# DRIVERS OF SHARE PRICE MOVEMENTS WHEN EARNINGS ARE NEGATIVE

## A STUDY ON SAAS COMPANIES

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**Drivers of Share Price Movements When Earnings are Negative: A Study on SaaS Companies**

Abstract:

This paper examines the drivers of share price movements for Software-as-a-Service (SaaS) companies for the period 2014-2019 by including financial fundamentals and valuation multiples in a regression analysis. The primary purpose of this paper is to provide valuable findings for practitioners to base their investment decisions upon when investing in SaaS companies. We run ten regressions, divided into three OLS regression models, three fixed effects regression models and four additional OLS regression models with different datasets to test the robustness of our findings. The dependent variable is share price and the independent variables are the following: sales, EBITDA margin, earnings per share, free cash flow, EV/Sales, P/BV, an annual time dummy variable, a firm size dummy variable and a firm-specific dummy variable. The findings show that sales and the EV/Sales ratio are significantly correlated with the share price movements. Indicating that both financial fundamentals and the investor sentiment has driven the strong performance of the dataset during the five-year period. Whereas the latter could be driven by either higher expectations on future cash flows or a lower discount rate when discounting future cash flows.

Keywords:

Software-as-a-Service, Share Price, Valuation Multiples, EPS, Investor Sentiment

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# 1. Introduction

The purpose of this paper is to identify what drives the share price behaviour of Software-as-a-Service (SaaS) companies, either financial fundamentals or changes in valuation multiples. The efficient market hypothesis (EMH) states that the stock market is efficient in terms of incorporating all publicly available information in stock prices (Fama, 1970) and it is therefore impossible to earn an abnormal return by trading on based on publicly available information (Brown, 1978). However, the SaaS companies included in this dataset have had a total return of 577% the last five years, compared to 65% for the broad index S&P 500. Our interest in this sub-sector derives from the increased relevance and investor interest of SaaS businesses (McCarthy, et al., 2017) along with the extraordinary valuation multiples. To conduct this analysis, we perform a multiple regression analysis, including selected financial key performance indicators and two valuation multiples as independent variables and the share price as the dependent variable. 51 B2B focused SaaS companies from the American stock market are included in the dataset and quarterly data between 2014 and 2019 has been collected.

SaaS is a delivery model that provides access to software and its functions remotely (Nerino, 2007). SaaS companies maintain a number of factors, such as 1) recurring payments, 2) high customer retention rates and 3) consistent product updates. Large subscription-based companies that benefit of the cloud computing system include the streaming services Netflix and Spotify where the cloud enables consumer access to a large amount of content. The SaaS companies analysed in this paper are all, in contrast to Netflix and Spotify, B2B focused, in order to keep a homogenous dataset to facilitate easier comparison. A large difference between B2B and B2C SaaS business models is that the former's growth partially derives from customer upgrading their existing subscription plan whereas the latter's customers usually pay a fixed fee throughout the customer lifecycle. The different behaviours of consumers and businesses, when acting as customers, is also the reason why B2B SaaS companies possess a higher rate of recurring revenues and customer retention. Simply put, the growth dynamics are different between the two.

Earnings per share (EPS) is generally considered one of the most important factors to determine share price and firm value (Stern, 1970; Liu, et al., 2007). However, the SaaS business model is structured in a way where there are heavy costs, mainly research & development (R&D) and sales & marketing (S&M), upfront in order to enhance long-term growth and performance (Chakravarty & Grewal, 2011). Therefore, many SaaS companies have a negative EPS in the current state (most are in an early stage of growth) and it is thus a weak indicator of share price behaviour (Liu, et al., 2007). Revenue and, especially, free cash flow growth is more than twice as important for the valuation of SaaS companies as profitability (Cohen & Neubert, 2018). Also, looking at the enterprise-value-to-sales (EV/Sales) ratio, which is 9.8x for our analysed SaaS companies compared to 2.3x for the S&P 500, versus the EBITDA margin, which is 6.6% for our SaaS companies and 19.7% for the S&P 500 (both metrics as of 31 Dec 2019), one can guess that this sub-sector of technology companies is driven by other metrics than the common ones in the US stock market, namely the S&P 500 in this paper.

The model that SaaS companies use is not a new idea. During the dot-com bubble in the late 1990s, there were several companies that offered software as application service providers (ASP). The goal of these providers was to eliminate the need to load software on the local workstations. However, broadband Internet access and computer technology were not at a point that made such technology viable. Besides having a more solid technology to leverage on, today's SaaS companies are taking a more focused approach, providing single-issue solutions rather than providing total solutions as in the late 1990s (Nerino, 2007). Moreover, there are some key differences in the public market environment that cause distinctive disparities between the two. Firstly, the valuations were vastly more extreme during the dot-com bubble. The price-to-earnings (P/E) ratio for the S&P 500 information technology index was above 50x in March 2000, while the same index is trading at 21x as of May 2020 (FactSet, 2020). Also, the SaaS companies constitute a much smaller share of the broad index compared to the technology companies during the dot-com bubble (Capital Group, 2017). Secondly, a coined term during the bubble was "Get Big Fast". Being profitable was much less prioritised than revenue growth and share prices soared far more than fundamental indicators (Thompson, 2019). Even though only a few of the SaaS companies in the dataset are profitable, most of them possess extraordinarily high margins, at least regarding gross profit, with an average gross margin of 70%. Finally, there are major differences between the business models of the SaaS companies and the peaking companies during the bubble. The internet was on the rise in the early 2000s and most companies were consumer-oriented (Wheale & Amin, 2003), which theoretically have weaker lock-in effects than B2B companies.

Ratio analysis is one of the instruments used for measuring the financial performance of companies. EPS is a carefully examined metric that is often used as a barometer to measure a company's profitability per unit of shareholder ownership (Cohen & Neubert, 2018). Due to the limited number of SaaS companies with a positive EPS, we also include sales, earnings before interest, taxes, depreciation and amortization (EBITDA) and free cash flow (FCF) in the regression analysis. Moreover, we include the EV/Sales and price-to-book (P/BV) ratios to analyse investors' willingness to pay for one unit of ownership of sales and equity. The dataset is divided into two groups where companies with an enterprise value (EV) equal to or larger than USD 5 billion are categorized as Large Companies whereas small and medium enterprises (SME's) have an enterprise value less than USD 5 billion.

The regression results show that in the pooled analysis sales and EV/Sales are the only independent variables that are significantly correlated with the share price. The coefficients for the metrics are at 0.326 and 0.423, respectively, with 99% confidence. For Large Companies, sales and EV/Sales are correlated with 99% confidence and P/BV with 90% confidence, with coefficients at 0.350, 0.262 and 0.146, respectively. For SME's, sales, EBITDA margin and EV/Sales are correlated at 99% confidence and FCF is correlated at 95% confidence. The coefficients are at 0.432, 0.226, 0.534 and 0.132, respectively. Interestingly, EPS is not correlated with share price in neither the pooled nor the divided analysis. Looking at the regression with the firm-specific fixed effect the results illustrate similar patterns. However, despite smaller changes in the coefficients, the EBITDA margin is not significantly correlated with share price for SME's, instead the P/BV is correlated at 99% confidence, with a coefficient of -0.075.

The literature on drivers of share price movements is extensive. The following papers in this section have inspired us and our analysis touch upon the similarities and differences between the findings, meaning that this paper is not a replication of a previous study. The reason is mainly that the empirical studies on SaaS companies are limited. As the business model of SaaS companies is very different from many others', with negative earnings despite extraordinary high gross margins and a high rate of recurring revenues, for instance, this paper adds value to the field of share-price-driver studies. Also, these companies are on the rise and the share price performance demonstrates a huge investor interest (McCarthy, et al., 2017). Thus, this paper can be of use for investors that want to understand the share price behaviour of a growing cluster of the stock market. Moreover, Alteryx and Autodesk, two companies included in the dataset, have recognized total addressable markets of USD 73 billion (Alteryx, Inc., 2020) and 49 billion (Autodesk Inc., 2019), compared to revenues of USD 418 million and 2,600 million, respectively. These are just two examples that illustrate the long runway for potential growth that lies ahead of the SaaS companies. Thereby, while SaaS companies have grown aggressively over the last several years, it is still clear that there is plenty of room for future growth.

Before 1981, much of the finance literature viewed the present value of dividends to be the principal determinant of the level of share prices. However, LeRoy and Porter (1981) and Shiller (1981) found that, under the assumption of a constant discount factor, share prices were too volatile to be consistent with movements in future dividends. This conclusion, known as the excess volatility hypothesis, argues that share prices exhibit too much volatility to be justified by fundamental variables (Balke & Wohar, 2006). Accordingly, our results show a strong correlation between EV/Sales and share price but there is a significant correlation between fundamental variables and share price as well. Notably, the sample size for testing the correlation between dividends and share price is too small to provide value.

Fama and French (1993, 2015) showed that the return of a stock is based on its Beta to the market portfolio, its size, its value, its profitability and its investments needs. Thus, a higher Beta and being a smaller company is positively correlated with share price return and accordingly, the SaaS companies have an average five-year Beta of 1.15 and an average market cap of USD 12 billion [USD 9 billion if excluding Salesforce.com Inc. (Salesforce) from the dataset], which is only slightly above the USD 8.2 billion market capitalization threshold of being included in the S&P 500. However, the model asserts that companies with a high book-to-market (B/M) ratio, robust profitability and conservative investments in assets should outperform. For 2019, the SaaS companies had an average net income margin of -7% (S&P 500: 11%) and an average growth in total assets of 45% (S&P 500: 9.7%). At last, the B/M ratio was 0.05x for the SaaS companies (0.28x) as of 31 December 2019. The model is thus rejected on three out of five components, given the outperformance of SaaS companies the last five years compared to the S&P 500.

There is a general view that EPS is the main fundamental driver of share prices. Liu, et al. (2007) concluded that earnings data dominate all other value drivers (sales, EBITDA, book value and operating cash flow). However, when the earnings are negative the data illustrates a much weaker such correlation (Liu, et al., 2007). Among the companies analysed in our dataset, only 12 out of 51 had a positive EPS in 2019 and, in line with previous findings, it is also the least correlated financial metric in the analysis.

However, the price of a company's stock reflects and incorporates investors' beliefs regarding the future cash flows the company will generate (Campbell, et al., 2010; McCarthy, et al., 2017) and a significant portion of stock price movement occurs because investors revise their expectations of future cash flows (Chen, et al., 2013). Moreover, Steven and Ruback (1995), as well as Damodaran (2005), have shown that a discounted cash flow (DCF) model is an appropriate method for company valuation. Accordingly, the findings in this paper illustrate that investors have a positive sentiment towards the SaaS companies' future cash flows despite current negative earnings.

# 2. Theoretical Framework

## *2.1 Software-as-a-Service*

Software-as-a-Service is a newly emerging business model in the software industry. Subscription SaaS service will allow organizations to save their IT investment on infrastructure, networking, hardware, software, and personnel costs. SaaS providers play the role of outsourcing vendors who offer the contracting service to their clients by charging a monthly or annual fee. After that, SaaS providers will handle all needed services, including application software's maintenance, customization, and updating (Chou & Chou, 2008). The cloud is the backbone that provides life to the SaaS companies' businesses. The cloud application services market (the applicable market for SaaS companies) is expected to register a CAGR of 15.8% until 2022 (WisdomTree, 2019).

Over the last decade, cloud SaaS businesses have eclipsed traditional software companies as the new industry standard for deploying and updating software. Cloud-based SaaS companies provide software applications and services via a network connection from a remote location, whereas traditional software is delivered and supported on-premise. This key difference in distribution leads to several distinct fundamental advantages for cloud vs traditional software (WisdomTree, 2019). In terms of product characteristics, cloud software enables speed, ease and low cost of implementation. It is installed via a network connection and it does not require the higher cost of setup and installation of traditional software. Customers can easily also add product enhancements over the cloud without an additional sales cycle. Therefore, the same provider can grow as the customer grows over time. This in combination with the fact that cloud software becomes embedded in client workflow the switching costs are high and client retention is low. Moreover, SaaS companies employ a subscription-based revenue model with smaller and more frequent transactions, while traditional software businesses rely on a single large, upfront transaction. The SaaS model can result in a more predictable, annuity-like revenue stream for cloud software providers (WisdomTree, 2019).

## *2.2 Fama and French Models*

### *2.2.1 Fama and French Three-Factor Model*

Fama and French (1993) revisited some of the evident shortcomings of the CAPM model by expanding it into a three-factor asset pricing model. Besides the market return factor included in the CAPM, the new model incorporated a size factor based on the market capitalization of firms and a value factor defined as the equity book-to-market (B/M) ratio. The underlying reasoning for the two added variables is that they are proxies for common risk factors in returns and that they are related to economic fundamentals. The study showed a negative relationship between size and average excess returns as well as a positive relationship between the B/M ratio and average excess returns. The resulting model is described as:

$$Rit - Rft = \alpha i + \beta iM*(RMt - Rft) + si*SMBt + \mathrm{h}i*HMLt + \varepsilon it \quad (1)$$

where $Rit$ is the return on security or portfolio "i" for period t, $Rft$ is the risk-free rate, $RMt$ is the return on the value-weighted market portfolio, $SMBt$ is the difference between the returns on diversified portfolios of small and large cap stocks, $HMLt$ is the difference between the returns on diversified portfolios of high B/M stocks (value stocks) and low B/M stocks (growth stocks), and $\varepsilon it$ is a zero-mean error term. The Fama-French Three-Factor model achieved a 90% explanation rate of variation in returns, which was higher than the CAPM's explanatory power of 70%. Furthermore, Jegadeesh and Titman (1993) discussed the existence of a momentum effect, Ang, Hodrick, Xing, and Zhang (2006) documented a negative relationship between idiosyncratic volatility and average returns suggesting that the three-factor model cannot price portfolios correctly. Lastly, Amihud (2002) and Pastor and Stambaugh (2003) found that liquidity risk should be a priced risk factor.

### *2.2.2 Fama and French Five-Factor Model*

Fama and French (2015) found another way to improve their three-factor model, as a response to cited literature above. In the recent study, they present the five-factor model that supplements their former model with operating profitability and investment factors. Their decision to add these two factors is motivated by the dividend discount model, which says that the market value of a stock is the discounted value of expected dividends. They came up with three statements about expected stock returns. Firstly, a higher B/M ratio implies a higher expected return – an observation already captured by the value factor in the Fama and French (1993) three-factor model. Secondly, higher expected earnings suggest a higher expected return – the idea behind adding the operating profitability factor. And thirdly, higher expected growth in assets implies a lower expected return – motivation for adding the investment factor.

As it is evident that the three-factor model is not able to explain all variance in returns, much of it might come from profitability and investment. Fama and French (2015) use NYSE stocks which are sorted into different sets of LHS portfolios. They prove that the five-factor model produces lower intercepts and can explain a higher degree of the variation in returns, than the three-factor model. To test the validity of the asset pricing models, GRS tests developed by Gibbons, Ross and Shanken (1989) are conducted. Fama and French acknowledge in their study that the five-factor model is rejected using the GRS-test, proving that it is still not a complete model for predicting returns but rather a simplification of reality. Moreover, adding the two additional variables makes the value factor, measured as the B/M ratio, a redundant factor. In 2015, they also expanded their research by performing their study on international markets and found that their model holds in these markets as well. The model is constructed as:

$$Rit - Rft = \alpha i + \beta iM*(RMt - Rft) + si*SMBt + \mathrm{h}i*HMLt + ri*RMWt + ci*CMAt + \varepsilon it \quad (2)$$

where $RMWt$ is the difference between the returns on diversified portfolios with high (robust) operating profitability and low (weak) operating profitability, and $CMAt$ is the difference between the returns on diversified portfolios with low growth in total assets (conservative) and high growth in total assets (aggressive).

## *2.3 Efficient Market Hypothesis*

The theory of market efficiency first introduced by Fama (1970) is an economic theory which stipulates that the prices of assets will incorporate information to the degree that they reflect the security's actual intrinsic value. It further stipulates that investors are rational, can understand information correctly and act upon said information. There are no arbitrage opportunities available in the market according to this theory (Brown, 1978), except for limited time periods when investor irrationality might give rise to them. However, those instances of price discrepancy are quickly corrected by rational investors bidding for the securities until they converge to intrinsic value once again.

There are three levels of efficiency, the first of which is weak-form efficiency. It implies that current prices of assets will incorporate all historical information, essentially rendering the data of past prices performance of a security useless to investors since it is already incorporated in the current price. The second level is semi-strong-form efficiency which is an extension of the weak-form efficiency. It states that asset prices also reflect all publicly available information such as the information contained in regulatory filings. Lastly, there is the strong-form efficiency which suggests asset prices incorporate all information, i.e. even information known only to company insiders (Maverick, 2020).

### *2.4 S&P 500*

The S&P 500 is a stock market index that tracks the stocks of 500 large U.S. companies. S&P stands for Standard and Poor, the names of the two founding financial companies. Investors use it as the benchmark of the overall market, to which all other investments are compared. As of March 13, 2020, the S&P 500 has an average 10-year annual return of 7.99%.

As of February 2020, the total market capitalization of the S&P 500 is USD 24.4 trillion, and it captures 80% of the American stock market. To qualify for the index, a company must be in the United States, have an unadjusted market capitalization of at least USD 8.2 billion. At least 50% of the corporation's stock must be available to the public. Its share price must be at least USD 1 per share. It must file a 10-K annual report. At least, 50% of its fixed assets and revenues must be in the United States. Finally, it must have at least four consecutive quarters of positive earnings.

As of March 13, 2020, the S&P 500 sector breakdown includes: Information Technology: 24.4%, Health Care: 14%, Financials: 12.2%, Communication Services: 10.7%, Consumer, Discretionary: 9.9%, Industrials: 8.9%, Consumer Staples: 7.2%, Energy: 3.6%, Utilities: 3.5%, Real Estate: 3.1% and Materials: 2.5% (S&P Global Inc., 2017).

### *2.5 Hypotheses*

We hypothesize that the future profitability potential, and thus cash flows, is a main driver for the positive investor sentiment for this sub-sector. This stems from the fact that the price of a company’s stock reflects and incorporates investors’ beliefs regarding the company’s future cash flows (McCarthy, et al., 2017). However, as current profitability measures are burdened by high R&D and S&M costs, we believe such metrics will have a weak correlation with stock movements. Thus, since the SaaS companies are in a growth phase (29.3% revenue growth for 2019, compared to 4.85% for the S&P 500), we believe that sales and FCF are the strongest financial indicators of a SaaS company’s development (Cohen & Neubert, 2018) and that EPS will have no significant impact on the share price behaviour (Liu, et al., 2007). However, since larger companies generally are more mature and thus closer to a steady-state, we believe that profitability measures, i.e. EPS and EBITDA margin, will have a stronger impact on the share price movements, compared to SME's.

*Hypothesis 1: Sales and FCF are the financial metrics that have the highest correlation with the share price movements of SaaS companies*

*Hypothesis 2: EPS has not a significant correlation with share price movements of SaaS companies*

*Hypothesis 3: Profitability measures have a higher correlation with the share price movements for large SaaS companies, compared to smaller SaaS companies*

Moreover, since financial fundamentals are not as volatile as share price movements (Balke & Wohar, 2006) and multiple valuation is industry standard among practitioners (Plenborg & Piementel, 2016) we believe that in line with more SaaS companies proving their true potential, i.e. growing into a steadier state, the investor sentiment has improved. Thus, we believe that EV/Sales has a strong correlation with the share price movements, that has been very positive the last years, meaning that investors are willing to pay more for each unit of sales in SaaS companies.

*Hypothesis 4: EV/Sales has a significant correlation with the share price movements of SaaS companies*

## 3. Data and Methodology

### *3.1 Data*

To conduct the research, we primarily use data from the S&P Capital IQ database accessed through the Wharton Research Data Service (WRDS). The Capital IQ database contains a wide range of financial metrics from all instances of a company's filings from press releases, initial and all subsequent filings. The Capital IQ database Covers 88,000 public companies with 45,000 active public companies representing 99% of the world's market capitalization. Detailed estimates covering over 19,000 active companies from over 670 active contributors with over 40 data measures including EPS, Revenue, EBITDA and more. We also validated the quality of the data from Capital IQ by checking the financials for a random set of companies on their published interim reports. Moreover, FactSet's database, an open data and software solution providing financial data for more than 126,000 users worldwide, is used in order to retrieve financial data on the S&P 500 index.

The exported dataset contains more than 25,000 observations for 66 companies, dating from 31 December 2019 back to 31 March 2014, on a quarterly basis. The chosen companies are derived from GP Bullhound's SaaS company index. GP Bullhound is an international investment bank with a great focus on the technology sector and with ten offices worldwide. To increase the possibility of finding statistically significant variables with a certain level of validity, we filter our dataset to exclude companies that have been listed on the New York Stock Exchange (NYSE) or Nasdaq less than one year (i.e. IPO in 2019). We also exclude companies with a market capitalization less than USD 1 billion in an effort to avoid external factors on share price movements, such as issues of stock liquidity. The observed companies are listed on either NYSE or NASDAQ. All companies, except Salesforce and ServiceNow Inc. (ServiceNow), have a market capitalization (as of March 17th) between USD 1-50 billion. Salesforce has in contrast, a market capitalization of around USD 144 billion and ServiceNow also exceeds the range at a market capitalization of around USD 53 billion.

The quarterly observations include data points on market capitalization, share price, sales, gross profit, earnings before interest, depreciation and amortization (EBITDA), net income, earnings per share (EPS), free cash flow (FCF), deferred revenue, enterprise value-to-sales (EV/Sales) ratio, EV/EBITDA, price-to-book (P/BV) ratio and customer count. However, in our analysis, we include only share price, sales, EBITDA margin, EPS, FCF, EV/sales and P/BV. Share price and EPS is measured in terms of US dollars, sales and FCF in USD millions, EBITDA margin in percentages, EV/Sales and P/BV as factors. Market capitalization and net income were used to check if share repurchases or issuance of shares have had an impact on share price and EPS, respectively, and thus the result, which seems not to be the case.

The companies included in the dataset are clearly more focused on growth rather than profitability in their early business life cycles. Therefore, we believe that gross profit would be the most appropriate profitability metric since it is not burdened by the companies' heavy growth initiatives that include large R&D and S&M costs. Deferred revenue is an item that can be found on a company's balance sheet and is considered a strong indicator for future performance since it can act as an estimate for future revenues. This is particularly true for a business that focuses on recurring revenues, and as investors very much consider the future performance of companies when investing, we believe it would have a significant correlation with the share price movements. However, both gross profit and deferred revenue are strongly correlated with sales. Thus, those metrics are excluded to avoid issues regarding multicollinearity, which would negatively impact the robustness of our models.

Furthermore, we believe that the customer count could have a material impact on valuation and thus share price movements. The increased popularity of subscription-based businesses has brought with it an increase in the public disclosure of data on (but not limited to) customer churn, customer/subscriber acquisition costs, average revenue per user (ARPU), and customer lifetime value (CLV) (McCarthy, et al., 2017). However, only a small fraction of the companies reported homogenous customer counts in their interim reports and hence, this metric is excluded. EV/EBITDA is also excluded due to too few "meaningful" multiples, i.e. not negative, in the dataset. Subsequently, for the same reason, we do not include the P/E multiple.

To begin our study of trying to understand stock price movements as a function of financial metrics, a dataset covering 51 American companies is examined. As previously mentioned, we exclude a) recently listed companies and b) companies with market capitalizations of less than USD 1 billion. Furthermore, we exclude any quarterly observation, for any company, that does not provide numbers for all of the metrics. For example, if the EV/Sales multiple for ServiceNow in the first quarter of 2015 is not provided, we do not use data for ServiceNow from the first quarter of 2015 in our analysis. Naturally, we will not be able to run regressions with numbers from every quarter between 2014-2019. The dataset that we end up with after this elimination of observations consists of 720 observations for each variable examined. Thus, we eliminate 504 observations from a total of 1,224 observations.

## *3.2 Methodology*

### *3.2.1 Precautionary Measures*

In all our regressions, we use robust standard errors to avoid skewness in our results. We also test for any issues of multicollinearity by calculating Variance Inflation Factors of our independent variables, as can be seen in **table 8** in the **Appendix.** We use a threshold of 10 and if we see factors greater than 10, it is a sign of issues of multicollinearity and we may need to change the models to mitigate this. Fortunately, we see that no variable has a factor over 10 and we can therefore conclude that our models do not suffer from multicollinearity. For each regression, we present standardized beta coefficients. Since our independent variables are measured in different units (dollars, percentages and multiples) we must adjust for this in order to improve comparability between the independent variables.

### *3.2.2 Dependent and Independent Variables*

Our dependent variable for all regressions is share price, which is retrieved directly from Capital IQ. For the regressions, we use "lagging" share price data since we believe it will capture stock price movements in a more accurate and harmonised way, since share prices can move significantly following earning releases. The reasoning is that we will trace the share performance based on known fundamentals instead of estimates and speculations. As an example, share prices from the second quarter of 2014 will be matched with financial metrics (sales, EBITDA margin, EPS, etcetera) from the first quarter of 2014.

In order to analyse share price movements, we use some independent variables, summarized in **table 1**.

**Table 1.**. Variable Definitions

| Variables | Definitions |
|---|---|
| Sales | Net Sales (measured in MUSD) |
| EBITDA Margin | Earnings Before Interest, Taxes, Depreciation and Amortization, divided by Net Sales (measured in percentages) |
| Earnings per Share | Company's reported Net Income, subtracted by preferred dividends, divided by the number of total common outstanding shares during the reporting period (measured in USD per share) |
| FCF | EBITDA subtracted by amortization of Debt Issuance Costs, net increases in Net Working Capital, Capital Expenditures while adding back Stock-Based Compensations (measured in MUSD) |
| EV/Sales | Enterprise Value (Market Capitalization subtracted by Net Debt) divided by Net Sales during the relevant reporting period (measured as ratios) |
| P/BV | Share Price divided by the Book-Value per Share (measured as ratios) |
| Year (Dummy) | Annual time dummy variable |
| Class (Dummy) | Firm size dummy variable |
| Firm (Dummy) | Firm specific dummy variable |

*The table presents all the variables included in our analysis*

When choosing our independent variables, we must consider whether each of the variables are reasonable to include and whether there will be a problem of high correlation with another variable or not. We believe that chosen financial metrics are reasonable to include, based on existing literature on valuation of companies and the SaaS business model.

The chosen financial metrics for our models are sales, EBITDA margin, EPS, FCF, EV/Sales and P/BV. The dataset excludes initially chosen independent variables due to multicollinearity and non-meaningful values. However, we believe that sales, EBITDA margin and FCF are among the important variables for companies with negative earnings (Liu, et al., 2007; Cohen & Neubert, 2018). EV/Sales and P/BV are on a trailing twelve months basis and illustrate investors' willingness to pay for one unit of ownership of two different variables, since share prices are more volatile than fundamentals (Balke & Wohar, 2006). Once again, trailing numbers are used in order to measure reported numbers and not estimates. EPS is included for the sake of the general view that it is an essential driver of share price movements (Liu, et al., 2007; Stern, 1970).

We incorporate time fixed effects by including annual time dummy variables for each respective year. By doing this, we aim to account for external factors impacting share price movements such as macroeconomics shocks (e.g. economic recessions).

For the firm size dummy variable "Class", we categorise Large Companies with an EV equal to or greater than USD 5 billion. Consequently, SME's have EV less than USD 5 billion. This way, we hope to potentially see if there are any difference in how these variables impact stock price movements across companies with different maturities or sizes. In total, there are 26 Large Companies and 25 SME's, providing us with an even split in terms of companies per group. These are seemingly small groups of companies and we must bear this in mind when drawing conclusions. Using a small number of companies in the study reduces the statistical power of our analysis. We categorize the companies based on their EV as of March 17th, 2020. The reason for this is to look at how the Large Companies' share prices and corresponding variables have grown and whether there is a difference between the drivers of these companies and those that have not grown into this group yet, i.e. SME's. We do not control for companies' historical size and we must be aware that some of the companies that we classify as Large Companies today, possibly had an EV less than USD 5 billion during a certain time period in our dataset. Of course, this will reduce the statistical power in our models where we divide the dataset into these groups as the categorization probably does not hold true for the entire time period.

The firm-specific dummy variable "Firm" is incorporated in part of our analysis. By adding firm specific fixed effects, we control unobserved heterogeneity (firm characteristics) and therefore decrease the risk of suffering from omitted variable bias in our study. This assumes that these unobserved heterogeneities are constant over time. One drawback of firm-specific fixed effects is that they can reduce the statistical power of the models. This is because firm-specific effects exclude cross-sectional variance between firms (Eckbo, 2008).

*3.2.3 OLS Regression Models and Analysis*

In total, we will estimate ten different regression models. We use ordinary least-squares regressions (OLS) to estimate the relationship of our independent variables and the share price. Our main model (**Model 1**) that we test is the following:

$$\mathrm{SP}_{t+1} = \beta_0 + \beta_1 Sales_t + \beta_2 EBITDAmargin_t + \beta_3 EPS_t + \beta_4 FCF_t + \beta_5 EVSales_t + \beta_6 PBV_t + \beta_7 Year_t + \beta_8 Class + \varepsilon \quad (3)$$

Where $\varepsilon$ is the error term with a mean at zero and $t$ indicate the relevant period. We show that SP has subscript $t+1$ since we use lagging share prices.

Our main model tests the relationship between our independent variables and share price movements, by pooling the dataset. Additionally, we estimate two separate models for each respective class of company (Large Companies vs SME's) by using STATA's "if" command when running the regressions. **Model 2 and 3**:

$$\mathrm{SP}_{t+1} = \beta_0 + \beta_1 Sales_t + \beta_2 EBITDAmargin_t + \beta_3 EPS_t + \beta_4 FCF_t + \beta_5 EVSales_t + \beta_6 PBV_t + \beta_7 Year_t + \varepsilon \quad (4)$$

Model 2 and 3 are almost identical to the main model, but the difference here is that we test Large Companies (Model 2) and SME's (Model 3) separately. Therefore, we will not include the firm size dummy variable in these models.

As we want to test the robustness of our results, we also estimate three more models where we add firm-specific fixed effects. **Model 4**:

$$\mathrm{SP}_{t+1} = \beta_0 + \beta_1 Sales_t + \beta_2 EBITDAmargin_t + \beta_3 EPS_t + \beta_4 FCF_t + \beta_5 EVSales_t + \beta_6 PBV_t + \beta_7 Year_t + \beta_8 Class + \beta_9 Firm + \varepsilon \quad (5)$$

As a result, Model 4, 5 and 6 will only compare share price movements and corresponding independent variables within each firm rather than comparing different firm's share price movements and independent variables with each other.

Similar to Model 2 and 3, we drop the firm size dummy variables for **Model 5 and 6:**

$$\mathrm{SP}_{t+1} = \beta_0 + \beta_1 Sales_t + \beta_2 EBITDAmargin_t + \beta_3 EPS_t + \beta_4 FCF_t + \beta_5 EVSales_t + \beta_6 PBV_t + \beta_7 Year_t + \beta_8 Firm + \varepsilon \quad (6)$$

Furthermore, we will estimate four additional models. All models are similar to our main model (Model 1), but in each model we adjust the dataset to test the robustness of our results. The aim is to see whether the results of our main model is dependent on certain thresholds. We estimate **Model 7, 8, 9 and 10**:

$$\mathrm{SP}_{t+1} = \beta_0 + \beta_1 Sales_t + \beta_2 EBITDAmargin_t + \beta_3 EPS_t + \beta_4 FCF_t + \beta_5 EVSales_t + \beta_6 PBV_t + \beta_7 Year_t + \beta_8 Class + \varepsilon \quad (7)$$

In **Model 7**, we exclude Salesforce from our list of companies in our analysis. This is done to see if the biggest company in our dataset largely impact the outcome and hence skew the results in any type of way. Salesforce has an EV of around USD 144 billion, compared to the second-largest company in our dataset, which is ServiceNow at an EV of USD 53 billion. The difference in size is large and hence interesting to see if it has any impact on the results.

In **Model 8, 9 and 10**, we will run regressions for all companies with three different time periods in order to see if the results of our main model are sensitive to the chosen time period of 2014-2019. In Model 8 the chosen time period is 2014-2016, for Model 9 it is 2015-2018, and in Model 10 it is 2017-2019.

# 4. Results

## *4.1 Sample Data Statistics*

In **table 2** we present the descriptive statistics for All Companies, i.e. Model 1 and 4. We see that we have 720 data points for each of the variables. Moreover, we see that the mean share price is around USD 54, with average sales of USD 234 million. We also see, as expected, that the average company has negative EBITDA margin, at -4.4% and EPS of USD -0.14. The average company has around USD 50 million in FCF and EV/Sales and P/BV multiples of 8x and 20x. In the correlation matrix, we see that there is a significant correlation between share price and all independent variables, except EPS and the P/BV multiple, at the one per cent level. EPS correlates significantly at the five per cent level while P/BV does not correlate significantly at any of the presented levels. What we can also see is that sales and EV/Sales have the highest correlations, with sales at 0.393 and EV/Sales at 0.550.

**Table 2**. Descriptive Statistics of Sample Data – All Companies (Model 1 & 4)

| | | | | | Correlation Among Variables | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Variables | N | Mean | SD | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| (1) | Share Price | 720 | 54.45 | 42.97 | 1.000 | | | | | | |
| (2) | Sales | 720 | 233.77 | 469.58 | 0.393*** | 1.000 | | | | | |
| (3) | EBITDA Margin | 720 | -4.4% | 0.24 | 0.163*** | 0.150*** | 1.000 | | | | |
| (4) | EPS | 720 | -0.14 | 0.49 | 0.120** | 0.143*** | 0.762*** | 1.000 | | | |
| (5) | FCF | 720 | 49.56 | 156.72 | 0.309*** | 0.755*** | 0.120** | 0.0972** | 1.000 | | |
| (6) | EV/Sales | 720 | 8.4x | 4.66 | 0.550*** | 0.037 | -0.031 | -0.104** | 0.0891* | 1.000 | |
| (7) | P/BV | 720 | 20.0x | 28.52 | 0.021 | -0.061 | -0.053 | -0.057 | -0.051 | 0.072 | 1.000 |

* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

In **table 3** we see descriptive statistics for the Large Companies in our pooled dataset. For this group, we have 369 data points for each variable. Large Companies have average share prices of around USD 73 and sales of USD 378 million. EBITDA margins at 0.0% and EPS of USD -0.08. Large Companies has an average FCF of USD 87 million and EV/Sales and P/BV multiples of 10x and 17x, respectively. Again, most independent variables correlate significantly at the one per cent level. However, in contrast to previous findings, EBITDA margin and EPS do not correlate significantly with share price while P/BV do. Unlike the pooled dataset, EV/Sales (0.430) and P/BV (0.358) correlates the highest with share prices for a Large Company.

**Table 3.** Descriptive Statistics of Sample Data - Large Companies (Model 2 & 5)

| | | | | | Correlation Among Variables | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Variables | N | Mean | SD | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| (1) | Share Price | 369 | 72.69 | 49.09 | 1.000 | | | | | | |
| (2) | Sales | 369 | 378.19 | 620.77 | 0.314*** | 1.000 | | | | | |
| (3) | EBITDA Margin | 369 | 0.0% | 0.23 | -0.030 | 0.121* | 1.000 | | | | |
| (4) | EPS | 369 | -0.08 | 0.46 | 0.003 | 0.147** | 0.765*** | 1.000 | | | |
| (5) | FCF | 369 | 86.54 | 211.08 | 0.233*** | 0.739*** | 0.091 | 0.097 | 1.000 | | |
| (6) | EV/Sales | 369 | 10.4x | 5.09 | 0.430*** | -0.129* | -0.251*** | -0.301*** | -0.032 | 1.000 | |
| (7) | P/BV | 369 | 16.5x | 10.06 | 0.358*** | -0.106* | -0.186*** | -0.111* | -0.079 | 0.532*** | 1.000 |

Large Companies: Enterprise Value > 5 bn USD
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

Looking at the class of SME's, we have 351 data points for share price, as can be seen in **table 4**. This is a bit under the number of observations for Large Companies and the explanation for this can be divided into two parts: firstly, Large Companies have generally been listed for a longer period of time compared to SME's. Secondly, the group for Large Companies include one more company. Both factors lead to a smaller sample size for our analysis. SME's have an average share price of USD 35, which is ~50% less than the average share price for the Large Companies. The mean value of sales is also substantially less compared to for Large Companies, amounting to USD 82 million. EBITDA margins for SME's are worse than for Large Companies, on average -9.0%. Average EPS is USD -0.20, and SME's generates on average USD 11 million in FCF. EV/Sales multiple is at 6x and P/BV at 24x. Like the pooled dataset, all independent variables, except for P/BV, correlate significantly at the one per cent level with share price. EV/Sales correlates the most (0.509), closely followed by FCF (0.477) and sales (0.461).

**Table 4.** Descriptive Statistics of Sample Data - SME's (Model 3 & 6)

| | | | | | Correlation Among Variables | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Variables | N | Mean | SD | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| (1) | Share Price | 351 | 35.28 | 23.25 | 1.000 | | | | | | |
| (2) | Sales | 351 | 81.93 | 51.87 | 0.461*** | 1.000 | | | | | |
| (3) | EBITDA Margin | 351 | -9.0% | 0.24 | 0.360*** | 0.214*** | 1.000 | | | | |
| (4) | EPS | 351 | -0.20 | 0.50 | 0.231*** | 0.164** | 0.752*** | 1.000 | | | |
| (5) | FCF | 351 | 10.68 | 25.53 | 0.477*** | 0.532*** | 0.187*** | 0.035 | 1.000 | | |
| (6) | EV/Sales | 351 | 6.3x | 3.00 | 0.509*** | -0.164** | 0.060 | 0.001 | 0.141** | 1.000 | |
| (7) | P/BV | 351 | 23.6x | 39.23 | 0.004 | 0.048 | 0.004 | -0.032 | -0.014 | 0.051 | 1.000 |

SME's: Enterprise Value < 5 bn USD
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

### *4.2 OLS Regression Results*

The first part of our OLS regression analysis is conducted with the pooled dataset, with the regression results of Model 1-3 presented in **table 5**.

For Model 1, the total sample size is 720 observations. Three out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales and the firm size dummy variable. We see that the first two variables have positive and significant standardized coefficients of 0.326 and 0.423, indicating that both variables have the most significant impact on share price variance in our main model. The firm size dummy variable is negative at -0.131, indicating that on average, all else equal, an SME will have share price of USD 0.13 lower than a Large Company.

For Model 2, the total sample size is 369 observations. Two out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales. P/BV is significant at the ten per cent level. We see that the first two variables have positive coefficients of 0.350 and 0.252, indicating that sales have a bigger impact on Large Companies compared to the average company for All Companies and that EV/Sales has a less of an impact on share price movement compared to the average company. Unlike in Model 1, P/BV is significant and seem to have a material impact on share prices in Model 2.

For Model 3, the total sample size is 351 observations. Three out of six independent variables are statistically significant in the model at the one per cent level; Sales, EV/Sales and EBITDA margin. All variables have positive coefficients of 0.432, 0.226 and 0.534, respectively, indicating that both sales and EV/Sales have a greater impact on the share prices of SME's compared to the average company for All Companies and Large Companies. Unlike in Model 1 and 2, EBITDA margin is significant and seem to have a material impact on share prices in Model 2. Furthermore, FCF is significant at the five per cent level and have a positive coefficient of 0.132.

We can conclude that sales and EV/Sales are statistically significant for all three models in the pooled dataset, with impacts of varying magnitude on share price movements.

**Table 5**. OLS Regression Results - Pooled

| | All Companies (Model 1) | Large Companies[1] (Model 2) | SME's[2] (Model 3) |
|---|---|---|---|
| Variables | | | |
| Sales | 0.326*** | 0.350*** | 0.432*** |
| | (7.66) | (7.46) | (8.58) |
| EBITDA Margin | 0.075 | 0.024 | 0.226*** |
| | (1.27) | (0.28) | (3.88) |
| Earnings per Share | 0.051 | 0.041 | -0.022 |
| | (0.69) | (0.36) | (-0.41) |
| FCF | -0.034 | -0.040 | 0.132** |
| | (-0.93) | (-0.98) | (2.97) |
| EV/Sales | 0.423*** | 0.262*** | 0.534*** |
| | (10.63) | (3.71) | (17.19) |
| P/BV | 0.020 | 0.146* | -0.045 |
| | (1.34) | (2.47) | (-1.28) |
| SME's (Dummy) | -0.131*** | | |
| | (-4.95) | | |
| Sample Size | 720 | 369 | 351 |
| R-Squared | 0.817 | 0.833 | 0.886 |
| Adj. R-Squared | 0.813 | 0.828 | 0.882 |

Standardized regression coefficients are reported, with t-values in parenthesis
1) Sample reduced to only Large Companies ( EV >5 bn USD)
2) Sample reduced to only SME's ( EV <5 bn USD)
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

The second part of the OLS regression analysis is conducted with firm-specific fixed effects, with the regression results of Model 4-6 presented in **table 6**.

For Model 4, the total sample size is 720 observations. Two out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales. We see that the two variables have positive and significant standardized coefficients of 0.283 and 0.425, indicating that both variables have the largest impact on share price variance in this model. The firm size dummy variable is not significant and is negative at -0.106. The lack of significance is likely an effect of the reduced statistical power of firm fixed effects.

For Model 5, the total sample size is 369 observations. Two out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales. P/BV and FCF are significant at the ten per cent level. We see that the first two variables have positive coefficients of 0.259 and 0.409, indicating that EV/Sales once again have a larger impact on share price movements compared to sales. Interestingly, both FCF and P/BV have negative coefficients of -0.062 and -0.145, respectively, which is not in line with the findings for the pooled dataset. However, we bear in mind that the results for the regressions with firm fixed effects will have a lower statistical power as previously discussed.

For Model 6, the total sample size is 351 observations. Three out of six independent variables are statistically significant in the model at the one per cent level; Sales, EV/Sales and P/BV. The first two variables have positive coefficients of 0.313 and 0.426, respectively, indicating that both sales and EV/Sales have a greater impact on the share prices of SME’s compared to the average company for All Companies and Large

Companies. This is very much in line with the results for Model 1-3. Unlike in Model 4 but similar to Model 5, P/BV is significant and negative in Model 6 at -0.075.

**Table 6**. Fixed Effects Regression Results

| Variables | All Companies (Model 4) | Large Companies[1] (Model 5) | SME's[2] (Model 6) |
|---|---|---|---|
| Sales | 0.283*** | 0.259*** | 0.313*** |
| | (9.00) | (5.56) | (5.12) |
| EBITDA Margin | -0.003 | 0.001 | 0.054 |
| | (-0.06) | (0.02) | (1.00) |
| Earnings per Share | 0.059 | 0.047 | 0.027 |
| | (1.04) | (0.59) | (0.75) |
| FCF | -0.041 | -0.062* | 0.000 |
| | (-1.64) | (-2.11) | (-0.00) |
| EV/Sales | 0.425*** | 0.409*** | 0.426*** |
| | (8.15) | (5.06) | (12.51) |
| P/BV | -0.026 | -0.145* | -0.075*** |
| | (-1.70) | (-2.21) | (-3.61) |
| SME's (Dummy) | -0.106 | | |
| | (-1.50) | | |
| Sample Size | 720 | 369 | 351 |
| R-Squared | 0.925 | 0.940 | 0.955 |
| Adj. R-Squared | 0.918 | 0.934 | 0.951 |

Standardized regression coefficients are reported, with t-values in parenthesis
1) Sample reduced to only Large Companies ( EV >5 bn USD)
2) Sample reduced to only SME's ( EV <5 bn USD)
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

Our results are in line with the findings of Liu et al. (2007) with regards to the weak correlation between EPS and share price behaviour when there are negative earnings. We see that EPS has no significant correlation with share price in any of our models, making it reasonable to assume that EPS does not have a material impact on and do not correlate significantly with the share prices of the SaaS companies in our dataset. We do see in **table 2** and **table 4** that EPS correlates significantly with share price, though not relatively high, but this does not suffice as evidence that EPS do have a material impact on share price behaviour as we do not see any significant relationship for any of the regression models.

For all regression models, we find that there is a significant correlation between some fundamental variables and share price, confirming the findings of Balke & Wohar (2006). In total, EV/Sales is the strongest indicator of share price movements but however, the notion that stock prices exhibit too much volatility to be justified by fundamental variables goes against these findings.

### *4.3 Additional Tests of Robustness*

The third part of our OLS regression analysis is conducted by further testing our main model's robustness in four new models, with the regression results for Model 7, 8, 9 and 10 presented in **table 7**.

In Model 7, the total sample size is 696 observations. Two out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales. We see that the two variables have positive and significant standardized coefficients of 0.381 and 0.402, indicating that both variables have the biggest impact on share price variance in this model. Reassuringly, we see the same two financial metrics as significant in this model. This finding adds to the robustness of our results in Model 1. However, we see that the firm size dummy variable is not significant at any of the levels shown. This is not in line with our main model, and we should, therefore, be aware of the impact that Salesforce has on our dataset in the model and not overstate the statistical power of our results.

In Model 8, the total sample size is 212 observations. Three out of six independent variables are statistically significant in the model at the one per cent level; Sales, EV/Sales and EBITDA margin. All variables have positive coefficients of 0.432, 0.621 and 0.415. We also see that EPS and P/BV are statistically significant at the ten per cent level, with coefficients at -0.207 and 0.064. Clearly, the results differ from our main model as we have new statistically significant variables (EPS and P/BV). We also see that the firm size dummy variable is not significant, while it is in our main model. This could be explained by the fact that in this specific time period, a lot of SME's may not have been listed yet and hence, we do not have an appropriate amount of data to achieve high statistical power. As mentioned, the total sample size is 212 observations for this model, in comparison to 720 total observations in our main model. This is a large difference and could explain the difference in the results.

In Model 9, the total sample size is 402 observations. Two out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales. Both variables have positive coefficients of 0.425 and 0.429, respectively. Furthermore, EBITDA margin is significant at the five per cent level and have a positive coefficient of 0.206. Again, the results of this model differ from the main model, but not the same extent as Model 8. We continue to see a non-significant firm size dummy variable. The sample size is still quite small in comparison to the main model, which must be taken into consideration regarding the findings of Model 9.

In Model 10, the total sample size is 508 observations. Two out of six independent variables are statistically significant in the model at the one per cent level; sales and EV/Sales. We see that the two variables have positive and significant standardized coefficients of 0.382 and 0.485, indicating that both variables have the largest impact on share price variance in this model. In this model we see similar results as in Model 1, with sales and EV/sales as the only two significant financial variables. In contrast, we do not see a significant firm size dummy variable here.

**Table 7**. Robustness Tests of OLS Regression Results - Pooled

| Variables | Excl. Salesforce[1] (Model 7) | 2014-2016[2] (Model 8) | 2016-2018[3] (Model 9) | 2017-2019[4] (Model 10) |
|---|---|---|---|---|
| Sales | 0.381*** | 0.432*** | 0.425*** | 0.382*** |
| | (5.85) | (8.31) | (8.25) | (6.72) |
| EBITDA Margin | 0.071 | 0.415*** | 0.206** | 0.029 |
| | (1.64) | (5.53) | (2.97) | (0.40) |
| Earnings per Share | 0.029 | -0.207* | -0.085 | 0.090 |
| | (0.60) | (-2.27) | (-1.20) | (1.04) |
| FCF | 0.090* | -0.052 | -0.035 | -0.056 |
| | (2.01) | (-1.01) | (-0.68) | (-1.27) |
| EV/Sales | 0.402*** | 0.621*** | 0.429*** | 0.485*** |
| | (11.28) | (16.93) | (11.57) | (12.93) |
| P/BV | -0.000 | 0.064* | 0.022 | 0.022 |
| | (-0.02) | (2.57) | (0.96) | (1.09) |
| SME's (Dummy) | -0.024 | 0.045 | -0.046 | 0.022 |
| | (-0.80) | (1.03) | (-1.24) | (1.09) |
| Sample Size | 696 | 212 | 402 | 508 |
| R-Squared | 0.836 | 0.900 | 0.810 | 0.808 |
| Adj. R-Squared | 0.833 | 0.896 | 0.806 | 0.804 |

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

Dataset for Model 1 but:
1) excluding Salesforce
2) time period reduced to years 2014-2016
3) time period reduced to years 2016-2018
4) time period reduced to years 2017-2019
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

### *4.4 Conclusion of Results*

To conclude, we find that: 1) Sales shows a significant correlation with the share price of SaaS companies both in the pooled and the divided analysis and both with and without the firm-specific fixed effect. Partly confirming our hypothesis and the findings of Liu, et al. (2007) and Cohen & Neubert (2018) but contrasts to the argument that share prices exhibit too much volatility to be justified by fundamental variables (Balke & Wohar, 2006). However, FCF shows no significant correlation with share price in this study but is not as weak as EPS. Partly confirming the findings of Liu, et al. (2007) and partly in contrast to our hypothesis and the findings of Cohen & Neubert (2018). 2) Interestingly, EPS shows no significant correlation with share price throughout the entire study, in line with previous literature (Liu et al., 2007; Cohen & Neubert, 2018) and our hypothesis. 3) Profitability metrics seem to have a small material impact on share price behaviour. These variables show no significant correlation throughout the whole study except for SME's, in contrast to the findings of Stern (1970) and our hypothesis but partly confirms the findings of Liu et al. (2007). 4) EV/Sales shows a significant correlation throughout the study and is in almost all cases more correlated with share price than what sales is. Being the strongest driver of share price in this study is in line with the argument that share prices exhibit too much volatility to be justified by fundamental variables (Balke & Wohar, 2006) and that share price movements can depend on changes in investor sentiment (Campbell, et al., 2010). Lastly, Fama and French's three-factor and five-factor models were rejected early.

## 5. Implications & Conclusions

The findings show that sales and EV/Sales are the strongest drivers of share price movements for SaaS companies, with the latter showing a slightly higher coefficient in most cases. Our interpretation is that the strong performance of SaaS companies in the last five years is largely due to investors' willingness to pay more for one unit of sales. We believe this is rooted in an improved investor sentiment for this sub-sector, which can either depend on investors estimating higher expected cash flows or by a lower discount rate of cash flows (Campbell, et al., 2010; Chen, et al., 2013) when performing a DCF valuation (Kaplan & Ruback, 1995; Damodaran, 2005). The average EV/Sales multiple for the companies in the dataset has increased from 3.8x in December 2014 to 9.8x in December 2019. A high-level interpretation of those numbers suggests that if all other factors were held constant, the share performance of these companies would have been 156% over the course of five years, solely due to multiple expansion. Thus, a large portion of the strong performance is driven by fundamentals, since the constituents of valuation of a firm are cash flow and discount rate (Campbell, et al., 2010; Chen, et al., 2013). However, a higher value of one unit of ownership in sales finds support in the discussion of SaaS companies' business models, with a strong value proposition for customers, high flexibility in the cost base and a high rate of recurring revenues. Translating to a potential strong cash flow generation in the future. EBITDA margin shows no significant correlation with share price in any model except for SME's and EPS shows no significant correlation in any model, indicating that investors should be inclined to prioritise sales growth over profitability measures in investment decisions regarding SaaS companies. To conclude, hypothesis 1 is partly supported by the findings in this paper, while hypothesis 2 and 4 are strongly confirmed. Hypothesis 3 is, however, rejected. The findings of this study are in line with papers discussing the share price movements as dependent on changes in investor sentiment and thus either cash flow expectations or discount rate changes (Campbell, et al., 2010; Chen, et al., 2013). However, in line with the findings of Liu, et al. (2007) and Cohen & Neubert (2018) and in contrast to the excess volatility hypothesis (LeRoy & Porter, 1981; Shiller, 1981; Balke & Wohar, 2006), a large portion of the share price movements of SaaS companies is driven by sales.

Investigating share price in our analysis has its limitations by nature. Since it is a market-based price it relies on the efficient market hypothesis, first introduced by Fama (1970). Inefficiencies in the market would distort movements in share prices and potentially raise doubt on any results obtained. In an ideal study, other key variables such as size of the addressable target market, churn rate, customer retention rate and capital efficiency would be included in the models as they are especially important for SaaS companies (McCarthy, et al., 2017). Furthermore, a large amount of intrinsic corporate value lies within intangible or qualitative measures of the firm. Examples of this include stability of the earnings power, owner-specific business relationships, business traffic attributable to search engines and their algorithms, level of competition within the business niche, and type of customers targeted by the company (Cohen & Neubert, 2018). Such measures would contribute to the explanation of the strong performance of the SaaS companies since the financial statements do not tell the whole truth. Additionally, it would be valuable to conduct interviews with practitioners to understand what investors value when investing in SaaS companies. The ideal analysis would, therefore, include more qualitative research of the share price behaviour.

However, due to the qualitative nature and difficulty to extract those metrics we choose to focus on financial measures and bear in mind that our analysis will not be as complete as we would have wished it to be. We chose to focus on B2B SaaS companies, but the analysis could also include B2C SaaS companies, in order to find potential differences in share price drivers between the two and increase the number of companies in our study and subsequently the sample size. As mentioned previously, the statistical power in our findings are burdened the small number of companies in our dataset. Additionally, for a future study, it would be appropriate to use a longer time period and potentially more frequent observations (monthly, weekly) in an effort to capture share price movements more accurately after earnings releases. As our study falls short on these issues mentioned, it reduces the statistical power and our ability to detect true significant results. However, our findings are based on the models and methodologies we have discussed in this paper.

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# Appendix

The variance inflated factors of the variables in Model 1, 4 & 7 are shown in **table 8**. None of the factors exceed the threshold of factor 10 for multicollinearity.

**Table 8**. Variance Inflated Factors, VIF - Model 1, 4 & 7

| | All Companies (Model 1) | All Companies (Model 4) | Excl. Salesforce (Model 7) |
|---|---|---|---|
| Variables | | | |
| Sales | 2.53 | 2.84 | 1.56 |
| EBITDA Margin | 2.45 | 2.45 | 2.45 |
| Earnings per Share | 2.44 | 2.44 | 2.46 |
| FCF | 2.36 | 2.36 | 1.29 |
| EV/Sales | 1.48 | 1.73 | 1.52 |
| P/BV | 1.04 | 1.04 | 1.04 |
| Class (Dummy) | 1.53 | 4.48 | 1.73 |
| Year (Dummy) | 1.13 | 1.37 | 1.22 |
| Firm (Dummy) | Not included | 5.91 | Not included |
| Mean VIF | 1.87 | 2.73 | 1.66 |

**Table 9** presents all the annual time variables produced in Model 1, 4 and 7.

**Table 9**. Annual Time Dummy Variables Produced for Regression Models

| | All Companies (Model 1) | All Companies (Model 4) | Excl. Salesforce (Model 7) |
|---|---|---|---|
| Variables | | | |
| Year 1 Dummy | 0.062* | -0.008 | 0.003 |
| | (2.57) | (-0.36) | (0.11) |
| Year 2 Dummy | 0.093*** | 0.057* | 0.002 |
| | (3.76) | (2.28) | (0.08) |
| Year 3 Dummy | 0.128*** | 0.130*** | 0.010 |
| | (4.04) | (4.51) | (0.28) |
| Year 4 Dummy | 0.243*** | 0.298*** | 0.096 |
| | (5.43) | (8.16) | (1.96) |
| Year 5 Dummy | 0.374*** | 0.453*** | 0.193*** |
| | (8.63) | (10.83) | (3.77) |

Year 1 implies 2015, Year 2 2016, Year 3 2017, Year 4 2018, Year 5 2019
Standardized regression coefficients are reported, with t-values in parenthesis
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)