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B2B Credit Risk Management

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Dissertation presented as partial requirement for obtaining the Master’s degree in Statistics and Information Management

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B2B CREDIT RISK MANAGEMENT: A PROPOSAL FOR EXPECTED CREDIT LOSSES (CECL) MEASUREMENT AND IMPLEMENTATION UNDER THE NEW FINANCIAL ACCOUNTING STANDARDS

by

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ABSTRACT

Since the latest global financial crisis there is an increase importance in the role of lending market, specially by policy interest and bank regulation. In this article it is proposed a methodology to implement credit risk assessment to estimate the expected credit losses on trade account receivable for B2B companies as it is required by the new accounting standard CECL (Current Expected Credit Loss). The EL (Expected Loss) calculation is the multiplication of PD (Probability of default), by LGD (Loss Given Default) and EAD (Expected at Default). The main focus of this study is the estimation of probability of default with the use of logistic regression model to a dataset from around 350 companies in the Automotive Aftermarket Parts sector in Portugal. The model proposed showed the most significant financial ratios and other qualitative variables in predicting the entities´ credit worthiness with 86.8% of accuracy, 31.7% of sensitivity and AUC of 74.2%. An additional objective is, with the model result, support the B2B companies not only comply with CECL but also better assess the customer's creditworthiness and therefore develop a sound credit risk policy and management.

KEYWORDS

Bad debt; Credit risk; Trade Receivables; Probability of default; Scoring.

INDEX

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

ACAP	Associação Automóvel de Portugal
AIC	Akaike Information Criterion
ALLL	Allowance for Loan and Lease Losses
ASU	Accounting Standards Update
AUC	Area Under the ROC Curve
B2B	Business to Business
CAE	Código de Atividade Económica
CECL	Current Expected Credit Losses
DPAI	Divisão do Pós Venda Automóvel Independente
DSO	Days Sales Outstanding
EAD	Exposure at Default
EL	Expected Loss
FASB	Financial Accounting Standard Board
IRB	Internal Risk Base
LGD	Loss Given Default
OECD	Organization for Economic Co-operation and Development
PD	Probability of Default
ROC	Receiver Operating Characteristic Curve
SME	Small and Medium-sized Enterprises
SOB	Share of Business

1. INTRODUCTION

The critical role of the lending market (consumer credit, mortgages, credit cards) in the latest global financial crisis has increased academic research, policy interest, and bank regulation in this area. The banking regulatory framework changes, brought by the revised Basel Committee on Banking Supervision (BCBS) Accords (later adopted by national legislation in many countries and regions, for instance, the European Capital Requirement Directives and the US Regulatory Capital Rules) introduced stronger risk management requirements for banks, with capital requirements tightly coupled to estimated credit portfolio losses (Ashofteh & Bravo, 2019, 2021; Richard Chamboko & Bravo, 2020).

The Financial Accounting Standards Board (FASB) issued, on 16 June 2016, an Accounting Standards Update (ASU) that improves financial reporting by requiring timelier recording of credit losses on loans and other financial instruments held by financial institutions and other organizations.

The recently adopted IFRS9 and FASB's Current Expected Credit Loss (CECL) standards introduce revised expected credit loss or impairment calculation rules requiring financial institutions to calculate expected loss for the banking book over the entire life of the exposures, conditional on macroeconomic factors, on a point-in-time basis, that is, recalibrating PDs where necessary to reflect the effects of the current economic conditions. The new standards replace the current Allowance for Loan and Lease Losses (ALLL) accounting standard. New standards focus on the estimation of expected losses over the life of the loans, while the current standard relies on incurred losses. To estimate expected credit losses under CECL, institutions will use a broader range of data than accepted today by accounting principles (GAAP and IFRS9). These data include information about past events, current conditions, and reasonable and supportable forecasts relevant to assessing the collectability of the cash flows of financial assets (FASB, 2016).

The new standard affects all organizations that hold financial assets and net investments in leases that are not accounted for at fair value with changes in fair value reported in net income. It has different effective dates based on the type of reporting entity. Public business entities that file financial statements with the Security and Exchange Commission will have to comply by 2020, and smaller publicly traded banks must adopt the new standard by 2023.

As discussed by KPMG in its report when FASB announced an accounting standard update for the treatment of credit losses, banks and other financial institutions immediately recognized the significance of the change. As a result, financial institutions started preparing for implementation well ahead of the effective date. Manufacturers, consumer goods entities, and many other corporate entities outside the financial industry are also significantly impacted by this new accounting standard. However, many of these entities have been less proactive about preparing for the change (KPMG, 2019).

CECL may significantly impact how both financial and nonfinancial entities calculate credit loss reserves. However, for non-financial entities, this new approach also requires a major shift in perspective, because for the first time they will need to measure potential credit losses from a forward-looking perspective, in particular related to long-term trade receivables. With little or no experience forecasting or modeling economic conditions, and potentially insufficient data available to do so, corporates are facing a complex challenge to comply with CECL (KPMG, 2019).

Appropriate risk assessment is one of the most important aspects of the activity of financial institutions. The Basel Accords are recommendations on banking laws and regulations and aimed to safeguard the solvency of the banks and overall economic stability. The Basel II Accords (starting in 2004 but implemented in 2008) have incorporated the credit risk of assets held by the financial institution to determine minimal capital requirement, this is the main difference between Basel I and Basel II requirements.

Since 2008 there is a reinforcement of the risk management process in the bank sector, allowing the possibility of internal risk modeling (Internal Rating Base - IRB) in the computation of minimum capital requirements. Encouraged by regulators, banks devoted significant resources to develop an Internal Ratings Based approach (IRB) for the calculation of risk-weighted assets for credit risk to better support decisions when granting loans, to quantify expected credit losses, and to assign the mandatory economic capital (Richard Chamboko & Bravo, 2020).

Part of this approach is to estimate the probability of default, the bank is obliged to prepare a model to estimate the likelihood of insolvency for each loan granted. The other parameters Loss Given Default (LGD) and Exposure at Default (EAD) are provided by the regulation or in the case of Advanced IRB the banks are allowed to estimate all the risk parameters.

In the years since the global financial crisis, financial institutions have made substantial investments to upgrade their risk management programs and comply with ever more demanding regulatory requirements. All these investments can easily justify why the financial sector is more prepared to comply with the new requirements of CECL than the non-financial corporations.

Besides the necessity to comply with CECL, it is undeniable the relevance and importance of good credit risk assessment for non-financial companies. The empirical results obtained in García-Teruel & Martínez-Solano (2010) show, for about 47197 Small and Medium-sized Enterprises (SME) in Europe over 1996-2002 period, that the level of accounts receivable (accounts payable) over assets for the countries considered ranges from 39.28% in Spain (28.52% in France) to 19.18% in Finland.

For most non-financial companies, especially the Business to Business (B2B), credit management is a part of account receivable management. The focus is on collections, cash flow, and DSO (days of sales outstanding). The risk of default is not considered upfront. Instead, the risk is recognized only after the default, which represents an important risk to the company related to the outstanding trade account receivable.

Considering the existence of a credit risk assessment the analysis would be based on a judgmental model, based on soft information, such as, for instance, what is called the “5C Model” – “character”, “capacity”, “capital”, “conditions” and “collateral” of the potential customer applicant – and the final decision is based on the best judgment of the analyst.

Over the past fifty years, bankruptcy prediction has been a field of increasing interest to researchers all around the world. Many academic studies have been dedicated to exploring a corporate failure prediction model with the best accuracy. In a systematic literature review, (Shi & Li ,2019) found over 496 articles from the Scopus database for the period of 1968 – 2017 covering the subject of credit risk management, most of them, 83.5%, during the decade of 2008-2017. As stated by (Gissel, Giacomino, & Akers, 2007), the focus of future research should be on the use of the existing predicting models and if necessary, refined, since many of which have been shown to have high accuracy and predictive power.

To assess credit risk, in developed markets, lenders typically consider historical loan application and loan performance data collected regularly from a small number of sources based on long-standing banking and credit relationships to develop credit-scoring models to evaluate the ability to repay, the willingness to repay, and identify fraud. These methods are less effective in emerging economies and among low-income unbanked segments of the population and motivated the increasing of non-traditional data sets (e.g., mobile operators, utilities, retailers, and direct-sales companies' data) to sophisticate their credit bureaus and credit rating services (Ashofteh & Bravo, 2021a).

The primary intention of this study is to analyze the methodologies and models available on credit losses prediction and to find the most appropriate for non-financial corporations, with a focus on B2B business models where most of the customers are SMEs, aiming to estimate the expected credit losses under CECL requirements.

The EL will be calculated considering the combined effect of the PD, the LGD and the EAD, as follows:

$$EL = PD \times LGD \times EAD \tag{1.1}$$

There are several models to estimate the PD. The present study will explore logistic regression, as it assumes that predicted outcomes are a linear function of the predictors through a logit transformation, it is the most used methodology to estimate PD.

With regard to LGD, which is also a very important measure to estimate regulatory capital under Basel II, the number of studies on recovery has been relatively low, most of them studying the importance of factors that affect LGD, like contract and borrower characteristics, and industry and macroeconomic conditions, regarding modeling methodologies, there are just a few (Qi & Zhao, 2011).

The Basel Committee, in its consultative document ("Basel Committee on Banking Supervision Consultative Document The Internal Ratings-Based Approach," 2001), stands that under the foundation methodology, LGD is estimated through the application of standard supervisory rules, which differentiate the level of LGD based upon the characteristics of the underlying transaction, including the presence and type of collateral. The supervisory rules and treatments were chosen to be conservative. The starting point proposed by the Committee is the use of a 50% LGD value for most unsecured transactions, with a higher LGD (75%). In this study, it is going to be applied the use of 50% LGD, since it is considered appropriate to the sample analyzed.

EAD is the total value an institution is exposed at the default moment. Banks often calculate an EAD value for each loan and then use these figures to determine their overall default risk. For the B2B case, the EAD is the value of the account receivable for each customer. The biggest difference compared with banks is that the balance has a different dynamic, since the customer is, at the same time, paying the bills and issuing another bill (buying new goods), which can keep the value flat, higher, or smaller compared with the last value reported.

The additional goal of this study is, after the development of the models within the estimation of the expected loss, is to suggest a scoring system to classify the customer's creditworthiness and to provide B2B companies enough information to build a sound credit risk management framework.

This study is structured as follows. The first section presents reviews of the research literature about credit risk and scoring models with special attention to SMEs and the B2B studies. In the second section, it describes the methodology starting with the presentation of the main characteristics of the Automotive Aftermarket Industry in Portugal, focusing on tires and spares parts dataset and then the estimation of the model necessary to predict expected loss. The third section presents and discusses the empirical results and makes suggestions about credit management and credit policy for B2B companies. The last section concludes.

2. LITERATURE REVIEW

2.1 CREDIT RISK AND SCORING MODELS

Financial institutions can use external scoring or rating assessment from specialized agencies; however, they are applicable only for large companies. In most cases, an internally developed risk assessment method (*Internal Rating Approach*) is used. The use of the bank's own rating boards, called master scales, is a common practice. Entities with low risk levels are grouped and assigned to one rating class. Each rating class has a top and bottom threshold expressed by the default probability.

A wide range of statistical techniques are used in building the scoring models, most of these statistical, and some of those non-linear. Models are applicable to build an efficient and effective credit scoring system that can be effectively used for predictive purposes. Traditional credit-scoring models applying single-period classification techniques (e.g., logit, probit) to classify credit customers into different risk groups and to estimate the probability of default are still the most popular data mining techniques used in the industry (Chamboko & Bravo, 2019a,b).

Since then, several techniques have been developed to help decision-makers and analysts in predicting financial failure by considering both traditional statistical methods and more sophisticated (e.g., advanced machine learning) modeling approaches and alternative sets of predictor features. Standard models using external ratings provided by external credit assessment institutions have also been successfully applied. The set of classification algorithms used in credit scoring includes individual classifiers and homogeneous and heterogeneous ensembles (Ashofteh & Bravo, 2021a).

Individual classifiers employing single statistical or operational research methods include techniques, such as weight of evidence measure, regression analysis, discriminant analysis, probit analysis, logistic regression, linear programming, Cox´s proportional hazard model. Classifiers using machine learning methods include neural networks (NN), support vector machine (SVM), decision trees (DT), genetic and evolutionary algorithms (GA), k-nearest-neighbor (KNN), and genetic programming (GP), are all widely used techniques in building credit scoring models by credit analysts, researchers and lenders (Abdou & Pointon, 2011; Chamboko & Bravo, 2016; 2019a,b; Jones & Hensher, 2004).

A study made by (Abdou & Pointon, 2011) extensively reviewing 214 articles, books, and thesis in credit scoring emphasizes that there is no ideal credit scoring modeling procedure, which would guide the analyst in the choice of specific variables, cut-off score, validation method, and sample size. What is best depends on the details of the problem, the structure of the data, the features of the application. Furthermore, a comparison between different statistical approaches demonstrates that sophisticated techniques, such as neural networks, and genetic programming perform better than more conventional techniques, such as discriminant analysis and logistic regression, in terms of their higher predictive ability. However, the results of some studies revealed that the predictive capabilities of both approaches were sufficiently similar to make it difficult to distinguish between them.

Historically, the dominant methods used to establish scoring models and similar phenomena with binary explanatory variables were discriminant analysis, like the well-known Z-Score (Altman, 1968) and logistic regression. Over time, with the development in computer technology and capacity, logistic regression became the most widely used tool for building scoring models.

The popularity of logistic regression resulted from, among others, the reliability of estimations based on the available scope of data and the range of probability results contained within the range 0 to 1, which simplifies the interpretation of the phenomenon that is being explained. The logit model range conveniently gives the probability of default of the client and the estimated coefficients can be interpreted separately as the importance or significance of each of the independent variables in the explanation of the estimated probability of default.

(Ohlson, 1980) applied the conditional logit model to the default prediction study for the first time. Professor Altman and Sabato (Altman & Sabato, 2007) developed a distress prediction model specifically for the SME sector using a logistic technique and compares the results with other models, principally the discriminant analysis (Z-Score).

The present study attempts to address the evaluation of SMEs' performance based on financial ratios analysis. Comprehensive discussions on the corporate performance evaluation framework through the use of financial ratios can be found in (Barnes, 1987), where he identifies two main uses of financial ratios. The traditional use of measurement of a firm performance compared with the standard within the industry and for predictive purposes.

2.2 SMEs and the B2B Sector

Across the OECD (Organization for Economic Co-operation and Development economies), SMEs account for 99% of all businesses and between 50% and 60% of the value added. Almost one person out of three is employed in a micro firm with less than 10 employees and two out of three in an SME (*OECD SME and Entrepreneurship Outlook 2019 Policy Highlights*, 2019).

Credit risk is the most important financial risk inherent in nearly all institutions, financial or non-financial. The B2B entities have mostly SMEs as customers, therefore special attention must be addressed to this reality.

It is important to show the significance of modeling the credit risk of SMEs separately from that of large corporations. Only a few studies focused on modeling credit risk specifically for SMEs: (Edmister, 1972) analyzes 19 financial ratios and, using multivariate discriminant analysis, develops a model to predict small business defaults. (Altman & Sabato, 2007) develop a distress prediction model specifically for the SME sector and analyze its effectiveness compared to a generic corporate model. Other authors as (Voulgaris, Doumpos, & Zopounidis, 2000) with the application of a multiple criteria decision aid method (UTADIS - UTilités Additives DIScriminantes) developed a decision model that classifies the SMEs into performance ratings.

Regarding credit risk on customers of B2B Market, there are also a few studies, (Yuan & Yang, 2012) made a model by selecting customers' credit risk indicators of the domestic textile industry on the electronic trading market in China using factor analysis method, clustering method, and ordered-logit model, they found an easy model to use for its linearity and good reference value for the classification of customers credit risk.

3. METHODOLOGY

3.1. DATA – AUTOMOTIVE AFTERMARKET PARTS INDUSTRY

This study is based on information from around 350 companies in the Automotive Aftermarket Parts sector in Portugal. The data is a complete set of financial statements over the period 2012 – 2019 (Informa D&B) and the history of a trade account receivable dataset of the same companies over the same period. The source is a tire supplier under a disclosure agreement. The purpose is to analyze the payment behavior and the most significant variables to construct a default prediction model.

All data collected is treated and cleared with the use of Tableau® Prep Builder. The dashboards and graphics are produced with the use of Tableau® Desktop. The statistical procedure is processed with R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria https://www.R-project.org/.

The portfolio considered is mostly of SME (95.1%) and, considering the definition given by the EU (EU recommendation 2003/361), the dataset decomposes as shown in Table 3.1:

Company category	Staff headcount	Turnover	or	Balance sheet total	Portfolio
Micro	< 10	≤ € 2M		≤ € 2M	70,6%
Small	< 50	≤ € 10M		≤ € 10M	14,8%
Medium-sized	< 250	≤ € 50M		≤ € 43M	9,7%
					95,1%

Table 3.1 - SME Category and Portfolio

Although the information refers to around 350 entities, not every entity has the data for every single year for both sources, financial information, and payment behavior historical. The entities considered were those where it was possible to find both information for each year. Since it was not possible to see the evolution of every entity throughout the years, the data was considered as a panel of 2370 entries.

Further exploring the dataset, it is mandatory to see if the information collected by the sample is representative of the Portuguese aftermarket reality. To better know and understand the market there is a report provided by *Associação Automóvel de Portugal* (ACAP) and its special department *Divisão do Pós Venda Automóvel Independente* (DPAI) where it can be found the financial information of retail market of spares, tires and mobility service called *Observatório do Pós Venda* ("DPAI | Mercado Estatistica," n.d.). It is published annually since 2014 and represent the total number of entities with economic activity code (*CAE - Código de Atividade Económica – Pós Venda Automóvel Independente 453, 45310, 45320, 45200)* related to Automotive Aftermarket.

The report shows the evolution of the number of entities, turnover, and financial management ratios as an aggregated number and it is an important benchmark to further compare our results and findings.

As suggested by the report and to be aligned with the definition of EU, the portfolio is classified by the turnover volume, from A to H (Table 2). For the portfolio considered it is necessary to add two extra groups compared with the ACAP table, group G "from 10M € to 50M €" and group F "Above 50M €". There is also a small change on Group F called Small Business (from 2.5M€ to 10M€).

ACAP

Group	Turn Over	2014		2019	
A	until 125k€	335	**32%**	290	**26%**
B	from 125k€ to 250k€	249	**24%**	240	**22%**
C	from 250k€ to 500k€	208	**20%**	258	**23%**
D	from 500k€ to 1M€	135	**13%**	169	**15%**
E	from 1M€ to 2,5M€	81	**8%**	100	**9%**
F	above 2,5M€	39	**4%**	42	**4%**
		1047		**1099**	

Portfolio

Group	Turn Over	2014		2019	
A	until 125k€	11	**3%**	3	**2%**
B	from 125k€ to 250k€	45	**14%**	15	**8%**
C	from 250k€ to 500k€	51	**16%**	37	**19%**
D	from 500k€ to 1M€	68	**21%**	38	**20%**
E	from 1M€ to 2,5M€	60	**19%**	38	**20%**
F	from 2,5M€ to 10M€	48	**15%**	29	**15%**
G	from 10M€ to 50M€	27	**8%**	22	**12%**
H	Above 50M	14	**4%**	9	**5%**
		324		**191**	

Table 3.2 - Left table source ACAP – Right table source our dataset

The literature about default prediction methodologies is substantial, but one clarification must be addressed, it is the definition of "failure". In most papers, including (Altman & Lobato, 2007), the definition of failure is filing for bankruptcy or liquidation. In this study, the definition of default will be the inability to pay its financial obligation within the agreed term.

The accounts receivable´s historical dataset has all information regarding billing date, billing due date, and payment date. It is noted that analyzing the data by document will lead to several situations of false default since there are invoices not paid because of pending claims and/or court disputes.

This study finds out that the best way to analyze the payment behavior is through DSO, where we take into consideration the yearly average account receivable balance of the customer and the total purchase value of the year.

$$\mathrm{DSO} = 360 \text{ x } \frac{\text{Account Receivable Average}}{\text{Annual Purchase}} \tag{3.1}$$

Knowing that the tire supplier doesn´t practice terms above 90 days (as standard) and even with installments campaigns, rarely one could have more than 120 days as average as an approved term. Also knowing that the allowance (before CECL) for bad debt calculation is made after 90 days past due, it is assumed that a customer defaults when its DSO value is higher than 180 days. The dummy variable is created as follows: "1 = default" and "0 = not default".

The table below shows the distribution of the results of the calculation of the DSO by year. The average of DSO above 180 days is 12%, the lowest value is 9% in 2012 and the highest is 15% in 2015. It is important to note that, on average, 47% of the DSO is lower than 60 days.

DSO	2012	2013	2014	2015	2016	2017	2018	2019	Total	%
Negative	7	10	11	5	10	17	9	4	73	3%
0-30	48	70	43	59	50	37	36	24	367	15%
30-60	93	105	92	83	91	77	80	71	692	29%
60-90	84	62	74	69	65	59	50	38	501	21%
90-120	34	39	37	30	45	38	31	21	275	12%
120-180	30	20	22	27	22	25	18	10	174	7%
>180	**30**	**34**	**45**	**32**	**44**	**45**	**35**	**23**	288	12%
Total	**326**	**340**	**324**	**305**	**327**	**298**	**259**	**191**	**2370**	
>180/ total	9%	10%	14%	10%	13%	15%	14%	12%	12%	

Table 3.3 - DSO -Days Sales Outstanding distribution

3.2 SELECTION OF THE RATIOS

Based on the profile of the portfolio, the present paper begins exploring the methodologies proposed for SMEs. The approach of the model is to analyze a complete set of financial ratios and identify the most predictive variables affecting the creditworthiness of the entity. Besides the financial ratios, other variables are considered since the use of these variables may improve the model as those predictors can better discriminate against all types of SMEs.

There is a special ratio called SOB – Share of Business, this ratio indicates the level of partnership between the tire supplier and the after-market entity. It is computed with the tires sales value by year reported by the tire company divided by the cost of goods reported by each entity. This ratio is not considered in Table 3.4, since it is a mix of internal data of the tire company with the entities analyzed.

About the financial ratios, four categories describe the most important aspects of the financial health of the companies: liquidity, activity/efficiency, leverage/coverage, and profitability. There are many possible candidates' ratios as useful to predict firms' default, based on the literature explored above, it is chosen 11 different ratios among the 4 categories.

In Table 3.4 there are four columns, the category, the ratio formula, the ratio name, and the expected impact of the variation of the ratios in the model. Important to note that there is a ratio also called DSO, but in this case, it is the average number of days that it takes the entities, not the tire supplier, to collect payment for a sale.

Ratio Category	Ratio Formula	Ratio Name	Expected Impact
Liquidity	Cash + Net Receivables / Current Liabilities	Quick Ratio / Acid Test	+
	Current Asset / Current Liabilities	Current Ratio	+
Activity / Efficiency	Account Receivable / Total Sales *360	DSO	-
	Cost of Goods / Inventory	Inventory Turnover	+
	Sales / Total Assets	Asset Turnover	+
Leverage / Coverage	EBIT / Interest Expenses	Interest Coverage Ratio	+
	Equity / Total Asset	Equity Ratio	+
	Equity / Total Liability	Equity to Debt Ratio	+
Profitability	Net Income / Sales	Net Profit Margin	+
	Net Income / Assets	Return on Assets	+
	(Sales - Cost of goods) / Sales	Gross Profit Margin	+

Table 3.4 - Financial Ratios – Variables Selection Process

3.3 DATA EXPLORATION

The dataset provides additional qualitative information, as the hierarchy of each entity. There are Car Dealers (companies that sell new or used cars and provide maintenance service), Distributor (multibrand tires distributor), Fleets (companies that own fleets of cars or commercial vehicles for renting purposes), Retail Competition (car repair shops affiliated with a competition brand), Retail Franchise (car repair shops affiliated with the brand owner of the data) and Retail Independent (car repair shops with no affiliation to any brand). Another important information is available, the number of employees of each company.

Note that SMEs might be somewhat arbitrarily classified as either small or medium sized firms using either sales or assets as the size criteria. In this study the entities are split by size using the value of sales, eight classes were created as indicated in Table 3.2.

After preprocessing the data, some transformations became necessary. For instance, the Group H, referred in Table 3.2 composed with entities with more than €50M of turnover, was not considered in the model, since those entities are not considered SMEs, the focus of this work. Important to highlight it that the fleets have a particular business type, the ratios must be seen with a different approach and cannot be comparable with the other business as retail, distributors, and car dealers. Fleets are services providers and do not sell goods. There is no stock and the ratio share of the business is not applicable for this hierarchy. For those reasons, the fleets were also not considered in the model.

For the outliers, some of them were not considered in the dataset, as the negative DSO or values positive but due to a negative numerator and denominator (account receivable and sales). The "NA" values were replaced by the average of the variable in order to not impact the results of the analysis.

Removing entities with sales above 50M, fleets and the outliers the number of entities was reduced to 1924, and the level of loss of the portfolio was reduced from 12% to 7.3%. Table 3.5 summarizes the main characteristics of the variables considered.

Variables		Summary					
Numerical		**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
	Gross.Profit.Margin	-2,885	0,174	0,260	0,263	0,338	1,000
	Return.on.Assets	-65,566	0,000	0,110	-0,030	0,039	1,000
	Net.Profit.Margin	-1,260	0,000	0,008	-0,005	0,028	0,620
	Interest.Coverage.Ratio	-263168	0,000	3,000	5999	17,00	6153691
	Asset.Turnover	0,08	0,84	1,29	1,90	1,99	145,29
	Inventory.Turnover	0,07	1,98	3,77	8,71	6,30	2024,89
	Current.Ratio	0,00	1,01	1,49	2,08	2,40	29,25
	DSO	-0,83	28,44	64,78	85,51	117,72	916,47
	Quick.Ratio	0,00	0,41	0,82	1,14	1,39	17,70
	Equity.Ratio	-3429,10	13,99	30,66	26,54	50,42	100,00
	Equity.to.Debt.Ratio	-97,17	16,19	44,08	91,44	101,00	2579,24
	Employees	0,00	4,00	7,00	15,88	15,00	424,00
	SOB	0,00	0,01	0,04	0,11	0,14	0,97
Factors		**Qt**		**%**		**%Default**	
Sales.Interval	1 Until 125K	66		3,4%		16,7%	
	2 From 125K to 250K	256		13,3%		5,9%	
	3 From 250K to 500K	382		19,9%		8,4%	
	4 From 500K to 1M	416		21,6%		6,5%	
	5 From 1M to 2.5M	349		18,1%		8,3%	
	6 From 2.5M to 10M	287		14,9%		5,9%	
	7 From 10M to 50M	168		8,7%		6,0%	
H0 - Hierarchy	Car Dealer	269		14,0%		4,5%	
	Distributor	67		3,5%		0,0%	
	Retail Comp	350		18,2%		4,9%	
	Retail Franchise	217		11,3%		3,7%	
	Retail Indeped	1021		53,1%		10,2%	
Dependent							
Loss	Default	141				7,33%	
	No Default	1783					
Others							
	Loss Average	28532,24					
	Acc. Receivable Average	34040,20					
	Sales Average	131832,23					

Table 3.5 - Summary of the variables considered in the model

The above summary provides evidence of the variables relevant to the model, the categorical variables *Sales Interval*, with its group *1 Until 125K* showing a default level of 16.7%, more than two times higher than the portfolio average. Also, the category *H0 – Hierarchy*, with its group *Distributor* with a default rate of 0%.

Some of the financial ratios show a wide dispersion, especially the *Interest Coverage Ratio*, *Equity Ratio* and *Equity to Debt Ratio.* Since the values considered outliers have already received treatment, we must evaluate the impact of such dispersion in the model and evaluate the necessity to make a log transformation, in other words to reduce or to remove the skewness of our original data.

3.4. MODEL DEVELOPMENT

This section develops the model to predict the probability of default.

3.4.1. Estimating PD

The statistical model is built using classical statistical models, primarily logistic regression.

Binary responses are commonly studied in many fields, examples include presence of diseases, a decision of a consumer to buy a product or a situation of a possible default. The purpose of the analysis is to study how a set of predictor variables X is related to a dichotomous response variable Y. It is defined the response to be Y=0 or Y=1, with latter denoting the occurrence of the event of interest. Often a dichotomous outcome can be studied by calculating proportions of the sample, for example the proportion of the defaults within a portfolio of customers.

Letting X denote the vector of predictors $\{X_1, X_2, \ldots, X_k\}$, a first attempt at modeling the response would use the ordinary linear regression model

$$E(Y|X) = X\beta, \tag{3.2}$$

since the expectation of a binary variable Y is Prob(Y = 1). However, such a model by definition cannot fit the data over the whole range of the predictors since a purely linear model E(Y|X) = Prob(Y = 1|X) = X β can allow Prob(Y = 1) to exceed 1 or fall below 0. The statistical model that is generally preferred for the analysis of binary responses is instead the binary logistic regression model, stated in terms of the probability that Y = 1 given X, the values of the predictors:

$$Prob(Y = 1|x) = [1 + \exp(-X\beta)]^{-1}, \tag{3.3}$$

As before, Xβ stands for β0+β1X1+ β2X2+…+ βkXk, and P stands for f(x) the regression parameters β are estimated by the method of maximum likelihood, see the function below:

$$P = [1 + \exp(-x)]^{-1}, \tag{3.4}$$

This function is called a logistic function and it is plotted in Figure 1. This function has an unlimited range for x while P is restricted to range from 0 to 1.

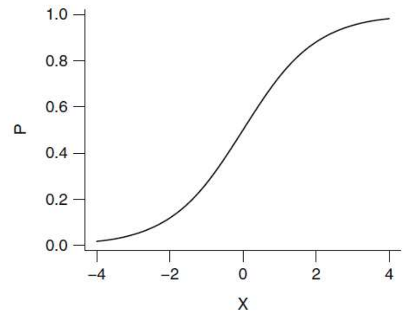

Figure 3-1 – Logistic Function

For future derivations it is useful to express x in terms of P. Solving the equation above for x by using

$$1 - P = \exp(-x)\,/[1 + \exp(-x)] \tag{3.5}$$

yields the inverse of the logistic function:

$$x = \log\left[\frac{P}{1-P}\right] = \log[odds\ that\ Y = 1\ occurs] = logit(Y = 1). \tag{3.6}$$

Since the logistic model is a direct probability model in terms of Prob{Y = 1|X}, it is only assumptions relate to the form of the regression equation. These assumptions are most easily understood by transforming Prob(Y=1) to make a model that is linear in Xβ:

$$\begin{aligned} logit(Y = 1|X) = logit(P) = \log\left[\frac{P}{1-P}\right] \\ = X\beta, \end{aligned} \tag{3.7}$$

where P = Prob(Y = 1|X). Thus, the model is a linear regression model in the log odds that Y = 1 since logit(P) is a weighted sum of the Xs. If all effects are additive, the model assumes that for every predictor Xj, where j assume 1, 2, …, k.

$$\begin{aligned} logit(Y = 1|X) = \beta_0 + \beta_1 X_1 + \cdots + \beta_j X_j + \cdots + \beta_k X_k \\ = \beta_j X_j + C, \end{aligned} \tag{3.8}$$

where if all other factors are held constant, C is a constant given by

$$C = \beta_0 + \beta_1 X_1 + \cdots + \beta_{j-1} X_{j-1} + \beta_{j+1} X_{j+1} \ldots + \beta_k X_k \tag{3.9}$$

The parameter β_j is then the change in the log odds per unit change in X_j if X_j represents a single factor that is linear and does not interact with other factors and if all other factors are held constant. Instead of writing this relationship in terms of log odds, it could just as easily be written in terms of the odds that Y = 1:

$$odds(Y=1|X) = \exp(X\beta), \tag{3.10}$$

and if all factors other than Xj are held constant,

$$odds(Y=1|X) = \exp\left(\beta_j X_j + C\right) \tag{3.11}$$

$$= \exp\left(\beta_j X_j\right)\exp(C).$$

The regression parameters can also be written in terms of odds ratios. The odds that Y = 1 when Xj is increased by d, divided by the odds at Xj is

$$\frac{odds\ (Y=1|X_1, X_2, \dots, X_j, +d, \dots, X_k)}{odds\{Y=1\big|X_1, X_2, \dots, X_j, \dots, X_k\}} \tag{3.12}$$

$$= \frac{\exp\left[\beta_j\left(X_j + d\right)\right]\exp(C)}{\exp\left[\beta_j X_j\right]\exp(C)}$$

$$= \exp\left[\beta_j X_j + \beta_j d - \beta_j X_j\right]$$

$$= \exp\left(B_j d\right).$$

So, the effect of increasing X_j by *d* is to increase the odds that Y=1 by a factor of exp(β_jd), or to increase the log odds that Y=1 by an increment of β_jd. The ratio of the odds of response for an individual with predictor variable values X* compared with an individual with predictors X is

$$odds\ ratio = \frac{\exp(X^{*}\beta)}{\exp(X\beta)} \tag{3.13}$$

$$= \exp\ (X^{*} - X)\beta$$

As exposed above, the logistic model quantifies the effect of a predictor in terms of an odds ratio or log odds ratio. An odds ratio is a natural description of an effect in a probability model since an odds ratio can be constant (Harrell , 2015).

3.4.2. Testing Statistical significance of individual regression coefficients

Like ordinary regression, hypothesis testing is needed, for both single parameter, and multiple parameter tests. The likelihood-ratio test used to assess overall model fit can also be used to assess the contribution of individual predictors to a given model. The likelihood ratio test for a particular parameter compares the likelihood of obtaining the data when the parameter is zero (L0) with the likelihood (L1) of obtaining the data evaluated at the MLE of the parameter.

$$G = -2\ln\left(\frac{L_0}{L_i}\right) = -2(lnL_0 - lnL_i) \tag{3.14}$$

This statistic is compared with a X^2 distribution with 1 degree of freedom. To assess the contribution of individual predictors one can enter the predictors hierarchically, then compare each new model with the previous model to determine the contribution of each predictor (Park, 2013).

Akaike Information Criterion (AIC) determines the relative information value of the model using the maximum likelihood estimate and the number of parameters in the model.

$$AIC = 2\,K - 2\ln\,(L) \tag{3.15}$$

Where K is the number of parameters (independent variables) used and L is the log-likelihood estimate. Given a set of candidate models for the data, the preferred model is the one with the lowest AIC value, since this measure rewards goodness of fit, as assessed by the likelihood function, but adds a penalty term for models with higher parameter complexity, since more parameters means a model is more likely to overfit.

The Wald test can be used to assess the contribution of individual predictors or the significance of individual coefficients in a given model. It is the ratio of the square of the regression coefficient to the square of the standard error of the coefficient, it is asymptotically distributed as a Chi-square distribution. Each Walt test is compared with a Chi-square with 1 degree of freedom (Park, 2013).

$$W = \frac{\beta_j^2}{SE_{\beta j}^2} \tag{3.166}$$

3.4.3. Validation of Predicted Values

When developing models for prediction, the most critical metric regards how well the model does in predicting the target variable on out of sample observations. The process involves using the model estimates to predict values on the training set. Afterwards, compares the predicted target variable versus the observed values for each observation.

Confusion Matrix is a quick way to summarize how well this classifier works. In this table the observed values for the dependent outcome and the predicted values (at a user defined cut-off value) are cross-classified. For example, if a cutoff value is 0.5, all predicted values above 0.5 can be classified as predicting an event, and all below 0.5 as not predicting the event. Then a two-by two table of data can be constructed with dichotomous observed outcomes, and dichotomous predicted outcomes.

		Actual	
		False (0)	**True** (1)
Predicted	**False** (0)	True Negative **(TN)**	False Negative **(FN)**
	True (1)	False Positive **(FP)**	True Positive **(TP)**

Table 3.6 – Confusion Matrix

If the logistic regression model has a good fit, we expect to see many counts in the TN and TP cells, and few in the *FP* and FN cells. There are three main ratios that are often computed from a confusion matrix for a binary classifier:

Accuracy – overall, how often is the classifier correct – (TP+TN)/Total

Sensitivity – when it is True (1), how often it predicts True (1) – TP/(TP+FN)

Specificity – when it is False (0), how often it predicts False (1) – TN/(TN+FP)

Extending the above two-by-two table idea, rather than selecting a single cutoff, the full range of cutoff values from 0 to 1 can be examined. For each possible cutoff value, a two-by-two table can be formed. Plotting the pairs of sensitivity and one minus specificity on a scatter plot provides an ROC (Receiver Operating Characteristic) curve. The area under this curve (AUC) provides an overall measure of fit of the model. The AUC varies from 0.5 (no predictive ability) to 1.0 (perfect predictive ability). Larger AUC indicates better predictability of the model. Points above the diagonal dividing the ROC space represent good classification results (better than random), while points below represent the poor results (worse than random).

4. RESULTS AND DISCUSSION

4.1 RESULTS SIMULATION

To estimate the regression coefficients of the model the maximum likelihood method is used. After testing several sample sizes, a random sample of 50% of the records was considered the most appropriated for the accuracy of the results. First, a logistic regression model was fit to the sample of 962 records, and then this model was applied to the entire original dataset, consisting of 1924 records, to predict the variable *Default*. For the qualitative variables the reference category must be disclosed, for *Sales Interval*, with seven categories, the first one is the reference base *1 – Until 125K* and for the variable H0 – Hierarchy, with five categories, the category *Car Dealer* is the base.

There are two possible combinations of predictive variables, **Model 1** and **Model 2**. The preliminary results, Model 1 in Table 4.1, are collected applying the use of the stepwise procedure (forward and backward) for regression models. The procedure selects the predictive variables through an automatic procedure in which, in each step, a variable is considered for addition to or subtraction from the set of explanatory variables based on some prespecified criterion (e.g., AIC, BIC). The other result considered, called Model 2 (Table 4.2) is a manual selection of the variables considering the preliminary results and the best knowledge of the data summarized before. The comparison of the models is presented in Table 4.3.

The preliminary results proposed by the stepwise procedure are a good indicator of the most relevant variables to the model. All the coefficients follow the expectations and confirm most of the assumptions that can be obtained from the summary of the variables presented in the Table 3.5.

The results can be statistically significant, but they are unbalanced, there is a significant importance given to *SOB* and *H0 – hierarchy - Distributor*. The coefficients are high (negatively), driving the probability to be zero at a minimum value.

Regarding the financial ratios, two ratios were considered significant (P Value <0.05) *Asset Turnover* and *Equity to Debt Ratio*, with the last one showing low relevance due to its coefficient being close to zero. Other two financial ratios may be considered beside presenting P Values >0.05, they are *Gross Profit Margin* and *DSO* with P Values <0.08.

Interesting to note that none of the ratios regarding *Liquidity (Quick ratio and Current Ratio)* were selected. On the other hand, two of four selected ratios are related to *Activity/Efficiency (DSO* and *Asset Turnover).*

The selection proposed by the stepwise procedure, does not look the most effective. Before further additional tests to this model, it was decided to try another combination of predictive variables, find in the Table 4.1 the Model 2 proposal.

Model 1	Variables	Estimate	Std. Error	z value	Pr(>|z|)
Intercept		-0.759	0.693	-1.095	0.274
Numerical					
	Gross.Profit.Margin	-1.283	0.701	-1.829	0.067 .
	Asset.Turnover	-0.494	0.201	-2.457	0.014 *
	DSO	0.003	0.002	1.777	0.076 .
	Equity.to.Debt.Ratio	-0.005	0.002	-2.681	0.007 **
	SOB	-28.240	4.776	-5.913	0.000 ***
Factors					
Sales.Interval	1 Until 125K	Reference			
	2 From 125K to 250K	-1.834	0.634	-2.891	0.004 **
	3 From 250K to 500K	-0.839	0.584	-1.437	0.151
	4 From 500K to 1M	-0.946	0.590	-1.604	0.109
	5 From 1M to 2.5M	-0.837	0.594	-1.410	0.159
	6 From 2.5M to 10M	-2.120	0.666	-3.181	0.001 **
	7 From 10M to 50M	-0.513	0.719	-0.713	0.476
H0 - Hierarchy	Car Dealer	Reference			
	Distributor	-13.530	611.500	-0.022	0.982
	Retail Comp	0.744	0.615	1.209	0.227
	Retail Franchise	3.920	0.853	4.594	0.000 ***
	Retail Indeped	2.009	0.522	3.852	0.000 ***
	Null deviance	555,86 on 961 degrees of freedom			
	Residual deviance	394,07 on 945 degrees of freedom			
	AIC	428.07			
	Fisher Scoring iterations	16			

Table 4.1 – Model 1 – Stepwise Regression Procedure

While running the variables combination, there was an additional motivation to include, at least, one of the ratios of each category, since it is expected to have a broader view of the creditworthiness of each entity. In the Model 2 it was possible to consider, at least, one of the financial ratios of each group and keep the other variables statistically significant. Also, number of *employees* was added, although it is not a financial ratio, it can be considered a reference to *Activity/Efficiency* management as it is *DSO*. Important to note that both has positive signals.

Asset Turnover and *Gross Margin* are still present, with higher estimate β and higher statistical significance. *Equit to Debt* was replaced by *Equity Ratio* also with higher relevance.

Withdrawing the two variables *SOB* and *H0-Hierarchy* allowed the other variables to increase its importance. Further analyses must be addressed to the relation between *SOB* and the entities considered as defaulted. It is possible, due to credit control, that the entities with negative payment behavior have had sales constraint, justifying the low *SOB.*

Model 2	Variables	Estimate	Std. Error	z value	Pr(>|z|)
Intercept		-0.642	0.540	-1.190	0.234
Numerical					
	Gross.Profit.Margin	-1.570	0.676	-2.322	0.020 *
	Asset.Turnover	-0.462	0.148	-3.121	0.002 **
	Current.Ratio	-0.130	0.085	-1.518	0.129 .
	DSO	0.002	0.001	1.655	0.098
	Equity.Ratio	-0.006	0.002	-2.773	0.006 **
	Employees	0.009	0.004	2.166	0.030 *
Factors					
Sales.Interval	1 Until 125K	Reference			
	2 From 125K to 250K	-0.958	0.586	-1.633	0.102
	3 From 250K to 500K	-0.353	0.538	-0.655	0.512
	4 From 500K to 1M	-0.701	0.556	-1.261	0.207
	5 From 1M to 2.5M	-0.344	0.558	-0.616	0.538
	6 From 2.5M to 10M	-1.375	0.643	-2.137	0.033 *
	7 From 10M to 50M	-1.385	0.888	-1.559	0.119
	Null deviance	555,86 on 961 degrees of freedom			
	Residual deviance	509,48 on 949 degrees of freedom			
	AIC	535.48			
	Fisher Scoring iterations	8			

Table 4.2 - Model 2 – Manual Selection of the variables

4.2 RESULTS VALIDATION AND COMPARISON

After the potential combination of variables were presented by the Model 1 and Model 2, it is important to summarize the tests performed for each proposal regarding statistical significance (Table 4.3) and predictive accuracy (Tables 4.4 and 4.5).

Results	AIC	Log-Likelihood
Model 1	428.07	-197.03
Model 2	535.48	-254.74

Table 4.3 - Results Comparison – Statistical Significance

The first two measures, Akaike Information Criterion (AIC) and Log-likelihood, are methods for assessing statistical quality of the models. They are related since AIC is low for models with high log-likelihoods.

The AIC is a scoring for models' comparison relative to each other, meaning that AIC scores are only useful in comparison with other AIC scores for the same dataset. A lower AIC score is better, since its require less information (lower number of independent variables) to predict almost the exact same level of precision. The Log Likelihood value is a measure of goodness of fit for any model, higher the value, better is the model. The preliminary result (Model 1) performed better for both tests, indicating that it is the model with the best relative quality, now it is important to analyze the classification regarding accuracy.

Firstly, we set the threshold of this Confusion Matrix as 0.5, this is the cut-off to classify all the values greater than threshold as 1 and lesser than that as 0.

		Confusion Matrix - Cut-off = 0,50		
Results	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Model 1	0.925	0.050	0.983	0.742
Model 2	0.937	0.000	0.999	0.672

Table 4.4 - Confusion Matrix – Cut-off 0.5

Both models proposed by the Model 1 and Model 2 showed high accuracy, above 92%, although with zero sensitivity power, meaning a high level of type II error, which means that the models are failing to identify true defaults.

To better understand the ability of the models to identify the true positives, the cut-off of the confusion matrix was reduced to 0.25, find the results in the Table 4.5.

		Confusion Matrix - Cut-off = 0,25		
Results	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Model 1	0.868	0.317	0.905	0.742
Model 2	0.925	0.033	0.984	0.672

Table 4.5 - Confusion Matrix – Cut-off 0.25

In reducing the threshold there is a trade-off between accuracy and sensitivity, the Model 1 increased its ability to identify the true defaults, while this effect is smaller in the Model 2.

The ROC curve shows the trade-offs between sensitivity and specificity, the curve plots the two parameters true positive and false positive rates. AUC provides an aggregate measure of performance across all possible classification thresholds, the higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes. The Model 1 presented the highest result 0,742.

In general, an AUC of 0,5 suggests no discrimination between default and not default, while an AUC between 0,70 and 0,80 is considered acceptable, above 0,8 is considerable excellent result.

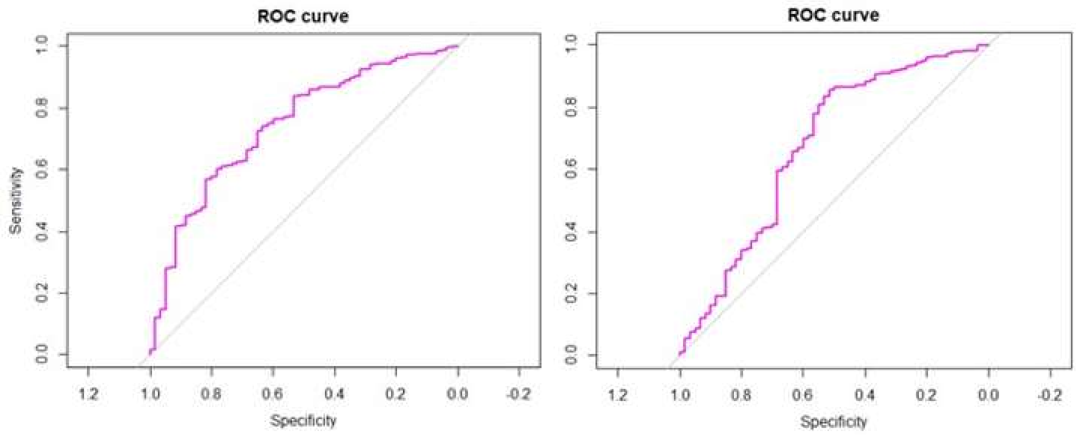

Figure 4-1 - Left – ROC Curve Model 1 / Right – ROC Curve Model 2

With the results presented, it is difficult to advocate in favor of the Model 2, although future research must be addressed to understand the possible relationship between the qualitative variables *Sales Interval* and *H0 – Hierarchy*.

Additionally, the effect of the high negative coefficient of *SOB,* already discussed in Section 4.1, indicating that a higher *SOB*, the higher the probability of success, a higher bond between the stakeholders may indicate a contractual obligation and in some cases warrantees regarding credit defaults.

4.3 MODEL ESTIMATES

The equation of the model considering all predictive variables proposed in the Model 1 is the following:

$$\log\left(\frac{p}{1-p}\right) = \beta_{0+}\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 \quad (4.1)$$

$$+\beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_{11} + \beta_{12} X_{12} + \beta_{13} X_{13} + \beta_{14} X_{14} + \beta_{15} X_{15}$$

where p is the mean of the variable *Default,* β_0 is the *intercept*, X_1 is the variable *Gross Profit Margin*, X_2 is the variable *Asset Turnover*, X_3 is the variable *DSO*, X_4 is the variable *Equity to Debt Ratio*, X_5 is the variable *SOB*, X_6 is the dummy variable for *Sales interval = 2 From 125k to 250K*, X_7 is the dummy variable for *Sales interval = 3 From 250k to 500K*, X_8 is the dummy variable for *Sales interval = 4 From 500k to 1M*, X_9 is the dummy variable for *Sales interval = 5 From 1M to 2,5M*, X_{10} is the dummy variable for *Sales interval = 6 From 2,5M to 10M*, X_{11} is the dummy variable for *Sales interval = 7 From 10M to 50M*, X_{12} is the dummy variable for *H0- Hierarchy = Distributor*, X_{13} is the dummy variable for *H0-Hierarchy= Retail Competition*, X_{14} is the dummy variable for *H0- Hierarchy= Retail Franchise* and X_{14} is the dummy variable for *H0- Hierarchy= Retail Independent.*

In logistic regression models, rather than looking at the coefficients β_i per se, it is more preferable to focus on the values of Odds Ratio, as indicated in the Equation (3.12), since they represent the influence that the increase/decrease in an independent variable X_i has in the probability of the dependent variable Y becoming 1.

The estimates for the coefficients βi of the logistic regression model in Equation (4.1) are presented in Table 4.6, along with the computations of Odds ratio (exp(βi)) and the correspondent 95% confidence intervals.

Model 1	Variables	β	OddsRatio	Confidence Intervals		
				2.50%	97.50%	
Intercept		-0.759	0.468	0.111	1.734	
Numerical						
	Gross.Profit.Margin	-1.283	0.277	0.051	0.893	.
	Asset.Turnover	-0.494	0.610	0.403	0.887	*
	DSO	0.003	1.003	1.000	1.007	.
	Equity.to.Debt.Ratio	-0.005	0.995	0.991	0.998	**
	SOB	-28.240	0.000	0.000	0.000	***
Factors						
Sales.Interval	1 Until 125K	Reference				
	2 From 125K to 250K	-1.834	0.160	0.045	0.553	**
	3 From 250K to 500K	-0.839	0.432	0.138	1.385	
	4 From 500K to 1M	-0.946	0.388	0.123	1.260	
	5 From 1M to 2.5M	-0.837	0.433	0.136	1.415	
	6 From 2.5M to 10M	-2.120	0.120	0.031	0.439	**
	7 From 10M to 50M	-0.513	0.599	0.141	2.432	
H0 - Hierarchy	Car Dealer	Reference				
	Distributor	-13.530	0.000	0.000	5.26E+02	
	Retail Comp	0.744	2.104	0.651	7.581	
	Retail Franchise	3.920	50.400	9.527	282.094	***
	Retail Indeped	2.009	7.456	2.913	23.330	***

Table 4.6 - Estimates for the coefficients of the logistic regression model

The estimate for the coefficient of the variable *DSO* is positive, which causes that exp(β) in this case is greater than 1, meaning that an increase in this variable would reflect an increasing chance of defaulting. Since exp(β) =1.003, which states that for each percent point increase in the *DSO* level (and maintaining the rest of the variables constant), the Odds Ratio of defaulting increases 0.3%.

On the other hand, the coefficients of the variables *Gross Profit Margin*, *Asset Turnover*, *Equity to Debt Ratio* and *SOB* are negative, meaning that an increase of these variables will reduce the chance of defaulting. For example, for the variable *Gross Profit Margin*, exp(β)=0.277, means that for each percent point increase the likelihood of having a default is lowered by 72.3%. Similarly, if the *Asset*

Turnover increases one percent, the Odds Ratio of defaulting decreases 39%. For *Equity to Debt Ratio* the effect is smaller 0.9%. About the *SOB*, the interpretation of Odds Ratio close to zero is similar to the interpretation of infinity, meaning a large difference, in this case, represents a 100% reduction in the Odds Ratio.

For the variable *Sales Interval*, there are seven dummy variables, with *Sales Interval =1 Until 125K* as the reference category. All the coefficients of these dummy variables are such exp(β)<1. This represents that all these *Sales Intervals* (2, 3, 4, 5, 6 and 7) have less chances of defaulting than the reference.

The variable *H0- Hierarchy* has five dummies, with *H0= Car Dealer* being the reference. In this case only *H0= Distributor* has a negative coefficient, with Odds Ratio close to zero. The understanding of this effect can be taken from the summary (Table 3.5), this group showed zero default cases. The other groups, *H0= Retail Competition, H0= Retail Franchise and H0= Retail Independent* have 2.1, 50.4 and 7.4 more times, respectively, the odds of defaulting than the reference group (Car Dealer).

4.4. Expected Loss and Scoring

Different ways of developing credit scoring models have evolved over the years. According to many studies various regression analysis methods are the most suitable techniques due to the combination of implementation easiness, robustness, and predictive abilities.

Credit scoring's primary strength is its ability to rank risk, with the necessity to estimate ELs the model to estimate probability of default become even more helpful.

Table 4.7 shows a suggestion of rating classification based on the PD. The values of Odds Ratio are possible outputs of the logistic regression, with the use of the Equation (3.7) we have the calculation of the PD (based on the Odds Ratio). The number of categories, five, was arbitrary selected. The value of the PD for each category was selected assuming the average default rate of the portfolio analyzed (7.3%) as the medium rating, letter C. The other levels were built with a ratio of 2. The best rating classification is the letter "A" with 4 times less PD than the letter C and the lowest rating, letter "E" with 4 times riskier than letter C.

Other possible ways to set the rating levels should be accessing the PD distribution of the whole portfolio. The final model also should consider the tire company historical loss and its tolerance (risk appetite) of future credit losses.

As indicated in Section 1, the LGD used is the value recommended by the Basel Committee, 50%. The EAD is the trade account receivable balance of each customer at a specific period, in the table there is an example of 100 thousand. The calculation of the EL is done with the use of Equation (1.1)

Odds Ratio	PD	LGD	EAD	EL	Rating
0,020	2%	50%	$100.000,00	$1.000,00	A
0,042	4%	50%	$100.000,00	$2.000,00	B
0,087	8%	50%	$100.000,00	$4.000,00	C
0,176	15%	50%	$100.000,00	$7.500,00	D
0,429	30%	50%	$100.000,00	$15.000,00	E

Table 4.7 - Ratings and Expected Loss

In Table 4.7, it is possible to see the use of model to produce EL, as it is required under the new accounting standards. Although, the relevance and importance of this model goes beyond complying with the CECL. The values shown in the column related with EL must be seen as a real cost and must be considered in the customer profitability analysis.

The rating is completely based on the PD values. The other variables, LGD and EAD, must be managed in order to control the evaluated risk of each rank. In the case of high risk, a collateral should be requested, and its values should impact the LGD to the lowest possible level. The EAD should be considered maximum exposure, or the credit limit. All three variables, PD, LGD and EAD should be combined to produce the lowest possible EL.

5. CONCLUSION

This study developed a methodology to implement credit risk assessment to estimate the expected losses on trade account receivable for B2B companies as it is required by the new accounting standards. It also provided enough material to shift the perspective of the credit assessment to a forward looking, not only to comply with CECL, but to develop a sound credit risk management.

The analyzed portfolio is representative of the Portuguese Automotive Aftermarket Parts sector. It was possible to see the evolution of the profile of these companies from 2014 to 2019, with the reduction of the number of entities with turnover, below 500 000 euros. The entities within this group were responsible for 50.1% of the numbers of defaults while representing 34.7% of the number of customers.

The portfolio is mostly SMEs, from the automotive industry although with different business value propositions, processes, and complexities. There are car dealers, tire distributors, fleets, and retail. The fleets were not considered in the model due its singularity compared with the other groups, although this group has a default rate higher than the average, 16.1% vs 12% (Table 3.5).

In this study, the definition of default follows a specific rule: DSO above 180 days. The calculation takes the average account receivable and divides it by the total sales in one year. With the use of average, it is not assessed the impact of agreed terms (from 30 to 90 days), nor the financial installments (until 180 days), on what we call *delinquency*, number of days above the agreed terms.

It was considered as account receivable the values open, still to be collected, not considering the values already recognized as loss and reclassified as bad debt. There is also the possibility of overdue values due to claims and disputes.

This paper explored the use of financial ratios as it is considered the most suited way to assess creditworthiness of SMEs. The use of ratios and not absolute values was a way to "normalize" the sample, although some values showed a high dispersion. A Log transformation of the financial ratios would increase the interpretability of the patterns and increase the model statistics inference power.

It is known that a failure predictions models could be improved using qualitative variables as predictors since it is possible to better discriminate between SMEs. In an attempt to do so, it was considered as a classification of entity size, *sales interval* and type of entities*, H0-Hierarchy.* Although some of the dummy variables showed low relevance and significance to the model.

Another special ratio was added, the variable *SOB* showed to be high related with the dependable variable, an exploration of the relation between the variables should be performed. Future analysis also must be addressed between the two categorical variables *Sales Interval* and *H0- Hierarchy,* they may be somehow correlated, the retail groups would belong to the lowest sales interval groups, and the Car Dealers and Distributors would belong to the highest turnover groups.

As present before, there were two models' proposals, Model 1 based in the Stepwise procedure and Model 2. The Model 2 is a model based in manual combinations of independent variables without the inclusion of the variable *SOB* and including only one of the two variables *H0- Hierarchy and Sales Interval.* Model 2 showed highest accuracy (92.5%), but with low sensitivity (3.3%), returning an AUC of 67.2%. While the Model 1 showed lower accuracy (86.8%), but better sensitivity (31.7%), returning a higher AUC, 74.2%. The Model 1 also showed the highest statistical significance, AIC 428.07 vs 535.48 and Log-likelihood -197.03 vs -254.74.

In the model proposed by the Model 1, the explanatory variables related with financial ratios found relevant were *gross profit (Odds ratio 0.27), Asset Turnover (Odds ratio 0.61), DSO (Odds ratio 1.003)* and *Equity to Debt Ratio (Odds ratio 0.991), with the last two significant but with low impact*, leaving behind all ratios related with the group *Liquidity*. Two of four ratios are from the group Activity/Efficiency, although the ratio *Gross Profit*, from Profitability group showed the highest relevance to the model. The risk of default decreases with the positive increment of all these variables, beside *DSO,* the unique variable with a positive impact related with probability of default.

From the categorical explanatory variables, it was found that *Car Dealer* and *Distributors* are the categorical dummies with the lowest risk rate compared with the retails, especially the *Retail Franchise* (Odds Ratio 50.4 and $p<0.01$). From the explanatory variable *Sales Interval,* it was found that the risk of default decreases with entities with sales above 125 000 euros, with the dummy group *6 From 2.5M to 10M* showing the highest relevance and significance (Odds Ratio 0.12 and p<001).

Before using this model to estimate the probability of default and therefore the EL, it is recommended future validation through a series of others statistical tests, as Goodness-of-Fit tests (like Hosmer-Lemeshow) and Residual Analysis (like Pearson) and the assumptions of the model have to be verified.

Other statistical methods could be applied, but the advantages of using logistic regression were already presented. As the dependable variable being binary, the model scores between zero and one, representing the probability of default and it gives an important significance of each independent variable, since each of the coefficients can be analyzed separately. One recommendation about the application of the logit regression would be the application of this method individually for each hierarchy group, especially the groups of retail, since they represent more than 50% of the portfolio.

Most of the improvements for future work should be focused on data, such as increasing the completeness and quality, but also increasing the exploration of the categorical variables and the validation about the relation between them.

The information available in Table 4.7 can be used and adjusted beside the variance of PD. For instance, the presence of warrants may imply a different LGD, and the EAD could be used as a method of attribution of adequate credit limit considering all the other variables.

Another suggestion is to extend the scope of the analysis and the use of this information with the introduction of the profitability of each customer. The relation between risk/reward is a powerful source of knowledge, not only regarding a particular customer but especially when assessing the characteristics of the portfolio. This information should be available to all stakeholders at every decision process, not only to the credit risk management team.

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