Find EBITDA with both financial and non-financial information in a valuation perspective

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Abstract

Value of companies from startups to large companies are often the centre of discussions at a top management level. Indicators that are influencing this value are more or less obvious, but which one has the greatest impact and how to value it? Because EBITDA is related to the enterprise value according to the EBITDA multiple valuation, it will be at the heart of this research. We will try to determine a relationship between the EBITDA performance and diverse company criteria through a regression analysis. Also, the variables used in the model are voluntarily easily accessible and not too complex in order that even non-professional analyst could use it. Then, based on the EBITDA multiples theory, investors would be able to valuate and compare the best investment they could make.

Keywords: Business valuation, EBITDA accessible model, weighting of performance factors

1. Introduction

The famous quote "Price is what you pay, value is what you get" (Buffet, 2008) describes well the concept of value: it is a non-tangible perception of how much a business will be profitable from the present to the long-term. Believing that one company will be highly valuated tomorrow because of the current and the past events is taking a risk and accepting to earn less than the amount initially invested (Burksaitiene, 2009). Uncertainty starts from this point: investors know almost all the past and current information about the company they are interested in but only the future will tell them if they make a profit (Damodaran, 2006).

Long-term investments made by individuals, banks, corporation in M&A transactions, VCs or PE firms must ensure that the business they want to fund will be a winning bet (Mnejja, Sahut & Teulon, 2012). Finding a company with an increasing trend in sales, in net income or in net profit margin that lasts in time is not enough to be sure to have a positive ROI in the long-term. This is especially true with startups that have been created a short time ago: their expenses are very high at first, then their incomes are growing but how long will it take for them to become profitable? Only a few of them will exceed the desired break-even point. Investors are looking for a huge profit by taking stakes into companies with a possible large increase in terms of valuation in the

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future (Liu, 2021). They must rank the different opportunities they have by finding the best profit-risk ratio (Chauhan & Kumar, 2019).

Investors base their opinion mainly on financial reports issued by companies. From it, they calculation financial ratios and try to forecast sales and future earnings by interpreting the future market trend, like in the DCF valuation method. However, projected figures are not always accurate. There is also a whole context to consider, including the strategy of the company, its projects, its assets and its competitive environment (Mock & Monroe, 2011). The problem is that all the useful quantitative and qualitative information is not convenient to gather because it requires time to be accessed, analysed and understood (Allenström & Njurell, 2010). A model that would include both financial and non-financial data could reduce the investor's risk by making an overall estimation according to the past and present data. It would be, by definition, more complete and more accurate than a pure financial model.

Reducing all the risks faced during a valuation analysis of company is the main goal of this research by using at the same time financial and non-financial data. We define non-financial information as textual data or numerical data not related to accounting or financial calculations. Most of current literature dealing with relationship between the enterprise value and different variables explores direct valuation approaches (Broström et al, 2015). This paper focus exclusively on the EBITDA multiple valuation method and principally in EBITDA (the multiple used is left to the discretion of the user). We will not try to bridge a gap but rather to popularize valuation for beginners and to make the first valuation approach easier for analysts. As EBITDA is a driver of the enterprise value according to the EBITDA multiple valuation method, this research will assume that drivers of EBITDA are the same drivers of the enterprise value. In addition, EBITDA is a well-known intermediate financial measure that is often displayed by companies and one of the main metrics checked by analysts. For accessibility reasons and in order to make this research useful to as many investors as possible, including non-professionals, the data used will be quite accessible and not too specific. Finally, would it be possible to reduce the risk taken by analysts by creating a simple model suggesting an optimal EBITDA regarding general financial and non-financial variables?

According to many papers, DCF and multiples are the two most used valuation methods. In EV/EBITDA is identified as the most used multiple with 84% (Nyborg, K. G. et al, 2016). We assumed that the EBITDA multiple valuation method is one of the best methods to reach the right EV thanks to the multiple derived from the past transactions. These completed transactions have been approved by both a seller and a buyer, so we can expect that the EV of the deal is close to the real value of the company. The objective is to compare the true EBITDA of a company and its theoretical EBITDA in order to know if the company is doing well according to its characteristics. Based on a sample of thousands of companies from all over the world, this research will highlight some key elements that have a positive or a negative impact on the EBITDA of the company, and therefore on its valuation. The regression will indicate the most influencing variables and it would be a very useful tool for analysts, managers and every stakeholder, like the Altman Z-score (1968) indicates with an accuracy of 90% if a company is going into bankruptcy in the short term with some of its data gathered in a simple equation.

This study will first discuss about the concept of valuation, its role and the different ways to approach it. Then, the upstream processes will be explained and some checks will be done in a preliminary stage before doing several linear regressions related to different situations. Finally, findings will be explained in view and the future research trajectory will be discussed.

2. Literature review

Value is a key concept in finance that gives a great glimpse about how a business is recognized as a tool to generate cash in the long-term while taking into consideration the cost of capital required to run the company (McKinsey & Company Inc et al., 2020). This definition shows the importance that benefits exceed the cost of capital in order to have a positive ROC. From another point of view, valuation could be seen has the fair price at which someone could pay to acquire all assets (Parker, 2016).

Business valuation goes beyond typical finance professions and is generally more or less directly one of the main concerns of the top management. They need to know the value of their company over time to understand how their business' performances can be interpreted on the long-run and how they are performing among their contenders. T. Krulicky, J. Horak and K. Skulcova (2021) write about the purpose of knowing the value of a business. According to them, decision-makers must be aware of the day-to-day value of their company to anticipate growth or development phases in order to lead it in the best direction. Valuation may also be useful to identify value drivers and to plan strategy changes for the company: valuation models are defined as a complement of other financial indicators to get a big picture (Mukhambetov et al., 2020).

Nevertheless, even if valuation is a core recurring subject in finance, it does not imply that valuation is a simple exercise. Calculation of value is complex because companies are composed of objective elements, such as tangible assets, and subjective elements like intangible assets or goodwill. This observation made by Ionita and Stoica (2009) shows the complexity of rightly measuring the value of a company.

Even if valuation formulas are established, each one must be interpreted relatively to the environment of the analysed company. Indeed, all valuations based on the forecast of company's benefits lean on parameters evaluated at the discretion of the analyst. As Doña et al. (2011) said, there is a significant part of events probability in this calculation of value, and depending on which side you are looking to the company, you can have a different result. It explains why analysts often suggest several scenarios during their presentations.

That is why Matschke and Brösel (2010) presented the functional business valuation in response to all the possible way to calculate value. They recognized that several values exist for one company and in consequences they aimed to create an independent notion of value through a specific procedure. The main goal was to calculate a business value in an objective manner by avoiding any conflict of interest.

Many points of view can be taken to calculate the value of a company. Different potential buyers of a same company, even if they want to buy it at a low price, would probably not agree on the value of a target as well as a buyer and a seller would probably not agree. This example highlights the difficulty to find the right value, even in the most objective way. In addition, the fact that sellers and buyers are often negotiating the final price shows that a good valuation is within an acceptable range. Many methods exist and they give more or less the same result, but the difference is significant enough to make buyers and sellers sceptical. Thus, analysts take time to calculate their own value thanks to their own calculated parameters.

This paper will mainly discuss the EM (including the EBITDA multiple) and the DCF methods because they are among the most used techniques, and they are both applied in theory at university and in practice by financial analysts. However, they do not play the same role for all financial analysts. Chastenet and Jeannin (2007) shows that DCF is often seen as the principal valuation method while EM is calculated as a monitoring tool in order to verify the result found previously. EM seems to be indeed more trustable because it only uses historical facts and transactions that reassure the buyers about a fair price (Declerck, 2016) whereas DCF requires a lot of inputs estimated by the analyst. Also, Schueler (2020) highlights that the main strength of the EM method is that you can easily and quickly find a worth that for sure is not too far from reality.

Regarding the type of information used in valuation, reports are considered as the preferred source of information used by investors (Coram, Mock & Monroe, 2011). Audit reports are ranked at the first place with 46%. They conclude that non-financial information is less used when financial results are negative. However, according to the study conducted by Sievers, Mokwa and Keienburg (2013), "only" 51% of the value of a company is given by financial statements, accounting information and similar deals data. The authors successfully achieve the same percentage by using both non-financial data and similar transactions data. In addition, when the authors of this article tried to combine financial and non-financial information in a same model, they obtained a R-squared of 62%. It brings light to the potential added value of non-financial information. Unfortunately, companies are communicating specifically on financial information and strategy in accordance with the most requested information by investors. Laskin (2016) has analysed how well the non-financial information is communicated to investors to enhance the company's value and he explains that non-financial information is not often communicated because investors generally do not pay a significant attention to it.

Yang (2008), Behn and Riley (1999) and Goh, Lam and Leil (2019) are three research works that focus on financial performance and non-financial information in a specific industry. For instance, the first one looks in detail at the patent information available to predict future financial performance and enterprise value of biotechnology companies. The second one examines the financial performance of a U.S airline company and all figures concerning current customers' experience. Finally, the third one establishes a relation between the number of tangible assets in a casino, such as the number of table games or slot machines, and its market valuation. This research was very relevant for this thesis because they proved a reliable link between at least some very specific non-financial information related to an industry and the financial performance of this same industry. The objective is to go beyond these prior literatures by finding less precise non-financial information to find a quite global model that bridges the gap between financial performance and valuation on the one hand, and financial and non-financial information in the other hand.

One could argue that between two tech companies having exactly the same capital structure and the same earnings, investors would prefer to put their money into that one which set up a good cybersecurity package. Thus, value of a company is impacted by non-financial elements. This demonstration done by Hutchins & Miles (2019) shows indirectly that many kinds of non-financial information can be used by analysts, such as binary data (the company is equipped against cybersecurity threats) and progressive data (the company is not equipped at all, well equipped or very well equipped).

To sum up the main ideas, as the title of the paper of Welsh and White (1981) said, "A small business is not a little big business". This sentence means that there is very rarely a notion of proportionality between companies. Beyond the size of them, financial and non-financial elements of a small and a big company differ in sense (sign of the coefficient) and in magnitude (measure of the coefficient). The concept of comparability is of major importance in this essay because the objective is to find several key elements on which analysts can lean on to compare businesses whatever their size, their industry and more. For instance, the authors take the example of startups at a very early stage, which cannot be valuated like other traditional companies because of the lack of relevant financial figures about them and their innovative market. However, Wildt (2019) shows that a good comprehension of their activity can be extracted from scorecard the analysis of risk factors. In addition, Hirschey et al. (2001) suggests that the patent quality measured by the number of citations is a reliable information to perceive the ongoing equity value for all kind of industry. It implied that a global model could be built and could gather several types of industries over the world through different criteria, neither too specific nor too wide, and that is very encouraging for our regression.

Current valuation techniques can lead to a right valuation but it implies that the investor has made a good choice about the input parameters and it takes time to check all the potential hypotheses. It could be even more convenient if the result was easy to calculate with an understandable weight associated to each value-driver. The utopian goal of this study is to prevent people from choosing wrong scenarios or models, as Kiss (2015) identified the selection problem of the appropriate valuation techniques. By using one general model, analysts will not hesitate anymore between the market trends hypothesis or compatibility of one model with the company studied.

Another important element is that professional analysts are favoured because of their access to database or financial reports (audited or not) to the company in which there are interested. This inequality between people who want to valuate a company is not covered by literatures, and especially not solved. This thesis' objective is to propose a multi-functional model that relies on ease of use and data accessibility. The final user of this new model will just have to fix the inputs in the equation and he will quickly get a value whatever the industry is thanks to the regression analysis done thereafter. An investor could quickly have an idea about several opportunities because of the efficiency and the speed of the developed tool.

3. Research method

One of the main goals of this study is to find the theoretically standard EBITDA according to both financial and non-financial characteristics of a company. If the result generated by the regression equation is lower than the valuated company's real EBITDA, then this company deserves a great attention because it has a better result than businesses with the same criteria.

Otherwise, it means that other companies generally have higher EBITDA with the same inputs. This approach of the value of a company is interesting for financial analysts, professionals or not, who are looking for a quick and easy-to-use comparison tool regarding their classic methods, which required complex data sometimes not accessible to everyone. It could be also interesting for executive managers to know which key drivers can boost their EBITDA according to other businesses in the sample have done. However, note that even if the generated EBITDA could be used for an EM valuation, this tool does not provide the multiple required for the calculation and let the user the entire responsibility for choosing it.

The 452 independent variables and the dependent variable used in this paper came from the Orbis renowned database, except one independent variable coming from Google AI research. Orbis was selected has the main source of the collected data because it gathers reliable information about millions of companies worldwide and it allows to its users to download results of several companies at the same time. The 6 313 observations are corresponding to the 6 313 companies with an EBITDA strictly greater than 0 for which Orbis has data on almost every variable at the end of December 2020, when the dataset was downloaded. The date of foundation variable was extracted from Google thanks to a short Python program designed exclusively for this paper. Except this last variable, others have been chosen arbitrarily according to the data available on Orbis. For the financial variables, all essential intermediate financial concepts were selected. Regarding the non-financial variables, almost all available data on Orbis was selected because Orbis is indeed above all a financial database.

Type of variable	Type of data	Variables	Unit or Subvariables	Number of missing values	Percentage of missing values	Number of valid values	Percentage of valid values
Independent	Non-financial	Date of creation	Numerical (year)	0	0%	6 313	100%
		Nb of employees 2019	Numerical	0	0%	6 313	100%
			Percentage variation (vs 2018)	0	0%	6 313	100%
		Nb of current advisors	Numerical	0	0%	6 313	100%
		Nb of subsidiaries	Numerical	0	0%	6 313	100%
		Nb of publications	Numerical	0	0%	6 313	100%
		DM Female	Binary	32	1%	6 281	99%
		DM Age	Numerical	260	4%	6 053	96%
		Risk rating	7 types of country risk (7 dummy variables)	792	13%	5 521	87%
			7 types of sector risk (7 dummy variables)	792	13%	5 521	87%
		Type of entity	9 types of company (9 dummy variables)	0	0%	6 313	100%
		Industry sectors	28 categories (28 dummy variables)	0	0%	6 313	100%
		DM major	162 subjects (162 dummy variables)	5 451	86%	862	14%
		DM nationality	114 nationalities (114 dummy variables)	497	8%	5 816	92%
		Headquarters country	96 countries (96 dummy variables)	0	0%	6 313	100%
	Financial	Cost of employees 2019	Numerical (USD)	0	0%	6 313	100%
			Percentage variation (vs 2018)	0	0%	6 313	100%
		DM Compensation USD	Numerical (USD)	5 650	90%	663	11%
		Turnover 2019	Numerical (USD)	0	0%	6 313	100%
			Percentage variation (vs 2018)	0	0%	6 313	100%
		R&D expenses 2019	Amount in USD	0	0%	6 313	100%
			Percentage variation (vs 2018)	76	1%	6 237	99%
		Closing price December 2019	Numerical (USD)	589	9%	5 724	91%
			Percentage variation (vs 2018)	784	12%	5 529	88%
		Nb shares December 2019	Numerical	591	9%	5 722	91%
			Percentage variation (vs 2018)	786	12%	5 527	88%
		Market Capitalization 2019	Numerical (USD)	591	9%	5 722	91%
			Percentage variation (vs 2018)	786	12%	5 527	88%
		Earnings per share 2019	Amount in USD	591	9%	5 722	91%
			Percentage variation (vs 2018)	786	12%	5 527	88%
		Net debt 2019	Numerical (USD)	950	15%	5 363	85%
			Percentage variation (vs 2018)	1 125	18%	5 188	82%
		Profit margin 2019	Numerical (USD)	0	15%	6 313	100%
			Percentage variation (vs 2018)	1	18%	6 312	100%
		Net profit 2019	Amount in USD	0	0%	6 313	100%
			Percentage variation (vs 2018)	1	18%	6 312	100%
Dependent	Financial	EBITDA USD 2019	Amount in USD	0	0%	6 313	100%

Table 1. List of all variables selected in the database

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4. Results and analysis

The regression analysis will give a great glimpse of the relationship between EBITDA (our valuation metrics) and both the financial and non-financial parameters that influence it. Regression coefficients are interesting because they give a concrete idea of the weight and the direction of a variable in relation to another. Thus, by giving the impact of each characteristic of a company, the regression equation will by the final tool that will try to partially solve the risk faced by any investor and answer the problem of each manager that want to know which controller lever active to increase EBITDA.

We could expect a great explanatory power of the financial variables, as they are a core concern of analysts for a long time. Turnover, profit and profit margin should be very related to EBITDA, but also all financial and non-financial information that bring a light to the size of the business. In addition, because of the importance of type of industry when analysts use the EM valuation method, we can expect this variable to greatly influence the theoretical EBITDA. We can also anticipate that an important noise caused by some outlier companies with a too low or too high EBITDA in view of its capacity. Finally, as Nguyen et al. (2018) have discussed, we could hardly forecast DM data can influence the earnings of a company.

Before starting the analysis, note that only the adjusted models are displayed above. It means that for all the different models created, all the results showed in this study are extracted after having eliminated p-values superiors to 0,10. It means that the independent variables disclosed here have a meaningful role in the equation with 90% level of confidence.

4.1 Model 1.1 – all independent variables with more than 96% valid values

Mean dependent var	4.94e+08	S.D. dependent var	2.17e+09
Sum squared resid	4.04e+21	S.E. of regression	8.23e+08
R-squared	0.856340	Adjusted R-squared	0.855785
F(23, 5958)	1544.124	P-value(F)	0.000000

Table 1. Regression general outputs of model 1.1

	coefficient	std. error	t-ratio	p-value	
const	2.62960e+07	1.85188e+07	1.420	0.1557	
Nbofemployees2019	-11961.1	388.371	-30.80	2.06e-193	***
Nbofcurrentadvis~	-4.31120e+06	2.31751e+06	-1.860	0.0629	*
Noofsubsidiaries	584172	98646.1	5.922	3.36e-09	***
Nbofpublications	-5679.51	779.555	-7.286	3.62e-013	***
Retail	-1.90957e+08	5.67989e+07	-3.362	0.0008	***
MiningExtraction	4.91252e+08	5.37622e+07	9.138	8.60e-020	***
Construction	-1.76657e+08	5.84821e+07	-3.021	0.0025	***
Communications	5.53593e+08	5.66852e+07	9.766	2.31e-022	***
Utilities	2.32679e+08	6.13115e+07	3.795	0.0001	***
Wholesale	-9.41803e+07	4.90314e+07	-1.921	0.0548	*
CostsemployeesUS~	0.214154	0.00947330	22.61	1.26e-108	***
TurnoverUSD2019	0.100909	0.00154486	65.32	0.0000	***
NetProfitUSD2019	1.12261	0.0152488	73.62	0.0000	***
Profitmargin2019	-1.62902e+06	668741	-2.436	0.0149	**
GB	7.14205e+07	3.71911e+07	1.920	0.0549	*
HK	4.04984e+08	9.57059e+07	4.232	2.36e-05	***
IT	1.50263e+08	7.18133e+07	2.092	0.0364	**
ES	3.25497e+08	1.16517e+08	2.794	0.0052	***
IE	3.33701e+08	1.36983e+08	2.436	0.0149	**
AU	2.96296e+08	1.53659e+08	1.928	0.0539	*
CA	2.36819e+08	1.29501e+08	1.829	0.0675	*
CW	5.52429e+09	5.91649e+08	9.337	1.37e-020	***
PA	1.24256e+09	4.76083e+08	2.610	0.0091	***

Table 1. Regression general outputs of model 1.1

This first OLS tried to use the largest number of independent variables while maintaining a large sample. Once corrected, the model has 23 significant variables according to the p-values. As it might have been expected, the model seems to be troubled by headquarters countries variables. Even if the adjusted R-squared is great and F statistic is very low, these categorical variables seem to have too much power in the equation while having a large standard error. For instance, a little business in Great Britain cannot be so much positively impacted just because of their presence in their country. We hope that this issue will be corrected in the following model. However, the very high SD give an idea of the dispersion of the set of companies included in the sample that will be present during all the study.

4.1.1 Model 1.2 – all independent variables with more than 96% valid values except related to countries variables

Mean dependent var	4.94e+08	S.D. dependent var	2.17e+09
Sum squared resid	4.13e+21	S.E. of regression	8.32e+08
R-squared	0.853036	Adjusted R-squared	0.852716
F(13, 5968)	2664.653	P-value(F)	0.000000

Table 2. Regression general outputs of model 1.2

Here, only 13 variables were kept in this model for the same adjusted R-squared and the same number of observations than in model 1.1. According to the statistical outputs, the independent variables used are explaining at 85% the variations of EBITDA and the whole model seems to be significant but the mean distance between the observations and the predicted values is still huge.

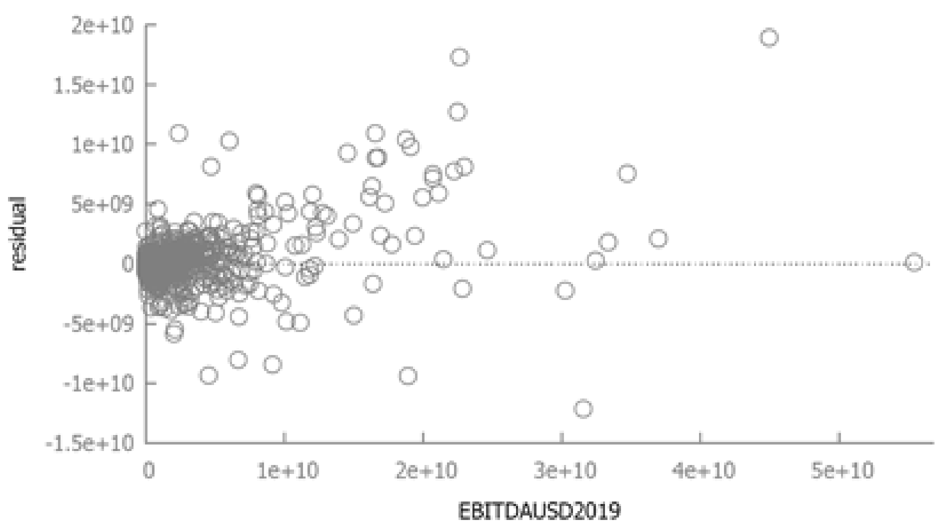

Figure 1. Graphical representation of model 1.2's residuals

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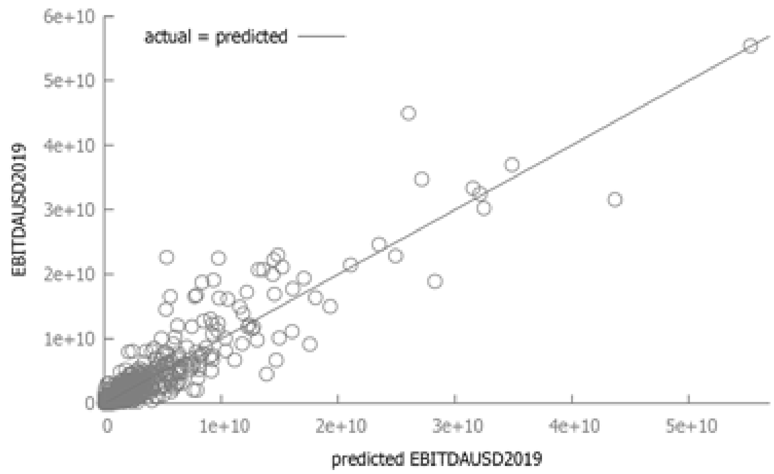

Figure 2. Graphical representation of model 1.2's regression accuracy

When EBITDA is lower than 8 billion USD, the model seems to fit data correctly. Residuals are bigger for EBITDA especially between 10 and 20 billion USD. However, we can say that high SE is mainly driven by a minority of predictions. This issue is directly related to the fact that mean values are greatly affected by extreme values. Also, the graphics show that the model undervalues most of the outliers.

	coefficient	std. error	t-ratio	p-value	
const	2.33148e+07	1.41458e+07	1.648	0.0994	*
Nbofemployees2019	-11954.2	392.012	-30.49	6.14e-190	***
Noofsubsidiaries	668582	98835.9	6.765	1.46e-011	***
Nbofpublications	-5244.56	784.140	-6.688	2.46e-011	***
Retail	-1.91709e+08	5.73250e+07	-3.344	0.0008	***
MiningExtraction	5.22114e+08	5.40913e+07	9.652	6.93e-022	***
Construction	-1.85707e+08	5.90571e+07	-3.145	0.0017	***
Communications	5.56801e+08	5.72015e+07	9.734	3.16e-022	***
Utilities	2.53793e+08	6.16402e+07	4.117	3.88e-05	***
Wholesale	-9.81560e+07	4.95233e+07	-1.982	0.0475	**
CostsemployeesUS~	0.212812	0.00956214	22.26	1.76e-105	***
TurnoverUSD2019	0.101987	0.00155627	65.53	0.0000	***
NetProfitUSD2019	1.10195	0.0151870	72.56	0.0000	***
Profitmargin2019	-1.49915e+06	674161	-2.224	0.0262	**

Table 3. Regression coefficients of model 1.2

According to the coefficients founded, turnover and net profit is positively related to EBITDA, unlike profit margin. Also, giving higher wages to employees benefits more the EBITDA than it increases expenses. On the contrary, hiring new employees negatively impacts the EBITDA. Concerning non-financial data, more subsidiaries can be associated with more business activity, more cash inflows and a higher EBITDA. In addition, many industries are present in this model. Some of them add a positive value to EBITDA (like mining extraction) and others make EBITDA decrease (like the retail sector) but the accuracy of the coefficients is not good regarding the SE. The coefficient could be true for mining and extractions companies, because they are often large firm and established for a long time. But in the case of communications companies, a positive impact of 556 million USD in the EBITDA of a little agency is not

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realistic. Another unexpected finding is related to the number of publications that is decreasing EBITDA. One could have predicted that more publications is a guarantee of innovation and high profits, but it seems that these publications imply costly research.

4.2 Model 2 – all independent variables with more than 96% valid values and all non-financial variables with more than 87% valid values

Mean dependent var	5.49e+08	S.D. dependent var	2.36e+09
Sum squared resid	3.65e+21	S.E. of regression	8.73e+08
R-squared	0.863826	Adjusted R-squared	0.862945
F(31, 4792)	980.5879	P-value(F)	0.000000

Table 4. Regression general outputs of model 2

The model 2 shows slightly better statistics than the model 1.1. Actually, model 2 should be closer to reality on paper: adjusted R-squared is 1% more accurate and the F significance is also equal to 0. However, model 2 was built with one thousand observations less than model 1 and it has 18 independent variables more than model 1. Therefore, model 2 is rejected in comparison to model 1.1.

4.3 Model 3 – all independent variables with more than 96% valid values and DM major "variable

Table 5. Regression general outputs of model 3

Mean dependent var	1.60e+09	S.D. dependent var	4.51e+09
Sum squared resid	1.93e+21	S.E. of regression	1.53e+09
R-squared	0.888940	Adjusted R-squared	0.885026
F(29, 823)	227.1512	P-value(F)	0.000000

The main regression performance indicators of model 3 are not sufficient to beat model 1.1. Actually, it has 16 independent variables more than model 1.1 and its sample size is around six times smaller than model 1 for an improvement of only 3% of the adjusted R-squared. In addition, model 3's SE is worse than the one of model 1.1. Therefore, model 3 will not be further explored.

4.4.1 Model 4.1 – all independent variables with more than 96% valid values and all financial variables with more than 82% valid values

Mean dependent var	5.62e+08	S.D. dependent var	2.36e+09
Sum squared resid	3.17e+21	S.E. of regression	8.03e+08
R-squared	0.884951	Adjusted R-squared	0.884341
F(26, 4904)	1450.816	P-value(F)	0.000000

Table 6. Regression general outputs of model 4.1

Model 4.1 looks perform ant but model 1.2 proves that it is possible to obtain good overall performance with less variables (26 here versus 13 in models 1.2). We are looking forward the next model.

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4.4.2 Model 4.2 – all independent variables with more than 96% valid values and all financial variables with more than 82% valid values except related to countries variables

Mean dependent var	5.62e+08	S.D. dependent var	2.36e+09
Sum squared resid	3.23e+21	S.E. of regression	8.11e+08
R-squared	0.882496	Adjusted R-squared	0.882114
F(16, 4914)	2306.621	P-value(F)	0.000000

Table 7. Regression general outputs of model 4.2

This model is very interesting because its adjusted R-squared is higher by 3 points than model 1.2 while keeping a wide sample and a restricted number of independent variables. Also, there is an improvement of SE.

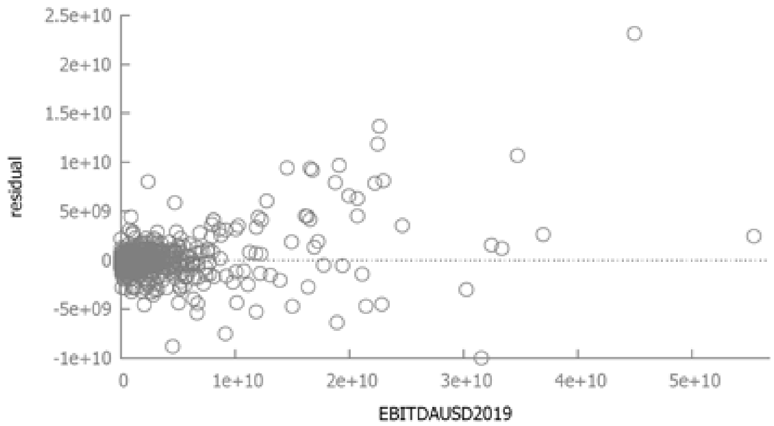

Figure 3. Graphical representation of model 4.2's residuals

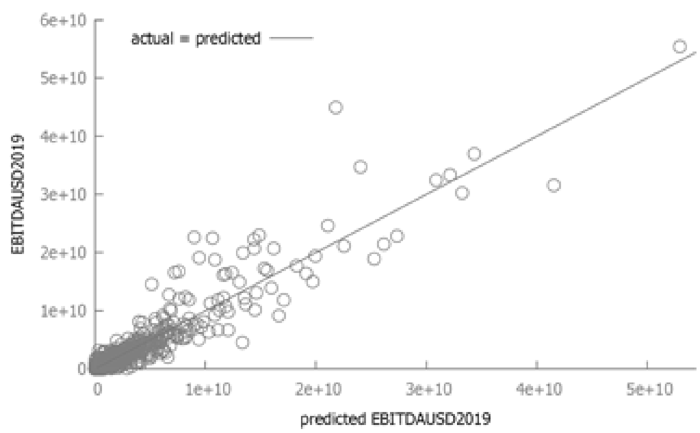

Figure 4. Graphical representation of model 4.2's regression accuracy

This residual plot in function of EBITDA values gives additional information on the explanatory power of model 4.2. It suggests that errors are still present but less important than in model 1.2.

	coefficient	std. error	t-ratio	p-value	
const	5.42599e+06	1.48709e+07	0.3649	0.7152	
Nbofemployees2019	-10781.4	396.656	-27.18	1.11e-151	***
Nbofpublications	-3547.77	836.141	-4.243	2.25e-05	***
Retail	-1.71283e+08	6.28475e+07	-2.725	0.0064	***
MiningExtraction	5.44787e+08	5.69517e+07	9.566	1.71e-021	***
Construction	-1.60571e+08	6.48282e+07	-2.477	0.0133	**
Communications	4.74861e+08	5.97204e+07	7.951	2.27e-015	***
FoodTobaccoManuf~	-1.09744e+08	5.54160e+07	-1.980	0.0477	**
PropertyServices	-1.07187e+08	5.60256e+07	-1.913	0.0558	*
CostsemployeesUS~	0.168875	0.00928525	18.19	1.38e-071	***
TurnoverUSD2019	0.0816184	0.00168257	48.51	0.0000	***
RDexpensesUSD2019	-0.192900	0.0280016	-6.889	6.33e-012	***
NbsharesDec2019	0.0110020	0.00177725	6.190	6.49e-010	***
MarketCap2019	0.0172766	0.00106221	16.26	5.61e-058	***
Netdebt2019	0.0835814	0.00287204	29.10	6.32e-172	***
NetProfitUSD2019	0.937996	0.0190925	49.13	0.0000	***
Profitmargin2019	-1.44037e+06	735452	-1.958	0.0502	*

Table 8. Regression coefficients of model 4.2

Model 4.2 draws some similar conclusions as model 1.2. For instance, the coefficients related to the number of employees, the number of publications, the cost of employees, the turnover, the net profit, the profit margin and several industry sectors are quite the same. However, new added independent variables like R&D expenses, number of shares, market capitalization and net debt have appeared.

4.5.1 Models 5.1 – all independent financial variables

Mean dependent var	1.85e+09	S.D. dependent var	5.08e+09
Sum squared resid	1.68e+21	S.E. of regression	1.64e+09
R-squared	0.896900	Adjusted R-squared	0.895413
F(9, 624)	603.1553	P-value(F)	4.4e-301

Table 9. Regression general outputs of model 5.1

This model is a good indicator to situate the performance of models studied above in comparison with traditional pure financial models. For the first time, linearity in parameters assumption is respected. Adjusted R-squared of model 5.1 is a little bit better than other models. However, this model is less relevant due to the poor number of observations of the director manager annual compensation variable and the SE is higher than before.

4.5.2 Models 5.2 – all independent financial variables except director manager annual compensation variable

Mean dependent var	5.43e+08	S.D. dependent var	2.32e+09
Sum squared resid	3.88e+21	S.E. of regression	8.71e+08
R-squared	0.859140	Adjusted R-squared	0.858920
F(8, 5121)	3904.267	P-value(F)	0.000000

Table 10. Regression general outputs of model 5.2

By removing the director manager annual compensation variable, the model 5.2 has a less restricted sample, it successfully reaches an adjusted R-squared of 86% with only 8 independent variables and it keeps a similar SE than model 4.2. This model also meets the linearity assumption.

Table 11. Regression coefficients of model 5.2

	coefficient	std. error	t-ratio	p-value	
const	3.36659e+06	1.42754e+07	0.2358	0.8136	
CostsemployeesUS~	0.0968084	0.00922053	10.50	1.58e-025	***
TurnoverUSD2019	0.0539208	0.00141520	38.10	6.98e-280	***
RDexpensesUSD2019	-0.163550	0.0276278	-5.920	3.43e-09	***
NbsharesDec2019	0.0127470	0.00188591	6.759	1.54e-011	***
MarketCap2019	0.0156074	0.00111223	14.03	6.36e-044	***
Netdebt2019	0.0980830	0.00300816	32.61	4.61e-212	***
NetProfitUSD2019	0.971756	0.0200846	48.38	0.0000	***
Profitmargin2019	-1.78694e+06	752971	-2.373	0.0177	**

All the independent variables present in model 5.2 are also present in model 4 with more or less the same coefficient. Unfortunately, it means that the added value of non-financial variables is relatively low in model 4. In addition, only the constant and the profit margin variable have a higher SE 4. In consequence, financial coefficient values are more reliable in general compared to non-financial ones.

4.6.1 Models 6.1 – all independent non-financial variables

Mean dependent var	2.15e+09	S.D. dependent var	5.29e+09
Sum squared resid	5.89e+21	S.E. of regression	3.28e+09
R-squared	0.640354	Adjusted R-squared	0.616071
F(37, 548)	26.37080	P-value(F)	4.72e-98

Table 12. Regression coefficients of model 6.1

In the same manner than with model 5, model 6.1 is a comparative model gathering only non-financial variables. It has a poor adjusted R-squared regarding precedent models, and a large part of this score could certainly be attributed to an overfitting model (37 independent variables included in the model for only 548 observations) but it respects the linearity assumption of OLS. To finish with, it has the highest SE of all models analysed.

4.6.2 Models 6.2 – all independent non-financial variables except director manager academic major variable

Mean dependent var	5.47e+08	S.D. dependent var	2.35e+09
Sum squared resid	1.56e+22	S.E. of regression	1.80e+09
R-squared	0.418028	Adjusted R-squared	0.413344
F(39, 4846)	89.25275	P-value(F)	0.000000

Table 13. Regression coefficients of model 6.2

The model 6.2 uses all the non-financial variables, except the director manager academic major that restricts the sample. The adjusted R-squared is very low and is worse than model 6.1, even if the SE is slightly better than model 6.1. These bad scores translate the difficulty to draw a good model including only non-financial items.

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4.7.1 Models 7.1 – all independent variables

Mean dependent var	3.02e+09	S.D. dependent var	6.96e+09
Sum squared resid	1.82e+20	S.E. of regression	9.62e+08
R-squared	0.984334	Adjusted R-squared	0.980914
F(43, 197)	287.8566	P-value(F)	6.2e-156

Table 14. Regression coefficients of model 7.1

To conclude this analysis, model 7.1 takes all the independent variables present in the sample. In the same way as previous models with restraining variables such as except director manager academic major variable and director manager annual compensation variable, adjusted R-squared is very high because of the overfitted model (43 variables for only 197 observations). We observe that it met the linearity assumption.

4.7.2 Models 7.2 – all independent variables except the two most restraining variables

Mean dependent var	6.31e+08	S.D. dependent var	2.58e+09
Sum squared resid	2.89e+21	S.E. of regression	8.61e+08
R-squared	0.889771	Adjusted R-squared	0.888895
F(31, 3900)	1015.513	P-value(F)	0.000000

Table 15. Regression coefficients of model 7.2

The model 7.2 removes the two most restraining variables in terms of valid values. According to the general outputs, this model has a similar adjusted R-squared than model 4.2, a bigger SE and more variables. Then, there is no specific interest to explore further model 7.2.

4.7.3 Models 7.3 – all independent variables except the two most restraining variables and countries related variables

Mean dependent var	5.93e+08	S.D. dependent var	2.47e+09
Sum squared resid	2.99e+21	S.E. of regression	8.35e+08
R-squared	0.886486	Adjusted R-squared	0.885983
F(19, 4282)	1760.018	P-value(F)	0.000000

Table 16. Regression coefficients of model 7.3

With the same reasoning, model 7.3 is equivalent to model 4.2 in terms of adjusted R-squared and SE, but it uses more variables to achieve this result.

4.8 Model 8 – same model as model 4.2 but sample of companies with a limited EBITDA of 1 billion USD

Mean dependent var	1.28e+08	S.D. dependent var	2.04e+08
Sum squared resid	4.78e+19	S.E. of regression	1.04e+08
R-squared	0.741993	Adjusted R-squared	0.740706
F(22, 4409)	576.3506	P-value(F)	0.000000

Table 17. Regression general outputs of model 8

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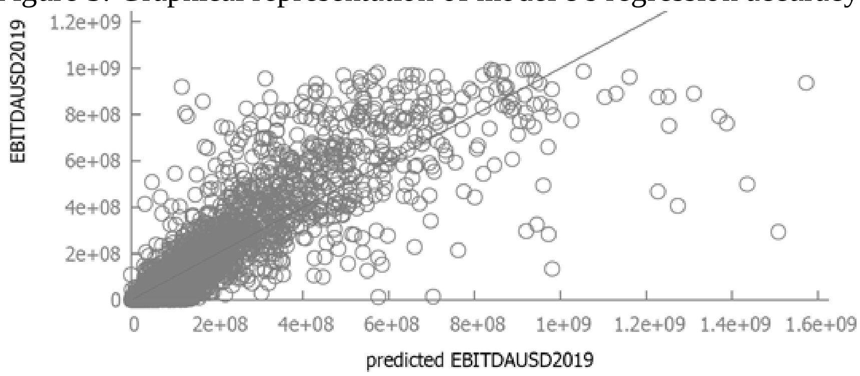
Finally, this last model tried to solve one of the main defaults of model 4.2: reduce large errors that seems related to high EBITDA. We selected the same variables as model 4.2 but only EBITDA inferior to 1 billion USD is present in the sample used. Adjusted R- squared is disappointing regarding what was achieved in model 4.2 but there is a significant improvement of SE as expected.

Figure 5. Graphical representation of model 8's regression accuracy



This representation of model 8 regression gives a more comprehensive view of residuals. Even if the SE is lower in this model, EBITDA are also lower in comparison to model 4.2. Thus, SE is still very high proportionally to EBITDA.

4.9 What lesson should be drawn from these models?

A total of 14 models were built during the analysis of the dataset in order to cover all of the most relevant gathering of data. Some models were created to overcome missing values of the sample, others were created to separate financial and non-financial data or to optimize the findings. The final objective was to find an ultimate model that could predict EBITDA with the less significant error but also to interpret the coefficient attached to each independent variables to draw concrete conclusions that could be applied in real business operations. Model 4.2 is the best model found but its answer to the original question is nuanced. It gives much information about which variables are related to EBITDA and in which direction they influence EBITDA but it only gives an idea of their impact on EBITDA. Coefficients cannot clearly weight the power of parameters as shown by SE. Nevertheless, this paper hopes to open the door to a new way of thinking valuation and to take the first step towards the simplification of financial diagnostic.

5. Discussion

5.1 Conclusions and practical recommendations

The most complete regression model with the best statistics is named model 4.2. It includes sixteen variables: 8 financial variables and 8 non-financial variables. Regarding the objective of generalizing valuation for all, the intended result is achieved because it requires only 16 general variables that require quite accessible data. However, the analysis of the pure financial model 5.2 and the accuracy failure of the pure non-financial model 6.2 proves that financial variables are explaining the great majority of the overall relationship with EBITDA. Therefore, the mix of

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non-financial and financial data is not really a success due to the poor significance of non- financial information.

According to the research of Sievers, Mokwa and Keienburg (2013), the present results are great. They found indeed an adjusted R-squared of 62% when they tried to establish the value of a company through a mix of financial and non-financial data. Our valuation model reached a score of 88%. This study reaches a good accuracy score, even if errors can be very important in some situations and models are not in line with all OLS conditions. Regression models are by definition a statistical tool and do not forget to take a step back before making a conclusion based on this analysis. In the same way, keep in mind that EBITDA is a controversial measure: it is a non-GAAP measure and companies are sometimes sharing an adjusted version of it to embellish their results (Bouwens et al., 2019).

5.2 Limitations and future directions

Perhaps a more accurate regression equation with smaller errors would have been calculated if the study was divided in intervals. Therefore, extreme values would not have influenced the regression coefficients. Miloud, Aspelund and Cabrol (2012) said that even if valuation is a widespread topic in finance, it must be acknowledged that traditional methods were not developed for all companies, and it is the case here. The high SD translates indeed a difficult sample to fit in one model. However, the study would have created a complex result, not general enough to reach the "easy to use" initial goal.

Unfortunately, the sample used for building the regression equation was not optimal. For instance, few variables did not have as many observations (like DM compensation) as the others and some characteristics have been overrepresented (like US companies). This unequal repartition has negatively impacted the regression accuracy. Also, some observations were not updated recently (some chairmen were no longer at the company). It is also regrettable that non- financial databases are poor in quantity of information and in number of variables.

This paper promotes current and future research about non-financial variables that could explain at least a part the remaining 12% of the EBITDA independent variable according to model 4.2. Millions of non-financial characteristics that can define a company still exist. In addition, this study also supports all research that will try to make a similar model but in a restricted geography, with only one type of industry or in a specific range of EBITDA to avoid a too important dispersion of data. In a similar way, the problem of the investment choice with several parameters could be analysed with a decision tree or a random forest, as it was done by Madaan, M. et al (2021) regarding loan agreement.

Recently, more and more literatures have been mentioning EVA like Steward (2019). It is less prevalent than EBITDA in financial works, but it is a very relevant indicator. It measures in the same time cost of debt (like it is done by the net profit) and cost of equity. Then, in the view of both an external investor or executive manager, EVA tells what is exactly the threshold at which a company is creating value for itself, after having paid all creditors and shareholders.

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Table of acronyms and abbreviations

CEO – Chief Executive Officer
DCF – Discounted Cash Flow
DF – Degree of Freedom
DM – Director Manager
EBITDA – Earnings Before Interest, Taxes, Depreciation and Amortization
EM – Enterprise Multiple
EV – Enterprise Value
EVA – Economic Value Added
FCF – Free Cash Flow
GDP – Gross Domestic Product
M&A – Merger and Acquisition
NWC – New Working Capital
Nb – Number
OLS – Ordinary Least Squares
PE – Private Equity
R&D – Research and Development
ROI – Return On Investment
SE – Standard Error
SD – Standard Deviation
USD – United States Dollars
VC – Venture Capital
VIF – Variance Inflation Factor
WACC – Weighted Average Cost of Capital

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