Investigating an alternative approach to SaaS company valuation: Using '*Rule of 40*' metrics as indicators of Enterprise Value

Master Thesis

EY Transaction Advisory Services
Strategy & Operations

Author:	*Bas Hottenhuis (s1570714)*	
Supervisor:	*Dr. B. Roorda*	*(University of Twente)*
2nd Supervisor:	*Dr. R.A.M.G. Joosten*	*(University of Twente)*
Company Supervisor:	*M.N. de Beyer*	*(EY TAS S&O)*

Master Industrial Engineering & Management
Specialization: Financial Engineering & Management
University of Twente

February 28, 2020

UNIVERSITY OF TWENTE.

Abstract

Company valuation has always been highly difficult and a reason for discussion. Especially the valuation of Tech companies and 'Software as a Service'-companies (SaaS) is challenging as the most-used valuation methods are mainly focused on traditional companies with a higher amount of fixed assets. Conventional valuation methods are often based on discounted cash flows (DCFs). These are not in the same way applicable for Tech/SaaS companies since they typically have different company characteristics (e.g. hardly any fixed assets) which lead to unreliable DCF results.

We introduce an alternative point of view: the 'Rule of 40'. Conceptually, this rule of thumb states that there is a direct trade-off between a company's growth and margin, which can therefore be added together to give an indication of a firm's performance. The sum of the growth and margin is in the case of this research used as an indicator for the level of the firm's valuation multiple.

To find the most significant indicator, we compare 20 different combinations of Rule of 40 indicators and valuation multiples. This analysis is carried out using linear regression, in which we focus on the results of the slope and R-squared. Tech companies are retrieved using S&P's General Industry Classification Standards (GICS), and SaaS companies are selected based on a list of the 50 largest SaaS companies in America. The Tech company analysis does not result in any significant relations. Therefore we decided to focus on SaaS companies. The most significant relationship is found to be Rule of 40 indicator 'Free Cash Flow Margin + Revenue Growth', in combination with the valuation multiple 'TEV/Revenue'. Based on our literature review, we extended the applicability of the Rule of 40 by looking at different sectors with similar characteristics. E-commerce companies are also selected using GICS. The regressions for E-commerce also result in 'FCF margin + Revenue growth' as the most significant indicator in combination with 'TEV/Revenue'. From this, we conclude that the trade-off principle is applicable to both SaaS as well as E-commerce.

The regressions for SaaS and E-commerce both do not result in a relationship that is significant enough to use for company valuation. Since the concept cannot be applied to valuation we test the robustness of our analyses in two different ways. We reconsider the growth + margin concept by checking the relationships using Spearman ranked correlation. The results suggest the same indicators to be most significant, which confirms earlier findings. For the second robustness check, we use winsorizing, which adjusts our data to decrease the effect of outliers. The check shows that the results for SaaS are more robust than for E-commerce. Possible reasons for this are sticky demand, customer loyalty, and customer base-scalability, which all have a positive effect for SaaS.

The final conclusion is that there is a significant relationship, but that it cannot directly be used for company valuation since the relationship is not significant enough. This research adds to the existing literature with a comprehensive evaluation of the predictive powers of Rule of 40-based indicators for company valuation multiples. Another addition to the literature is the extension towards a different industry, which had not been done before. For further research, we advise using the most significant indicator from this report as a starting point for more elaborate regression research in which more variables are added such as company size, age, the percentage in recurring customers or industry subcategory within SaaS. This will lead to a more reliable source for SaaS company valuation. A point of discussion remains to which extent the conclusions are applicable to smaller companies since the current research is focused on large companies.

Acknowledgements

With this thesis, I finalize my life as a student and start with the first steps of my professional career. Before doing so, I would like to thank a few people who have supported me during the period in which I wrote my thesis.

First of all, I want to thank Berend Roorda for being my first supervisor at the University of Twente. Berend helped me with keeping the right focus and making the right decisions at times when I got stuck. I also want to thank Reinoud Joosten for being my second supervisor at the university and for giving his feedback in the final phase of writing my thesis.

In the past six months, I had the opportunity to be part of the 'Strategy & Operations' team within 'Transaction Advisory Services' at EY. Here, the most important people to discuss my thesis with, were Melissa de Beyer and Mark Reich. Especially Melissa helped me to keep the EY focus that was needed. She made sure that this thesis is also useful for EY, for which I am very thankful. Apart from this support, all my other colleagues also helped me by giving a very good view on the job of a consultant in this department. For this help and all the fun times at EY, I would like to thank all my colleagues very much.

Finally, I would like to thank my friends, girlfriend, and family for supporting me during the writing of my thesis.

I hope you enjoy reading this thesis.

Bas Hottenhuis
Amsterdam, February 28, 2020

Table of Contents

List of Abbreviations

ARR	Annual Recurring Revenue
B2B	Business to Business
B2C	Business to Consumer
CAPEX	Capital Expenditures
CCA	Comparable Company Analysis
CE	Customer Equity
CLV	Customer Lifetime Value
COGS	Costs Of Goods Sold
CTA	Comparable Transaction Analysis
DCF	Discounted Cash Flows
EBITDA	Earnings Before Interest, Taxes, Depreciation & Amortization
GICS	General Industry Classification Standards
IPO	Initial Public Offering
LTV/CAC	Lifetime Value / Customer Acquisition costs
NYSE	New York Stock Exchange
OPEX	Operating Expenses
R&D	Research & Development
ROC	Return on Capital
SaaS	Software as a Service
(T)EV	(Total) Enterprise Value
WACC	Weighted Average Cost of Capital

List of Tables

List of Figures

1 Introduction

Before Twitter went public on the NYSE, their annual loss over the last year was 79 million dollar. On its IPO date in 2013, Twitter had a valuation of 24 billion dollar. In 2016, LinkedIn was bought by Microsoft for 26 billion dollar although they were loss-making, and similarly, WhatsApp was bought by Facebook in 2014 while having zero revenues or profit. How is this possible?

1.1 General topic introduction

This thesis dives in the fundaments of valuation methods and specifically aims to create insights in the valuation of technology firms, or more specifically, SaaS companies (Software as a Service). In general, company valuation is already considered as something very challenging. Valuation often depends on the individual opinions of people and their interpretations of the (financial) facts of a company. Especially Tech-company valuations are complex as they differ greatly in some of the basic aspects that are fundamental for most common valuation methods. We try to find a pattern in the current values of Tech and SaaS companies.

Why is it so difficult to value SaaS companies?

Traditional valuation methods are not designed for the characteristics of Tech companies (Damodaran, 2001). For example: some valuation methods work with a multiple on the EBITDA. In that case, a firm's value is based on its earnings, which is multiplied with a certain multiple. Due to the nature of Tech companies, it is not uncommon for them to have negative earnings for some years. Working with a multiple would imply that the company has a negative value in that case (Copeland, T., T. Koller and J. Murrin , 2000). However, even Tech companies with negative earnings can still be worth billions of dollars. How this is possible and how this can be worked around is an interesting point of discussion for this paper.

1.2 Concept of the Rule of 40

One of the most fundamental concepts of this thesis is the Rule of 40-number. This number is determined by summing a company's growth percentage and its margin percentage. Many interpretations of which growth and margin should be used exist, but the general interpretation of the Rule of 40 number is always the same (revenue growth + operating profit as a percentage of revenue). The Rule of 40 number indicates how well a company is performing, where 40 is seen as a boundary for really good company performance with a promising future (Latka, 2019). The higher the number, the higher the company value is also one of the basic perceptions that exist about this Rule of 40 number. Therefore, we use the Rule of 40 number as an indicator for company value, which is discussed extensively in Chapter 4: Non-traditional points of view for company valuation.

1.3 Company background

This research is conducted with the professional guidance and support of the Amsterdam office of EY. EY, a 877 million euro revenue company, with its 260.000 employees, is a world-wide firm offering services in four main areas: Assurance, Tax, Advisory and Transaction Advisory Services (TAS). This research is carried out within TAS, and specifically within the department 'Strategy & Operations' (S&O). S&O provides several services focused around transactions. One of the services that is offered by S&O is Due Diligence research to create insights in synergies and risks. They also support integration process after an acquisition with as a major goal value creation. In addition to those two things, S&O also guides carve-out processes.

1.4 Research motivation and relevance

The assignment that EY proposed is not a specific current problem but a general challenging matter. EY is now facing how technological changes bring up challenges in company valuation for Tech and SaaS companies. Where classic valuation methods do not completely cover the valuation anymore, the challenge arises on where the value indicators lie.

Solving this problem will have a practical contribution by being able to assess a range within which a company value lies in a rather easy way. Determining this without having access to broad financial data of the company is especially useful at the start of a possible project engagement.

2 Research formulation and approach

In this chapter, we discuss our main research question, as well as the sub research questions. The questions mentioned in this chapter are the main guideline of the research and will also provide the general structure of this report discussed in Section 2.3.

2.1 Main research question

This thesis answers our main research question, which is the guideline for determining the sub questions as well. The main research question for this thesis is:

Can factors which are based on the 'Rule of 40' provide an indication for company valuations in the Tech/SaaS industry and can the concept be extended to other sectors as well?

2.2 Sub research questions

To be able to answer our main research question we divide our research into sub questions. The latter are partially literature based, and partially practical. The first few research questions are discussed in Chapter 3 to 6, and based on literature. The practical questions are discussed in the execution of the quantitative part: Chapter 7 to 9. The sub questions are mentioned below:

Literature based sub questions:

1. Which different characteristics do Tech/SaaS companies have when it comes to valuation and which valuation approaches can be used for them?
2. Which are the alternative/non-traditional points of view for company valuation, based on the Rule of 40?
3. Which are the arguments for the underlying Rule of 40 indicators?
4. Which approach can be used to find possible relations between the indicators and multiples?

Practical sub questions:

5. Which companies can be used for the analysis and which data can be used?
6. Which indicator has the greatest predictive powers when combined with a valuation multiple?
7. Is it possible to apply the predictive power of the indicators in practice?

2.3 Research approach

The sub questions mentioned in the previous section form the general structure of our report. Each question is answered in a new chapter, which results in our research structure which is shown below.

Research question		Chapter
	Introduction	1
	Research Formulation and Approach	2
1	Which different characteristics do Tech/SaaS companies have when it comes to valuation and which valuation approaches can be used for them?	3
2	Which are the alternative/non-traditional points of view for company valuation, based on the Rule of 40?	4
3	Which are the arguments for the underlying Rule of 40 indicators?	5
4	Which approach can be used to find possible relations between the indicators and multiples?	6
5	Which companies can be used for the analysis and which data can be used?	7
6	Which indicator has the greatest predictive powers when combined with a valuation multiple?	8
7	Is it possible to apply the predictive power of the indicators in practice?	9
	Conclusions and recommendations	10
	Discussion	11

Table 1: Thesis chapter structure.

As shown above, we start (Chapter 3) with a literature review on the general differences in valuations for Tech/non-Tech companies as well as valuation methods that can be used for Tech and SaaS companies more specifically. In Chapter 4, we discuss alternative and non-traditional points of view, which is based on more current information sources like business blogs/sites and mostly focused around the Rule of 40. After that, in Chapter 5, we dive deeper to find out what the motivations are for the different indicators. Damodaran (2010) describes one of the problems of research into predictive powers of indicators as being the model becoming a "black box". In that case, you can end up with a model that predicts the outcomes really well, but at the same time you have little sense of the underlying causes of the relationship, which we want to prevent from happening. In Chapters 6 and 7, the best approach is determined for the practical research as well as which companies can be used best, after which the real analysis is started in Chapters 8 and 9. Finally we conclude the research with our conclusions and recommendations.

The first research questions are all literature based (Questions 1 to 4). Question 5 is based on publicly available data. This data is accessible through EY from S&P Global Capital IQ, which provides us with all the key financial data of public companies on all the major stock exchanges. The last research question is extended by doing a more thorough research in the relationships that have been found.

3 Academic literature review

In this chapter, the valuation fundamentals are discussed, as well as an overview on why Tech companies are different. We give a brief overview of the particularities of different valuation methodologies (Section 3.2). After that, some of the anomalies when it comes to valuation of Tech and SaaS companies are discussed as well (Section 3.3). No deep analysis or discussion is given on the technical background of the traditional valuation methods, since these have been discussed widely in study books and other literature. After that, in Section 3.4, we dive into the valuation methods that are used for Tech and SaaS companies, with a specific focus at CLV and cohort analysis, which is often used at EY. This will help us to get a better understanding of the most important principles when it comes to these kind of company valuations.

The general goal of this chapter is to find an answer for our first research question:

Which different characteristics do Tech/SaaS companies have when it comes to valuation and which valuation approaches can be used for them?

3.1 General: What are Tech and SaaS companies?

This chapter is the basis of our research, and therefore it is useful to specify the kind of companies that we consider. The definition of Tech companies that is used in this paper is based on literature, according to which there is a general way to classify a Tech company (Damodaran, 2001).

- Companies that actually deliver technology-based or -oriented products, hardware, and/or software.
- Companies that use technology to deliver products and/or services that are delivered in a more conventional way before.

Of course, these two main categories contain more sub categories as well, which will be discussed later on, if necessary. For now we only describe one extra subcategory that falls within the Tech category: SaaS companies. SaaS stands for ‘Software as a Service’, and as the explanation of this abbreviation already suggests, SaaS companies provide a service by delivering and maintaining software. The SaaS company hosts the application, and the software sits on the SaaS company’s server while its users have remote access. The users have access to the software through a subscription that covers the use and maintenance of the software.

3.2 Particularities of different valuation methods

In principle, a company’s value is based on its capacity to generate cash flows and the uncertainty that is associated with these specific cash flows (Gupta & Roos, 2001). In other words, the intrinsic value of a company is equal to the present value of the expected cash flows over the life of the company, discounted to reflect both the time value of money and the riskiness of the cash flows (Damodaran, 2010). Valuation methods that are often used and based on this same principle are DCF-valuations (Discounted Cash Flow). The main DCF methods (Copeland et al., 2000) are shown in Figure 1. As we see in this figure in the assessment column, none of the specified DCF methods are specifically suitable for Tech or SaaS companies since they focus on different assessment criteria.

Model	**Measure**	**Discount factor**	**Assessment**
Enterprise discounted cash flow	Free cash flow	Weighted average cost of capital	Works best for projects, business units, and companies that manage their capital structure to a target level
Economic profit	Economic profit	Weighted average cost of capital	Explicitly highlights when a company creates value
Adjusted present value	Free cash flow	Unlevered cost of equity[1]	Highlights changing capital structure more easily than WACC-based models
Capital cash flow	Capital cash flow	Unlevered cost of equity	Compresses free cash flow and the interest tax shield in one number, making it difficult to compare performance among companies and over time.
Equity cash flow	Cash flow to equity	Levered cost of equity[2]	Difficult to implement correctly because capital structure is embedded within cash flow. Best used when valuing financial institutions

Figure 1: Frameworks for DCF based valuations (Copeland et al. (2000))

Copeland et al. (2000) suggest two different methods that can be used for valuations: multiples (comparables) and real options. Multiples are often used as a check whether the forecasted values from the DCF were accurate and whether there are not any large differences. Therefore, we can say that multiples are mainly used for indicative purposes. Large differences between the indicative multiple valuation and the DCF valuation would imply that some calculation errors or wrong assumptions may have probably been made in the DCF calculation. The other method that can be used according to Copeland is as mentioned before, the real options method. This way of valuation is based on Black and Scholes (1973). It describes how to value a derivative without the need of estimating the future cash flows or cost of capital. Future cash flows and cost of capital are not needed to determine the potential value like in a DCF since this method only uses real time information about other similar 'real options'. The Black-Scholes model is based on the principle of 'replicating portfolio'. The most important underlying thought is that if there exists some portfolio of securities that can be traded, whose future cash flows mimic the security that is being looked at, then those two must have the same price/value (Black, Scholes, 1973). As a result of this, the conclusion is that as long as a suitable replication of the considered portfolio can be found, a suitable price of that portfolio is known as well. Many unsuccessful attempts have been made to apply this methodology to company valuations (Copeland et al. 2000). Intuitively the portfolio replication principle is already hard to apply for companies because it is practically impossible to "replicate" a company. For this reason, the concept is not widely used for corporate valuations.

[1] The unlevered cost of equity is the cost of equity of a hypothetical debt-free company

[2] The levered cost of equity is the cost of equity of a company with a non-zero net debt

3.3 Anomalies of valuation for the Tech/SaaS industry

As discussed, valuation of Tech companies differs from the traditional valuation methods in some ways. In this section, we discuss the problems and challenges when using the traditional valuation methods. First we discuss DCFs and Multiples, as mentioned in the previous section.

DCFs

As discussed in the previous section, many valuations are based on Discounted Cash Flows. To discuss why this is not always directly applicable for Tech companies, a short description of DCF is given. A more thorough explanation of DCF can be found in Appendix I. DCF is a valuation method often used to estimate the attractiveness of a potential investment. The DCF method uses future Free Cash Flow (FCF) projections and discounts them to determine an Enterprise Value (EV). The EV is used to determine the potential of the investment. If the value from the DCF is higher than the current cost of the relative investment, then it might be a good investment. The discount rate used in the DCF method is determined by calculating the Weighted Average Cost of Capital (WACC), which is a reflection of the risks of the cash flows from a debt/equity perspective. The exact calculations which are done for a DCF can be found in Appendix I.

We now analyze why this calculation is not always applicable. If we look at the components of the DCF, we have a future Cash Flow (CF_t) and the discount rate *r*. As already mentioned, it is not uncommon for technology firms to have negative operating income, which leads to negative free cash flows. Even in case the operating income is positive, it is still common for Tech firms to have large reinvestments which can also lead to negative FCF. This means if CF for now and the following year(s) is negative, then the other years will have to compensate greatly for a higher DCF result. The biggest impact factor in that case is the value that is chosen as "terminal value" of *t*. The value that is chosen for this *t* can often be the cause of unreliable DCFs, because either the terminal value is too low, or the terminal value is higher, but the predictability less reliable (Gupta et al., 2001).

Secondly, the growth rate that is used/predicted for the CFs in the future is also not always reliable. The CF_t is different for each year, since a certain growth rate is incorporated to calculate the Cash Flow for a specific year. This already gives problems as mentioned above since the longer the predictions are, the less reliable they get. But on top of this, there are more problems when using DCFs (and thus the growth rate). In the first place, Research and Development (R&D) expenses for technology firms are always rather high. The R&D expenses are mostly treated as operating expenses by accountants instead of capital expenditures (CAPEX). As a result of this, the reinvestment rates as well as the Return On Capital (ROC) are often not realistic for technology firms (if R&D is considered as operating expenses, then gross profit is lower, resulting in lower ROC (Gupta et al., 2001). Additionally, when operating expenses are not reliable, then the operating income is not reliable either, and as a result of that neither the gross profit growth rate (for Tech companies).

Lastly, concerning the DCF, we have to look at the discount rate *r*. The discount rate is based on the costs incurred for the financing of the assets. As mentioned, this is determined using the WACC. The WACC changes over time as Tech companies become larger and more mature/stable. Therefore, the WACC changes very often (from year to year), which obviously also brings a lot of uncertainty and unreliability for the DCF calculations, when it comes to the discount rate *r*.

When we take everything together, we can conclude that DCF might be less reliable for Tech companies in comparison with more mature and non-Tech companies.

Multiples of comparable companies/transactions

The principle of multiple valuation is based on the assumption that comparable/similar firms have the same valuation multiples. Just as with the DCF method, there are also difficulties when it comes to valuations of Tech or SaaS companies when using this method. In general, there are two main multiple based analysis options: Comparable Company Analysis (CCA) and Comparable Transaction Analysis (CTA). The most generally known multiple that is used is EV/EBITDA.

Firstly, as introduced in the preface, Tech companies with negative profits can still be worth billions. And negative profit often means negative EBITDA[3]. Obviously, a negative EBITDA also results in a negative EV/EBITDA ratio, resulting in a negative valuation (multiple). As these companies can still be highly valuable, this method does not seem to work when using the standard multiple. Other multiples should be used for Tech companies.

Secondly, Tech firm valuation is also challenging as there are either no comparable firms, or comparable firms are not at the same stage in the life cycle as the firm being valued and therefore not giving a reliable comparison (Gupta et al., 2001). Gupta et al. state there are two major occasions in a firm's life cycle where this valuation difficulty arises. Either when business angels or venture capitalists invest in the company, or when the company goes public with an IPO. In both cases, the firm being valued is private at the moment of valuation. Therefore, no information can be found at the financial markets with publicly available data. This also contributes to the fact that it is not always possible to use CCA or CTA for Tech and SaaS companies because comparable firms are hard to find as they are often still private.

Conclusion

Based on this section, we can say that DCFs or CCA/CTA are not reliable enough to use for Tech/SaaS firm valuation. The biggest problem with DCFs is that the growth rate is hard to predict, and that negative FCFs/high reinvestments are not compensated for enough in DCFs. Therefore it is harder to use DCFs for SaaS companies than mature/non-Tech companies. Concerning CCA/CTA, Tech and SaaS companies are "too new" in the market to have a reliable base of companies and transactions to use as comparables, which is also typical for this industry.

[3] The main difference between EBITDA and net profit is that the EBITDA measures the profits without considering factors as financing or accounting costs (Interests, depreciation and amortization) while net profit is equal to the total earnings minus all the expenses out of the revenue (Net income = Revenue – COGS – OPEX – other expenses- interest – taxes)

3.4 SaaS company valuation using Customer Lifetime Value

In this section we discuss valuation methods based on the current way of evaluating a company's value within EY. We first shortly mention the general lifecycle of a Tech company to give a better basis for the second part of this section, in which we discuss the concepts of LTV-CAC (Lifetime Value and Customer Acquisition Cost) and/or CLV (Customer Lifetime Value). The goal of this section is to get a better understanding of how to approach Tech/SaaS company valuation.

General

Damodaran (2010) describes the lifecycle of a company in relation to its revenues and earnings. In addition to this, he also describes the relative usefulness of several information sources. The framework (Damodaran, 2010) can be seen in Figure 2 below.

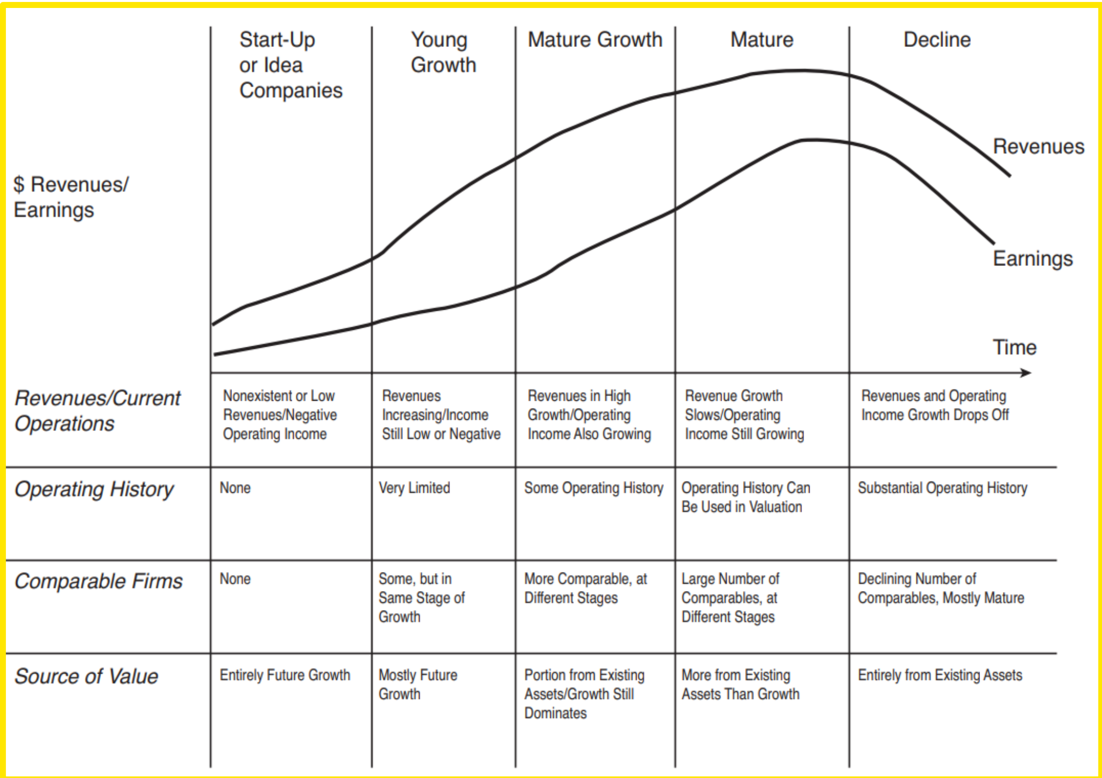
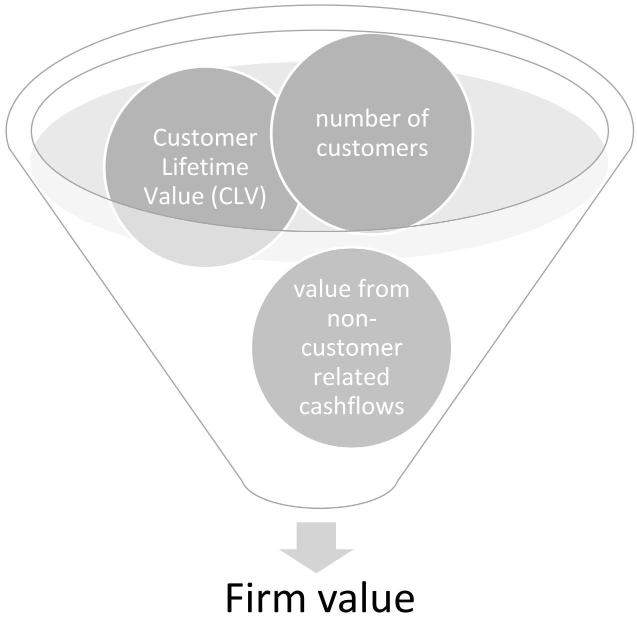


Figure 2: Valuation issues across the Life Cycle (Damodaran, 2010).

As can be seen in the figure, Damodaran (2010) specifically argues the importance of growth in the beginning (see 'Source of Value' in figure). After a while, when a company reaches maturity, the assets become more important as well. As discussed before, Tech companies are generally not asset heavy companies. In addition to this, we can also argue that the Tech sector is relatively new, which therefore has more companies that have not reached maturity/decline yet. In this research, we are going to look at companies that are publicly traded. These companies are not part of the start-up class of companies either. Therefore, the companies that are discussed in this paper are in their late stages of 'Young Growth' or early stages of 'Mature Growth'.

Basic concept of CLV

One of the concepts that is often used at EY to consider a Tech or SaaS company's performance and value is CLV. Customer Lifetime Value is defined by Bauer and Hammerschmidt (2005) as a supplier oriented view on the customer's economic value to a company. Or in other words: what is the customer worth for the supplier/company. This customer-based evaluation technique is necessary in case traditional financial approaches fail. CLV is a metric that measures all the profit streams that come from a customer during its entire customer life cycle. Gupta and Lehmann (2006) argue that the value that customers provide for the company is one of the most important aspects to consider firm value. The main idea of this customer centered approach is that all cashflows that are normally used in valuations are a result of the customer behavior and their purchases. If you can determine the value of a single customer over its lifetime with the company, you can also determine an estimation of the value of all the existing customers by multiplying the CLV with the current number of customers. At EY, CLV is done even more specifically by determining the value of every separate customer, and adding those together. When you have an estimation of the value of all the customers together, you also have a great part of the company value. The only things that should be added to the value of the customers is the value of cashflows that are not related to the customers (e.g. income tax rate and changes of net working capital), and then the value of the company can be derived. Bauer and Hammerschmidt (2005) also describe which factors should be incorporated for the non-customer related cashflows and how to calculate those factors. For now, we do not discuss this any further as this is a relatively small part compared to the customer related cashflows.



CLV components

CLV generally incorporates three core components (Reinartz and Kumar 2000, Blattberg et al. 2001, Bauer et al. 2001): the revenue, the costs and retention rate (rate at which the customer base is developing). Estimating these three components can be a challenging task, for which a lot of data are needed before being able to get a reliable result. When the three components have been determined, the CLV_{i0} describes the CLV of one single customer *i* in cohort *0*, and can be calculated using the following equation:

$$CLV_{i0} = \sum_{t=0}^{T} r_i^t \frac{(R_{ti} - C_{ti})}{(1+d)^t}$$

In which we see the top part of the fraction as Revenue minus the Cost, which is the margin (for customer i in period t). r_i^t is the retention rate of customer *i* in period t, which is the rate at which the current customer base is developing. The *d* mentioned in the bottom part of the fraction is the discount rate that is appropriate, which is the same as the WACC for the company. Big T is the total length of the projection period.

Determining firm value

Now that we know how to determine the CLV, we can work towards a firm value. As described earlier in this section, the CLV is a term that is applicable for one single customer *i*. If we want to determine a firm value based on this, we first have to determine the value of the total customer base. Bauer et al. (2001) define this as the Customer Equity (CE), which is determined by summing the CLVs over v_s , the number of customers in cohort s. A cohort is a group of customers that joined during a specific moment in time. For that reason, a customer cannot move across cohorts. To determine the total CE, we have to calculate the following:

$$CE = \underbrace{\sum_{s=0}^{T} \frac{1}{(1+d)^s} \underbrace{\sum_{i=(v_{s-1}+1)}^{v_s} \underbrace{\sum_{t=s}^{T} r_i^t \frac{(R_{ti}-C_{ti})}{(1+d)^t}}_{\text{Lifetimevalue single customer } i \text{ in cohort } s}}_{\text{Total of lifetimevalues of all newly acquired customers of cohort } s \text{ ``value of cohort } s\text{''}}}_{\text{Total sum of the equities of all the cohorts, discounted to the present ``overall CE''}}$$

According to Bauer et al. (2001), the firm's value can now be determined by taking the CE, minus the fixed cost, investments in working capital and fixed capital and taxes, plus the continuing value and non-operating assets and the market value of debts.

An example of the results of a cohort analysis can be seen in Figure 3 on the next page. Every color represents a cohort as mentioned above. So every cohort is basically the value of CE_s in a that specific year. We also see that this changes every year, for every cohort. The total sum of all the stacked bars on the far right of the figure is the total CE in terms of unique customers per yearly cohorts. The red line in the figure shows the revenue percentage of the newly acquired customers. It can be used as a measure of how dependent a company is on the acquisition of new customers. As described earlier, we can now use the CE to determine company value if we also know the other data needed.

But, as the goal of this thesis was to create a quick and easy way to say something useful about a firm's value, based on generally available data, we encounter problems with this method. The CLV method needs a lot of (historical) input data that is only available internally at companies. Therefore, this method is only useful when extensive data is available and not in the starting phase of a project.

However, we can still state that this method provides us with a few key insights that can be used when considering certain metrics as indicators for company value. Especially the fact that really basic financial data are used to get insights of the company value is useful. The development of the different cohorts is really important, but Bauer et al. (2001) still state that you can basically determine the company value based on your CE. CE is no different depending on the relative sizes of the cohorts, but is always just the sum of the last measured moment. So, this tells us something about the fact that it is possible to determine company value from a snapshot of data at some moment in time.

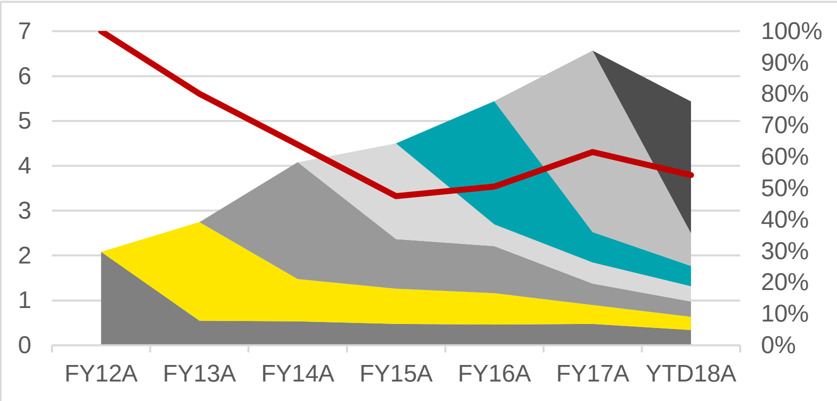


Figure 3: Example of cohort analysis using CLV.

4 Non-traditional points of view for company valuation

In this chapter we describe our motivation for choosing the Rule of 40, and why it is interesting to use. After that, we elaborate more on the principle that lies in the Rule of 40 metric about adding up growth and margin of a company. Then finally, we discuss the different interpretations from literature that describe which metrics to choose. The major goal of this chapter is to answer the second research question:

Which are the alternative/non-traditional points of view for company valuation, based on the Rule of 40?

4.1 Motivation for choosing the Rule of 40

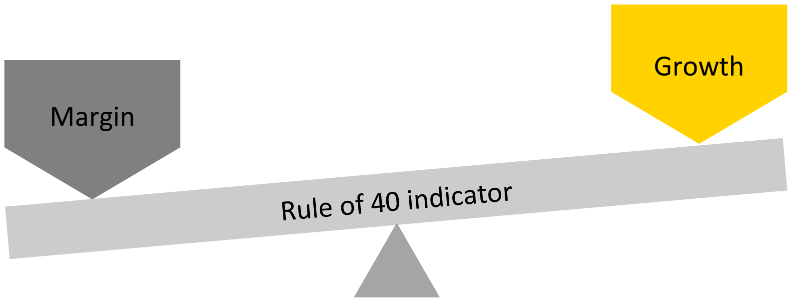
In the previous section, we discussed the problems that occur when trying to value a Tech company using traditional approaches. We also discussed other methods that can be used if a lot of data are available (in the case of CLV). In this section, we explore alternative valuation principles and points of view. The goal is to create a comprehensive literature framework which will be the basis of the rest of the research.

We have concluded that the DCF method causes problems when valuing Tech companies because cashflows and growth rates are not stable over the years. A standard multiple approach with CCA or CTA is also not directly useful due to problems with selecting the right comparables. However, according to Gupta et al. (2001), the majority of valuation methodologies used in finance for high Tech and high growth companies are based on comparable companies in comparable financial market environments (Gupta, 2001; Markowitz, 1959; Modigliani and Miller, 1958). Therefore, it is interesting to look at the possibilities of multiple valuation with a refreshing new view, based on the Rule of 40.

As the subject of Tech and SaaS company valuation is really current, there is not a lot of literature on this topic. The most recent information and points of discussion are mostly found in online sources like business blogs and other websites that often discuss business related topics. One of the interesting things that can be found is the concept of "The Rule of 40%". The Rule of 40 is basically a rule of thumb which can be used to tell whether a company is performing "well" or not. The basic Rule of 40 indicator (as far as it is fully defined) is the sum of the metrics 'operating profit' and 'revenue growth'. The Rule of 40 says that the Rule of 40 number is a company's growth percentage added together with the margin percentage. If these two numbers add up to 40 (and if the firm is able to maintain it over the years) then that indicates a company is performing well and will stay to perform well in the future. As mentioned before, this thesis explores the different uses of the Rule of 40 metric, and investigates the most significant indicator in comparison with a certain multiple. However, there are different interpretations possible when using the Rule of 40. In the next section, we discuss what the Rule of 40 metrics are based on in the first place, after which we analyze different literature sources with different interpretations of these metrics.

4.2 Growth + Margin principle

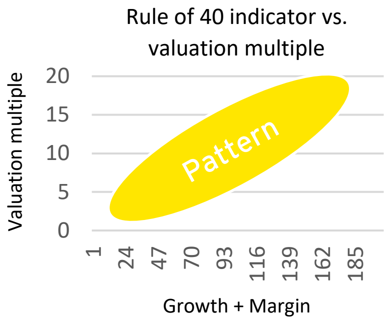
As mentioned in the literature chapter, Bauer et al. (2005) stated that in the context of CLV, marketing expenses are considered as investments in your customer assets, which will create long-term value for the firm. This specific statement already covers a major part of the Rule of 40: using marketing to acquire new customers (i.e. "create growth") to create long term value. So if we look at a company with a good margin, but little growth, then the idea is that this company can sacrifice a part of its margin to create growth ("activating the marketing machine" (Reich. M., 2019; de Beyer, M., 2019)). On the other hand, the opposite can be done as well: if a company is growing really hard, but not making a lot of profit they can sacrifice a part of their growth by not investing in marketing anymore and in that way increasing their margin. The Rule of 40 suggest that the growth and margin are in some way directly linked and work as communicating vessels. Which growth and margin percentage to choose, is still a point of discussion, which is elaborated on in the next section.



Depeyrot and Heap (2018) state that in 2015, venture capitalists started to popularize the concept of the Rule of 40 to use as a high-level metric for the health of SaaS companies. They also mention that the concept is applicable to software companies in general, since they have many matching characteristics which are fundamental for the Rule of 40 application. Broader research shows that some suggest to use the Rule of 40 for Tech companies in general. Bain also discusses the existence of different interpretations on which metrics should be used, which again shows the relevance to further investigate this.

4.3 Rule of 40 interpretations

So, the general and basic idea is to use 'revenue growth' in combination with 'operating profit as a % of revenue' (as relative metrics for growth and margin). To connect this metric to company valuation, the metric is often put out against a valuation multiple. This results in a graph like shown on the right, in which different company's information can be plotted as a scatter plot, which should show a certain pattern if there is a connection between the two. This also makes sense to do, since we are searching an indication of value, for which multiples are really suitable to use (see Chapter 3).



Sleeper (2017) adjusted the basic concept of the Rule of 40 by changing the multiple to EV/Gross Profit, set out against 'Gross Profit Growth Rate + FCF margin' as an indicator. Sleeper focusses on SaaS companies specifically. In this brief research, a few other indicators like net income margin are also considered, but at that time, the above mentioned combination of multiple and indicator seemed to be most accurate. Sleeper (2018) later updated his own research and found that there had been a shift in the aspects which had the highest predictive power. The findings are that using just growth as an indicator now resulted in a higher correlation.

Latka (2019) also focusses on SaaS firms and argues that i

t is better to apply the Rule of 40 at a later life cycle stage of the company. If the company is still rather small ($10m ARR company) then it might actually sacrifice relatively much margin to "buy" growth by investing in customer acquisition. The metrics that he uses for the Rule of 40 are 'revenue growth' and 'FCF margin'.

Epstein and Harder (2016) underwrite that growth comes at a cost and do not think the Rule of 40 is perfect. Therefore they propose an adjusted Rule of 40 using a 'Efficiency Score'. They argue that the Efficiency Score measures the efficiency of a company using the following calculation:

$$Efficiency\ Score = Company's\ growth\ \% + Free\ Cash\ Flow\ \%$$

The basis is still the same as with the Rule of 40, regarding a sum of 40 or above is considered great. The difference with Epstein and Harder in comparison with Sleeper (2017) is that they use the basic multiple EV/Revenue.

Kellogg (2013) is a supporter of the growth as well. He basically says that $\frac{growth\ rate\ \%}{10} + 1$ is your revenue multiple. The growth considered is the 'revenue growth'.

Depeyrot and Heap (2018) discuss the Rule of 40 in an article which argues that the Rule of 40 is indeed a powerful tool, but that growth is the dominant indicator, which most often has the biggest impact on the Rule of 40 metric of a firm.

Table 2 shows an overview of the different indicators and multiples mentioned above.

	Revenue Growth	Operating Profit % of revenue	Gross profit growth	FCF % of revenue	Multiple used
Basic Rule of 40	X	X			EV/Revenue
Sleeper (2017)			X	X	EV/Gross profit
Sleeper (2018)			X		EV/Gross profit
Latka (2019)	X			X	-
Epstein & Harder (2016)			X	X	EV/Revenue
Kellogg (2013)	X				EV/Revenue
Depeyrot and Heap (2018)	X	X			-

Table 2: Literature overview - Rule of 40 indicators and multiples.

As can be seen in the table, the Rule of 40 is shaped as a certain Growth percentage, combined either with or without a profit percentage. The different indicators that we have found are as follows:

- Growth + Margin:
  - Revenue Growth + Operating Profit as % of Revenue (EBITDA Margin).
  - Gross profit Growth + Free Cash Flow as % of Revenue (FCF Margin).
  - Revenue Growth + Free Cash Flow as % of Revenue (FCF Margin).
- Just growth:
  - Revenue growth.
  - Gross profit growth.

Apparently the first choice to be made is the one between 'revenue growth' or 'gross profit growth'. The second choice is between either operating profit (EBIT(DA)) or FCF, both as a percentage of the total revenue.

In Chapter 5 we discuss the meaning of the mentioned indicators and ratios. We also discuss why these metrics are most useful and what might be the reason for possible correlations with company value. This will give a basis to be able to put up hypotheses on the best possible relationships.

5 Motivation for underlying multiples and indicators

In this chapter we discuss the reasons why the indicators and multiples as mentioned in the previous chapter are being used or what could explain the usefulness of those specific indicators. We first look at the metrics/indicators found in the previous chapter. After that, we analyze the two multiples that we have found to put out against our Rule of 40 metrics. At the end of the chapter, we also discuss hypotheses on the best relationship between indicator and multiple. These hypotheses are the guideline for the following analysis in Chapter 8. The main goal of this chapter is to answer our third research question:

Which are the arguments for the underlying Rule of 40 indicators?

5.1 Metrics/indicators

In the previous chapter, we found two growth metrics and two margin metrics, in the following combinations:

- Revenue Growth + Operating Profit as % of Revenue (EBITDA Margin).
- Gross profit Growth + Free Cash Flow as % of Revenue (FCF Margin).
- Revenue Growth + Free Cash Flow as % of Revenue (FCF Margin).

Apart from these combinations, we also saw that literature suggests that the 'revenue growth' and 'gross profit growth' can be used separately as indicator. To be able to make well substantiated hypotheses, we discuss the underlying motivation for all the different metrics by discussing them separately. Therefore, we first discuss the growth metrics, after which we discuss the margin metrics. This will result in the right basis for our hypotheses.

Growth: 'revenue growth' and 'gross profit growth'

The difference between revenue and gross profit is whether the cost of goods sold (COGS) are incorporated in the calculation or not. Revenue is the total sum of the money that is earned by the operations of a company. To calculate gross profit based on the revenue, we have to subtract the COGS. COGS are all the costs that are directly used to provide a service or to deliver a product. COGS includes e.g. raw materials, labor etc., but does not include indirect expenses as sales or distribution. When looking at company value, the most commonly looked at indicator is 'revenue growth'. If we look back at the basic principle of company valuation by Gupta et al (2001), a company's value is based on its capacity to generate cash flows and the uncertainty that is associated with these specific cash flows. Obviously, both 'revenue growth' and gross profit growth are closely related to a company's capacity to generate cash flows. So in that sense, they both seem suitable to use as the multiple for this research.

The ‘revenue growth’ is the most direct indicator which tells us how much a company made in total without taking into account all the costs that they face. As we are looking for a quick indicator of company value, the revenue is a clear number that gives a really quick idea of the general performance of a company. Gross profit on the other hand tells us more about the real performance of the company since this describes how much money remains after the standard costs for delivering a product or service. For example: a company can have decent revenues while they sell all their products with a net loss. In that sense, taking ‘revenue growth’ does not directly show us the successfulness of a firm, and gross profit might therefore be a better indicator. However, gross profit can be adjusted using different interpretations of accounting rules which result in it being a bit less reliable. So although ‘revenue growth’ does not tell us everything, it is still more reliable, and therefore could be better to use as an indicator for a research like this.

Margin: operating profit as a % of revenue and free cash flow as a % of revenue

The two margin indicators identified in Chapter 4 are the operating profit and the free cash flow, both as a percentage of revenue. They both indicate which part of the revenue eventually remains after all costs are paid. The main difference between the two indicators is that Operating profit includes the CAPEX. To calculate the Free Cash Flow, you have to subtract the CAPEX. But, as already discussed in Section 3.3, it is often considered a problem to determine what belongs to CAPEX and what not for Tech and SaaS companies. As mentioned in that section, improving the software and information systems is often considered as operating expenses. If this is the case, then the operating profit will most likely automatically be higher than is really the case. This automatically results in a value for operating profit that is less reliable. Therefore, investors tend to trust Free Cash Flow more than operating profit because all the expenditures are already taken off, and you are left with the actual free cash that is left. Another reason why FCF is a better metric to use for this research is because of the basic trade-off between growth and margin which is mostly based on marketing expenses being used to lower margins and increase growth. If we follow this reasoning, then FCF is even more a suitable indicator to use since marketing expenses have been subtracted from this value already. Another interesting thing to note is that not only investors seem to prefer Free Cash Flow, but also CEOs of large Tech companies like Amazon and Salesforce (relatively Jeff Bezos and Marc Benioff) are strong supporters of a focus on free cash flow.

“

„It’s not about having the best profit margins but about free cash flows” – Marc Benioff, *CEO at Salesforce*

5.2 Multiples

The multiples that have been identified in Chapter 4 are ‘EV/Revenue’ and ‘EV/Gross Profit’, from which the multiple EV/Revenue is the most widely used and general accepted multiple. Since both multiples have EV in the numerator, this is not a point of discussion. So, we have to make a consideration between the denominators: revenue and gross profit. If we consider our discussion in Section 5.1 our statement that EV/Revenue is used more than EV/GP in general makes sense. In that section, we looked at revenue and GP and we came to the conclusion that GP is more vulnerable for interpretation of accounting rules than revenue, which suggested that it might be better to use Revenue than GP. If we stick to this reasoning then the multiple EV/Revenue is also automatically more interesting to use for this research.

5.3 Hypotheses

So far, we have found several indicators that can be used for the Rule of 40 based on different sources. Based on literature, we also analyzed the indicator and multiples, to get a deeper understanding of the reason why they could be indicative for a firm's value. We are now able to put together our main hypotheses for the rest of this research, which are based on a few key findings.

Key findings and conclusions for hypotheses to be based on (based on Chapter 3, 4 and 5):

1. The indicator that will most likely have the best results is a certain combination of growth and margin because of the fundamental principle of the trade-off. (So, 'revenue growth' and 'gross profit growth' are not used as indicators).
2. 'Revenue growth' is a better indicator than 'Gross Profit growth' since the latter is more sensitive for different applications of accounting principles.
3. Free cash flow is more reliable than operating profit since it is a metric that is harder to manipulate using different accounting rules interpretations in determining what belongs to CAPEX or OPEX.
4. Free Cash Flow is more logical to incorporate in the Rule of 40 metric because the marketing costs are then also subtracted, which must be the case when the trade-off principle is right.
5. Consistency requires to have the growth metric used for the Rule of 40 indicator to match with the denominator of the multiple
6. The fundamental idea of the Rule of 40 metric of being able to make a trade-off between growth and margin is mainly applicable because of online marketing expenses having a direct effect on company growth.

Following Arguments 1 to 5, we are able to form our first hypothesis, which can be tested in the practical execution of this research. The first hypothesis is as follows:

Hypothesis 1:

The combination of Rule of 40 indicator and valuation multiple that gives the strongest relation is 'Revenue Growth + FCF as a percentage of revenue' in combination with 'TEV/Revenue'.

Linked to the sixth argument, and based on the trade-off principle, the concept of combining the indicator with the valuation multiple should also be applicable to comparable industries which can use marketing (lowering margins) as direct tool to increase their growth. The industry that matches this condition best is the E-commerce industry (Reich, 2019; van Weele,2019). Therefore, our second hypothesis is as follows:

Hypothesis 2:

E-commerce is a comparable industry in which the Rule of 40 indicator has predictive power for the valuation multiple.

6 Approach for finding possible relations

Before starting the practical part of this research, the quantification method is determined. The starting point of looking for a relation is to look at correlations. Correlation research looks at the statistical relationship between two random variables or certain data. Since correlation measures a co-relationship, it can also return positive results coincidentally. But that is not sufficient for this research as we try to find a specific predictive power of one variable for the other. A different way of analyzing interdependencies is the use of regression. Regression is used to predict the variation of a dependent variable, based on the variation of an independent variable (e.g. How can X predict Y). The form which can already be used with just one dependent and independent variable is linear regression. Furthermore, multiple regression can also be used, or even more complicated regressions. In this chapter, we discuss the different sorts of regressions that we can use for this research. The research question that is answered in this chapter is:

Which approach can be used to find possible relations between the indicators and multiples?

6.1 Linear regression

Linear regression is as mentioned above the most basic form of regression, where there is only one variable (x) that predicts the other variable (y).

The general formula for linear regression is

$$y = a + bx + u$$

Where:

$$\begin{aligned} y &= dependent\ variable \\ a &= intercept \\ b &= slope \\ x &= independent\ variable \\ u &= regression\ residual \end{aligned}$$

The result of this regression is a straight line which gives the best approximation of all the individual data points. To tell whether a linear regression line is a good predictor of the input data, the mostly used measure is the so called R-value or the R-squared. R-squared is a number which describes the proportion of variance of a dependent variable (y) that is explained by the independent variable (x) in the model. So, in this case of this research, the R-squared value represents to which extend the variation of our Rule of 40 indicator explains the variation of the chosen valuation multiple.

But, according to Lewis-Beck and Sakalaban (1990), we must also be cautious with the interpretation of the R-squared value. This is especially the case when estimations are done where R-squared values are compared for models which are estimated with different data sets. Sometimes, the R-squared can be rather high, while the actual explanatory power of *x* for *y* is non-existent. However, when using the same data, which is in our research the case, we can draw conclusions based on the R-squared about the power of the relation between the Rule of 40 indicator relatively to another Rule of 40 indicator. Therefore, it makes sense to just look at the R-squared in this research.

6.2 Multiple (linear) regression

Multiple linear regression, or just multiple regression, is in basis the same as linear regression but with more independent variables. When expressing that in the same way as the linear regression, we have the following:

$$y = a + b_1 X_1 + b_2 X_2 + u$$

The variables used are basically the same as with the linear regression discussed in Section 6.1. But, here we see that the difference between the independent variables is denoted with subscripts. And of course, even more slopes and independent variables can be added as well. The advantage of multiple regression compared to single linear regression is that we can combine 2 or more variables to see whether they together are able to predict the dependent variable Y even better. The problem with adding too many variables however is that there is a risk of adding variables that "predict" the dependent variable without having a direct effect on it in reality. The R-squared value as discussed in the previous section is applicable in the same way for multiple regression as for single linear regression.

6.3 Methodology used for this research

Now that we have discussed the basic forms of looking at interdependencies between variables, we can decide on which method can be used best for our research. If we look back at the main goal of this research, we see that we have several dependent and several independent variables. The goal is to analyze which Rule of 40 indicator is the best predictor for a certain valuation multiple. Looking at the effect of just a single indicator (an independent variable) and its effect on a valuation multiple (dependent variable), the most intuitively logical method to use is Linear Regression. On top of that, the argument of Lewis-Beck et al. (1990) mentioned at the end of Section 6.1 is not necessarily problematic since we are comparing several indicators and their relative explanatory power. Linear Regression is a suitable regression method to be used for this research and to be able to pick the most significant Rule of 40 indicator and valuation multiple.

Multiple Regression, or an even more advanced form of regression might also be used as an extension on finding valuation indicators. In that case we would exceed our current research goals, so for now we stay with single linear regression with a model fitness evaluation based on the R-squared. Adjusted R-squared is not used as the models in this research only evaluate the relation between a single independent and a single dependent variable. Adjusted R-squared is only relevant when using multiple regression.

7 Company and Data selection

In the previous chapters, we have identified the metrics for the indicators that are used for this research. We also identified the multiples that we want to use to be able to connect those metrics to company valuation. We now have to identify which companies we can use for our analysis, and which data can be found that is suitable for our research. The research question that we solve in this chapter is pretty straightforward and is as follows:

Which companies can be used for the analysis and which data can be used?

We answer this question by first looking at the company selection (Section 7.1), after which the data selection is explained and justified in Section 7.2.

7.1 Company selection

The kind of companies that are mostly looked at when using the Rule of 40 are SaaS companies. However, we have also found sources that indicate that the Rule of 40 could be useful for Tech companies in general as well. We first identify Tech companies in general. After that, we make a selection of SaaS companies. To finalize our company selection we will identify E-commerce companies. The E-commerce company selection is needed to test our second hypothesis about the extension possibilities of the concept of the Rule of 40 (testing the applicability on other sectors).

One of the most commonly known and generally accepted industry classification method is the 'S&P global industry classification method'[4] (GICS). This industry classification can also be found in the databases of Capital IQ. When analyzing the different classifications, we conclude that the sector which is the most representative for the Tech industry is 'IT Services'. For the exact company selection procedure, with all the applicable subcategories, please find the steps enclosed in Appendix II.

For the SaaS company selection however, we cannot just pick a category from the Global classification methods. The one that comes the most close to SaaS is the 'Software' category. However, Software is still too broad when looking at SaaS companies specifically. For this reason we choose to look at alternative approaches to come up with a reasonable list of real SaaS companies. A different classification method that is generally accepted as well is the SIC method. But also using this classification method, we can still not get a list of specific SaaS companies[5]. Therefore, we choose to base our SaaS company selection on a list of the 50 largest publicly traded SaaS companies from Sonders, M. (2019). The complete list of companies can also be found in Appendix

[4] https://www.unm.edu/~maj/Security%20Analysis/GICS.pdf

[5] https://www.siccode.co.uk/search/saas-software & https://en.wikipedia.org/wiki/Standard_Industrial_Classification

II). This list consists of US companies traded on major stock exchanges. We chose for the list of US companies to make sure that the selected companies operate in the same market conditions which can help to easier recognize patterns in our data.

Finally, a selection of E-commerce companies has to be made. Just as with the SaaS classification, E-commerce is also a narrow and specific way to classify companies. However, GICS provides an classification category that can very well be used for the E-commerce companies. The category is called "Internet and Direct Marketing retail" which gives us a list of 48 companies. This list is also shown in Appendix II. The list of companies that is eventually selected consists of companies that are traded on major European stock exchanges. We decided to use this criteria since the US list in Capital IQ consisted of less than 30 companies and would therefore not give reliable results.

7.2 Data selection

As explained in Chapter 4, the indicator that is used for the Rule of 40 slightly differs between different sources. We found the following data to be relevant:

Multiples:	- EV/revenue
	- EV/Gross Profit
Growth:	- Revenue growth
	- Gross Profit Growth
Margins:	- Operating profit as a % of revenue
	- FCF as a % of revenue

If we look at the financial statements however, we are not able to retrieve these data easily because it is specified differently in the financial statements. Also when using the databases of Capital IQ, not all of the data can be found in the exact same formulation as mentioned in our online sources. Therefore, the data that are retrieved for our data research, in relation to the desired data uses a different formulation. The final selected data for the indicators/multiples can be seen in Figure 4.

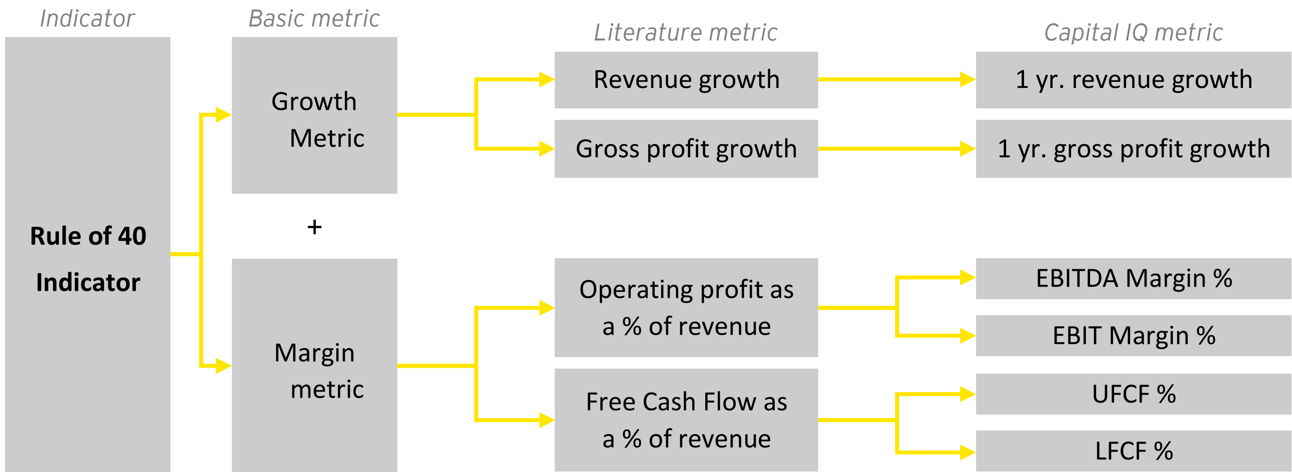


Figure 4: Data selection explanation (from Rule of 40 indicator to useful data metrics).

The above shown data can be retrieved for all the selected companies from Section 7.1. After all the individual metrics are selected, we can put them together to come to our Rule of 40 indicators ("Growth + Margin").

In Table 3, we see the margin metrics on the left side and the growth metrics on top. The combination of every growth and margin metric leads to our Rule of 40 indicators. For example, if we take the top row of the margins, and the first column of the growth, we have EBITDA Margin % and Total Revenues, 1 Yr growth %. The combination of these two metrics gives us a Rule of 40 indicator which we denote as G1+M1. And, in the same way, we also have G2+M1, G1+M2 etc.

<table>
<tr><td></td><td colspan="2" rowspan="3">Needed Data</td><td colspan="2">Growth</td></tr>
<tr><td></td><td>Revenue growth</td><td>Gross profit growth</td></tr>
<tr><td></td><td>Data in CIQ</td><td>Total Revenues, 1 Yr growth %</td><td>Gross Profit, 1 Yr growth %</td></tr>
<tr><td rowspan="4">Margin</td><td rowspan="2">Operating Profit % of revenue</td><td>EBITDA Margin %</td><td>G1+M1</td><td>G2+M1</td></tr>
<tr><td>EBIT Margin %</td><td>G1+M2</td><td>G2+M2</td></tr>
<tr><td rowspan="2">FCF % of revenue</td><td>Unlevered Free Cash Flow Margin %</td><td>G1+M3</td><td>G2+M3</td></tr>
<tr><td>Levered Free Cash Flow Margin %</td><td>G1+M4</td><td>G2+M4</td></tr>
</table>

Table 3: Data selection related to identified Rule of 40 aspects.

Needed Data	EV/Revenue	EV/Gross profit
Data in CIQ	TEV/Total Revenue	TEV/GP

Table 4: Data selection related to identified multiples.

Table 4 shows that the multiples can be found in Capital IQ in the same formulation as used in literature. As has just been discussed, every growth % (2 in total) can be combined with a margin % (4 in total). This gives us 8 combinations of ratios which we call our indicators (*G1+M1*, ..., *G2+M4*). For the rest of this research however, we decide to leave out the '+' sign for simplicity. So, from here on, G1+M1 equals G1M1.

To finalize this chapter, we show the summary statistics (Table 5) of all the different multiples and indicators that are used in this thesis. Interesting to note here is that the growth rates of SaaS companies are always positive, and margin in general is rather low. This is in line with what you would expect from SaaS companies. The table also indicates that the average multiples for E-commerce companies are lower compared to SaaS companies. This can be explained by the fact that SaaS companies have a higher recurring customer base due to contractual revenue. Whereas E-commerce companies depend on the acquisition of new customers through marketing, which makes it more cost-intensive.

SaaS	*TEV/Revenue*	*TEV/GP*	*G1*	*G2*	*M1*	*M2*	*M3*	*M4*	*G1M1*	*G1M2*	*G1M3*	*G1M4*	*G2M1*	*G2M2*	*G2M3*	*G2M4*
Mean	11.29	15.95	34.03	34.86	-3.20	-8.71	15.25	15.40	30.83	25.32	49.28	49.43	31.66	26.15	50.11	50.26
Standard Error	1.01	1.46	2.33	2.38	2.82	2.67	2.09	2.10	2.45	2.50	2.82	2.86	2.49	2.56	2.90	2.94
Median	10.74	15.87	32.98	33.12	-3.29	-7.18	15.07	14.83	31.04	25.36	48.66	49.17	29.38	25.35	49.55	49.60
Standard Deviation	7.18	10.34	16.50	16.80	19.93	18.91	14.81	14.85	17.30	17.70	19.95	20.24	17.63	18.13	20.50	20.77
Sample Variance	51.49	106.99	272.35	282.27	397.15	357.56	219.36	220.58	299.14	313.13	398.16	409.79	310.79	328.69	420.11	431.43
Kurtosis	-0.57	0.29	0.47	0.28	-0.17	-0.05	3.71	3.80	0.85	0.97	1.18	1.08	0.71	0.98	1.04	0.95
Skewness	0.39	0.61	0.77	0.54	-0.17	-0.30	0.66	0.66	0.07	0.36	0.35	0.33	0.34	0.58	0.31	0.29
Range	27.91	43.37	72.92	76.66	87.45	85.46	91.07	91.73	85.55	88.60	111.21	111.87	87.91	89.83	111.58	112.24
Minimum	0.00	0.00	6.67	3.23	-49.94	-55.32	-18.77	-18.85	-5.35	-9.57	-0.81	-0.88	-4.99	-8.06	1.19	1.12
Maximum	27.91	43.37	79.60	79.89	37.51	30.14	72.29	72.88	80.20	79.04	110.41	110.99	82.93	81.76	112.77	113.36
Sum	564.38	797.27	1701.45	1743.24	-160.04	-435.51	762.38	769.88	1541.41	1265.94	2463.83	2471.33	1583.19	1307.72	2505.62	2513.11
Count	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Confidence Level(95.0%)	2.04	2.94	4.69	4.77	5.66	5.37	4.21	4.22	4.92	5.03	5.67	5.75	5.01	5.15	5.83	5.90
E-commerce	*TEV/Revenue*	*TEV/GP*	*G1*	*G2*	*M1*	*M2*	*M3*	*M4*	*G1M1*	*G1M2*	*G1M3*	*G1M4*	*G2M1*	*G2M2*	*G2M3*	*G2M4*
Mean	2.87	6.24	12.45	8.98	-2.29	-4.90	0.78	-0.07	10.15	7.55	13.23	12.38	6.69	4.08	9.77	8.91
Standard Error	0.90	1.93	3.12	3.29	3.59	3.62	1.57	1.52	4.92	4.94	3.29	3.29	5.31	5.36	3.67	3.67
Median	0.98	2.50	8.82	7.75	1.42	-0.40	0.00	-0.01	14.22	12.83	11.59	11.27	13.09	11.28	11.84	11.69
Standard Deviation	6.23	13.34	21.62	22.76	24.88	25.11	10.89	10.50	34.11	34.22	22.78	22.82	36.77	37.16	25.41	25.42
Sample Variance	38.86	177.89	467.35	518.24	619.11	630.28	118.55	110.33	1163.18	1171.25	518.78	520.86	1351.86	1381.23	645.49	646.03
Kurtosis	27.38	35.27	0.74	2.06	17.24	16.87	1.00	0.84	6.09	6.07	1.19	1.27	5.50	5.29	2.65	2.60
Skewness	4.88	5.63	0.78	-0.66	-3.47	-3.43	0.29	0.10	-1.84	-1.85	0.38	0.34	-2.01	-1.99	-0.76	-0.76
Range	39.89	90.43	104.04	119.98	168.35	170.23	55.35	51.10	196.56	196.76	120.32	120.19	189.31	191.00	139.07	138.94
Minimum	0.00	0.00	-27.77	-63.39	-135.36	-138.50	-24.24	-24.39	-135.36	-138.50	-41.10	-42.22	-135.36	-138.50	-71.44	-72.57
Maximum	39.89	90.43	76.27	56.58	32.99	31.73	31.11	26.70	61.20	58.26	79.23	77.97	53.96	52.50	67.62	66.36
Sum	137.93	299.44	597.44	431.14	-110.16	-235.14	37.66	-3.28	487.28	362.30	635.10	594.17	320.98	195.99	468.79	427.86
Count	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48
Confidence Level(95.0%)	1.81	3.87	6.28	6.61	7.22	7.29	3.16	3.05	9.90	9.94	6.61	6.63	10.68	10.79	7.38	7.38

Table 5: Summary statistics of used multiples and indicators.

8 Quantitative analysis: finding the best predictor for company value

In the previous chapter we have selected companies and data to work with. We can now start with the practical analysis in which we consider eight different combinations of Growth + Margin, as well as just the growth rate. The research question that is answered in this chapter is:

Which indicator has the greatest predictive powers when combined with a valuation multiple?

8.1 Tech companies

Some literature sometimes suggests that the concept of the Rule of 40 can also be applied more broadly for Tech companies in general (e.g. Bernstein, 2019). Therefore we start our analysis by looking at the Tech companies. We apply linear regression to the selected data from the previous chapter (Chapter 7). An implementation in Python lets us compare the results quickly, from which we can conclude that Tech companies in general do not give any R-squared results higher than 0.01.

We therefore decide to narrow down our selection and to be more specific in terms of our selection method. We select the top 30 Tech companies from the Nasdaq (major American stock exchange that is mainly focused on Tech companies). When using the linear regression as identified, we retrieve twenty results for R-squared, which are shown in the table below. Table 6 shows that for the multiple 'TEV/GP' almost all of the results are again lower than 0.01. This means that there is no strong and significant relation for Tech companies when you look at Rule of 40 indicators compared to company valuations using that multiple. When we look at the column that describes the results of the regression with 'TEV/Revenue' we already see result that are slightly better.

indicator	TEV/Revenue	TEV/GP
G1	0.067	0.006
G2	0.135	0.007
G1M1	0.091	0.001
G1M2	0.152	0.004
G1M3	0.112	0.005
G1M4	0.114	0.005
G2M1	0.149	0.008
G2M2	0.192	0.025
G2M3	0.144	0.003
G2M4	0.146	0.003

Table 6: R-squared results for Tech companies using linear regression.

However, if we look at the graphs for these regressions (Figure 5), we see that the results are greatly influenced by one large outlier in the bottom left corner. The rest of the results are more widely scattered, and the R-squared results are still relatively low. Therefore, we conclude that the applied method does not work for Tech companies in general. This conclusion is also confirmed when validating our numerical results with scatter plots for 'TEV/GP' from Figure 5 that show no relationship. We cannot test our first hypothesis either and decide to no further consider Tech companies and focus on SaaS companies specifically, which is done in the next section.

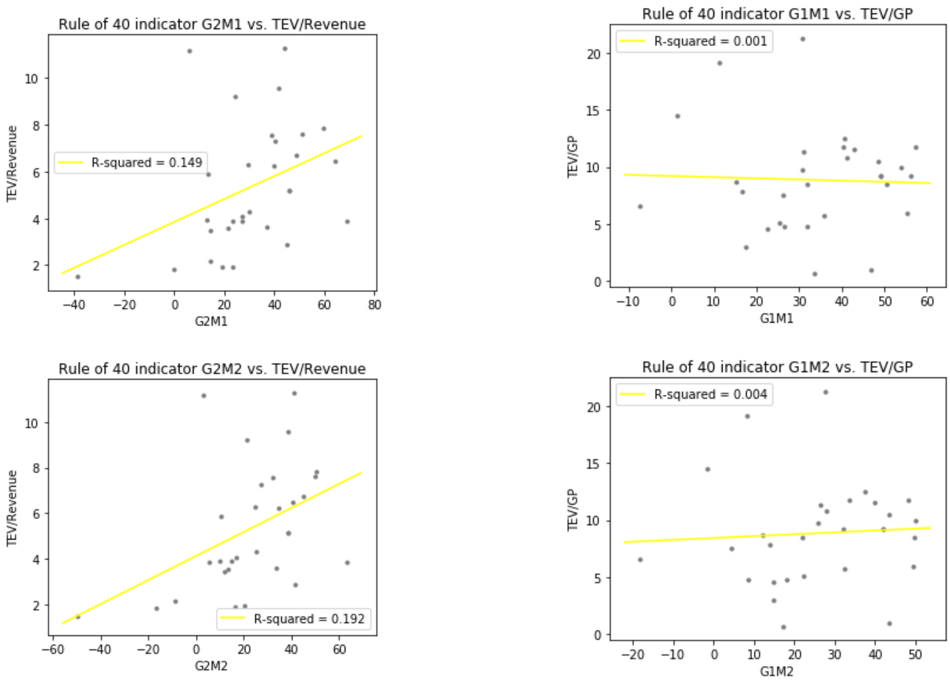


Figure 5: Tech companies - best (left) and worst (right) performing regression results.

Tech conclusion and link to literature

When considering the literature studied in Chapter 4, one may already expect similar results since there is only a rather limited literature base that suggests the Rule of 40 can also be applied more broadly for Tech and software companies. The majority of the literature focusses on SaaS companies, which can explain the bad results for the Tech company regressions.

8.2 SaaS companies

We have concluded that there is no relationship to be found when we look at Tech companies in general. This is due to the fact that the company classification is still too broad (Fiegenschuh, 2020). Therefore, we will now again test our first hypothesis as discussed in Chapter 5, but with a more specific industry classification (SaaS companies).

From Capital IQ, we collect all the required data for the selected companies. As discussed, we do a linear regression and we compare the Rule of 40 indicators in combination with the valuation multiples based on the R-squared values. Table 7 and Table 8 shows the results (two tables with exactly the same results). The first table is color-coded to horizontally determine the best indicator (G…M…). And the second table is used to vertically determine the best valuation multiple (TEV/…). More information about the regressions can be found in Tables 9 and 10. The slopes with a '*' indicate results that are significantly higher than 0 with a confidence level of 95%. Or in other words: all values with a '*' imply that the level of the Rule of 40 indicator has a significant effect for the level of the valuation multiple ("the higher the Rule of 40 indicator, the higher the valuation multiple").

indicator	R^2 TEV/Rev	R^2 TEV/GP
G1	0.341	0.334
G2	0.306	0.298
G1M1	0.0817	0.055
G1M2	0.150	0.113
G1M3	0.351	0.311
G1M4	0.359	0.319
G2M1	0.047	0.025
G2M2	0.117	0.082
G2M3	0.310	0.267
G2M4	0.318	0.276

Table 7: Linear Regression results for SaaS companies (1).

indicator	R^2 TEV/Rev	R^2 TEV/GP
G1	0.341	0.334
G2	0.306	0.298
G1M1	0.082	0.055
G1M2	0.150	0.113
G1M3	0.351	0.311
G1M4	0.359	0.319
G2M1	0.047	0.025
G2M2	0.117	0.082
G2M3	0.310	0.267
G2M4	0.318	0.276

Table 8: Linear Regression results for SaaS companies (2).

indicator	slope	intercept	R-square
G1	0.254*	2.648	0.341
G2	0.237*	3.126	0.306
G1M1	0.143	6.493	0.082
G1M2	0.188*	6.049	0.150
G1M3	0.229*	-0.217	0.351
G1M4	0.228*	-0.178	0.359
G2M1	0.106*	7.739	0.047
G2M2	0.158*	6.812	0.117
G2M3	0.210*	0.635	0.310
G2M4	0.209*	0.617	0.318

Table 9: Regression descriptives SaaS (dependent variable TEV/Revenue).

indicator	slope	intercept	R-square
G1	0.362*	3.619	0.334
G2	0.339*	4.162	0.298
G1M1	0.170	10.160	0.055
G1M2	0.237*	9.308	0.113
G1M3	0.313*	0.172	0.311
G1M4	0.311*	0.201	0.319
G2M1	0.113	12.132	0.025
G2M2	0.192	10.468	0.082
G2M3	0.282*	1.526	0.267
G2M4	0.283*	1.473	0.276

Table 10: Regression descriptives SaaS (dependent variable TEV/GP).

SaaS conclusion and link to literature

As we can see in the second table, the multiple TEV/Revenue gives better results than TEV/GP. When we look at the first table, we can clearly conclude that the best indicator to use is either G1M3 or G1M4, in combination with TEV/Revenue. G1M3 and G1M4 both represent a form of 'revenue growth % + FCF as a % of revenue' (either UFCF or LFCF). As we have now found that this Rule of 40 indicator in combination with the just mentioned valuation multiple gives the best results, we can test our hypothesis. The first hypothesis was formulated as follows:

The combination of Rule of 40 indicator and valuation multiple that gives the strongest relation is 'Revenue Growth + FCF as a percentage of revenue' in combination with 'TEV/Revenue'.

This is indeed what was found with our regression analysis. Therefore, we can confirm our first hypothesis: 'Revenue Growth + FCF as a percentage of revenue' give the most significant relation for company value when combined with 'TEV/Revenue'.

What is also interesting to note is that G1M1, G1M2, G2M1 and G2M2 have a really low R-squared, which represent 'Operating profit + Revenue growth' and 'Operating profit + Gross profit growth'. The best and worst performing regressions with multiple TEV/Revenue are also color coded in our previously discussed literature overview table, which is shown in Table 11.

	Revenue Growth	Operating Profit % of revenue	Gross profit growth	FCF % of revenue	Multiple used
Basic Rule of 40	X	X			EV/Revenue
Sleeper (2017)			X	X	EV/Gross profit
Sleeper (2018)			X		EV/Gross profit
Latka (2019)	X			X	-
Epstein & Harder (2016)			X	X	EV/Revenue
Kellogg (2013)	X				EV/Revenue
Depeyrot and Heap (2018)	X	X			-

Table 11: Literature overview with regression results color coding.

What is most surprising is the fact that the basic Rule of 40 metrics from our literature review seems to be the worst performing indicator when looking at predictive power for the valuation multiple. The indicator that has the highest predictive power is the one described by Latka (2019). Since this is the most recent article that is used in this research, a possible explanation for it being the strongest indicator could be that the Rule of 40 accuracy is highly dependent on time. Furthermore, we see that Sleeper (2017 & 2018) is strongly focused at the use of Gross Profit, but that it does not seem to be the best growth indicator to use for the Rule of 40. Epstein and Harder (2016) identified the same margin indicator, but also used Gross Profit growth. The reason why their combination of indicator and multiple does not work as well as Latka's combination is probably due to inconsistency of the growth indicator ('gross profit growth' instead of 'revenue growth') and the multiple (which uses revenue). Kellogg (2013) argued that just 'revenue growth' can be used best. When checking Tables 7 and 8 again, we see that this actually also gives rather good results. However, Latka's (2019) proposed metrics still gives better results.

As we have now identified G1M3 and G1M4 to be the best indicators to use in combination with TEV/Revenue for SaaS companies, we show the regression graphs below (Figure 6) for further visual inspection. The other graphs for all the regressions can be found in Appendix III. When looking at these graphs in the figure below, we still see that the data points that represent the different companies are not really close to the yellow line. This already suggests that the indicators cannot be used for trustworthy company valuation, which is discussed in our final conclusion as well.

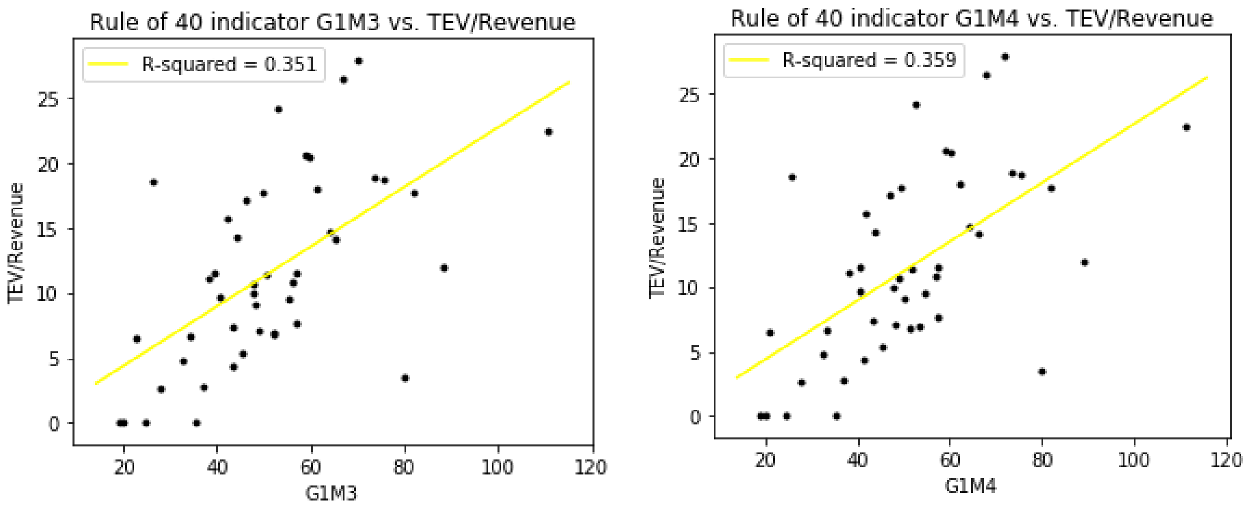


Figure 6: Regression graphs with highest R-squared results for SaaS companies.

8.3 E-commerce companies

We have confirmed our first hypothesis, and continue with the second hypothesis that was described in Chapter 5 as:

E-commerce is a comparable industry in which the Rule of 40 indicator has predictive power for the valuation multiple.

As discussed in the Chapter 7, we selected a list of E-commerce companies. We analyze the E-commerce companies in the same way as we did with the SaaS companies by applying linear regression and retrieving the R-squared values as our main results. The results of the regressions are shown in Tables 12 and 13. Again, we see two tables, both with the same values, but with different color coding. The first table easily shows the best indicator, and the second table shows the best valuation multiple.

indicator	R^2 TEV/Rev	R^2 TEV/GP
G1	0.196	0.204
G2	0.081	0.137
G1M1	0.252	0.212
G1M2	0.152	0.124
G1M3	0.446	0.338
G1M4	0.397	0.304
G2M1	0.115	0.145
G2M2	0.049	0.071
G2M3	0.270	0.253
G2M4	0.230	0.223

Table 12: Linear Regression results for E-commerce companies (1).

indicator	R^2 TEV/Rev	R^2 TEV/GP
G1	0.196	0.204
G2	0.081	0.137
G1M1	0.252	0.212
G1M2	0.152	0.124
G1M3	0.446	0.338
G1M4	0.397	0.304
G2M1	0.115	0.145
G2M2	0.049	0.071
G2M3	0.270	0.253
G2M4	0.230	0.223

Table 13: Linear Regression results for E-commerce companies (2).

For completeness, we again show descriptive information of the regressions, just as we did with the SaaS companies. The information can be found in Tables 14 and 15. Again, the slopes with a '*' indicate results that are significantly higher than 0 with a confidence level of 95%. Which means that the level of the Rule of 40 indicator has a significant effect for the level of the valuation multiple.

indicator	slope	intercept	R-square
G1	0.100*	0.381	0.196
G2	0.064	1.109	0.081
G1M1	0.121*	-0.803	0.252
G1M2	0.096*	0.074	0.152
G1M3	0.138*	-0.826	0.446
G1M4	0.133*	-0.596	0.397
G2M1	0.083	0.198	0.115
G2M2	0.055	1.072	0.049
G2M3	0.107*	-0.084	0.270
G2M4	0.100*	0.147	0.230

Table 14: Regression descriptives E-commerce (dependent variable TEV/Revenue).

indicator	slope	intercept	R-square
G1	0.143*	1.765	0.204
G2	0.118	2.295	0.137
G1M1	0.155*	0.533	0.212
G1M2	0.126	1.704	0.124
G1M3	0.169*	0.715	0.338
G1M4	0.162*	0.975	0.304
G2M1	0.131	1.192	0.145
G2M2	0.093	2.396	0.071
G2M3	0.145*	1.277	0.253
G2M4	0.138*	1.540	0.223

Table 15: Regression descriptives E-commerce (dependent variable TEV/GP).

E-commerce conclusion and link to literature

The first two tables show that the same indicators and multiples give the best results as with the SaaS companies: G1M3 and G1M4 in combination with 'TEV/Revenue'. So, we can conclude that the principle of being able to make a trade-off between the 'FCF as a percentage of revenue' with the 'revenue growth' can be applied for E-commerce companies in the same way as with SaaS companies. As discussed in our literature overview, using different datasets can change the level of the R-squared value without it directly implying a stronger or weaker relation. Therefore, we conclude that G1M3 and G1M4 are the best indicators in combination with 'TEV/Revenue'. But, based on this data, we cannot conclude that the relation of the Rule of 40 indicator in combination with the valuation multiple is stronger for E-commerce companies than for SaaS companies, since we have used different data sets. Based on our results and the above stated information we can also conclude that we are able to confirm our second hypothesis that E-commerce is a comparable industry in which the Rule of 40 indicator has a significant predictive power for the valuation multiple. We again show the regression graphs for further visual inspection (Figure 7).

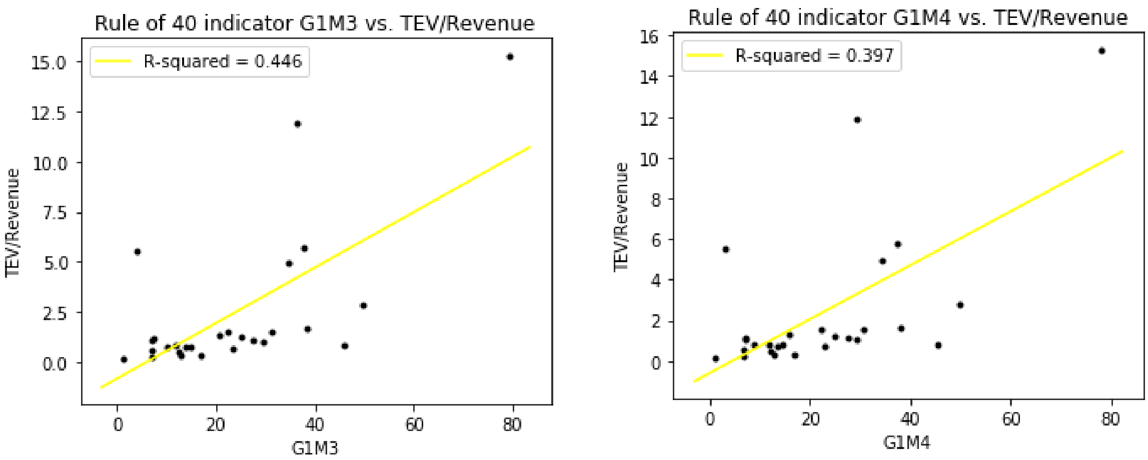


Figure 7: Regression graphs with highest R-squared results for E-commerce companies.

Figure 7 shows the two combinations of indicators and multiple with the most significant relation and the highest R-squared. The other graphs for all the regressions of the E-commerce companies can also be found in Appendix III. When looking at the graphs in the figure, we see a different pattern than for the SaaS companies. We see that the data points that represent the different companies are quite close to each other in a cluster for TEV/Revenue between zero and two. This clearly shows that E-commerce company valuation based on multiples is more reliable than for SaaS companies. But, the effect of an increasing multiple as the Rule of 40 indicator increases is not as present as for SaaS companies. The same conclusion holds for E-commerce companies as for SaaS companies: the Rule of 40 indicators cannot be used for trustworthy company valuation. What we also see is that the slopes for E-commerce are much lower than the slopes of the SaaS analysis. This means that the effect of G+M on the valuation multiple is less strong for E-commerce.

8.4 Conclusion of practical research

In this chapter, we first analyzed the Tech companies, and concluded that the trade-off principle does not work for those companies that had been selected. We narrowed down our Tech company selection and again saw that regression with the Tech companies did not provide any strong relationships. This means that the first hypothesis could not yet be confirmed. To confirm the hypothesis, we used our second company selection, which focused on SaaS companies. For the SaaS companies, we saw that the G+M principle worked significantly better than for Tech companies. In the section that was dedicated to SaaS companies, we also found that G1M3 and G1M4 are the indicators with the highest predictive powers for company valuation multiples. Therefore, we concluded that our first hypothesis can be confirmed. The first (confirmed) hypothesis is:

The combination of Rule of 40 indicator and valuation multiple that gives the strongest relation is 'Revenue Growth + FCF as a percentage of revenue' in combination with 'TEV/Revenue'.

By confirming this hypothesis, we have also found an answer to the sub research question of this chapter (Which indicator has the greatest predictive powers when combined with a valuation multiple?). In Chapter 5, we also formulated a second hypothesis which was focused around extending the G+M principle. In Section 8.3, we extended the G+M principle to a different industry from which we expected it to have the same crucial characteristics as SaaS companies. Here, we looked at E-commerce companies, that had been selected in Chapter 7. After we applied the same approach as for the SaaS companies by doing our regression analysis, we concluded that the G+M principle can indeed be applied for the E-commerce industry as well. The same indicator(s) gave the best results again, and thereby, we confirmed our second hypothesis as well:

E-commerce is a comparable industry in which the Rule of 40 indicator has predictive power for the valuation multiple.

By confirming this second hypothesis we can conclude that both of the hypotheses that were formulated in Chapter 5 have been confirmed. This means that the findings from literature were correct, and that the right interpretations and assumptions of literature have been made.

The practical execution of the research that has been carried out in this chapter adds to the existing literature in two ways. The first added value for literature is the comprehensive evaluation of combinations of different Rule of 40 indicators and valuation multiples. The second way in which this practical part of the research adds to the existing literature is by extending the reasoning behind the Rule of 40 and applying it to a different industry.

We have evaluated the outcomes of our research and confirmed our hypotheses. We can now combine the results. The main idea of the Rule of 40 is focused on SaaS companies. In the analysis, we found that the concept is not applicable to Tech companies in the same way as for SaaS companies. From this we can conclude that broadening the company criteria does not have successful results. Instead of broadening the company selection, we tried to get a grasp of why the Rule of 40 metrics are indicative for company valuations. The goal of doing this was to find another industry where the same principles are applicable. Based on the direct trade-off effect, we concluded that the industry to be selected needs to have a strong direct effect of marketing investments on growth potentials. The company sector which was selected to match this criteria best is E-commerce. As mentioned above, we also found a relation for E-commerce. This relation showed a slope that is lower than the slope we found for SaaS companies with similar R-squared results. The overall conclusion is therefore that the concept of the Rule of 40 is not suitable to be broadened considering the company selection, but is does have added value when extending the selection to another industry (although limited).

Possible explanations of the stronger effect for SaaS companies could be the concept of "sticky demand". This is the effect of future customers loyalty ("sticking to the same company"). SaaS companies already have a more sticky demand because of their business model while they serve their customers on subscription-base. E-commerce companies can "acquire" new customers by using their margin to invest in marketing and in that way create growth, but the demand is not as sticky as with SaaS, since customers can easily switch to competitors. Also, the services provided by SaaS companies is more suitable for a higher customer loyalty. Customers for SaaS products select a certain software that they are interested in and which suits their needs and which can also be tailored to their needs (which also makes it unlikely for them to change to a competitor). However, when it comes to E-commerce companies, products can often be acquired at competitors as well or are less suitable for tailored solutions. Lastly, the majority of SaaS customers are B2B (Business to Business) customers, where E-commerce also has B2C (Business to Consumer) customers. B2B customers are more loyal than B2C. So, the fact that both sticky demand and customer loyalty have a positive effect for the recurring revenue (and therefore a firm's valuation multiple) might explain a stronger effect for SaaS companies.

Lastly SaaS is also a more scalable business model than E-commerce. A new E-commerce customer always has some incremental costs (e.g. producing/buying the products, warehousing, logistics, etc.). SaaS on the other hand has hardly any extra costs when acquiring extra customers since they only have to sell a product which is already "produced". A SaaS company can easily increase their customer base without changing their software or services, which automatically results in higher relative earnings per new customer.

9 Robustness checks

We have now finished the literature based analysis as well as most of the practical part. The last research question that we designed at the start of this thesis was:

Is it possible to apply the predictive power of the indicators in practice?

As discussed before, the research did not show that any of the selected indicators in combination with the selected multiples resulted in R-squared values significant enough to be used for company valuation. Therefore, we decide to do a research extension in which the robustness of the regressions is analyzed. The goal of these robustness checks is to see how trustworthy our results are, and to which extent they can be used to build our conclusions on. In Section 9.1 we start with reevaluating the concept of the tradeoff principle between growth and margin. To do this, we use rank correlation. After that, in Section 9.2, we analyze the effect of outliers in our data on the final results. This is done to see how strong the core of our data is and to which extend the results are a good representation of our data.

9.1 Reconfirming the G+M concept using rank correlation

In the previous chapters, we have selected different indicators which are based on the Rule of 40. We also identified companies within different classifications to do our analysis with. In Chapter 8, we concluded that the indicators G1M3 and G1M4 had the strongest relation with TEV/Revenue. Based on the R-squared results, we have proven that the G+M principle does in fact have some explanatory power for company valuation, but that it is also not completely explanatory for the level of the valuation multiple. The two options for extension are to either try to get a higher R-squared or other similar indicator (with different methods) and in that way "prove" that the G+M principle can be used for company valuation, or we can add more variables to our regression and in that way give a better prediction for the multiple.

Since the focus of this thesis is built around the principles of the Rule of 40, we choose to investigate the first option: applying different methods to get a higher R-squared and in that way further proving the concept of the Rule of 40. The second option of adding more variables to the regression research will be out of the scope of this thesis and is therefore advised to be looked at in future research, focused on a more general valuation research.

We now want to identify a way to prove the principle of G+M. To do this, we choose to use rank correlation. Rank correlation is similar to standard correlation, but uses the ordinal value of the independent variable. In this way, the relation between the two variables does not have to result in a straight line as with linear regression, but it can also show non-straight line in which the order can still give perfect correlation. This is also implemented in Python, and the results can be seen in Table 16. We see that the Spearman correlation indeed results in higher coefficients. We also see that again G1M3 and G1M4 give the highest results for SaaS companies. However, if we look at E-commerce companies, we conclude that all the variables are quite close to each other, which can suggest that the relation for E-commerce is not as strong as with SaaS. This confirms our earlier findings of E-commerce having a less strong relation. The same possible explanations for this are again applicable (sticky demand, customer loyalty, scalability).

indicator	SaaS Companies	E-commerce companies
G1	0.622	0.573
G2	0.553	0.518
G1M1	0.238	0.695
G1M2	0.414	0.606
G1M3	0.621	0.617
G1M4	0.624	0.604
G2M1	0.149	0.618
G2M2	0.320	0.557
G2M3	0.539	0.523
G2M4	0.560	0.495

Table 16: Rank correlation results (Spearman correlation coefficient) for TEV/Revenue.

Another reason for the correlations being close to each other for the E-commerce companies can be found by studying the regression graphs shown in Chapter 8. Here we obviously see that the scatterplot for E-commerce companies is clustered more around similar multiples. This can increase correlation without resulting in high regression results. If this is the main reason for the correlation to be high, without having high regression results as well, we can trust the regression results better as we are mainly interested in explanatory powers of indicators for multiples (which is not found with correlation research).

We can conclude that the Rule of 40 indicator's predictive power for valuation multiples remains the strongest for SaaS. Although the results of the spearman correlation are all rather high for E-commerce, we do not see any real differences between the correlation coefficients, which means that the predictive power of a specific indicator is not as present as for SaaS companies. So, the Rule of 40 is more applicable to SaaS companies than to E-commerce companies.

9.2 Outlier analysis using winsorizing

Another way to analyze how robust the results are is to adjust some of the outliers and check whether the "core" of the data still gives similar results. This is especially interesting for the slope of the regression, since that shows how strong/steep the relationship between the variables is. If the slope of the regression changes a lot, then that indicates that the outliers impact the quality of the model by having a influence on the estimated model parameters that is disproportionate. We adjust our outliers using winsorizing. This method takes a certain percentage of the lowest and/or highest outliers, and adjusts these to the lowest/ highest value that comes first after the values. In this way the outliers are not deleted but adjusted to be closer to the core of the data.

	SaaS companies					*E-commerce companies*				
	Winsorizing upper …%					Winsorizing upper …%				
Variables used	0%	1%	2%	5%	10%	0%	1%	2%	5%	10%
'G1M3' & 'TEV/Revenue'	0.351	0.351	0.351	0.357	0.355	0.446	0.446	0.446	0.394	0.304
'G1M4' & 'TEV/Revenue'	0.359	0.359	0.359	0.364	0.361	0.397	0.397	0.397	0.341	0.273

Table 17: R-squared results for linear regression after applying winsorizing.

So, only by taking of the upper 5% and upper 10% we see a change in the R-squared values. The companies that are considered as outliers for SaaS are:
Winsorized upper 5%: *Okta, Coupa Software*
Winsorized upper 10%: *Okta, Coupa Software, Atlassian, Shopify*

The regression graphs after winsorizing are shown in Figure 8 below.

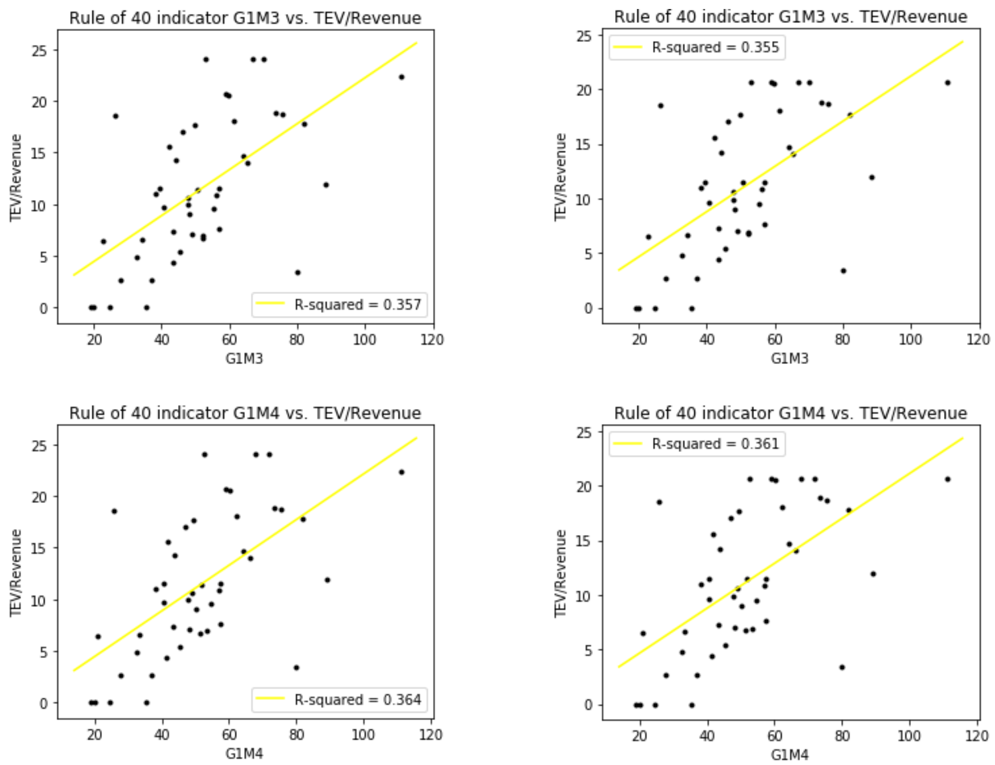


Figure 8: SaaS companies winsorized upper 5% (left) and upper 10% (right).

A data exploration does not result in any particularities into why the companies mentioned before are outlying data. The outliers do not have any specifically interesting characteristics with for example extraordinary combinations of growth and margin. In addition to that, we cannot find any other indicators either, which would explain why these companies show outlying data (e.g. recent mergers or IPOs).

Just as with the SaaS companies, we also winsorized the data of the E-commerce companies. The outliers that are adjusted are:
Winsorized upper 5%: *TakeAway*,
Winsorized upper 10%: *TakeAway, Trainline, Just Eat*

Figure 9 shows the 'after winsorizing'-regression graphs for E-commerce companies. What is interesting about the companies whose data has been adjusted is the fact that (in contrast to SaaS) it can be considered justifiable to delete the outliers of the E-commerce companies based on company characteristics. Trainline had its IPO in June 2019 (thus less than a year's data available), which makes the data that is available for Trainline less reliable. For TakeAway and Just Eat it is also justifiable to adjust their data using winsorizing since the two companies were in the middle of a merger negotiation process at the time the data was retrieved, which can explain an extraordinary high valuation multiple.

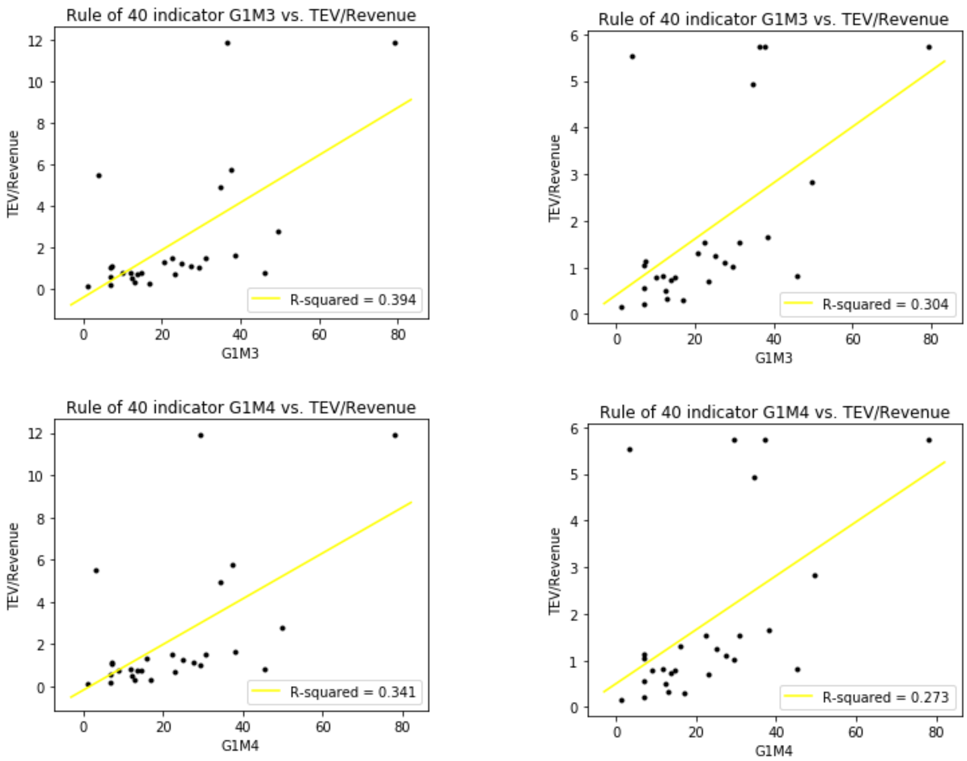


Figure 9: E-commerce companies winsorized upper 5% (left) and upper 10% (right).

Now that we have looked at the specific outliers, it is (as mentioned at the start of this section) interesting to have a look at the impact of the winsorizing on the slopes of the regressions. Table 18 shows the slope and R-squared of the original regression as shown in Chapter 8 as well as the slope and R-squared after winsorizing the upper 5% as discussed in this chapter. Interesting to note is that winsorizing does have practically no effect on the SaaS companies while it does have a stronger effect on the E-commerce companies. The underlying reasons for this are clear, since the outliers for E-commerce were relatively extreme, and therefore had a big impact on the regression slope. The maximum values for SaaS were relatively close to the rest of the data, which explains why adjusting the outliers for SaaS does have hardly any impact on the slope and the R-squared.

	SaaS companies				*E-commerce companies*			
	Before winsorizing		After winsorizing (upper 5%)		Before winsorizing		After winsorizing (upper 5%)	
Variables used	slope	R-squared	slope	R-squared	slope	R-squared	slope	R-squared
'G1M3' & 'TEV/Revenue'	0.229*	0.351	0.222*	0.357	0.138*	0.446	0.114*	0.394
'G1M4' & 'TEV/Revenue'	0.228*	0.359	0.221*	0.364	0.133*	0.397	0.108*	0.341

Table 18: Change in regression slope after winsorizing the upper 5%.

So, we concluded that we do not have a strong reason to adjust the outliers for the SaaS companies, and even if we adjust those outliers, it has hardly any effect on the results. This indicates a robust core that represents the total data very well. For the E-commerce companies however, we do have some indications that it might be justifiable to adjust the outliers. Also, deleting those outliers does have a relatively big impact on the slope and R-squared of the E-commerce company results. Summarizing our conclusions, we can state that the SaaS analysis is much more robust than the E-commerce analysis. So, we can conclude that the Rule of 40 is still a real SaaS rule.

10 Conclusions and recommendations

10.1 General conclusions

We started our practical research with analyzing normal Tech companies and conclude that the Rule of 40 indicator does not have any strong predictive powers for Tech companies in general since the regressions resulted in very low R-squared values. After that, we narrowed down our company selection and looked at SaaS companies. After doing the regression analyses for SaaS companies, as shown in Chapter 8, we found two indicators that have the highest relative predictive powers: G1+M3 and G1+M4. These indicators represent 'Revenue Growth + FCF margin' in combination with 'TEV/Revenue'. We added to the existing literature by doing a comprehensive evaluation of different Rule of 40 indicators while looking at their explanatory powers for valuation multiples. As a result of that, we found that currently 'Revenue Growth + FCF margin' is the best predictive indicator for the valuation multiple 'TEV/Revenue'.

We also tested the G+M concept for the E-commerce industry. Here we found that the same indicators have the highest R-squared, from which can be concluded that the concept can indeed be applied for the E-commerce industry as well. This application of the G+M principle to give an indication for company valuations has not been found in literature, and in that way adds to the literature by finding some of the reasons behind why the Rule of 40 works, and how it can be applied in different sectors as well. This can be a good start for further research.

Based on the SaaS and E-commerce analysis, we conclude that the Rule of 40 indicator does in fact contain some information for company valuation. This effect is significantly higher for SaaS and E-commerce than for Tech. Our regressions resulted in R-squared values which were not higher than 0.5, which means that the Rule of 40 indicator is not completely explanatory for company valuations. Our main research question was formulated as follows:

Can factors which are based on 'the Rule of 40' provide an indication for company valuations in the Tech/SaaS industry and can the concept be extended to other sectors as well?

To answer our research question, we can conclude that the Rule of 40 indicator does not have enough predictive powers to make a reliable estimation of company value but that it can be extended to a different sector.

After answering our research question, we did some additional analyses, to check the robustness of our results. The robustness checks confirmed the concept of the direct trade-off between growth and margin. Outlier detection and adjustment showed that the analysis for SaaS is relatively robust, while the results for E-commerce were less robust. This again confirms our earlier expectations and findings, which is why we can conclude that the Rule of 40 concept works best for SaaS companies.

Our expectations for the underlying reasons for this are mainly linked to sticky demand, customer loyalty, and the scalability of SaaS companies.

10.2 Recommendations for further research

As mentioned in the previous section, our indicators of Enterprise Value do not have enough predictive powers to make a reliable estimation of company value. Therefore, one of the main and most important recommendations of this report is to continue this research by taking 'Growth + Margin' as a basis for a more difficult regression were more variables are added to be able to get a model that gives a more reliable indication for company value. Variables that can be added to do the multiple regression are for example company size, age, the percentage in recurring customers or industry subcategory within SaaS.

Another recommendation for further research is to investigate the effect of the development of the strongest indicator over time. We found that the indicator that is the most significant predictor for the valuation multiple was also suggested to be the strongest indicator by the most recent literature. Therefore, it might be very well possible that there is a strong shift over time of which indicator is the most significant. Fiegenshuh (2020) also confirmed that he considered this as a highly possible scenario since he has been watching the Rule of 40 over the last few years.

Our final recommendation for future research also results from personal conversations with Markslag (2020) and Fiegenschuh (2020). They consider one of the possible problems for the relatively low R-squared results to be that the company selection is still too broad. A possible way of getting higher R-squared result, and thereby being able to better predict company value is to subcategorize SaaS companies in smaller sectors (e.g. healthcare-related SaaS, logistics related SaaS, etc.)

10.3 Practical relevance

This research has been carried out with the professional guidance of EY, which is why we finalize this chapter by discussing the relevance of the outcomes in the context of the sector focus of the S&O department. The goal of this section is to evaluate if there is a practical value of this research that can potentially be used for projects or project proposals in this field of work. It is useful to first put our key findings in short:

- The Rule of 40 metrics do have a significant and stronger relation to a firm's value for SaaS companies than for traditional companies.
- The analyzed indicators do not have a strong relation for Tech companies in general.
- The indicators do have a significant effect on a firm's value for SaaS companies.
- The concept of using Rule of 40 metrics as an indicator for company value is – however limited – also applicable for E-commerce companies.
- No relation of the analyzed metrics is strong enough to use for company valuation.

Now it is interesting to consider the usefulness for EY's sector focus. Our research is not directly usable for firm valuation/M&A. However, the insights retrieved during this research are useful during project proposals and the starting phase of a project. The main takeaway is that there is a significantly stronger "communicating" effect between growth and margin for SaaS companies than for other industries. Therefore, the conclusions of this research are most useful in projects for SaaS companies. The G+M principle can be used as a quick indicator of a company's health and performance. A company with a rather low sum of growth and margin might be an indication of bad performance. In projects for different industries, a negative margin might imply bad company performance. This research quantifies the trade-off principle and thereby creates a stronger position for SaaS companies with low margins and high growth. This first insight is like we mentioned before, mainly useful at the start of an engagement when little to no information is available yet.

The second way in which this research is useful, is that it shows how difficult (SaaS-)company valuation can be, and that the Rule of 40 does not have enough indicative powers to be used in firm valuation. Therefore, this research can be used for EY to convince potential clients even more of the crucial role that EY can play by getting insights into companies' performance by using for example LTV/CAC, in which the S&O department is specialized in. In that way, these insights will also contribute to making a stronger business case in future projects.

11 Discussion

As the research is finished and conclusions and recommendations have been made, the report is finalized by discussing some of the assumptions in this reports or other things that might have been missed which could possibly have a great effect on the results of this research.

Data selection
First of all, as has been discussed earlier, the focus for the company selection in this research was only on large American companies which are publicly traded. The main rationale behind this was to have reliable data for the analysis. However, conclusions about which indicators can be used best for company valuations are therefore also based on large companies only. It is not that straightforward that smaller SaaS companies will show the same results as well. This paper can therefore be used as an indication on which metrics can be used for further research, but may not be used as conclusion toward the complete SaaS industry. Interesting research questions would be e.g. does this relationship hold for startup companies or other companies that are still in an early stage of their lifecycle?

First mover advantage
Another interesting point of discussion is to incorporate the first mover advantage. Online, this is also a widely discussed subject. Take WhatsApp as an example, which we mentioned in our introduction. This company was one of the first large online communication apps. Because a majority of people is using this app (a so called critical mass), it is hard for other parties to enter the market, which probably means that the "first-movers" have an advantage and therefore also a higher valuation multiple.

Rule of 40 – effect of the 40% threshold
Furthermore, this research is completely focused on Rule of 40 indicators in combination with valuation multiples. However, the effect of the Rule of 40 on its own has not been discussed. We did not look at any effect as the "magical threshold" of 40 was passed, which can also reveal certain characteristics that have been looked over now.

Research design
Lastly, it is important to realize that this research is completely focused around the Rule of 40 metrics that could be found in the selected literature. The goal of this research was not to find a perfect way to do a firm's valuation. For firm valuation, it might be interesting to look at other indicators or multiples as well, at which we did not look as they were not present in the selected literature. One possibly better multiple to use might be a consensus forward multiple (based on the expectations for next year) instead of taking the multiple that is based on historical data (last twelve months). Other ways of finding a stronger relation or ways to make a better valuation estimation is to incorporate more company characteristics like networking effect (for multiple regressions).

12 References

Literature

Achleitner, A-K., Lutz, E. and Schraml, S. (2010) 'Quantitative valuation of platform technology based entrepreneurial ventures', Int. J. Entrepreneurial Venturing, 1, (4), 352–366.

Bauer, H., & Hammerschmidt, M. (2005). Customer-based corporate valuation: Integrating the concepts of customer equity and shareholder value. Management Decision, 43, (3), 331-348.

Bernstein, D. (2019, June, 4). *The Rule of 40 in Tech M&A*. Retrieved from https://www.corumgroup.com/insights/rule-40-tech-ma

Black, F. and M. Scholes (1973) The pricing of options and corporate liabilities. Journal of Political Economy, 81, 637-659

Blattberg, R.C., Getz, G. and Thomas, J.S. (2001) Customer equity: Building and managing relationships as valuation assets. Harvard Business School Press, MA.

Copeland, T., T. Koller and J. Murrin (2000) Valuation: Measuring and Managing the Value of Companies. John Wiley & Sons, NY.

Damodaran, A. (2001). The Dark Side of Valuations: Valuing Old Tech, New Tech, and New Economy Companies. Prentice Hall, NJ.

Damodaran, A. (2018). The Dark Side of Valuation: Valuing Young, Distressed, and Complex Businesses. Pearson Education, London.

Depeyrot, T., Heap, S. (2018, December, 20). *Hacking Software's Rule of 40.* Retrieved from https://www.bain.com/insights/hacking-softwares-rule-of-40/

Epstein, J., Harder, J. (2016, November, 29). *How to estimate a company's health without really trying*. Retrieved from https://techcrunch.com/2016/11/28/how-to-estimate-a-companys-health-without-really-trying/

Goedhart, M., Koller, T., Wessels, D., (2016, February). *Valuing high-tech companies.* Retrieved from https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/valuing-high-tech-companies

Gupta, O. & Roos, G. (2001). Valuation of Private Technology Firms - A Discussion Paper on Dealing with the Associated Problems.

Gupta, S. and Lehmann, D.R. (2006) Customer Lifetime Value and Firm Valuation, Journal of Relationship Marketing, 5:2-3, 87-110.

Kellog, D. (2013, June, 5). *What Drives SaaS Company Valuation? Growth!.* Retrieved from https://kellblog.com/2013/06/05/what-drives-saas-company-valuation-growth/

Latka, N. (2019, June, 20). *What is the Rule of 40 for SaaS Companies?*. Retrieved from https://blog.getlatka.com/what-is-the-rule-of-40-for-saas-companies/

Lewis-Beck, M., & Skalaban, A. (1990). The R-Squared: Some Straight Talk. Political Analysis, 2, 153-171. doi:10.1093/pan/2.1.153

Markowitz, H. (1959) Portfolio Selection: Efficient Diversification of Investment. John Wiley & Sons, NY.

Modigliani, F. and Miller, M.H. (1958) The Cost of Capital, Corporation Finance and the Theory of Investment. The American Economic Review, 48, 261-297.

Sleeper, J. (2017, May, 11). *Valuation Multiples Are Useless On Carvana - Here's The Real Driving Factor*. Retrieved from https://seekingalpha.com/article/4072175-valuation-multiples-useless-carvana-real-driving-factor

Sleeper, J. (2017, May, 14). *Growth or Profitability? The Simple Equation Behind SaaS Valuation Multiples Gives a Surprising Answer.* Retrieved from https://www.sleeperthoughts.com/single-post/SaaSValuationMultiples

Sleeper, J. (2018, November, 2). *Saas Multiples Update - Forget Cash Flow; Growth is King.* Retrieved from https://www.sleeperthoughts.com/single-post/SaaSMultiples2018

Sonders, M. (2019, February). *The 50 Largest Public SaaS Companies in 2019.* Retrieved from https://www.mikesonders.com/largest-saas-companies/

Expert references

Beyer, de, M. (2019, December), business communication

Beyer, de, M. (2019, November), business communication

Fiegenschuh, D. (2020, January), video call

Markslag, W. (2020, December), business communication

Reich, M. (2019, December), business communication

Reich, M. (2019, November), business communication

Weele, van, S. (2019, October), business communication

Appendix I – DCF calculations

The main text describes DCF in general and mentions the WACC as the discount factor. When the WACC and the Future Cash Flows are determined, the value of a firm can be determined using the following formula:

$$DCF = \frac{CF_1}{(1+r)^1} + \frac{CF_2}{(1+r)^2} + \ldots + \frac{CF_n}{(1+r)^n}$$

Where: $CF_t = Cash\ Flow\ in\ year\ t \qquad (t = 1, .., n)$

And $r = Discount\ rate\ (WACC)$

The WACC measures the firm's cost to borrow money. The WACC depends on the firm's debt and equity (capital structure). The WACC is calculated as follows:

$$WACC = \frac{E}{V} * Re + \frac{D}{V} + Rd + (1 - TC)$$

Here:

$Re = Cost\ of\ equity$
$Rd = Cost\ of\ debt$
$E = Market\ value\ of\ the\ firm's\ equity$
$D = Market\ value\ of\ the\ firm's\ debt$
$V = E + D = Total\ market\ value\ of\ the\ firm's\ financing$
$E/V = Percentage\ of\ financing\ that\ is\ equity$
$D/V = Percentage\ of\ financing\ that\ is\ debt$
$Tc = Corporate\ tax\ rate$

The higher the WACC, the less likely the firm is to create value, since they have more cost of borrowing money.

Appendix II – Company selection

Tech companies

We use the Global Industry Classification Standard (GICS®) to select our data.

The main categories of GICS are:

- [ ] Energy
- [ ] Materials
- [ ] Industrials
- [ ] Consumer Discretionary
- [ ] Consumer Staples
- [ ] Health Care
- [ ] Financials
- [ ] Information Technology
- [ ] Communication Services
- [ ] Utilities
- [ ] Real Estate

Our area of interest is the Information Technology, which can be split up in the following:

- [ ] Information Technology
  - [ ] Software and Services
    - [ ] IT Services
    - [ ] Software
  - [ ] Technology Hardware and Equipment
    - [ ] Communications Equipment
    - [ ] Technology Hardware, Storage and Peripherals
    - [ ] Electronic Equipment, Instruments and Components
  - [ ] Semiconductors and Semiconductor Equipment
    - [ ] Semiconductors and Semiconductor Equipment

In which we focus on Software and Services:

- [ ] Information Technology
  - [ ] Software and Services
    - [x] IT Services
      - [x] IT Consulting and Other Services
      - [x] Data Processing and Outsourced Services
      - [x] Internet Services and Infrastructure
    - [x] Software
      - [x] Application Software
      - [x] Systems Software
  - [ ] Technology Hardware and Equipment
  - [ ] Semiconductors and Semiconductor Equipment

Which gives us a total of 307 different companies.

Of the 307 selected companies, there are "gaps" in the data because some data is unknown or cannot be specified (declared as NM). To make sure we only work with reliable data, we delete those lines/companies, which is why we end up with 262 companies in total.

SaaS companies

The list of SaaS companies as discussed by Sonders (2019) is shown below. For the analysis, we again delete companies where data is unknown. We also delete companies who's growth+margin is below 0, since we are focusing on successfulness of companies. Companies with negative growth and margin are not considered successful. The data has been retrieved at 06 November, 2010.

Salesforce.com
Workday
ServiceNow
Square
Atlassian
Shopify
Veeva Systems
Twilio
Paycom Software
The Ultimate Software Group
Dropbox
Okta
DocuSign
Zendesk
RingCentral
HubSpot
Xero
Proofpoint
Elastic NV
New Relic
Zscaler
Pivotal Software
RealPage
Coupa Software
athenahealth

MongoDB
Wix.com
CarGurus
Anaplan
Alteryx
Paylocity
Medidata Solutions
Pluralsight
2U
j2 Global
LogMeIn
Cloudera
Smartsheet
Avalara
Ellie Mae
Cornerstone OnDemand
Qualys
Five9
Q2 Holdings
Mimecast
Box
BlackLine
Zuora
AppFolio
Appian

Ecommerce companies

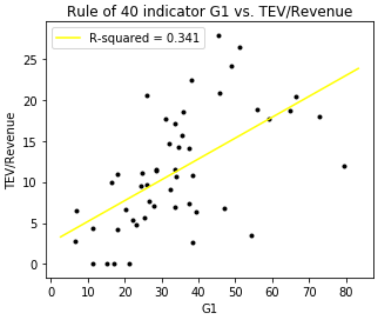
The list of E-commerce companies has been constructed as described in the main text. Same data selection procedures as with the SaaS companies have been followed

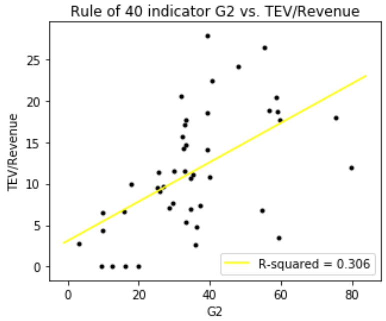
AO World plc
artnet AG
ASOS Plc
Beate Uhse AG
boohoo group plc
Boozt AB (publ)
Bygghemma Group First AB (publ)
Cnova N.V.
Delivery Hero SE
Delticom AG
Design Your Home Holding AB (publ)
Dustin Group AB (publ)
eDreams ODIGEO S.A.
ePRICE S.p.A.
Farfetch Limited
Footway Group AB (publ)
Global Fashion Group S.A.
GoCo Group plc
Groupe LDLC société anonyme
HelloFresh SE
HolidayCheck Group AG
home24 SE
Hostelworld Group plc
Jumia Technologies AG
Just Eat plc
(Invalid Identifier)
Kumulus Vape S.A.
lastminute.com N.V.
Lauritz.com Group A/S
Manutan International SA
Moneysupermarket.com Group PLC
Mountain Alliance AG
N Brown Group plc
Ocado Group plc
On the Beach Group plc
Online Brands Nordic AB (publ)
Passat Société Anonyme
Pharmasimple SA
Prosus N.V.
Qliro Group AB (publ)
Rocket Internet SE
Shop Apotheke Europe N.V.
Sleepz AG
Sportamore AB (publ)
SRP Groupe S.A.
Studio Retail Group plc
Takeaway.com N.V.
TAKKT AG
Toupargel Groupe SA
Trainline Plc
Travel24.com AG
Uhr.de AG
Urb-it AB (publ)
Vente-Unique.com SA
Vialife SA
Westwing Group AG
(Invalid Identifier)
Zalando SE
zooplus AG

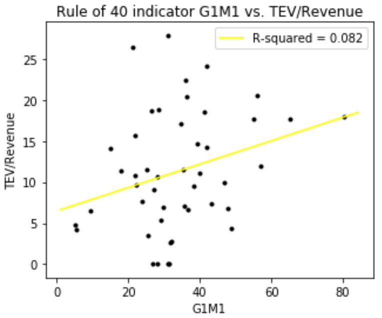
Appendix III – Visualization of linear regressions for SaaS and E-commerce

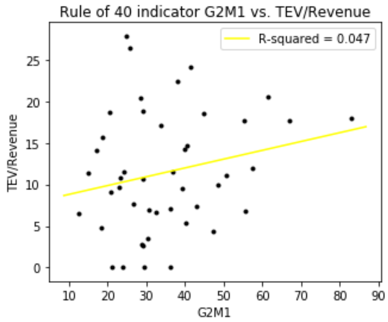
SaaS companies

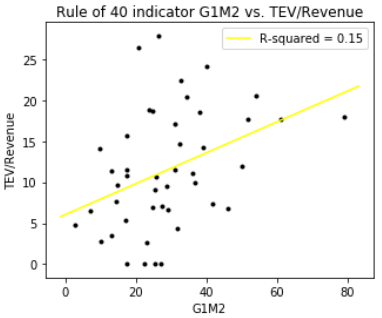
TEV/Revenue

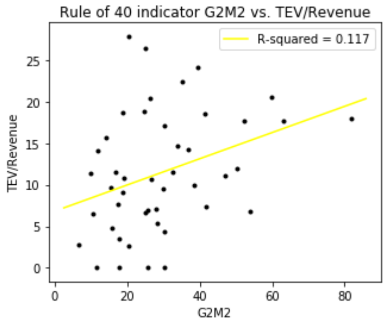


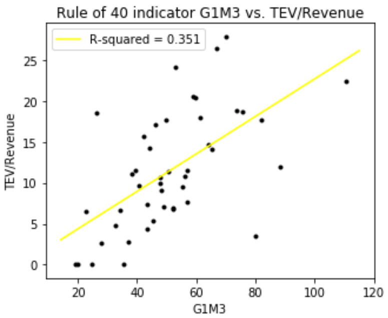


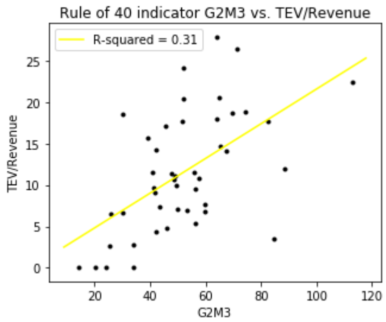


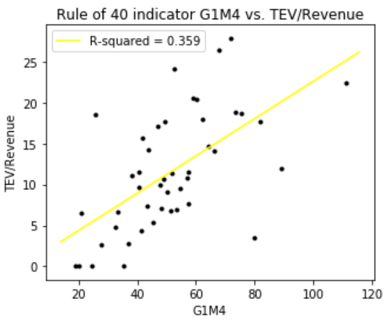


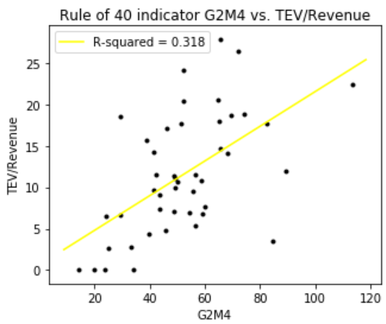


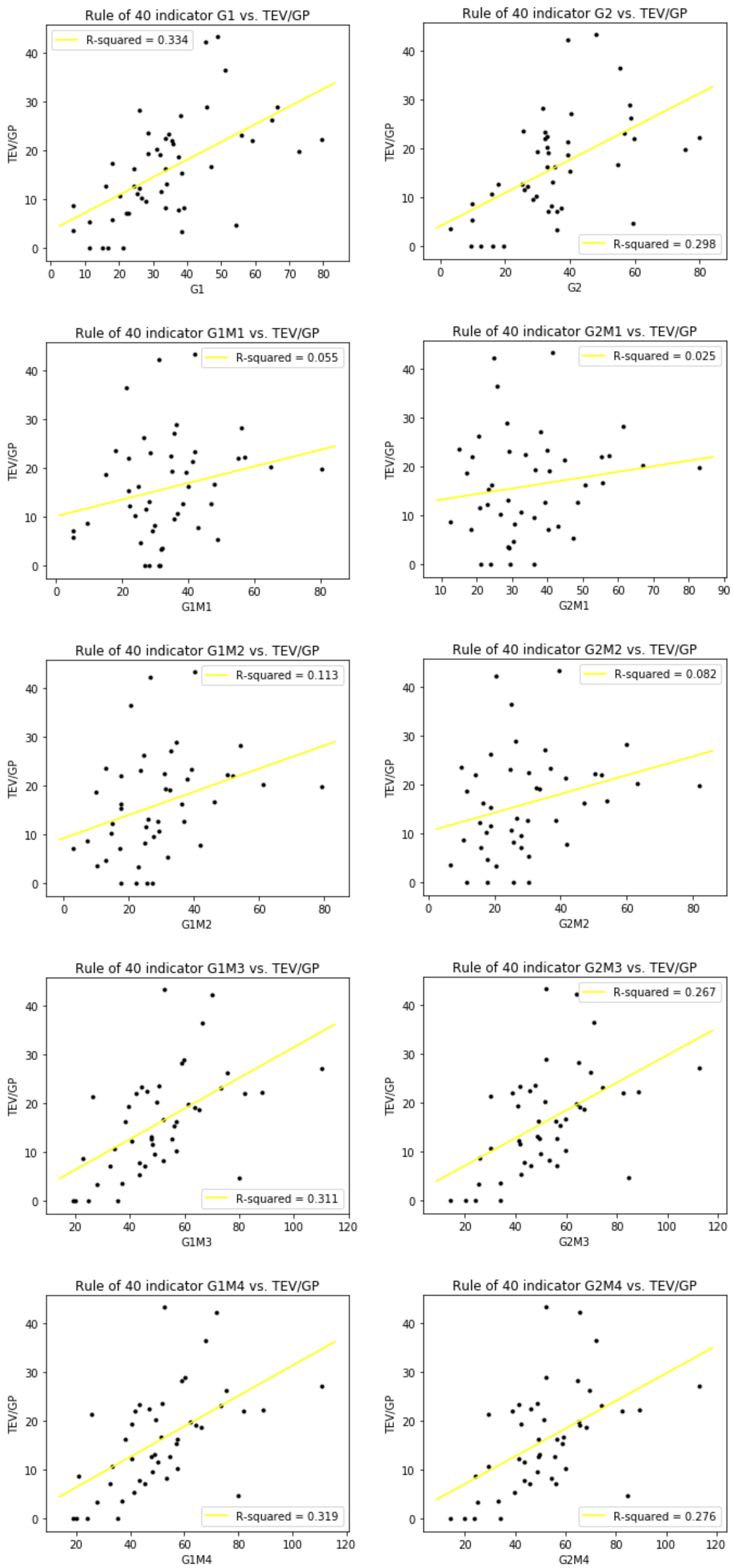










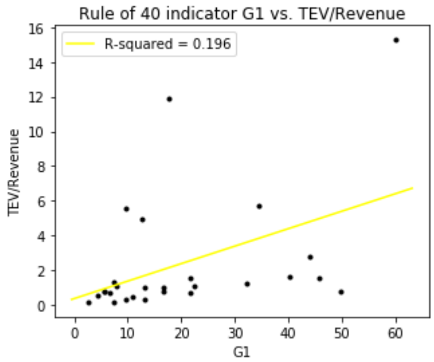


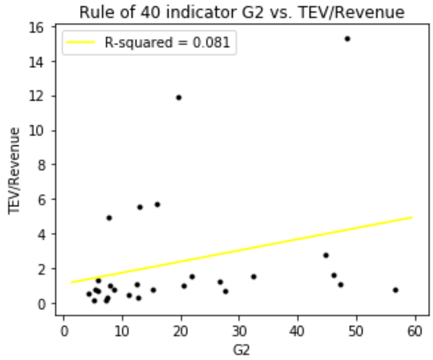
SaaS companies

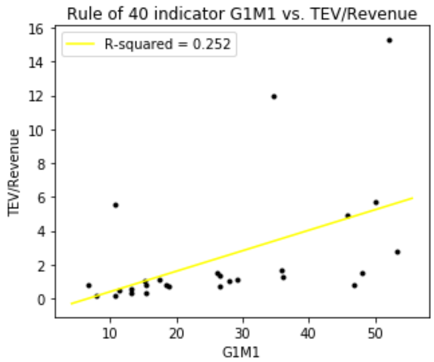
TEV/GP

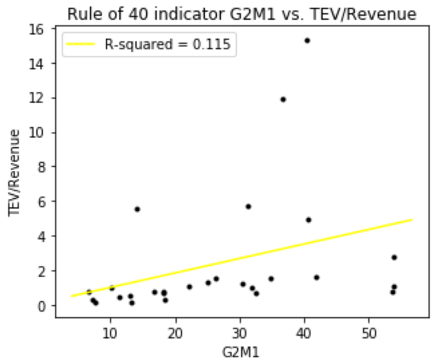
E-commerce

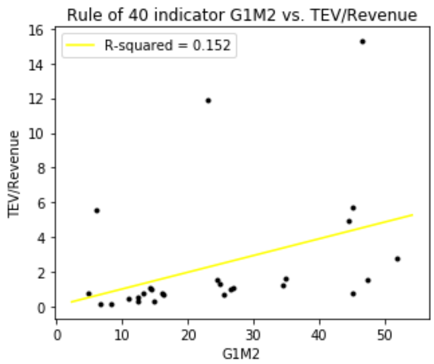
TEV/Revenue

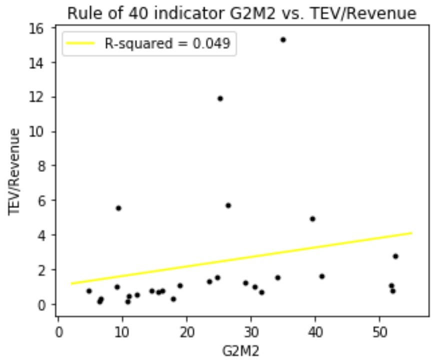


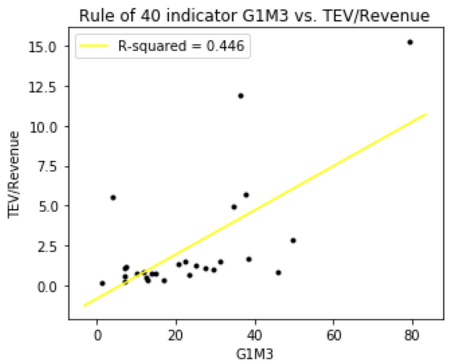


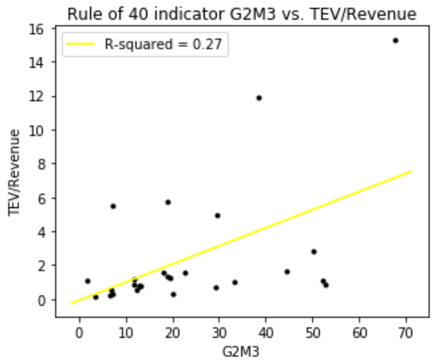


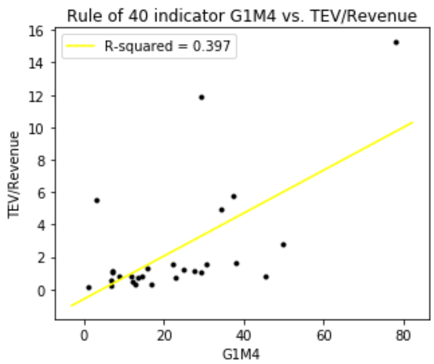


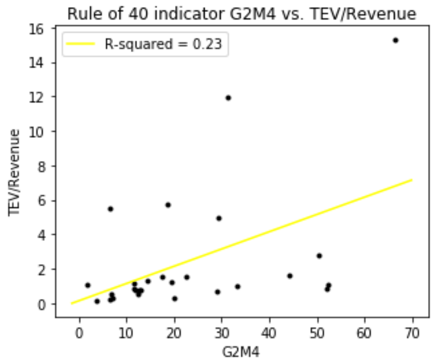












E-commerce

TEV/GP