of stock price value. The following hypothesis is therefore developed:

- **Hypothesis 1**: Revenue illustrates a positive significant impact on SaaS companies' share price movements.

3.2.2 Customer Acquisition Cost

Key metrics other than financial fundamentals have become widely used when valuing subscription enterprises (McCarthy et al., 2017). As previously discussed, there are several issues with putting a fair value on SaaS companies. Krafft et al. (2005) argue that internet start-ups in their early stages of growth cannot be valued based on cash flow projections or bottom-line profits. Because SaaS companies in their early stages generally spend a significant amount of money on customer acquisition and R&D, cash flow is typically negative. Instead, customer-centric performance measures could be used to determine share price due to its ability to capture value drivers in companies (Krafft et al., 2005).

One measure that has gained considerable attention in marketing literature is customer acquisition cost (CAC). CAC is the money spent by a firm to acquire one new customer and demonstrates how efficiently a company obtains customers through its sales and marketing efforts (Gupta et al., 2004). As such, it is a proxy for a company's ability to acquire customers and generate revenue from them and a business's marketing strategy can be considered successful if its CAC is lower than its competitors (Smale, 2021). Multiple studies have researched CAC's implications for firm profits and found that optimizing CAC positively affects retention and profitability (e.g., Livne et al., 2011; Reinartz et al., 2005). Golec & Gupta (2014) tested how stock market returns correlate with CAC and found a negative relationship. They also argue that investors will punish high-growth firms that overspend on acquiring customers as it inhibits the company's potential to build a profitable customer base. Furthermore, Schulze et al. (2012) found that the number of acquired customers strongly influences shareholder value. Therefore, firms that compete to acquire subscription users and are inefficient in doing so will most likely be valued lower by investors.

Subscription-based businesses in their early stages of growth will require marketing expenditures to attract new customers. For a retailer, sales and marketing expenses generate revenue reasonably quickly. As a result, a ratio such as sales and marketing expense as a percentage of revenue (S&M %) provides a useful approximation of sales efficiency. However, for a subscription business, sales and marketing expenses generate subscription fees that are reflected in revenue only over the course of the contract. Thus, revenue for a given quarter is not a proxy for sales and marketing efficiency during that quarter but is the outcome of all the prior periods S&M expenses (O'Driscoll, 2010).

Since the majority of SaaS businesses do not publicly disclose their customer base, calculating CAC is challenging. Most research in this area examined the impact of CAC on company performance by using expert estimates or non-disclosed customer data (Gupta et al., 2004; Kumar & Shah, 2009). Following the adoption of ASC 606 and IFRS 15, however, companies are now required to disclose subscription revenue in a consistent manner that enables comparisons between companies in the same industry (Ernst & Young, 2020). The CAC ratio, which is defined as net new recurring revenue divided by sales and marketing expenses, is a metric that captures the exact dimensions as customer acquisition cost. However, the number is entirely based on public GAAP data, making it available to investors and comparable between companies (O'Driscoll, 2010).

- **Hypothesis 2**: Customer acquisition cost ratio illustrates a positive significant impact on share price movements for SaaS companies.

3.2.3 Financial Profitability and Share Performance

Traditionally, investors use comparable multiples to determine the value of a share's price. Liu et al. (2007) found that earnings per share (EPS) is a better valuation determinant than operating cash flow models (OCF). Similar results were found by Rusidiyanto et al. (2020), who tested the effects of financial earnings on share price movements and found a positive correlation between EPS and share price. Preda & Negru (2020) further tested the effects of Return on Assets (ROA) on share price movement and found a positive association. In contrast to the research mentioned above, Cohen & Neubert (2019) conducted a case study on Salesforce.com, a Fortune 500 company, and tested relative valuation methods such as Price-Earning-Ratio (PER), Price-Earning to Growth-Ratio (PEG), Price-Sales-Ratio, Price-Book-Ratio, and Price-Cash-Flow-Ratio in comparison to the traditional discounted cash flow valuation method (DCF). The findings suggest that relative valuation methods do not perform as well as the DCF when calculating the company's value.

Because reported earnings inform about past performance, they are not necessarily forward-looking. In general, the valuation of mature businesses with stable earnings is relatively uncomplicated (Cheong & Thomas, 2018). Larger businesses are often characterized by an elevated information environment when compared with smaller firms and can be regarded as an extensive portfolio of projects which limits the risk of unpredictable fluctuation (Plenborg & Pimentel, 2016). Furthermore, the cash flow stream is less complicated for these businesses, and historical financial fundamentals may be used as predictors for the future with limited uncertainty (Gupta et al., 2004). As a result, financial models relying on earning multiples perform admirably. In contrast, valuation of high-growth companies is more complex than valuation of mature companies with stable cash flow streams (Gupta et al., 2004). Besides, historical financial information of technology-based firms in fast-changing industries is of little value to investors. The majority of SaaS companies in an early development phase experience negative earnings due to high R&D and S&M expenditures. Thus, the SaaS business model renders some relative valuation methods and metrics inapplicable (Cohen & Neubert, 2019). Hayn (1995) contends that losses are less value-relevant than profits since they are transitory, as firms prefer to liquidate rather than suffer indefinite losses. This implies that net earnings are grossly inadequate for estimating the value of a share in a growing business. Therefore, it is of interest to investigate whether EPS affects the share price movements of SaaS businesses and whether there is a difference between larger firms and those in earlier stages of growth. As a result, the following hypothesis is developed:

- **Hypothesis 3**: EPS has a more positive impact on share price movements for large-cap SaaS companies than for mid- and small-cap SaaS companies.

3.2.4 Research & Development

Whether there prevails an association between research and development expenditures and future benefits of firms is a subject of attention. In part, the interest displays the growth of knowledge- and technology-based industries, which are especially active in R&D. Intangible assets are widely regarded as the primary source of value in modern businesses. Additionally, investments in intangible assets surpassed those in tangible assets over a decade ago (Lev, 2018). In some major technology industries, the amount of spending on R&D is larger than their earnings (Chan et al., 2001). Since SaaS companies require a digital platform adapted to several customers, significant R&D investments are required (Chou & Chou, 2008).

Previous research presents consistent evidence of an existing positive association between businesses' R&D outlays and both returns and share prices (Hirschey & Weygandt, 1985; Megna & Klock, 1993; Shevlin, 1991; Sougiannis, 1994; and Hand, 2001). Chambers et al. (2002) suggest that investors consider R&D when pricing shares because such expenses are expected to produce future benefits. Therefore, firms with intensive research and development expenditures should experience greater returns as they allocate resources to projects matching the business's abilities in terms of scale and competencies (Wernfelt, 1984; Vincente-Lorente, 2001; Chan et al., 2001).

The debate over the effect of firm size on the effectiveness of the innovation process was largely initiated by Schumpeter (1950). Schumpeter (1950) argues that the research and development process itself generates rapidly increasing returns to scale, and large firms have greater financial resources available to them. By contrast, small businesses frequently face credit constraints (Cabral & Mata, 2003). Greater financial reserves enable large firms to pursue more risky innovation projects, which typically yield higher expected returns. Additionally, increased cash flows enable large firms to undertake more expensive innovation projects, protecting them from competition from less solvent small firms. Schumpeter (1950) argues that large firms can leverage their market dominance to drive up the price of innovations they introduce. However, Spesha (2019) and Hall et al. (2010) found that sales growth is significantly and strongly positively related to R&D expenditures in small firms, while they are slightly negatively related to large firms' sales growth.

Spescha (2019) identified several possible reasons why small firms may be more efficient in their research and development activities. First, researchers' efforts in small firms are more inextricably linked to the firm's fate than they are in large firms. Second, skilled researchers with valuable ideas self-select into small firms, as they are generally more willing to work in environments where their actions directly impact their personal financial success. Third, small businesses typically have an advantage in terms of communication and coordination. Fourth, the probability of error increases exponentially with the size of the project. When these small-size advantages are added together, they appear to outweigh the large-size advantages. This relationship is especially apparent in growing industries consisting of many firms compared to industries with only a few dominant firms (Hall et al., 2010). Numerous new players enter SaaS markets regularly (Kidd, 2020), and it is therefore hypothesized that research and development expenditures correlate positively with the share price movements of SaaS companies, particularly smaller ones.

- **Hypothesis 4a**: The Research & Development to Sales ratio illustrates a positive significant impact on share price movements in SaaS companies.
- **Hypothesis 4b**: The Research & Development to Sales ratio illustrates a more positive significant impact on share price movements in mid- and small-cap SaaS companies compared to large SaaS companies

3.3 Market Efficiency Theory

According to Fama's (1970) market efficiency theory, an asset's price will be determined by all available information at a given point in time. The price will be accurate in light of the fact that all investors will have access to all information. Fama (1970) also postulated that investors are rational and have an accurate understanding of the information. Additionally, the investor is capable of acting in response to information, and the market is devoid of arbitrage opportunities (Brown, 1978). However, when investors behave irrationally, the market self-corrects, and asset prices gravitate toward their true value. To properly interpret the findings, it is assumed that the valuation of SaaS companies is based on the efficient market theories presented by Brown (1978) and Fama (1970), and thus that all information is available to and understood by all investors, as reflected in stock price valuation.

4. Data & Methodology

4.1 Research Approach and Research Method

This research paper aims to assess the statistical relationship between the dependent and independent variables with no influence from any extraneous relationship. Thus, the study aims to define, confirm, or validate relationships and generate generalizations that contribute to theory. The qualitative research approach is rejected because the researchers do not intend to develop a level of detail from high involvement in the actual environment. Instead, based on the choice of the research question, a quantitative study has been designed because it enables researchers to objectively measure reality using data (Williams, 2007). More precisely, the correlational research design was used because it permits researchers to predict an outcome in order to establish a relationship between observed variables (Anderson & Keith, 1997).

4.2 Data

Company financials were collected from Compustat Capital IQ database obtained through the Wharton Research Data Service (WRDS). Capital IQ's database consists of 88,000 public companies, making up for 99 percent of the world's market capitalization. Numerous quarterly and annual data points, such as revenue, EBITDA, and R&D expenditure, are available in the database. For this report, quarterly data was selected to identify share price movements within the period dating from 31 March 2010 to 31 December 2020. To increase the likelihood of identifying statistically significant variables with a high degree of validity, the dataset is filtered to eliminate companies that have been listed on the New York Stock Exchange (NYSE) or Nasdaq for less than one year as of 31 December 2020. Moreover, companies with a market capitalization of less than $300 million. Companies are typically classified as large-cap ($10 billion or more), mid-cap ($2 billion to $10 billion), or small-cap ($300 million to $2 billion) based on their market capitalization (Fernando, 2021). Closing price, highest price, lowest price, market capitalization, R&D expenses, quarterly revenue, and earnings per share are encompassed in each quarterly observation. Market capitalization and net income were used to ascertain whether issuance of shares or share repurchases had an effect on the share price or earnings per share of any company. However, this appears not to be the case. The final dataset extracted contains data on 74 SaaS companies of various sizes.

SaaS- and customer-related metrics like customer retention, subscription revenue, and the number of customers were collected from Public Comps. Public Comps collect data from SEC filings starting Q1 2010 and do not rely on or pay for any third-party vendor for financial information. The database is available for $99 per month and is believed to be reliable after rigorous cross-checking from several of the selected SaaS companies' S-1 general forms, 10-K annual reports, 10Q quarterly reports, and press releases. Additionally, the database is utilized by several private equity funds and venture capital firms, indicating that the data is transparent and of high quality. Public Comps SaaS company index was used to identify pertinent companies for the study. The firm-specific quarterly data points included in the dataset are annual recurring revenue and customer acquisition cost ratio.

Some SaaS companies have occasionally not published subscription revenue which results in missing CAC ratio values. There seems not to be a relationship between the data's missingness and any observed or missing values. Therefore, the analysis performed on the data may be considered unbiased (Bannon, 2015). The observations in the dataset begin with the date on which each SaaS company publicly discloses customer-related and sales-efficiency data, resulting in an unbalanced dataset. Consequently, quarterly observations for some companies may begin later than the point in time that they were listed on the stock exchange. For example, Mimecast Limited began trading on Nasdaq Global Select on November 19, 2015 but did not publicly reveal recurring revenue and customer count until the third fiscal quarter of 2017. Therefore, observations from Mimecast's third quarter of 2017 to the fourth quarter of 2020 are included in the dataset. The final dataset used to conduct the quantitative study consists of 1384 observations. Furthermore, customer count, churn rate, and customer lifetime value significantly affect company performance and valuation (McCarthy et al., 2017). However, since only a minor proportion of SaaS businesses register uniform customer counts in their interim reports, these metrics are omitted.

Table 1. Sample Selection

Class	Companies	% of Sample	Observations	% of Observations
Large Cap	34	45,9 %	714	51,6 %
Small- & Mid-Cap	40	54,1 %	670	48,4 %
Total	74	100 %	1384	100%

4.3 Dependent and Independent Variables

Share prices generally change significantly following earnings releases because investors typically use information in financial announcements to re-evaluate share prices (Ball & Brown, 1968; Firth, 1976). Moreover, distinct stock market reactions are frequently observed when announced earnings are unexpected in that they fall short or exceed expectations (Fink, 2021). Lagging share price data is used, which means that independent variables will be paired with the following quarters' closing share price. Therefore, the share price performance of individual stocks will be traced by known fundamentals rather than estimates in the regression analysis as it may capture such movements more accurately.

The regression models are calibrated using the following financial metrics: revenue, annual recurring revenue (ARR), customer acquisition cost ratio (CAC ratio), earnings per share (EPS), and research and development expense as a percentage of revenue (R&D). Revenue is expressed as current quarter total GAAP revenue in terms of MUSD, while ARR is measured as quarterly subscription revenue multiplied by four. The CAC ratio is calculated by dividing net new subscription revenue by the previous quarter's sales and marketing expenses. To illustrate, a company with a CAC ratio of 1 spends $1 on sales and marketing to generate $1 in incremental recurring revenue the following quarter. While spending a dollar to acquire a dollar in revenue may seem counterintuitive, the idea is that subscription-based enterprises with healthy retention and average software gross margins make that investment in sales and marketing profitable (O'Driscoll, 2010).

Variance inflation factors were calculated to determine whether an independent variable is highly correlated with one or more of the other independent variables. Multicollinearity is a concern because it increases the variance of coefficient estimates and makes them highly susceptible to model changes. Multicollinearity reduces the statistical power of the analysis, makes it more difficult to specify the correct model, and can cause coefficients to switch signs. Consequently, the estimated coefficients become challenging to interpret. A variance inflation factor greater than 10 indicates the presence of multicollinearity and necessitates modification of the regression model (Blalock, 1963). **Table 8** in the appendix compiles the independent variables' variance inflation factors, and the results suggest that total quarterly revenue and annual recurring revenue are multicollinear. However, this is not alarming as SaaS companies' turnover primarily consists of subscription revenue. ARR was, thus, excluded as an independent variable. Additionally, both share price and revenue include several outliers and consequently suffer from high levels of skewness and kurtosis. These independent variables are converted into a logarithmic form to make variable distributions less skewed (Feng et al., 2012).

A firm-size dummy was added to the dataset to test the effects of the independent variables on both large-cap SaaS companies and mid- and small-cap SaaS companies. Companies with a market capitalization equal to or more than $10 billion as of 31 December 2020 are categorized as large companies, while the remaining businesses are classified as small. Companies are typically classified as large-cap ($10 billion or more), mid-cap ($2 billion to $10 billion), or small-cap ($300 million to $2 billion) based on their market capitalization (Fernando, 2021). Correlational corporate finance studies in the past have relied on a variety of alternative measures of firm size. Examples of alternative size measures include sales, employees, total assets, and enterprise value (Shalit & Sankar, 1977). Due to the high correlation between these measures within industries, their coefficients are typically robust in terms of sign and statistical significance (Dang et al., 2018). Thus, market value is considered as a representative indicator of the size of SaaS companies.

Table 2. Variable Definition

Variables	*Definitions*
Revenue	Current quarter total GAAP revenue
Annual Recurring Revenue (ARR)	Quarter subscription revenue * 4
Customer Acquisition Cost Ratio (CAC)	Net New Recurring Revenue /Sales and Marketing Previous Quarter
Earnings Per Share	Reported net income, subtracted by preferred dividends, divided by the total common outstanding shares during the reporting period (measured in USD)
R&D Spending as a Percentage of Revenue	Current quarter total GAAP R&D expenses divided by net sales
Size (Dummy)	Firm size dummy variables

The table presents all the variables included in the analysis

4.4 Panel Data

Typically, panel data or longitudinal data refer to data sets that contain time series observations of a large number of individuals. As a result, panel data observations contain at least two dimensions. In the dataset, the time (T) dimension contains the quarterly observations, and the individual (N) are the companies observed. Traditional panel data is oriented around individual outcomes and numerous variables that influence those individual outcomes. It is uncommon to assume a joint contingent probability distribution for y dependent on x for all cross-sectional units, i.e., N at all times, T (Hsiao, 2007). Using panel data enables analysis and observation of the effects of independent variables on the dependent variable while taking into account the unique characteristics of each firm. Thus, panel data enables statistical analysis that can be used to explain phenomena that are common in individual markets or industries (Torres-Reyna, 2007).

The dataset consists of individual time-varying variables that fluctuate across cross-sectional units (companies) and vary over time, such as firm profits, revenue, and stock price. A common challenge with panel data is to control for the unobserved heterogeneity across individuals. The consequences of unobserved heterogeneity can be assumed to be random variables, fixed parameters, or a mixture of both. Therefore, panel data modeling aims at limiting the heterogeneous effects across individuals, making it possible to accurately model statistical inferences to predict an explanatory variable for a group of companies (Hsiao, 2007). As a result, model selection will be based on a series of robustness tests.

4.4.1 Fixed Effects Model

The fixed effects model assumes each individual has its unique characteristics. Something about an individual can potentially influence or bias the predictor variables, and the fixed effects model, therefore, account for this. Moreover, the fixed effects model also assumes that the time-invariant characteristics of the individual are not correlated with other individuals' unique characteristics. Hence, an individual’s error terms do not correlate with other individuals’ error terms. If that is the case, some random effects call for other models’ usage. The Hausman test can be used to determine whether or not the unique errors are correlated and will thus be used as a measure to determine the optimal model selection (Hsiao, 2007; Torres-Reyna, 2007). The advantage with a fixed effects model is that it allows for time- or company-specific effects as there might be an unobserved heterogeneity within the companies that the chosen model needs to capture. As a result, the fixed effects model may be summarized by the following equation:

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it}$$

Where α_i is the unknown intercept with (i=1...n) representing each entity. Y_{it} is the dependent variable, and X_{it} one independent variable. β_1 depicts the coefficient for the independent variable where u_{it} is the error term. The fixed effects model could also be expanded to account for time or entity-specific effects. If any unforeseen variation or special events, such as Covid-19, possibly have an effect on the outcome variable, it needs to be controlled for (Torres-Reyna, 2007).

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \ldots + \beta_k X_{k,it} + Y_2 E_2 + \ldots + Y_n E_n + \bar{o}_2 T_2 + \ldots + \bar{o}_t T_t + u_{it}$$

Where E_n is the entity and T_t is the time dummy variable. $\bar{o}_t$ is the time regression coefficient.

4.4.2 Random Effects Model

The distinction between random effects and fixed effects models is that the random effects model presupposes that individual variance is unrelated to the independent variables while the fixed effects model does not. The random effects model further presumes that the individual or time-specific effect is randomly distributed. Also, if the prior assumption is that the dichotomy between the companies in the panel data will affect the dependent variable, a random model should be used. The random effects model assumes that an individual's error term does not correlate with the predictor variable (Torres-Reyna, 2007; Baltagi, 2008). Nevertheless, since this is unknown, both a random and fixed model must be tested. The random effects model is, therefore:

$$Y_{it} = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it}$$

Where ε_{it} is the within entity error.

4.4.3 Pooled OLS Model

In the pooled ordinary least squares regression model, every unique row is assumed to be an individual observation. Therefore, the linear OLS regression presumes no variance across the individual companies and thus regresses the variables without considering time- or company-specific effects. Implications of the pooled OLS panel data model is that there is no unobservable heterogeneity, i.e., no unique firm characteristics. However, because it is unknown whether company- or time-specific effects exist, an OLS regression model needs to be tested. A Breusch-Pagan Lagrange test adds robustness to the model selection process and enables to determine whether or not unobservable heterogeneity of variance exists (Torres-Reyna, 2007).

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

4.5 Model Selection

When working with panel data, it is critical to select the appropriate model; fixed effects (FE), random effects (RE), or pooled ordinary least squares (POLS) (Torres-Reyna, 2007). A total of twelve panel data regression models were developed. To estimate the relationship between selected independent variables and share price movements, fixed and random effects models were first constructed for the entire sample and then for large-cap and mid-cap, and small-cap SaaS companies, respectively. Then, three POLS regression models that neither consider heterogeneity across groups or time were created.

Fixed Effects Model - (All companies/ Large-Cap/ Mid- and Small-Cap)

$$\text{Share price}_{it} = \beta_1 \text{Revenue}_{it} + \beta_2 \text{CAC}_{it} + \beta_3 \text{R\&D}_{it} + \beta_4 \text{EPS}_{it} + \alpha_i + u_{it}$$

Random Effects Model - (All companies/ Large-Cap/ Mid- and Small-Cap)

$$\text{Share price}_{it} = \beta \text{Revenue}_{it} + \beta \text{CAC}_{it} + \beta \text{R\&D}_{it} + \beta \text{EPS}_{it} + \alpha + u_{it} + \varepsilon_{it}$$

Pooled OLS - (All companies/ Large-Cap/ Mid- and Small-Cap)

$$\text{Share Price}_{i} = \beta_0 + \beta_1 \text{Revenue}_{i} + \beta_2 \text{CAC}_{i} + \beta_3 \text{R\&D}_{i} + \beta_4 \text{EPS}_{i} + \varepsilon_{i}$$

After that, a plot was created to visually examine if share prices have different means across companies and if it is reasonable to assume that all companies are homogenous (**Figure 2**). Three Hausman tests for individual effects further checked for heterogeneity across groups. The Hausman test checks whether the unique errors are correlated with the regressors; the null hypothesis is they are not. The random effects model will be chosen if the two models are similar since it is a more efficient estimator (Torres-Reyna, 2007).

$$W = ((\beta_{FE} - \beta_{FE})^2 \,/\, (\text{Var}(\beta_{FE}) - \text{Var}(\beta_{FE}))) \sim \mathscr{X}^2$$

Each p-value is significant at a 0,001 level, and the Hausman tests indicate that the differences in coefficients are systematic **(Table 9)**. The fixed effects model will therefore be used for each regression analysis. Additionally, **Figure 3** illustrates the heterogeneity of mean share prices across the quarters examined. To incorporate the phenomenon, time fixed effects models were developed for all companies, large-cap, and mid- and small-cap. A Breusch-Pagan Lagrange Multiplier test was conducted to check for time effects (Torres-Reyna, 2007). The p-values show significance at 0,001 levels (**Table 10)**, and it is therefore concluded that time fixed effects models are the most accurate.

Time Fixed Effects Model - (All companies/ Large-Cap/ Mid- and Small-Cap)

$$\text{Share Price}_{it} = \beta_1\text{Revenue}_{it} + \beta_2\text{CAC}_{it} + \beta_3\text{R\&D}_{it} + \beta_4\text{EPS}_{it} + \bar{\text{o}}_t\text{Year\_quarter}_t + \alpha_i + u_{it}$$

4.6 Robustness Tests

Certain precautions were taken to ensure the validity of the results. The main objective of the robustness tests was to decide whether the numerical results obtained from the time fixed effects regression analysis, quantifying hypothesized relationships between variables, are acceptable as descriptions of the data. This section will cover the statistical tests that were conducted.

Cross-Sectional Dependence

Panel data can exhibit widespread cross-sectional dependence, which occurs when all units within a cross-section are correlated. This is typically attributed to some unobserved common factors that affect all units, albeit in slightly different ways. If the omitted common factors are correlated with the regressors, the panel data standard estimators are inconsistent (Tugcu, 2018). A Breusch-Pagan LM test was conducted to check whether the residuals are correlated across entities (Hoechle, 2007), as shown in **Table 11** in the appendix. In macro panels with long time series, cross-sectional dependence is a concern. However, such contemporaneous correlation is not an issue for micro panels with observations from a few years and a large number of cases (Baltagi et al., 2012).

Serial Correlation

Serial correlation, alternatively referred to as autocorrelation, is the relationship between a signal and a delayed copy of itself as a function of delay. The Breusch-Godfrey test checks for the existence of serial correlation that has been omitted from a proposed model structure and which, if present, would imply that incorrect conclusions from other tests could be drawn or that suboptimal model parameter estimates would be obtained. The null hypothesis suggests that no serial correlation exists (Godfrey, 1996). A p-value of less than 0,001 for each time fixed effects model indicates serial correlation in idiosyncratic errors for each model **(Table 12)**. However, Fama & French (1986) demonstrate that serial correlation is commonly prevalent in stock returns. Like cross-sectional dependence, serial correlation is not a problem in micro panels with few years of observations (Torres-Reyna, 2007).

Stochastic Trends

To further assess the panel data's robustness, a test for the presence of unit roots was conducted. Unit roots, or non-stationary panel data, reveal that some sort of stochastic trend is present. As a result, an augmented Dickey-Fuller test was used to determine whether the data contains unit roots. The test's null hypothesis is that unit roots are present. Unit roots are problematic because, after a certain number is reached, every prediction becomes range-bound, at which point the time series loses predictive power (Banerjee, 1999). Nevertheless, a significance level of 0,001 (**Table 13**) indicates that no stochastic trend is present.

Heteroskedasticity

In statistics, a vector of random variables is said to be heteroscedastic if the random disturbance's variability varies through the vector's elements. Variability can be quantified here using the variance or some other statistical indicator of dispersion. As a result, heteroscedasticity is synonymous with the lack of homoscedasticity (Gujarati & Porter, 2009). Heteroscedasticity is a significant issue in regression and analysis of variance since it invalidates statistical tests of significance that conclude all modeling errors have the same variance (Goldberger, 1964). Nonetheless, heteroskedasticity in stock returns is a universal phenomenon considering that the variance of public stock returns is not constant over time but is proportional to the volume of shares traded. (Morgan, 1976; Schwert & Seguin, 1989)

To check for heteroskedasticity in the time fixed effects models, a studentized Breusch-Pagan test was conducted. The test's null hypothesis suggests homoskedasticity, which means that the error terms are constant. Heteroskedasticity was detected at a 0,01 significance level for **Model I** and **Model III (Table 14),** and to account for it, robust covariance matrices were used. More specifically, the time fixed effect models controlled for both heteroskedasticity and serial correlation by incorporating an Arellano-Bond estimator. When the robust covariance matrices were included, the change in the regression coefficients remained practically unchanged. However, Arellano does not provide an R^2 for the model, so it is unknown how much variance the model explains and, consequently, how strong it is. Thus, time fixed effects models are used instead of random effects models because they avoid overestimating effects and provide a more transparent portrayal of model strength.

5. Results

5.1 Descriptive Statistics

Table 2 summarizes the descriptive statistics for the 74 SaaS companies included in the sample. There are 1384 quarterly observations in total, but slightly fewer for the CAC ratio and share price. The absence of share price observations is explained by the fact that they are paired with the previous quarter's independent variables. Accordingly, the dataset includes observations of some companies' key figures from the quarter prior to their initial public offering. The mean share price for all SaaS companies included in the dataset is 76,37 USD, with a standard deviation of 87,61 USD. Quarterly revenue averages 272,56 MUSD, with a standard deviation of 546,14 MUSD. Earnings per share on average are negative, implying that several SaaS businesses are unprofitable. Additionally, this highlights the importance of examining alternative performance metrics and their impact on share price movements. Without regard for time or company effects, all independent variables correlate with share price at a 0,001 significance level. Revenue is the variable that correlates most with share price (0,354). Correlation coefficients between share price and CAC ratio as well as EPS are slightly lower, at 0,290 and 0,248, respectively. Lastly, research and development expenses to sales ratio are negatively correlated with share price.

Table 3 – Descriptive Statistics of Sample Data – All Companies

					Correlation Among Variables				
	Variables	N	Mean	SD	(1)	(2)	(3)	(4)	(5)
(1)	Share Price	1332	76,37	87,61	1,000				
(2)	Revenue	1384	272,56	546,14	0,354***	1,000			
(3)	CAC ratio	1312	0,91	0,96	0,290***	-0,042	1,000		
(4)	EPS	1384	-0,14	0,5	0,248***	0,338***	0,211***	1,000	
(5)	R&D %	1384	22,85 %	11,37%	-0,099***	-0,108***	-0,184***	-0,477***	1,000

**Significant at p <0.10 (two-tailed test)*

*** Significant at p <0.05 (two-tailed test)*

****Significant at p <0.001 (two-tailed test)*

Table 3 summarizes the statistics for SaaS companies with a market capitalization greater than 10 billion USD. In total, there are 714 quarterly observations but slightly lower for CAC ratio and Share price as certain values are missing. Large SaaS companies have a slightly higher average share price than the overall mean in **Table 2** and a slightly higher customer acquisition cost ratio. However, R&D % and EPS appear to be almost identical. As expected, average quarterly revenue is higher for large companies, with a mean of 430,74 MUSD and a standard deviation of 723,37 MUSD. The correlation coefficient between revenue and share price is somewhat lower for large companies (0,282). Additionally, all correlation coefficients are significant at a 0,01 level, except R&D percentage, which is significant only at a 0,1 level.

Table 4 – Descriptive Statistics of Sample Data – Large Companies

					Correlation Among Variables				
	Variables	N	Mean	SD	(1)	(2)	(3)	(4)	(5)
(1)	Share Price	691	117,64	121,48	1,000				
(2)	Revenue	714	430,74	721,37	0,282***	1,000			
(3)	CAC ratio	678	1,05	1,06	0,290***	-0,106**	1,000		
(4)	EPS	714	-0,08	0,57	0,235***	0,389***	0,251***	1,000	
(5)	R&D %	714	22,51 %	11,95%	-0,080*	0,155***	-0,199***	-0,453***	1,000

**Significant at p <0.10 (two-tailed test)*

*** Significant at p <0.05 (two-tailed test)*

****Significant at p <0.001 (two-tailed test)*

Table 4 summarizes the descriptive statistics for small companies in the sample, i.e., firms with a market cap of less than 10 billion USD. There are 670 quarterly observations in total but 641 and 634 for share price and CAC ratio. An investor can anticipate paying less than half as much (45,71 USD) for a share in a mid- or small-cap SaaS company as they would for a share in a large-cap SaaS company. Mean revenue is 103,97 MUSD with a standard deviation of 82,64 MUSD. All independent variables, except revenue, significantly correlate with share price. EPS and CAC ratio is positively correlated with share price, resembling large SaaS companies. However, R&D is slightly more negatively correlated with share price for small SaaS companies than large ones. A further disparity is that EPS is negatively correlated with sales.

Table 5 – Descriptive Statistics of Sample Data – Small Companies

					Correlation Among Variables				
	Variables	N	Mean	SD	(1)	(2)	(3)	(4)	(5)
(1)	Share Price	641	45,71	31,98	1,000				
(2)	Revenue	670	103,97	82,64	0,0511	1,000			
(3)	CAC ratio	634	0,78	0.94	0,304***	-0,073*	1,000		
(4)	EPS	670	-0,21	0.39	0,222***	-0,071*	0,11***	1,000	
(5)	R&D %	670	23,2%	10,7%	-0,219***	0,174***	-0,164***	-0,542***	1,000

**Significant at p <0.10 (two-tailed test)*

*** Significant at p <0.05 (two-tailed test)*

****Significant at p <0.01 (two-tailed test)*

5.2 Model I - All companies

The results of the time fixed effects models are presented in **Table 6**. **Model I** encompasses all 74 companies in the sample, with a total of 1384 observations. Each of the four independent variables has statistical significance, indicating that each variable accounts for a proportion of share price movements across the entire sample. Revenue, CAC ratio, and R&D% are statistically significant at a 0,01 level, while EPS is significant at a 0,05 level. Revenue has the highest unstandardized coefficient (0,797) of the four independent variables, followed by R&D percentage (0,715). CAC ratio and EPS both have somewhat lower regression coefficients of 0,045 and 0,086, respectively. The R^2 value indicates that the independent variables account for 0,697 of the sample's share price variance.

5.3 Model II - Large companies

Examining the results from **Model II**, similar results as in **Model I** are found. The sample contains 34 SaaS companies with a market capitalization greater than 10 billion USD, and the model is based on 714 observations. Revenue has a regression coefficient of 0,728, which is slightly less than the coefficient for the entire sample and is statistically significant at the level of 0,01. CAC ratio is positively associated with share price with a beta coefficient of 0,037. Hence, the predictive power of CAC is somewhat weaker than in **Model I** but yet significant at a 0,05 level. In contrast to **Model I**, the coefficients for R&D % and earnings per share are not statistically significant, implying that these variables do not affect the share price movements of large companies in the sample. **Model II** has the highest R^2 value (0,838) of the three time fixed effects models, indicating that it best fits the sample data.

5.4 Model III - Small Companies

Model III comprises 40 mid- and small-cap SaaS companies and contains 670 observations. Each of the four independent variables is statistically significant at a 0,01 level. Each of the regression coefficients is positive, indicating an increase in revenue, CAC ratio, EPS, or R&D % would result in a mean share price increase for mid- or small-cap SaaS companies. Although the CAC ratio is statistically significant for all fixed effects models, **Model III** has the highest coefficient. Thus, an equal increase in CAC ratios of two SaaS firms of varying sizes should most likely benefit the smaller of the two. Additionally, the coefficients for EPS and R&D % are also higher than for **Model I** and **Model II**. The highest coefficient is 0,99 for R&D percentage, followed by 0,212 for EPS and 0,061 for CAC ratio. Moreover, **Model III** has a lower R^2 than **Model I** and **Model II**, indicating that it has a poorer fit with the data than the two other time fixed effects models.

Table 7. Fixed Effects Regression results

	All Companies Model I	Large Companies[1] Model II	Small Companies[2] Model III
Variables			
Log (Revenue)	0,797*** (13,14)	0,728*** (10,88)	0,451*** (4,32)
CAC ratio	0,045*** (3,34)	0,037** (2,10)	0,061*** (3,49)
EPS	0,086** (2,99)	0,015 (0,51)	0,212*** (3,88)
R&D %	0,715*** (3,72)	0,023 (0,08)	0,99*** (4,05)
Nr. of Companies	74	34	40
Observations	1384	714	670
R-Squared	0,697	0,838	0,555
Adj. R-Squared	0,664	0,815	0,482

Standardized regression coefficients are reported, with t-values in parenthesis

1) *Market cap ≥ $10 bn*
2) *Market cap ≤ $10 bn*

** Significant at p <0.10 (two-tailed test)*

*** Significant at p <0.05 (two-tailed test)*

****Significant at p <0.01 (two-tailed test)*

6. Discussion

6.1 Revenue

The results demonstrate that revenue has a statistically significant effect on share price movements for large and mid-and small-cap SaaS companies. Previous literature suggests several conceivable reasons why revenue may be a significant determinant of SaaS companies' share price movements. To begin, it is possible that current accounting standards are insufficient and that investors view revenue as a proxy for future profitability. Second, because SaaS companies operate in highly technological industries, investors may anticipate faster growth rates in the future (Lev & Zarowin, 1999).

The results are in line with Newton & Schlecht (2016) and confirm that revenue is an adequate financial indicator when valuing SaaS companies. Since many SaaS companies spend large amounts on R&D and incur negative operating cash flow, traditional valuation methods might not prove sufficient. This, combined with a high level of uncertainty and a volatile market environment, suggests that revenue may be a good predictor of SaaS companies' success (Lev & Sougiannis, 1996; Lev & Zarowin, 1999). Additionally, from a strategic standpoint, as the SaaS market has proliferated, competition is fierce. Revenue growth may be viewed as a critical objective and indicator of a company's marketing success. Increased market share results in a strengthened competitive advantage and higher entry barriers (Chandler 2001; Spar 2001). This could explain why investors place a premium on revenue, as evidenced by the positive relationship between revenue and share price in the sample data.

Because the majority of SaaS companies' revenue streams are recurring, customer retention is critical. The results indicate that SaaS companies are valued upon their revenue generation, and thus retention rates will impact future revenues. The customer-company relationship can be quantified as a customer satisfaction score, and this metric will thus explain some level of the subscription model's success. Fornell et al. (2016) found a positive correlation between customer satisfaction and stock return attributed to an earnings effect reflected in the financial statement. They also found a link between customer satisfaction and retention, and thus a higher satisfaction could lead to increased retention and eventually higher recurring revenue.

This study does not capture any customer satisfaction rates. However, the strong correlation between revenue and share price might be explained by a customer-company relationship. Companies that provide superior value to their customers generate higher revenues due to higher retention rates (Kumar & Shah, 2009).

The findings do not establish the necessity of retention per se, but it does open up for discussion on why revenue appears to explain share price movements in SaaS companies. The revenue variable could be used to represent recurring revenue streams, which are prevalent in the SaaS business model. The findings may imply that firms that succeed in retaining customers will experience increased recurring revenue streams. Thus, the findings partially corroborate theories presented by Livne et al. (2011), Reichheld & Sasser (1990), and Gupta et al. (2004), stating that increased retention rates result in increased profitability and shareholder value in the long run.

6.2 Customer Acquisition Cost

The CAC ratio has a positive effect on the share prices of the SaaS companies in the sample. The findings corroborate Golec & Gupta’s (2014) conclusion that there is an association between share price and customer acquisition cost. This suggests that investors evaluate not only revenue growth but also a business's ability to acquire customers and generate revenue from them. Because the CAC ratio captures the relationship between net new recurring revenue and the effort required to generate it, it is a helpful metric for assessing a business model's overall performance. Thus, the findings are consistent with those of Smale (2021) & Krafft (2005), who conclude that subscription enterprises can not be valued solely based on cash flow forecasting, and that customer-centric metrics are more accurate predictors of the true intrinsic value of a business. Additionally, the results partially justify Schulze's (2012) finding that the number of acquired customers is positively associated with shareholder value. Furthermore, Livne et al. (2011) and Reinartz et al. (2005) found that customer acquisition costs affect both retention and profitability, reinforcing the notion that boosting CAC improves overall performance. Given that investors use earnings reports to revalue stocks (Ball & Brown, 1968; Firth, 1976; Fink, 2020), this may explain why investors view the CAC ratio as a reliable indicator of future profitability.

While results show that the CAC ratio has a positive effect on SaaS businesses' stock prices, it seems that the CAC ratio has a somewhat more significant effect on the share price movements of mid- and small-cap companies. The sample of small SaaS companies has a coefficient estimator of 0,061. This finding may be attributed to various factors, most notably the fact that small businesses experiencing rapid growth need to establish a solid customer base. Moreover, investors appear to value how efficiently companies operate towards this objective. The result is consistent with Golec & Gupta's (2014) finding that a correlation exists between CAC and rapid firm growth. Larger businesses nearing steady state may have more reliable revenue sources, and as a result, other performance metrics could be considered more critical.

6.3 Earnings Per Share

The time fixed effects models suggest that EPS positively correlates with share price movement in the sample data. However, when comparing large and small SaaS companies, EPS only accounts for a sizable proportion of share price in the latter. On an aggregated level (**Model I**), the findings are consistent with Rusidiyanto et al. (2020) and Liu et al.'s (2007) theories that EPS explains share price variation. However, EPS does not appear to be a good predictor of share price movement for large SaaS companies, supporting Cohen & Neubert's (2019) contention that relative earning multiples are insufficient estimators for SaaS company valuation.

Analyzing the impact of EPS for smaller SaaS companies, the results indicate that investors value the profit generated by smaller SaaS companies. In contradiction to **Hypothesis 3**, one explanation for this could be that large mature SaaS companies generate stable revenue streams (Plenborg & Pimentel, 2016). Hence, investors do not react as strongly to earnings releases as they do to those of smaller companies. It might be that the "earnings effect" is met with a greater appreciation for smaller SaaS companies that more often produce negative earnings in an early phase. However, because this research paper provides no evidence for the existence of such an effect in the sample of mid- and small-cap SaaS companies, no research-based conclusions on this subject can be drawn.

6.4 Research & Development Expenses

The paper at hand demonstrates that R&D explains a significant proportion of share price movements for SaaS companies. However, the study does provide evidence that R&D exerts a greater influence on share price movements in small SaaS companies than in large SaaS companies. Although both large-cap and mid- and small-cap companies in the study sample spend roughly the same percentage of revenues on R&D, the smaller SaaS companies' R&D expenses have a significantly greater impact on their share prices. Schumpeter's (1950) arguments in favor of large firm size as a strength in the R&D process appear to lack empirical validity**.** Thus, the findings corroborate Spescha (2019), indicating that several advantages of smaller firms appear to outweigh those of larger firms.

The study concludes that research and development expenditures significantly impact the share price movements of small SaaS companies, but not on the share price movements of large SaaS enterprises. There are several possible explanations for this finding. First, the SaaS industry is rapidly growing, and new players are regularly entering. According to prior research, small businesses in these markets are more reliant on innovation to remain competitive in the long run, and as a result, investors place a premium on such investments. Second, the R&D process appears to display significant diseconomies of scale (Spescha, 2019), and investors appear to take this into account when valuing SaaS companies. Small firms invest in R&D more efficiently than large firms and exhibit higher R&D-output elasticities than samples composed primarily of large corporations (Hall et al., 2010). A third explanation for the study's findings is that investors may view research and development activities in smaller SaaS businesses as less risky, as they typically invest in smaller projects (Spescha, 2019).

6.5 Extended Discussion

Table 7 presents growth multiples, average CAC ratios, and S&M as a percentage of revenue for ten SaaS companies included in the study sample in the period between Q4 2017 and Q4 2020. During the period, all of the businesses increased their revenue, some more than others. Additionally, these companies' CAC ratios and S&M expenses vary. Numerous conclusions can be drawn from these figures. By examining Shopify and Alteryx, the two companies with the highest revenue growth multiples, it is possible to determine that these two companies also had the highest average CAC ratio during the investigated period. Another finding is that both Pluralsight and Veeva Systems have grown at nearly the same rate over the three years. Veeva Systems, on the other hand, had a significantly higher CAC ratio than Pluralsight, at 1,19 and 0,42, respectively. Additionally, one can see that while Pluralsight spent more on sales and marketing than Veeva Systems, their marketing efforts resulted in less revenue.

During the 12 quarters of the investigation, Zendesk and Zuora, among others, had CAC ratios that were relatively similar. Anyhow, the three-year revenue growth multiples are slightly different. This result can be explained by the fact that Zendesk spent 49% of its revenue on sales and marketing, while Zuora spent 40%. Thus, the two businesses experience similar returns to their sales and marketing spending. Yext had the lowest CAC ratio (0,34). Although they grew revenue nearly as much as New Relic during the same time period, they had to spend 69 percent of their revenue on S&M to do so while New Relic spent 55 percent. Thus, the CAC ratio appears to be a good indicator of sales efficiency and return on sales and marketing investments.

Table 8. Revenue and CAC ratio

Company	Annualized Revenue Q4 2017 (MUSD)	Annualized Revenue 12 Quarters Later (MUSD)	3 Year Revenue Growth Multiple	Average CAC-ratio	S&M as % Revenue
Alteryx	$154,4	$642,1	4,16	3,05	48 %
Avalara	$245,5	$579	2,36	0,47	49 %
New Relic	$367,3	$665,4	1,81	0,42	55 %
Pluralsight	$198,6	$420	2,11	0,42	65 %
Shopify	$891,3	$3911	4,39	2,50	29 %
Veeva Systems	$743,9	$1587	2,13	1,19	17 %
Workiva	$218	$375,3	1,72	0,56	39 %
Yext	$192,1	$368,8	1,92	0,34	69%
Zendesk	$487,7	$1134	2,33	0,43	49 %
Zuora	$199,3	$317,2	1,59	0,41	40 %

7. Limitations

First, the study does not account for the independent variables' relative explanatory power. As a result, it is not possible to statistically conclude whether certain variables explain share price volatility in SaaS companies more or less than others. This is intriguing because it could have added another layer of analysis to the study. Second, the study examined the period from 2010 to 2020. The paper used a time fixed effects model, indicating that certain events or seasonalities in the model exist, but could potentially benefit from a period analysis to determine whether or not the significance of the predictive variables has changed over time. Third, **Model I** and **Model III** exhibit some heteroskedasticity, which may affect the outcome variables. On the other hand, several robustness tests have been used to account for this, which should mitigate these effects. Fourth, the study uses a broad definition of SaaS. However, several subgroups of SaaS businesses could have been analyzed. For instance, this study includes both B2C and B2B companies, allowing for a broader discussion of the findings. The relative importance of different types of businesses, on the other hand, could have added depth to the analysis. Fifth, because the data points are quarterly, it might be worthwhile to include more frequent data points, such as monthly or weekly data, to help deepen the analysis. Sixth, the study did not investigate whether the selected measures explained more of the value than traditional valuation models. A suggestion for future research in SaaS valuation is to compare other valuation models to the model developed in this study. Seventh, the panel data regressions fail to account for revenue volatility. Future panel data regression studies, for example, could benefit from including the sample companies' standard deviation of revenues over three years. Also, market capitalization has been used as a proxy for more or less growth intense companies. However, this is not true at all cases and other metrics could have been used, such as revenue growth for example.

8. Conclusion

This quantitative paper examined the effect of revenue, customer acquisition costs, research and development expenses, and earnings per share on the share price movements of SaaS companies listed on the New York Stock Exchange (NYSE) or Nasdaq. To determine whether such statistical relationships exist, a time fixed effects regression model was developed. Subsequently, a sub-sample study was conducted to assess whether there is a difference in the explanatory power of independent variables between large-cap SaaS companies and mid- or small-cap SaaS companies.

The current paper discovers evidence that revenue and customer acquisition cost ratio significantly impact the share price movements of all SaaS companies, regardless of size. This may imply that investors consider not only SaaS businesses' revenue growth but also their ability to acquire and retain customers successfully. However, revenue has a greater impact on the share prices of large-cap SaaS businesses than on those with less than $10 billion in market capitalization. Rather than that, investors appear to place a higher premium on the sales and marketing efficiency of mid- and small-cap SaaS companies than on larger businesses. After all, the SaaS industry is rapidly growing, and when it comes to competing for market share, returns on marketing are critical.

The findings did not support the study’s initial hypothesis regarding the effect of earnings per share on SaaS companies’ share price movements. On an aggregated level, EPS has a significant effect on SaaS companies’ share prices. However, as per the panel data regressions, EPS has a statistically significant effect on the share price movements of mid- and small-cap SaaS companies but no impact on the share prices of large-cap SaaS businesses. It might be that the “earnings effect” is met with a greater appreciation for smaller SaaS companies, which, on average, generate more negative earnings in their early stages.

The paper at hand has demonstrated that the R&D to sales ratio accounts for a sizable portion of the variation in share prices for SaaS companies. However, the study provides further evidence that R&D has a greater impact on share price movements in small SaaS companies than in large SaaS companies. While both large and small companies in the study sample spend roughly the same percentage of revenues on R&D, investors tend to place a premium on R&D investments in mid- and small-cap SaaS businesses. The findings are consistent with the initial hypothesis and are backed up by a substantial body of literature. Numerous possible explanations exist for why this phenomenon occurs. For instance, small businesses operating in rapidly growing markets rely significantly more on innovation to maintain long-term competitiveness. Moreover, their projects are typically less risky, and R&D has been demonstrated to exhibit significant scale diseconomies.

9. Contribution & Future Research

The purpose of this study is to contribute to the growing body of knowledge regarding the valuation of SaaS businesses. Furthermore, the study contributes to understanding the customer acquisition cost ratio, R&D, revenue, and earnings per share's impact on public SaaS companies' valuation. Additionally, it discusses possible explanations for why these financial metrics appear to have an effect on SaaS companies' share prices. Further research could assist investors in identifying reliable predictors of share price movements by determining the relative impact of various key ratios on share price movements. This could be accomplished by performing regression analysis using standardized beta coefficients.

The paper at hand does not provide any evidence on customer-centric performance measures such as churn rates, Customer Lifetime Value (CLV), and net dollar retention due to inconsistent disclosure across SaaS companies' interim reports. Once a large enough sample of SaaS companies publishes this type of customer data, future research could examine these metrics and their impact on SaaS company valuation, assisting in expanding the literature on SaaS.

Only a single time period was examined in this research study. Hence, it does not provide evidence of how the independent variables' importance has changed over time. A possible direction for future research could be to examine whether or not the CAC ratio and R&D have grown in importance in recent years. While this report focuses on SaaS companies listed in the United States, it would be interesting to investigate whether or not the findings are prevalent in other countries where SaaS is less established. Lastly, future research could examine whether there are any differences between B2B and B2C SaaS companies.

.

10. References

Amir, E., & B. Lev. (1996). Value-relevance of nonfinancial information: The wireless communication industry. *Journal of Accounting and Economics*, 22(1–3), 3–30.

Anderson, E. S., & Keith, T. Z. (1997). A longitudinal test of a model of academic success for at-risk high school students. *Journal of Educational Research*, 90, 259–266.

Ball, R. & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research,* 6(2), 159-178.

Baltagi, B., Feng, Q., & Kao, C. (2012). A Lagrange Multiplier Test for Cross-Sectional Dependence in a Fixed Effects Panel Data Model. *Journal of Econometrics,* 170(1), 164-177.

Baltagi, B. H. (2008). *Econometric Analysis of Panel Data*, Wiley.

Banerjee, A. (1999). Panel Data Unit Root and Cointegration: an Overview. *Oxford Bulletin of Economics and Statistics*, Special Issue, 607–629.

Bannon, W. (2015). Missing data within a quantitative research study: How to assess it, treat it, and why you should care. *Journal of the American Association of Nurse Practitioners*, 27(4).

Blalock, H. M. (1963). Correlated Independent Variables: The Problem of Multicollinearity, *Social Forces*, 42(1), 233–237.

Bonacchi, M., & Perego, P. (2012) Measuring and Managing Customer Lifetime Value: A CLV Scorecard and Cohort Analysis in a Subscription-based Enterprise Management. *Accounting Quarterly; Montvale,* 14(1), 27-39.

Brown, S. L. (1978). Earnings Changes, Stock Prices, and Market Efficiency. *The Journal of Finance*, 33(1), 17-28.

Brown, S., Kin, L., & Lys, T. (1999). Use of R2 in accounting research. *Journal of Accounting and Economics* 28(2), 83–115.

Cabral, L. M. B., & Mata, J. (2003). On the Evolution of the Firm Size Distribution: Facts and Theory. *The American Economic Review,* 93(4), 1075–1090.

Chambers, D., Jennings, R., & Thompson II, R.B., (2002). Excess Returns to R&D-Intensive Firms. *Review of accounting studies*, 7(2), 133-158.

Chan, L. K. C., Lakonishok, J. & Sougiannis, T. (2001). The stock market valuation of research and development expenditures, *Journal of Finance,* 56(6), 2431–2457.

Chandler, A. (2001). *Inventing the Electronic Century*. New York, NY: The Free Press.

Chandra, U., C. E. Wasley, & G. B. Waymire. (2004). Income conservatism in the U.S. technology sector. *Working paper*, University of Rochester.

Chandra, U., & Ro, B.T. (2008). The role of Revenue in Firm Valuation. *Accounting Horizons*, 22(2), 199–222.

Cheong, F.S., & Thomas, J. (2018). Management of Reported and Forecast EPS, Investor Responses, and Research Implications. *Management Science*, 64(9), 4277-4301.

Chou, D. D., & Chou, A. C. (2008). Software as a Service (SaaS) as an outsourcing model: An economic analysis. *Houston, Texas, Southwest Decision Science Institute Conference*.

Cohen, B., Neubert, M. (2019). How Do Corporate Valuation Methods Reflect the Stock Price Value of SaaS Software Firms?. *The ISM journal of international business*, 3(1), 9-14.

Collins, D. W., Maydew. E. L., & Weiss, I. S. (1997). Changes in the value-relevance of earnings and book value over the past forty years. *Journal of Accounting and Economics 24*(1), 39–67.

Costello, K., & Rimol, M. (2020). *Gartner Says Global IT Spending to Reach $3.9 Trillion in 2020.* Gartner. https://www.logicworks.com/blog/2020/05/SaaS-cloud-growth-gartner/

Dang, C., & Li, Z. F., Yang, C. (2018). Measuring firm size in empirical corporate findings. *Journal of Banking & Finance*, 86(1), 159-176.

Eliasson, A. (2013). *Kvantitativ metod från början* (3rd ed.), Studentlitteratur AB, Lund.

Ernst & Young. (2020). *A Closer Look at IFRS 15, the Revenue Recognition Standard: IFRS 15 Revenue from Contracts with Customers.* Ernst & Young. https://www.ey.com/en_gl/ifrs-technical-resources/a-closer-look-at-ifrs-15-the-revenue-recognition-standard-october-2020

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383-417.

Fama, E. F, & French, K. R. (1986). Common Factors in the Serial Correlation of Stock Returns. *UCLA: Finance*. Retrieved from: https://escholarship.org/uc/item/2jf8r7n7

Feng, C., Wang. H., Lu. N., Tu. X. M. (2012) Log-transformation: applications and interpretation in biomedical research. *Statistics in Medicine*, 32, 230–239.

Fernando, J. (2021, February 5). *Market Capitalization Definition.* https://www.investopedia.com/terms/m/marketcapitalization.asp

Fidelity Investments. (2021). *Software.* https://eresearch.fidelity.com/eresearch/markets_sectors/sectors/industries.jhtml?tab=learn&industry=451030

Fink, J. (2021) A Review of the Post-Earnings-Announcement Drift. *Journal of Behavioral and Experimental Finance*, 29.

Firth, M. (1976). The Impact of Earnings Announcements on the Share Price Behaviour of Similar Type Firms. *The Economic Journal*, 86(342), 296-306.

Flexera (2020). *State of the Cloud Report.* https://resources.flexera.com/web/pdf/report-state-of-the-cloud-2020.pdf

Fornell, C., Morgeson, F.V., & Hult, G.T.M., (2016). Stock Returns on Customer Satisfaction Do Beat the Market: Gauging the Effect of a Marketing Intangible. *Journal of Marketing*, 2016-09-01, 80(5), 92-107.

Gleaves, R., Kitshoff, J., Burton, J., & Bates, K. (2008). Accounting is from Mars, marketing is from Venus: Establishing common ground for the concept of customer profitability. *Journal of Marketing Management*, 24(7), 825-845.

Godfrey, L. G. (1996). Misspecification Tests and Their Uses in Econometrics. *Journal of Statistical Planning and Inference*. 49(2), 241–260.

Goldberger, Arthur S. (1964). *Econometric Theory*. New York: John Wiley & Sons. 238–243.

Golec, J., & Gupta, N.J. (2014). Do Investments in Intangible Customer Assets Affect Firm Value? *The Quarterly Review of economics and finance*, 54(4), 513-520.

Gujarati, D. N.; Porter, D. C. (2009). *Basic Econometrics* (5th ed.). Boston: McGraw-Hill Irwin, 400.

Gupta, S., Lehmann, D.R., & Stuart, J.A. (2004). Valuing Customers *Journal of marketing research*, 41(1), 7-18.

Gupta, S., Hanssens, D.M., Hardie, B., Kahn, W., Kumar. V., & Lin, N. (2006). Modeling Customer Lifetime Value. *Journal of Service Research*, 9(2), 139–55.

Hacigümüş, H., Balakrishna, R. I., Chen, L., & Mehrotra, S. (2002). Executing SQL over encrypted data in the database-service-provider model. *Proceedings of the 2002 ACM SIGMOD International Conference on Management of Data*, 216–227.

Hall, B. H., Mairesse. J., & Mohnen, P. (2010). Measuring the Returns to R&D. *Handbook of the Economics of Innovation 2*, 1033–1082.

Hand, J. R. M. (2001). The Economic Versus Accounting Impact of R&D on U.S. Market-to-Book Ratios, *Working Paper*, University of North Carolina.

Hand, J. R.M. (2015). Discussion of 'Customer Franchise—A Hidden, Yet Crucial, Asset.' *Contemporary Accounting Research*, 32 (Fall), 1050–52.

Hayn, C. (1995). The Information Content of Losses. *Journal of accounting & economics*, 20(2), 125-153.

Hirschey, M., & Weygandt, J. (1985). Amortization Policy for Advertising and Research and Development Expenditures. *Journal of Accounting Research,* 23, 326–335.

Hoechle, D. (2007). Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. *Stata Journal*, 7(3), 281-312.

Hsiao, C. (2007). Panel data analysis—advantages and challenges. Test (Madrid, Spain), 16(1), 1-22.

Kidd, C. (2021). SaaS in 2021: Growth Trends & Statistics, *BMC Blogs.* https://www.bmc.com/blogs/SaaS-growth-trends/

Kumar, V., & Shah, D. (2009). Expanding the Role of Marketing: From Customer Equity to Market Capitalization. *Journal of Marketing*, 73(6), 119-136.

Krafft, M., Rudolf, M., & Rudolf-Sipötz, E. (2005). Valuation of Customers in Growth Companies — A Scenario-Based Model. *Schmalenbach business review*, 57(2), 103-125.

Lee, J. N., Huynh, M. Q., Kwok, R. C. W., & Pi, S.M. (2003): IT Outsourcing Evolution--Past, Present, and Future. *Communications of the ACM*, 46(5), 84-89.

Lev, B. (2018). Ending the Accounting-for-Intangibles Status Quo. *European Accounting Review,* 28(1), 1-24.

Lev, B., & T. Sougiannis. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics,* 21(1), 107–138.

Lev, B., & P. Zarowin. (1999). The boundaries of financial reporting and how to extend them. *Journal of Accounting Research,* 37(2), 353–385.

Liu, J., Nissim, D. & Thomas, J. (2007). Is Cash Flow King in Valuations?. *Financial Analysts Journal,* 63, 56-68.

Livne, G., Simpson, A. & Talmor, E. (2011). Do Customer Acquisition Cost, Retention and Usage Matter to Firm Performance and Valuation? *Journal of Business Finance & Accounting,* 38(3-4), 334-363.

Mathrani, S., & Viehland, D. (2005). Using knowledge-based processes to improve enterprise system effectiveness. Retrieved from: http://74.125.155.132/scholar?q=cache:4u8vLp6yv6oJ:scholar.google.com/&hl=en&as_sdt=2000

McCarthy, D. M., Fader, P. S. & Hardie, B. G., (2017). Valuing Subscription-Based Businesses Using Publicly Disclosed Customer Data. *Journal of Marketing*, 81, 17-35.

Megna, P. & M. Klock. (1993). The Impact of Intangible Capital on Tobin's q in the Semiconductor Industry. *The American Economic Review,* 83, 265–269.

Mikulic, M. (2020). *Percentage of spending on research and development of total revenue from 2015 to 2019, by industrial sector*.* Statista. https://www-statista-com.ez.hhs.se/statistics/270324/expenditure-on-research-and-development-by-industry-sectors/

Mlitz, K. (2021). *Public cloud application services/software as a service (SaaS) end-user spending worldwide from 2015 to 2022.* Statista.

https://www-statista-com.ez.hhs.se/statistics/270324/expenditure-on-research-and-development-by-industry-sectors/

Morgan, I. G. (1976). Stock Prices and Heteroscedasticity. *The Journal of Business,* 49(4), 496-508.

Nerino, P. J. (2007). *Software As a Service.* Emerging Tools and Technology, 24(4), 28-31.

Newton, T., & Schlecht, I. (2016). How to value SaaS Companies. *Catalyst Investors*. Retrieved from: https://catalyst.com/2016/06/14/value-SaaS-companies/

O'Driscoll, R. (2010, April 20). Magic Number Math [Blog post], Retrieved from https://www.scalevp.com/blog/magic-number-math

Plenborg, T., Pimentel, R.C., (2016). Best Practices in Applying Multiples for Valuation Purposes. *The Journal of Private Equity*, 19(3), 55-64.

Preda, O.L., & Negru, E. (2020). The Correlation Between Financial Profitability And Stock Market Performance Of Companies Listed On The Bucharest Stock Exchange. *Journal of Economic and Social Development (Varaždin)*, 7(2), 26-40.

Reichheld, F. F., & Sasser, W. E. (1990). Zero defections: Quality comes to services. *Harvard Business Review*, September-October 1990, 105 – 111.

Reinartz, W., Thomas, J.S., & Kumar, V. (2005). Balancing, Acquisition and Retention Resources to Maximize Customer Profitability. *Journal of Marketing*, 69, 63–79.

Rusdiyanto., Hidayat, W., Tjaraka, H., Fitrisia, D., Fayanni, Y., Utari, W., Waras., Indrawati, M., Susanto, H., Tjahjo, J.D.W., Mufarokhah, N., Susetyorini., Elan, U., Samsi, N., Choiri., Syamsul, M., Widodo, M., Suyanto, H., Zainal., M., & Imanawati, Z., (2020). The effect of Earnings Per Share, Debt to Equity Ratio and Return on Assets on Stock prices: Case study Indonesian. *Academy of Entrepreneurship journal*, 26(2), 1-10.

Schulze, C., Skiera, B., & Wiesel, T., (2012). Linking Customer and Financial Metrics to Shareholder Value: The Leverage Effect in Customer-Based Valuation.

Journal of Marketing, 76(2), 17-32.

Schumpeter, J. A. (1950). *Capitalism, Socialism and Democracy* (3rd ed.). New York: Harper Perrenial.

Schwert, G. W., & Seguin, P. J. (1989). Heteroskedasticity in Stock Returns. *National Bureau of Economic Research*, 45(4), 1129-1155.

Shalit, S., & Sankar, U. (1977). The Measurement of Firm Size. *The Review of Economics and Statistics*, 59(3), 290-298.

Shevlin, T. (1991). The Valuation of R&D Firms with R&D Limited Partnerships. *The Accounting Review,* 66, 1–21.

Simpson, A. (2010). Analysts' Use of Nonfinancial Information Disclosures. *Contemporary Accounting Research*, 27(1), 249-288.

Singer, G. D. (2014). Reduce Risk With Recurring Revenues. *Trusts & Estates,* 153(9), 52–.

Smale, T. (2021, January 3). SaaS Valuations: How to Value a SaaS Business in 2021. *FE International*. Retrieved from: https://feinternational.com/blog/SaaS-metrics-value-SaaS-business/

Sougiannis, T. (1994). The Accounting Based Valuation of Corporate R&D. *The Accounting Review*, 69, 44–68.

Spar, D. L. (2001). Ruling the waves: cycles of discovery, chaos, and wealth from the compass to the internet. *Choice Reviews Online*, 39(08), 39–4707.

Spescha, A. (2019). R&D expenditures and firm growth - is small beautiful? *Economics of Innovation and New Technology*, 28(2), 156-179.

S&P Global, 2021. S&P Software & Services Select Industry Index. Retrieved from: https://www.spglobal.com/spdji/en/indices/equity/sp-software-services-select-industry-index/#overview

Torres-Reyna, O. (2007), *Panel Data Analysis Fixed and Random Effects using Stata*. Princeton University, Retrieved from: https://www.princeton.edu/~otorres/Panel101.pdf.

Trenz, M., Huntgeburth, J., & Veit, D. (2019) How to Succeed with Cloud Services? A Dedication-Constraint Model of Cloud Success. *Business & Information Systems Engineering,* 61(2), 181–194.

Tugcu, C. T. (2018). *The Economics and Econometrics of the Energy-Growth Nexus* (1st ed.). Academic Press.

Valuates Reports. (2020). *Software As A Service (SaaS) Market Size is Projected to Reach USD 307.3 Billion by 2026.* https://www.prnewswire.com/in/news-releases/software-as-a-service-SaaS-market-size-is-projected-to-reach-usd-307-3-billion-by-2026-valuates-reports-875840023.html

Vincente-Lorente, J. D. (2001). Specificity and opacity as resource-based determinants of capital structure: Evidence for Spanish manufacturing firms. *Strategic Management Journal*, 22(2), 157–177.

Waters, B. (2005): Software as a service: A look at the customer benefits. *Journal of Digital Asset Management*, 1(1), 32-39.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5, 171–180.

Wierckx, P. J. (2020). The Retention Rate IDusion: Understanding the Relationship Between Retention Rates and the Strength of Subscription-Based Businesses. *The Journal of Applied Business and Economics,* 22(14), 104-114.

Wiesel, T., Skiera, B., & Villanueva, J. (2008). Customer Equity: An Integral Part of Financial Reporting. Journal of Marketing, 72(2), 1–14.

Williams, C. (2007). Research Methods. *Journal of Business & Economics Research (JBER)*, *5*(3).

Xu, L., & Cai, F. (2009). Before and after 2000: revenue and high tech valuation. *International Business Journal,* 19(1), 26-35.

11. Appendix

Table 9: Variance Inflation Factors

Table 9. Variance Inflation Factors

Variable	log (Revenue)	log (ARR)	CAC	EPS	R&D%
VIF	15,1	13,8	1,05	1,08	2,5
1/VIF	0,07	0,07	0,95	0,93	0,4

A Variance Inflation Factor above 10 indicates presence of multicollinearity (Blalock, 1963).

Figure 2: Heterogeneity Across Companies

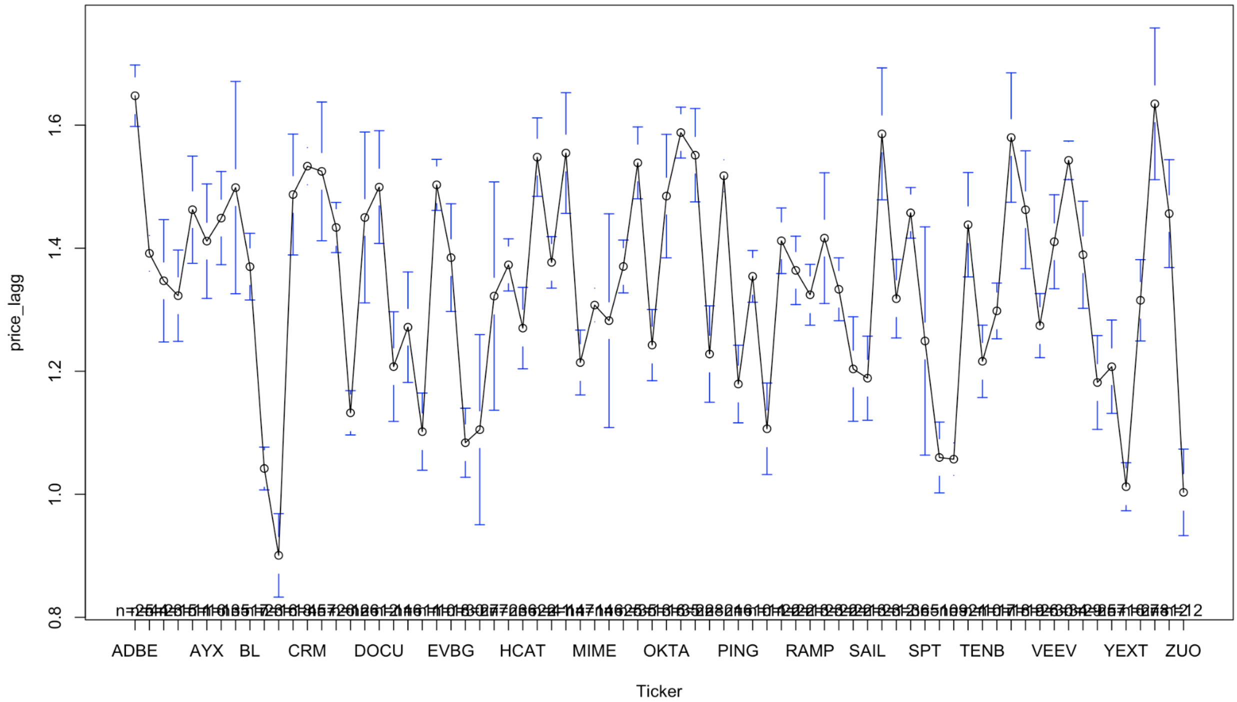

Table 10: Hausman Tests

Table 10. Hausman Tests

The Hausman test determines whether the coefficient difference is systematic. The null hypothesis is that there is no systematic difference. The p-values suggest that fixed effects models are the most appropriate.

Variable	All Companies	Large Companies[1]	Small Companies[2]
Chi-Square	129,7	22 293	51,2
Prob>chi2	< 2.2e^-16	<2.2e^-16	1.997e^-10

1) Market cap ≥ $10 bn

2) Market cap ≤ $10 bn

H0: difference in coefficients not systematic

Figure 3: Heterogeneity Across Time

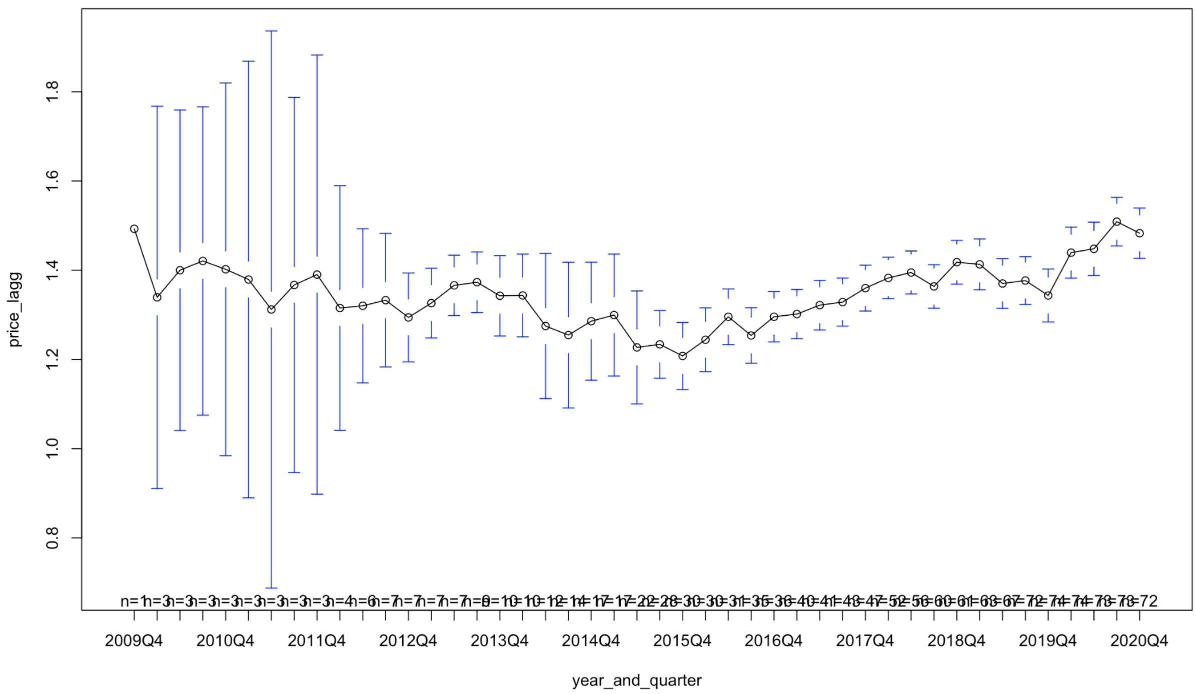

Table 11: Breusch-Pagan Lagrange Multiplier Test för Time Effects

Table 11. Breusch-Pagan Lagrange Multiplier Test for Time Effects

	Chi2	P-Value
Model I	278,6	<2.2e^-16
Model II	1041	<2.2e^-16
Model III	10,5	0,00119

HO: No individual and/or time effects exist (Torres-Reyna, 2007).

Table 12: Breusch-Pagan LM Test for Cross-Sectional Dependence

Table 12. Breusch-Pagan LM Test for Cross-Sectional Dependence

	Chi2	P-Value
Model I	8179,2	<2.2e^-16
Model II	1798,6	<2.2e^-16
Model III	2040,3	<2.2e^-16

HO: The residuals across entities are not correlated (Torres-Reyna, 2007).

Table 13: Breusch-Godfrey Test for Serial Correlation

Table 13. Breusch-Godfrey Test for Serial Correlation

	Chi2	P-Value
Model I	690,6	<2.2e^-16
Model II	351,8	<2.2e^-16
Model III	269,6	<2.2e^-16

HO: No serial correlation in idiosyncratic errors (Torres-Reyna, 2007).

Table 14: Augmented Dickey-Fuller Test for Unit Roots

Table 14. Augmented Dickey-Fuller Test for Unit Roots

	Dickey-Fuller	P-Value
Model I	-11.1	0,01
Model II	-10.1	0,01
Model III	-8.0	0,01

HO: No unit roots are present (Banerjee, 1993).

Table 15: Studentized Breusch-Pagan Test for Heteroskedasticity

Table 15. Studentized Breusch-Pagan Test for Heteroskedasticity

	BP	P-Value
Model I	132,9	6,634e^-10
Model II	54,9	0,2286
Model III	74,7	0,0047

HO: Error variances are all equal (Torres-Reyna, 2007).