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WHY BUSINESSES SUCCEED: FINANCIAL AND NON-FINANCIAL DETERMINANTS

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Abstract

Micro, small and medium enterprises correspond to 99.9% of non-financial firms in Portugal. These ventures suffer severely from internal and external factors that difficult their maintenance in the market. Matching data from *Orbis* and *Quadros de Pessoal*, the current paper studies how financial and non-financial dimensions contribute to the success of a business. Following a logistic regression approach, the designed prediction model precisely forecasts 95.65% and 77.61% of companies failing within one and five years after inception, respectively. It is also able to describe 72.14% of successful firms. The results uncover important insights for different stakeholders in the economy.

Keywords: SMEs, prediction model, non-financial determinants, logistic regression.

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1 Introduction

The year was 1973. A British economist by the name of Ernst Schumacher had just published an essay titled ”Small is Beautiful”, advocating that it required a touch of genius to create things smaller, less complex, and less violent. The author noted that the number of small businesses had been growing in nations like Britain and the United States, and that many of these small units were prosperous and provided society with fruitful developments. Nowadays, in Portugal, micro, small and medium enterprises (SMEs) represent 99.9% of all 1 301 000 non-financial firms, providing a job for 78.7% of the population employed, and ensuring 65.8% of the total gross value-added produced (INE 2022). However, geniality is not the sole precondition to be small, as those depending on an SME inherit a great deal of courage to maintain themselves in the market (Schumacher 1973). As a matter of fact, this idea is supported by data. Statistics for Portugal indicate that by the end of the first year after inception, 25% of small companies are expected to fail, with this value escalating to 55% by the end of the third year, and 68% in the fifth year - a number solely surpassed by Lithuania, in the European Union (Eurostat 2022).

The high failure rates observed motivated the scientific community to understand why small businesses fail or succeed. Researchers identified determinants of survival, growth and success, and constructed prediction models, generating a positive impact for entrepreneurs, investors, and society (Dennis and Fernald 2001). For entrepreneurs, Tinsley et al. (2011) defended that research on venture performance enhanced the recognition of corporate threats, culminating in more robust enterprises. The article stressed the importance to assist managers when diagnosing business risks due to two cognitive biases: a normalization of deviance, meaning a tendency over time to accept anomalies as normal; and an outcome bias, guiding managers to focus only on successful outcomes, rather than on the unseen processes behind. By identifying the factors driving progress, entrepreneurs were allowed to focus on critical dimensions, this way smoothing the aforementioned biases. Regarding investors, previous literature demonstrated that good-performing prediction models permit the collection of economic benefits, with even small improvements in the discriminatory power boosting earnings (Blochlinger and Leippold 2006; Agarwal and Taffler 2008; Bauer and Agarwal 2014). At last, small firms were found to promote competition, stimulate innovation, foster social cohesion, integrate diverse segments of the community into local economies, and reduce poverty and inequalities, although uniquely on a temporary basis due to the high mortality rates subsisting (Katua 2014; OECD 2019). In that sense, research contributing to hindering failure rates and transforming the temporary nature of dividends into a permanent one would also be benefiting society as a whole.

Nevertheless, the study on the drivers of prosperity remains uncompleted and ongoing in distinct dimensions to which we intend to contribute. First, this work advances with a prediction model for SMEs in the initial months of activity in the Portuguese commerce sector, being the first paper to our best knowledge to address the subject. In effect, Altman and Sabato (2008) referred that the number of models designed specifically for SMEs is exceptionally reduced, and Santos et al. (2015) emphasized the scarcity of studies concretely on Portuguese SMEs. Second, the model developed includes non-financial determinants, as we intend to *answer* whether that branch of metrics adds value to prediction models. This fills the gap identified by Jardin (2009) who noted that only a minority of studies in the field have employed non-financial regressors, although Lehmann (2003) and Grunert et al. (2005) shared pioneering evidence that qualitative dimensions of business performance may improve traditional financial models. Furthermore, the rare articles considering non-financial variables restricted the analysis to the location, legal form, size, age, and industry of the firm (Ptak-Chmielewska 2021; Gallucci et al. 2022). Altman et al. (2010) and Altman et al. (2015) additionally used predictors linked to court rulings, audit judgments, and resignations in the board, yet these indicators proved to be helpful only in the later stages of the failure process and not in the initial life of a venture. The same studies also tested indicators related to payment behavior and identified gains in the long-term forecast, but the information necessary to compile them is rather difficult to gather in young enterprises due to the lack of historical records. Ergo, and as a third contribution to the literature, we aim to elaborate new non-financial predictors that may be applied to businesses at inception, followed by an assessment of their effectiveness to provide an early warning about corporate health.

The prediction model constructed exhibits an out-of-sample accuracy of 95.65% and 77.61% for SMEs in the commerce sector failing within one and five years after inception, respectively. Successful enterprises are correctly described in 72.14% of forecasts. The development of the model is based on a logistic regression statistical technique and uses information about the initial months of activity of 1 340 companies founded between 2010 and 2014, combining data from *Orbis* and *Quadros de Pessoal*. For the purpose of the paper, an SME is defined as an enterprise employing less than 250 people, and whose annual turnover does not exceed 50 million euros, or whose annual balance sheet does not exceed 43 million euros, including micro-enterprises (INE 2022). The commerce sector encompasses retail and wholesale commerce, and the repair and maintenance of motor vehicles and motorcycles (INE 2007). The results unambiguously confirm that non-financial predictors increase the precision of traditional models and that the non-financial metrics introduced are effective at different cut-off values. The improvement is mainly explained by an enhancement in medium-term negative predictions. The asset turnover ratio, the initial size, a sole proprietorship nature, the proportion of staff with higher education, and the EBIT per hour worked are estimated to have a positive, statistically significant effect on the chances of a venture becoming successful. Important practical insights may be retrieved.

The remaining of the paper is organized in the following manner: section 2 reviews the previous literature; section 3 details the data used, the predictors analyzed, and the methodology employed; section 4 exposes the results of the study and reflects about the primary practical implications; and section 5 concludes with final remarks and suggestions for future research.

2 Literature Review

The ability to predict whether a business will fail or prosper is an ancient necessity. In the Early Roman Empire, the Romans already opted to extend credit uniquely to individuals with a record of successful ventures and a history of timely honoring commitments (Temin 2004). The judgment performed was rooted in qualitative information, and although financial systems evolved and credit rating agencies appeared, corporate performance continued to be assessed essentially based on qualitative inputs until the twentieth-century (Cohen and Carruthers 2014).

The paradigm shifted with the peak in business collapses during the Great Depression. Soon, several studies confirmed that failed and non-failed enterprises exhibited persistent differences in financial ratios up to six years before disruption (Fitzpatrick 1932; Smith and Winakor 1935). Identified this pattern, Beaver (1966) executed a dichotomous classification method to verify the usefulness of financial ratios to predict the failure or success of a firm, on a univariate basis. Not all ratios performed equally well, and failed and non-failed ventures were not predicted with the same precision, but the results were far more accurate than a random model. Thus, the author conjectured whether the simultaneous use of different financial ratios could improve the accuracy obtained. Altman (1968) advanced with this idea, developing a multivariate model using a multiple discriminant analysis (MDA) - a statistical method that classifies observations *a priori* into failed and non-failed enterprises, and proceeds to derive the linear combination that best discriminates both groups based on the entire set of variables compiled. The model delivered an impressive 95% accuracy describing businesses one year before failure, despite a drastic fall to 36% when based on data observed five years prior to bankruptcy. Hence, albeit Lauer (2016) reported some resistance by credit managers who saw scoring models as a threat, the results led multivariate studies to swiftly flood the literature, analyzing different financial ratios in varied industries and geographies (Blum 1974; Sinkey 1975; Springate et al. 1983).

Nonetheless, the diffusion of multivariate models exposed flaws in their development. First, there was no consensus on the definition of corporate failure and success. Altman (1968) defined failure as filling a bankruptcy petition, but other studies described it as organizational collapse or decline (Ropega 2011). Success was defined either as the mere avoidance of bankruptcy or measured by profit generation, market position and goodwill of customers (Gupta et al. 2013). This remains open to debate in the literature, but definitions usually depend on the nature of the data available. Second, the models designed were discovered unable to distinguish firms that effectively collapse from firms only in financial distress (Gilbert et al. 1990). In response, the proposal by Taffler (1984) to interpret the results as descriptions of financially distressed companies - rather than bankrupted - versus healthy counterparts was considered more adequate. The final criticism pointed out the theoretical drawbacks of the MDA technique. Ohlson (1980) identified three major limitations: i) it required distributional properties of the predictors that rarely hold, namely normal distribution and equal variance-covariance matrices across groups; ii) the interpretation of the output produced had little intuitive meaning since the model was an ordinal ranking device; and iii) the necessary matching procedure for observations was often done through arbitrary criteria. To overcome these obstacles, the author introduced the logistic regression model, while Zmijewski (1984) advanced the probit model, with both achieving robust results and surpassing the MDA method by late 1980s (Bellovary et al. 2007).

However, the uproar surrounding financial models motivated the re-appearance of studies prioritizing qualitative information. The most prominent one was the Lussier model, gathering fifteen qualitative factors contributing to the success of a business. The model asked the owners of failed and non-failed firms to describe the respective enterprises using a Likert scale [1], and analyzed the results through a logistic regression method. Applying this framework, Lussier and Corman (1996) attained a precision of 67.7% and 82.4% for failed and non-failed ventures, respectively. Yet, the forecast was based on *ex-post* data and researchers found the critical determinants to be inconsistent with previous research, which led them to suggest the model only as a complement to traditional prediction techniques. In any case, survey-based models inspired by the Lussier model became popular, regardless of further limitations preventing them from delivering unbiased diagnoses in a reliable and practical manner. First, partly due to the difficulty in convincing managers to disclose information, the sample sizes used in qualitative models are frequently not large enough to offer robustness to the conclusions (Marshall et al. 2013). Second, studies depending on voluntary participation commonly display a selection bias in observations, threatening the validity of the results (Franco and Ferreira 2021). And third, several variables included in qualitative models need to be measured subjectively. Consider the variable ”planning” in the Lussier model, whose owners are asked to value from one - ”the company has a specific business plan” - to seven - ”the company has no specific business plan” (Lussier and Corman 1996). Still, at no point the study defines what is a specific business plan, implying that respondents must use judgment to answer. This is an obstacle if owners are averse to self-introspection, as documented by Nandkeolyar et al. (2017) who reported that 46% of respondents (n = 517) blamed for their current problems either the government or new entrants with unethical products. Social psychology denominates this behavior as a self-serving bias: when an individual takes personal responsibility for desirable outcomes but externalizes the responsibility for undesirable ones (Shepperd et al. 2008). On that grounds, financial models remained the preferred methodology to assess corporate performance until today.

[1] Psychometric scale composed by a set of statements related to an event under study and to whom respondents are asked to indicate their level of agreement (Joshi et al. 2015). The Lussier model employs a seven-point scale.

In the new millennium, Lehmann (2003) and Grunert et al. (2005) presented evidence that the use of qualitative regressors improved prediction models. The timing matched the reform of the Basel Accord in 2004, which focused on SMEs and provided banks the flexibility to develop internal frameworks to assess credit risk (Charalambous et al. 2022). Both developments would converge in the study of Altman and Sabato (2008). The researchers noted that only a couple of models had been designed specifically for small businesses, and thus constructed a model based on data related to SMEs, founding it to achieve an accuracy 30% above a framework built on large corporate data. It was also acknowledged that precision could be raised if non-financial variables were included, leading Altman et al. (2010) to insert in the model predictors associated with court rulings, number of late filing days, and audit reports. As a consequence, correctness further increased by 13%. Motivated by these results, Altman et al. (2015) continued to work on qualitative factors and introduced new metrics linked to the payment behavior and resignations on the board. However, the analysis revealed that, with the exception of some regressors related to payment behavior, non-financial dimensions were effective uniquely closer to the moment of failure, implying there were missing indicators providing early warnings on the unsustainable nature of a given business. In addition, besides the frequent difficulty to reunite qualitative data, implementing variables on the payment behavior of young ventures is particularly cumbersome due to the lack of historical records. Therefore, Jardin (2009) refers that the number of models considering qualitative aspects is reduced and commonly restricted to the location, legal form, size, age, and industry of a firm (Ptak-Chmielewska 2021; Gallucci et al. 2022). Ergo, on the whole, non-financial predictors remain a widely untapped resource in the literature.

In Portugal, empirical prediction studies regarding SMEs are rare (Santos et al. 2015). The first paper in the field is dated thirty years after Altman (1968) and attributed to Martinho (1998)[2]. Vieira (2020), Parise (2020) and Pacheco et al. (2022) are the only works found to combine financial and non-financial indicators, but restricted to the usual location, legal form, size, age, and industry variables. Related to recently founded SMEs, the few studies identified are Silva et al. (2016) and Pinto (2019) with survey-based models inspired by the Lussier model, and Silva (2018) with a logistic regression model exclusively using financial predictors.

[2]Furthermore, although solely including financial determinants, it is worth emphasizing the contributions of Santos (2000), Barros (2008), Gonçalves (2011) and Santos et al. (2015).

3 Data and Methodology

The present paper aspires to develop a prediction model and identify internal, early financial and non-financial determinants of survival, growth and success for SMEs inserted in the Portuguese commerce sector. To address the research proposal, we combined data from *Orbis* and *Quadros de Pessoal* on companies founded between 2010 and 2014. In due course, the list of predictors is compiled, the methodology employed is detailed, and descriptive statistics are reported.

3.1 Data

Orbis is a database managed by Bureau van Dijk, a Moody's Analytics company. It contains financial information on private companies, providing access to detailed balance sheets and income statements. *Quadros de Pessoal* is an annual compulsory survey for all organizations in Portugal with wage earners at their service, except public administrations, institutes, and employers of domestic workers, collected by the Portuguese Ministry of Labour, Solidarity and Social Security. It includes data on every firm and establishment - as location, legal nature and industry - and on each worker - as age, education, monthly wages and hours worked.

To match the data between *Orbis* and *Quadros de Pessoal*, a method inspired by Card et al. (2016) was followed, although a more precise match was achieved (see A.1 Data Appendix).

3.2 Predictors

Previous literature focused on using the best-performing financial ratios to predict the success of a venture (Bellovary et al. 2007). Thus, this paper departs from past research to select sixteen financial regressors, dividing them across five categories, following Altman and Sabato (2008): i) leverage; ii) liquidity; iii) profitability; iv) coverage; and v) activity. In contrast, non-financial predictors remain an unexplored tool. Hence, their inclusion is mainly based on evidence from outside the area of prediction studies regarding the effect of qualitative dimensions on business performance. In general, we gather twenty-two candidate predictors summarized in Table 1.

We include in financial predictors the Current Assets to Current Liabilities and Working Capital to Total Assets. The univariate studies until the 1960s reported persistent differences in both ratios across healthy and non-healthy firms (Smith and Winakor 1935; Merwin 1942) and Beaver (1966) proved their usefulness. In a multivariate framework, Altman (1968) introduced two factors argued vital to describe corporate performance: the EBIT to Total Assets and Sales to Total Assets. In the upcoming years, multivariate studies identified additional regressors able to enhance forecasts, namely: i) Deakin (1972) found the Working Capital to Sales to be the most accurate within liquidity and activity ratios, followed by Current Assets to Sales; ii) Norton and Smith (1979) identified significant disparities in the Net Income to Total Liabilities one year before disruption; and iii) Kaplan and Urwitz (1979) emphasized the tight connection between Long-Term Liabilities to Total Assets, credit ratings and failure rates. Once research shifted towards smaller enterprises, Altman and Sabato (2008) advanced with a prediction model for SMEs, based on a set of financial metrics mainly focused on the liquidity and profitability of each firm, through ratios as Cash to Total Assets and EBIT to Sales. Coverage ratios considered the EBIT to Interest Expenses, but were the least represented in the study. On leverage ratios, the Current Liabilities to Equity was pointed out as the most powerful indicator. More recent studies have preferred ratios built around cash flows, especially the Cash Flow to Sales and Cash Flow to Current Liabilities, advocating these are less prone to be manipulated by managers (Bhandari et al. 2019; Rizzo et al. 2020). In Portugal, researchers found Equity to Sales to have a positive impact on the likelihood of success, while Cash to Current Liabilities has been frequently used even though mixed evidence about its impact (Santos 2000; Barros 2008; Santos et al. 2015).

About non-financial determinants, we start with three common variables in hybrid models: the initial size of the firm, given by the logarithm of total assets; a binary variable linked to the legal nature of the enterprise, equal to one for a sole proprietorship by shares, and zero for collective firms; and a binary variable on the location of the business, equal to one if located in the Lisbon Metropolitan Area, and zero otherwise. The few studies using qualitative metrics also account for the age and industry of each firm, which we control by restricting the analysis to recently founded ventures in the commerce sector. Then, three original qualitative predictors observable in the first months of activity are developed. First, the average remuneration per hour worked, coherent with findings that higher wages attract better and more motivated employees, reduce disciplinary issues, and enhance customer satisfaction (Mas 2006; Pfeifer 2010; Bó et al. 2013). Second, the proportion of employees with higher education, in line with evidence that graduated workers have better access to information and are more effective in learning new methodologies in the workplace (Doms et al. 2010). And third, the logarithm of EBIT per hour worked. This is a measure of productivity and efficiency based on an argument by Bryan and Joyce (2007) that metrics like Return on Invested Capital no longer reflect the processes of wealth creation. Instead, the authors suggested the use of profit per employee: the Return on Talent. The present paper considers EBIT, rather than profit, a more truthful description of productivity across labor forces as it isolates the impact from financial decisions, and total hours worked, rather than the number of employees, more informative on the real input required.

ID	Predictor	Type
X1	Current Assets / Current Liabilities	Leverage
X2	Long-Term Liabilities / Total Assets	Leverage
X3	Current Liabilities / Equity	Leverage
X4	Cash / Total Assets	Liquidity
X5	Working Capital / Total Assets	Liquidity
X6	Current Assets / Sales	Liquidity
X7	Cash Flow / Sales	Profitability
X8	EBIT / Sales	Profitability
X9	EBIT / Total Assets	Profitability
X10	EBIT / Interest Expenses	Coverage
X11	Cash Flow / Current Liabilities	Coverage
X12	Cash / Current Liabilities	Coverage
X13	Net Income / Total Liabilities	Coverage
X14	Sales / Total Assets	Activity
X15	Working Capital / Sales	Activity
X16	Equity / Sales	Activity
X17	LN(Total Assets)	Non-Financial
X18	Binary Predictor = 1 if Sole Proprietorship by Shares	Non-Financial
X19	Binary Predictor = 1 if Lisbon Metropolitan Area	Non-Financial
X20	Total Wage / Total Hours Worked	Non-Financial
X21	Employees with Higher Education / Total Employees	Non-Financial
X22	Log-Modulus(EBIT / Total Hours Worked)	Non-Financial

Table 1: List of candidate predictors. Financial regressors are selected based on previous prediction studies, and divided into five categories, following Altman and Sabato (2008). Non-financial regressors are composed of three qualitative variables considered in the rare prediction studies including non-financial metrics, while the remaining are based on evidence obtained from literature outside prediction studies.

3.3 Methodology

Coherent with the limitations pointed to the MDA technique in section 2, the methodology used in this study is logistic regression, as it is not restricted by the assumptions of multivariate normality and equal variance-covariance matrices across successful and failed businesses.

The objective is to depart from data collected in the first months of activity and calculate the probability of an SME surviving the initial five years after inception, in the commerce sector, with profits and no signs of financial distress, coherent with Taffler (1984). This probability may range between zero and one but never exceed these values. A regression restricted to such an interval requires the response variable to be a metric that can adopt positive and negative values, while linked to the probability modeled. Ergo, the logistic regression model introduces the logit measure, equivalent to the logarithm of the odds of an event, resulting in the formulation presented in Equation 1. In order to facilitate the interpretation of the coefficients, it is frequent to exponentiate them, guiding to an expression where the estimated parameters relate to changes in odds, and where the odd is the probability of the positive event divided by the probability of the negative event. This paper presents the estimated parameters using such formulation, described in Equation 2, while Equation 3 details how to calculate the probability of the firm being successful by the end of the fifth year after foundation with the output generated.

$$Logit_i = ln(\frac{p_i}{1 - p_i}) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_n X_{in} \tag{1}$$

$$Odds_i = \frac{p_i}{1 - p_i} = e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_n X_{in}} \tag{2}$$

$$p_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_n X_{in})}} \tag{3}$$

The parameters are estimated based on the Maximum Likelihood Estimator (MLE) and yield the coefficients more likely to have produced the observed data. Since the independent variable is assumed to follow a Bernoulli probability distribution due to its binary nature, the likelihood function is depicted as in Equation 4. Its maximization requires the first derivative to be calculated and set to zero, which leads to a unique estimate given the concave shape of the likelihood function (Amemiya 1985). Furthermore, Long (1997) proved that the MLE is consistent, asymptotically normal, and asymptotically efficient. Still, Hilbe (2015) noted that the maximization procedure of the likelihood function is commonly expedited by a logarithmic transformation that conduces to the same result, but eases the calculation of the first derivative (see Equation 5). At last, the solution is found through an iterative procedure. This paper considers the Newton-Rapson method, which initiates with a tentative solution, and proceeds to revise it until no more significant improvements can be achieved, as reported in Equation 6.

$$L(p_i, y_i) = \prod_{i=1}^{n} p_i^{y_i} \cdot (1 - p_i)^{1-y_i} \tag{4}$$

$$l(p_i, y_i) = \sum_{i=1}^{n} [y_i \cdot ln(\frac{p_i}{1 - p_i}) + ln(1 - p_i)] \tag{5}$$

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \tag{6}$$

Although not affected by part of the requirements present in the MDA methodology, the estimation procedure used in logistic regression relies on three assumptions: observations are independent; the predictors have a linear relationship with the logit; and no multicollinearity (Hair et al. 2019). In addition, the asymptotic nature of the consistency, normality and efficiency properties of the MLE requires the use of a large sample size. As a reference, we consider as the minimum threshold the 20 observations per variable advocated by Ploeg et al. (2014) and a minimum of 400 observations argued by Hosmer and Lemeshow (1989). Moreover, Hilbe (2015) and Hair et al. (2019) recommend the use of a validation sample to rule out over-fitting problems, i.e. when the estimated parameters over-represent the characteristics of the training sample at the expense of generalizing to the population. For that purpose, Gholamy et al. (2018) suggested a 70/30 relation between the size of training and validation samples.

3.4 Descriptive Statistics

From the 2 847 observations matched between *Orbis* and *Quadros de Pessoal*, 670 were firms dissolved, liquidated or in insolvency proceedings within five years after inception, labeled as negative observations. Hilbe (2015) proposed using a dependent variable with an equal number of negative and positive events[3], thus the remaining 2 177 observations are reduced to the 670 enterprises with the highest profits by the end of the fifth year, defined as positive cases. By demanding more than an active status to be described as a positive event, we restrict the analysis of successful SMEs to firms more prone to be financially healthy at the end of the period.

[3]Hilbe (2015) alerts for response variables composed by a majority of negative or positive events, creating an unbalance in data, which requires adjustments in the analysis performed as described by the author.

Within the group of successful firms, 11 (1.6%) collapsed before 2020, and 18 (2.7%) failed between the start of the COVID-19 pandemic and October 2022. About non-successful SMEs, 12%, 25%, 23%, 19% and 21% failed within one, two, three, four and five years post-creation, respectively. Table A.1 compares the mean and median of each variable between successful and failed SMEs. The results shall be interpreted carefully due to skewed distributions and extreme events. In that sense, Figure A.1 details the distribution of non-binary predictors with box plots.

4 Results

The final 1 340 observations are divided into training and validation samples following the 70/30 relation advocated by Gholamy et al. (2018). Hence, the training sample analyzed is formed by 938 observations, fulfilling both the criteria of 20 observations per regressor by Ploeg et al. (2014) and a minimum of 400 observations by Hosmer and Lemeshow (1989).

4.1 Selection of Financial Predictors

Because financial predictors are calculated departing from financial statements, it is frequent to observe a certain correlation across variables, which represents an obstacle to logistic regression models due to the assumption of multicollinearity. Therefore, prior to the development of any model, the sixteen candidate financial ratios are reduced to two financial regressors per type, based on the respective accuracy ratios, following Altman and Sabato (2008).

The accuracy ratio (AR) compares the performance of the model being analyzed to a model with perfect predictive power. As in Equation 7, Engelmann et al. (2003) proved this ratio to be a linear function of the Area Under the Receiver Operating Characteristic (AUROC). Per se, the ROC curve plots the trade-off between the true positive rate ($sensitivity$) and the false positive rate ($1 - specificity$) at different cut-off values, thereby being a commonly used metric of diagnostic ability. The values of the AUROC and respective AR for each financial metric are presented in Table 2. Based on the results, Table A.2 exposes the final list of predictors.

$$AR = 2 \cdot AUROC - 1 \tag{7}$$

ID	AUROC	AR	Type
X1	0.5613	0.1226	Leverage
X2	0.4754	-0.0492	Leverage
X3	0.6618	0.3236	Leverage
X4	0.5224	0.0448	Liquidity
X5	0.4920	-0.0160	Liquidity
X6	0.4687	-0.0626	Liquidity
X7	0.7275	0.4550	Profitability
X8	0.7324	0.4648	Profitability
X9	0.7322	0.4644	Profitability
X10	0.6530	0.3060	Coverage
X11	0.7181	0.4362	Coverage
X12	0.5343	0.0686	Coverage
X13	0.7241	0.4482	Coverage
X14	0.5384	0.0768	Activity
X15	0.4885	-0.0230	Activity
X16	0.6835	0.3670	Activity

Table 2: The AUROC and AR for each financial predictor. Based on the AR, calculated according to Equation 7, financial regressors are restricted to two per type in order to reduce the chances of multicollinearity. The ID remits to the predictors described in Table 1.

4.2 Models, Goodness of Fit and Predictive Accuracy

Three models are studied. Model I is uniquely composed of financial ratios, similar to traditional prediction frameworks. Model II adds three non-financial predictors related to the initial size, legal nature, and location of each venture, typically included in the rare studies considering qualitative dimensions of business performance. And model III responds to the shortage of indicators observable early in the life of an enterprise by introducing three non-financial metrics not contemplated in previous literature and linked to the average remuneration, education of the workforce, and productivity and efficiency of employees. To find which model performs better, the overall statistical significance and in-sample predictive accuracy of each model are tested.

Table 3 documents the statistical results. The analysis of the overall statistical goodness of fit begins with the Wald chi-squared test, described by Agresti (1990). The correspondent p-values below 0.0001 observed in all models allow us to reject the null hypothesis that the parameters associated with the group of explanatory variables are zero, even in the traditional financial model, this way signaling that the factors considered influence the chances of a firm becoming successful. Furthermore, the log-likelihood can be used to measure how well the MLE fits the data and how the three models compare to each other. For that purpose, the likelihood-ratio test is computed based on Equation 8, following Dunning (1993). This parametric test compares the likelihood of the data being observed between two frameworks, permitting us to infer whether the introduction of additional explanatory variables significantly improves the goodness of fit.

ID	Model I	Model II	Model III
X1	0.975	0.975	0.976
	(-1.17)	(-1.03)	(-0.99)
X3	1.001	1.001	1.001
	(0.53)	(0.46)	(0.49)
X4	0.365***	1.215	1.086
	(-2.67)	(0.44)	(0.19)
X5	0.583**	0.895	0.800
	(-2.40)	(-0.47)	(-0.97)
X8	1.950	1.939*	1.501
	(1.43)	(1.79)	(1.36)
X9	4.636***	1.427	1.062
	(2.66)	(0.85)	(0.27)
X11	1.122	1.140	1.100
	(1.26)	(1.27)	(1.27)
X13	0.838	1.094	0.878
	(-0.69)	(0.35)	(-0.75)
X14	1.019	1.098***	1.081***
	(0.84)	(3.20)	(2.85)
X16	1.289*	1.180	1.147
	(1.80)	(1.15)	(0.99)
X17		2.370***	2.240***
		(9.18)	(8.07)
X18		1.352*	1.405**
		(1.90)	(2.08)
X19		0.770	0.778
		(-1.34)	(-1.25)
X20			1.020
			(0.30)
X21			2.511**
			(2.53)
X22			1.151***
			(4.30)
Constant	1.822***	0.000***	0.000***
	(4.26)	(-8.56)	(-7.99)
Observations	938	938	938
Pseudo R^2	0.138	0.229	0.249
Log-Likelihood	-560.4	-501.0	-488.6
Wald Chi-Squared	74.5	173.0	210.6
Prob > Chi2	0.000	0.000	0.000

Exponentiated coefficients; z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The three logistic regression models. Exponentiated coefficients and z statistics in parentheses are reported. Information is provided on the number of observations, pseudo R^2, log-likelihood, Wald chi-squared statistic, and correspondent p-values. The ID remits to the predictors described in Table 1.

The values calculated are 118.74 comparing models I and II, and 24.94 comparing models II and III. Given the asymptotically chi-squared distribution of the likelihood-ratio statistic, both results correspond to p-values smaller than 0.0001, indicating that the non-financial predictors significantly improve the fit of the data, including the original variables constructed in this paper. Therefore, the statistical analysis realized corroborates the usefulness of the factors employed.

$$LR = -2 \cdot ln(\frac{L_{Nested}}{L_{Full}}) = 2 \cdot (l(M_{Full}) - l(M_{Nested})) \tag{8}$$

Before testing the predictive power of each model, a cut-off value must be defined to classify SMEs based on the probabilities estimated. The frequently assumed cut-off is 0.5, implying that an estimated probability higher than 0.5 corresponds to the prediction that the enterprise will remain profitable and without signs of financial distress by the end of the fifth year after inception, while the inverse means an expectation that the company will fail within the same period. Nevertheless, Altman and Sabato (2008) defended that the optimal cut-off value varies from user to user, depending on factors like risk tolerance, profit and loss targets, and efficiency and recovery costs. In that sense, risk-averse individuals demand higher cut-off values, as an inaccurate classification of failed firms gives place to more onerous consequences than the misclassification of a successful business. Ergo, the prediction accuracy is studied for a standard 0.5 and a higher 0.75 cut-off values. The results are presented in Table 4. Table A.3 highlights additional information on the precision for failed ventures by year of failure since inception.

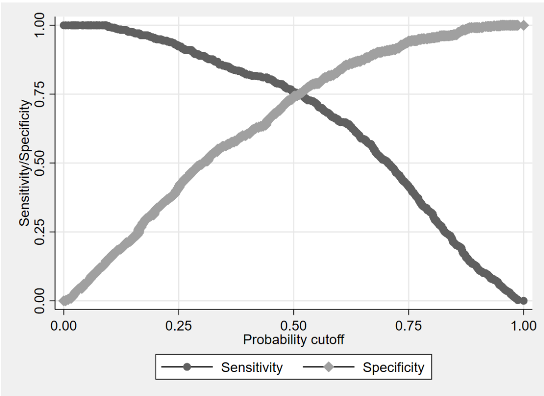
Model	Overall (%)	Success (%)	Failure within... (%)					PPV (%)	NPV (%)
			1-year	2-years	3-years	4-years	5-years		
Cut-off = 0.5									
I	68.44	81.66	64.41	62.01	60.76	56.80	55.22	64.59	75.07
II	73.67	77.40	77.97	79.89	75.00	72.00	69.94	72.02	75.58
III	75.05	75.69	77.97	82.12	79.17	75.57	74.41	74.74	75.38
Cut-off = 0.75									
I	52.88	6.82	98.31	98.88	98.96	98.93	98.93	86.49	51.50
II	63.97	34.33	93.22	95.53	94.44	93.60	93.60	84.29	58.77
III	67.80	41.36	94.92	96.65	95.14	94.67	94.24	87.78	61.65

Table 4: The predictive accuracy of each model, in the training sample, at different cut-off values. PPV and NPV figures are presented. PPV is the percentage of correct positive classifications. NPV is the percentage of correct negative classifications.

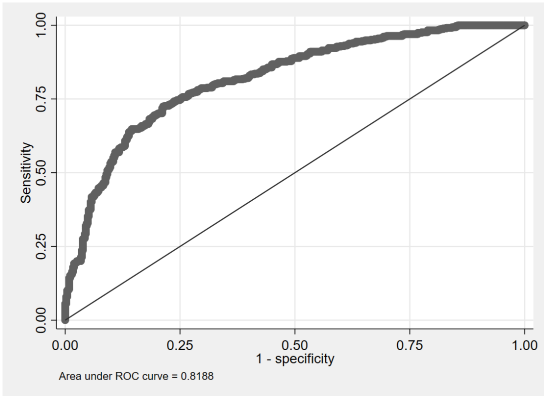
Regarding the standard 0.5 cut-off value, all models exhibit an overall accuracy above the 50% expected for a random model. However, the global precision in model I is improved by 7.64% in model II and 9.66% in model III. These advancements are driven by an increase in the correct descriptions of failed ventures by 26.66% in model II and 34.75% in model III, when compared to the traditional financial model. Non-financial predictors show a particular use to predict non-successful firms in the medium-term, as model I can only depict 46.41% of firms failing in the fourth and fifth years, while models II and III increase this percentage by 33.33% and 44.04%, respectively. For SMEs collapsing in the first three years, the improvements are significant, but lower: 23.44% in model II and 30.30% in model III. For positive events, model I shows the highest accuracy. Nonetheless, a closer look finds that the model classifies 63.22% of observations as future successes, well above the 53.73% in model II and 50.64% in model III. This data indicates that the traditional prediction model is more precise in identifying healthy businesses because it is more likely to classify an observation as positive, rather than better internalizing the drivers of success. A more meaningful metric is the percentage of correct positive classifications - Positive Predictive Value (PPV) - and the results convey that, besides a higher precision in forecasting negative events, models II and III improve the PPV observed in model I by 11.50% and 15.71%, respectively, affirming the dominance of hybrid models.

When raising the cut-off value, precision falls to reduce the risk of misclassifying a failed company. The traditional financial model is able to depict 98.93% of firms failing within five years post-foundation, but at the expense of only predicting 6.82% of successful ventures due to the attribution of a negative classification to 96.06% of the companies, compared to 79.64% in model II and 76.44% in model III. This propensity to classify an event as negative translates into a percentage of correct negative classifications - Negative Predictive Value (NPV) - 10.32% and 13.58% lower than in models II and III, respectively. Model III manages to achieve a 94.24% accuracy for failed businesses, while correctly forecasting 41.36% of positive events - a notable improvement by 20.48% compared to model II and comfortably above the 6.82% in model I. It is also worth noting that 87.78% of positive classifications in model III prove to be accurate, offering confidence to risk-averse users when labeling a firm as successful. Therefore, model III exhibits both the highest PPV and NPV, demonstrating its superior discriminatory power.

The analyses of the overall statistical significance and predictive abilities of the models yield the same conclusion: although traditional financial models can assist in the description of business performance, non-financial predictors enhance the assessment performed, and the new regressors constructed significantly improve the statistical goodness of fit and prediction power at both cut-off values studied. Coherent with these findings, Figure 1a shows the *specificity* and *sensitivity* values in model III at different cut-off values, conducting to the construction of the respective ROC curve in Figure 1b. The AUROC is frequently employed to measure the discriminatory capacity of a logistic regression framework, and Mandrekar (2010) advocates that an area above 0.8 is deemed "*excellent*"[4]. Model III displays an area of 0.8188, thereby confirming its robustness to describe the determinants of survival, growth and success for SMEs.



(a) The sensitivity and specificity plot



(b) The ROC curve

Figure 1: Figure 1a plots the different sensitivity - true positive rate - and specificity - true negative rate - values across different cut-offs used to draw the ROC curve in Figure 1b. The AUROC of model III is 0.8188 (see Figure 1b).

Acknowledged the capacity of model III, five factors stand out by displaying an individual statistically significant positive effect - at a 5% significance level - on the odds of an SME being successful by the end of the fifth year. The factors are: i) asset turnover ratio; ii) initial size of the firm; iii) possessing a sole proprietorship nature; iv) proportion of staff with higher education; and v) EBIT per hour worked. Nevertheless, quantifying the impact of predictors composed of information retrieved from financial statements is a rather complex mission, as the change in one regressor may directly imply a change in the remaining variables. Still, holding other factors at the respective means, two non-financial metrics are possible to interpret: the model estimates that a sole proprietorship has a probability of becoming successful 8.49 percentage points higher than collective counterparts, and a firm composed only of employees with higher education has a probability of prospering 21.99 percentage points above a similar venture without graduated workers. Figure A.2 plots the estimated probabilities at intermediate shares of graduated staff.

[4]Altman et al. (2015) also reinforced that the best predictive models approached a 0.75 - 0.80 AUROC.

4.3 Internal Validation

The robustness of the results obtained depends on the validity of the assumptions necessary in logistic regression models. The main assumptions concern the independence of observations, no multicollinearity, and linearity of the independent variables with the logit. To safeguard the first assumption, this paper used a stringent method to cross the population data between *Orbis* and *Quadros de Pessoal*, reducing the chances of repeated or incorrect matches. In addition, the division between training and validation samples was performed through a random sampling procedure. In regard to the remaining assumptions, statistical tests are carried out below.

For the purpose of avoiding multicollinearity, the present study narrowed the analysis to two financial predictors per type departing from the initial list of sixteen candidate financial ratios. Yet, this procedure does not guarantee that explanatory variables are uncorrelated. Thus, the assumption is tested by calculating the variance inflation factor (VIF) of each regressor, according to Equation 9, where R_i^2 is the coefficient of determination of regressing variable i on the other predictors. Menard (2001) argued that a VIF superior to 5 shall be analyzed, while a VIF above 10 is a sign of multicollinearity. Table 5 shows the VIF for each variable. The results suggest that multicollinearity is not an obstacle to the validity of Model III[5].

$$VIF_i = \frac{1}{1 + R_i^2} \tag{9}$$

ID	VIF	ID	VIF
X8	2.48	X1	1.42
X9	2.33	X5	1.40
X22	2.14	X4	1.32
X13	2.12	X14	1.19
X17	1.90	X21	1.17
X11	1.84	X18	1.06
X16	1.70	X19	1.05
X20	1.42	X3	1.01

Table 5: The variance inflation factor (VIF) for each explanatory variable in model III. The ID remits to the predictors described in Table 1.

The assumption on the linearity of the independent variables with the logit relies on two parts. In the first part, the logistic regression must be the adequate function to describe the event studied. This is frequently assessed with the Hosmer-Lemeshow test, which divides the training

[5] A cross-correlation table between the predictors included in the final model is depicted in Table A.4.

sample into deciles based on the predicted probabilities, proceeds to compute the number of expected events and non-events in each decile, and compares them to the actual outcome, with a non-significant chi-squared statistic signaling the logistic regression technique is appropriate (Hosmer and Lemeshow 1989). Following this procedure, we observe a p-value of 0.2193, confirming the suitability of the link function [6]. However, Altman and Sabato (2008) alerted that the Hosmer-Lemeshow test may guide to misleading results in the presence of high variability in predictors, thus the authors recommended plotting the squared residuals versus the estimated probability of each observation. A graph exhibiting an "X" pattern would validate the results obtained. Indeed, Figure 2 depicts the desired shape[7]. In the second part, all relevant dimensions and non-linear effects shall be captured in the final model. To test this requirement, we regress the observed outcomes on the estimated probabilities and estimated probabilities squared. In a correctly specified model, the predicted values will be statistically significant, while the squared values should not have much predictive power, or an argument could be made on the omission of relevant predictors and non-linear impacts. This course of action leads to evidence about the correct specification of model III (see Table A.6). Nonetheless, it is worth emphasizing that model III captures two non-linear effects through the use of logarithmic transformations that enhance the linearity of the variables with the logit. The variables transformed are the initial size of the firm given by total assets, and the EBIT per hour worked (see Figure A.4). All things considered, the findings collected support both parts of the present assumption.

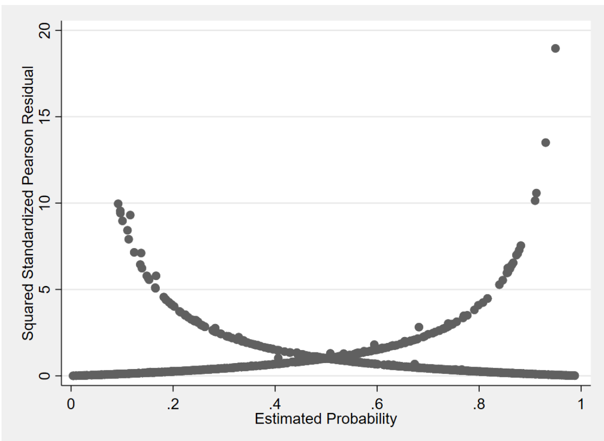


Figure 2: The squared standardized Pearson residuals versus the estimated probability, in model III.

[6]Table A.5 refers to the Hosmer-Lemeshow table conducing to this result.
[7]For comparison purposes, Figure A.3 presents the same graph for models I and II.

4.4 External Validation

After internally validating the final model, we proceed to externally validate the framework developed in order to rule out potential over-fitting problems. Therefore, models I, II and III are tested on a validation sample composed of the remaining 402 observations, equally divided across successful and failed SMEs in the Portuguese commerce sector. Similar to the training sample, two cut-off values are analyzed. Table 6 presents the results. Table A.7 contains further information on the predictive accuracy for failed SMEs by year of failure since inception.

Model	Overall (%)	Success (%)	Failure within... (%)					PPV (%)	NPV (%)
			1-year	2-years	3-years	4-years	5-years		
Cut-off = 0.5									
I	68.91	84.58	65.22	61.19	58.77	54.25	53.23	64.39	77.54
II	71.64	70.65	91.30	86.57	78.95	74.51	72.64	72.08	71.22
III	74.88	72.14	95.65	86.57	82.46	79.74	77.61	76.32	73.58
Cut-off = 0.75									
I	49.25	1.99	91.30	95.52	97.37	97.39	96.52	36.36	49.62
II	63.93	34.83	100.00	97.01	96.49	94.12	93.03	83.33	58.81
III	66.17	39.30	100.00	97.01	97.37	94.77	93.03	84.95	60.52

Table 6: The predictive accuracy of each model, in the validation sample, at different cut-off values. PPV and NPV figures are presented. PPV is the percentage of correct positive classifications. NPV is the percentage of correct negative classifications.

Using a standard cut-off value, we observe that the overall accuracy increases by 3.96% in model II and 8.66% in model III. As in the training sample, the improvement is linked to an increase in the precision related to failed businesses by 36.46% in model II and 45.80% in model III. Furthermore, non-financial predictors are confirmed to reveal a particular use in the forecast of medium-term failures: model I only correctly describes 45.98% of firms collapsing in the last two years, while models II and III enhance this value by 40.00% and 54.98%, respectively. Yet, there is also a significant increase in precision during the initial three years of life, namely 34.34% in model II and 40.31% in model III. The non-financial dimensions introduced in this study especially reinforce the negative medium-term forecast - compared to model II, model III registers a 10.70% improvement for ventures disrupted in the final two years and a 4.45% superiority for the first three years. Like in the training sample, model I has a higher accuracy rate in successful ventures, but caused by a larger share of positive classifications - 65.67% against 49.00% and 47.26% in models II and III, respectively. Studying the PPV, we confirm that model III possesses the highest value: 18.53% above model I and 5.88% above model II.

For the 0.75 cut-off value, all frameworks show large precision rates for non-successful SMEs. The fundamental difference resides in the prediction of healthy firms, with model I only able to forecast 1.99% of the events since it classifies 97.26% of observations as negative, versus 79.10% in model II and 76.87% in model III. Model II already achieves a precision of 34.83% for positive businesses, while model III raises this value by 12.83%. In addition, easing the concerns of risk-averse users, model III exhibits an 84.95% correctness when labeling a venture as successful - 133.64% above the traditional model. Overall, similar to the testing sample, model III displays the highest PPV and NPV, reflecting its superior discriminatory power.

Ergo, based on unambiguous evidence from training and validation samples, we conclude that non-financial determinants improve the accuracy of traditional financial models, collecting particular gains in the medium-term negative predictions, and that the framework including the new non-financial metrics developed is the best-performing model at both cut-offs analyzed.

4.5 Practical Implications

Previous studies advocated that research on the determinants of business failure and success benefits multiple agents. In particular, entrepreneurs, the parties that advise them and provide them capital, and society as a whole (Dennis and Fernald 2001). Thus, a reflection is made regarding the main practical implications of the results obtained for different stakeholders.

The construction of a robust prediction model based solely on information related to the first months of activity in an SME should signal entrepreneurs that the initial managerial decisions pursued and the early performance on the market are critical for the medium-term sustainability of the business, and thereby shall be carefully planned. In that sense, the estimated statistically significant parameters in model III suggest that owners should start by concentrating efforts on maximizing the productivity and efficiency of both assets and employees, while building an educated workforce as that is especially crucial for the future prospects of the firm. Although the remuneration paid to the staff was not found to have a significant impact per se, the data shows that graduated workers receive higher salaries and that should not deter managers[8]. In addition, founders may note that a sole proprietorship by shares, once controlled for its initial

[8]The remuneration per hour worked (X20) and the proportion of graduated employees (X21) exhibit a positive correlation of 0.346 (see Table A.4).

size, has a competitive advantage when compared to collective counterparts - a pattern already identified by Parise (2020). The reasoning behind this edge is out of the scope of the paper, but individual companies are often associated with characteristics that may be considered useful when beginning a venture, namely lower capital requirements, less bureaucracy and avoiding conflicts between partners since control resides in a single person (Berk and DeMarzo 2014).

For investors and institutions financing young SMEs in the Portuguese commerce sector, we offer a model to estimate the probability of a business being financially healthy by the end of the fifth year after inception. This reveals useful given the documented uncertainty surrounding businesses in the initial years of activity (Tomy and Pardede 2018). Furthermore, the findings retrieved along the process may permit financiers to collect additional benefits. First, there is unambiguous evidence that qualitative metrics improve the precision of the traditional financial model. This includes the non-financial regressors developed in the present paper and found to have an important contribution to the correctness presented at different cut-off values. In line with literature indicating that even small advancements in accuracy conduct to higher earnings for investors, we conclude that the current research is able to generate a positive economic effect for these stakeholders (Blochlinger and Leippold 2006; Agarwal and Taffler 2008; Bauer and Agarwal 2014). Second, compared to the traditional financial prediction models typically restricted to time horizons of one year due to the swift collapse in precision as the firm distances itself from the moment of failure, hybrid models enhanced the medium-term forecast, making it possible to detect earlier the success or failure of a business. Third, by paving the way to non-financial factors, we may compensate for the lack of reliable financial data on small, young firms. Altman et al. (2010) identified this problem as unaddressed by research and developed metrics linked to audit judgments and payment behavior, but of little use for recently founded companies due to the lack of historical records. Fourth, non-financial variables were decisive in reducing incorrect classifications of failed ventures, constituting a major progress due to the consequences arising from this type of error. And fifth, the hybrid framework with the new non-financial determinants constructed was unequivocally proved the best-performing model at the higher cut-off value, conciliating high accuracy rates for negative events with a robust precision for positive observations. In this manner, the model enlarges the set of investment opportunities available to risk-averse investors and banks facing strict controls on their risk exposures. All in all, if these features stimulate an extension of credit to a higher number of small businesses, we may be helping to reduce the financial constraints placed on SMEs that caused an increasing dependence on government subsidies in recent years (Ferrando et al. 2017).

Moreover, in case the previous findings promote a fall in Portuguese business mortality rates, then this paper will also have contributed to the multiple societal benefits generated by small businesses to assume a more permanent nature than the one identified so far by researchers. Nevertheless, two aspects may deserve the attention of policy-makers. First, enterprises with more initial total assets are estimated to have a higher probability of becoming successful, with important gains to be retrieved mainly at intermediate levels of the firm size (see Figure A.5). And second, no evidence was found of a competitive advantage by SMEs located in the Lisbon Metropolitan Area, the most urbanized center in Portugal (PORDATA 2022). This goes in line with the discovery by Phillipson et al. (2019) that small ventures in rural zones do not perform worse than their counterparts in urbanized zones, although facing significantly more barriers in obtaining finance, recruiting staff, and meeting regulatory burdens. Hence, without policy action, both factors may accentuate economic inequalities across social classes and regions, restraining the economic potential of less wealthy entrepreneurs and rural areas.

To conclude, may this study motivate other researchers to develop new and more accurate non-financial determinants that could improve the assessment of business performance. Apart from testing the findings in the present paper, researchers should try to understand the drivers behind the critical factors identified, as that would increase the public comprehension of the forces at play and surely enhance the assistance given to entrepreneurs and other stakeholders. We emphasize that the model constructed is restricted to internal determinants, but pioneering works started to use external determinants, such as economic growth, inflation and interest rates (Sousa et al. 2022; Travanca et al. 2022). As a matter of fact, Figure A.6 reveals that within the sample considered, the number of successful firms founded in 2010 and 2011 is reduced. This period coincided with the beginning of a financial crisis in Portugal, leading the country to request financial assistance from the International Monetary Fund in April 2011. Therefore, we believe that future research could refine the model constructed by including external factors.

5 Conclusion

In Portugal, 99.9% of non-financial firms are SMEs. However, although prior research identified several economic and societal gains created by these ventures, small enterprises are associated with high failure rates during the initial years of activity. Hence, the benefits produced are often described as temporary. In that sense, based on a logistic regression technique, the present paper developed a prediction model to analyze the internal financial and non-financial determinants of survival, growth and success in the Portuguese commerce sector at the inception year.

The results prove that non-financial regressors increase the accuracy of traditional financial models, especially by enhancing the prediction of medium-term negative events. Given the scarcity of qualitative metrics in the literature, new predictors applicable to young companies were built and found to improve the discriminatory power of the model at different cut-off values. Furthermore, five factors are estimated to have a positive, statistically significant impact on business performance: i) asset turnover ratio; ii) initial size; iii) being a sole proprietorship; iv) proportion of employees with higher education; and v) EBIT per hour worked.

In practice, the findings imply that early managerial decisions and market performance are crucial to the medium-term prospects of a business, suggesting potential focus areas for owners. Investors are encouraged to look beyond financial statements, since the use of non-financial indicators yields economic gains, allows an earlier detection of successful ventures, addresses the lack of financial information in small firms, and ensures a robust performance at a higher cut-off value. Altogether, these advancements may contribute to expanding the credit available to SMEs, but policy action is required to reduce inequalities across entrepreneurs and regions.

Future research shall explore new non-financial regressors, combine them with external determinants, as macroeconomic variables, and provide a framework to explain the mechanisms underlying each critical factor identified. This would enhance the assistance provided to the several individuals depending on small businesses, and daily faced with high failure rates that led Schumacher (1973) to emphasize the courage required to maintain themselves in the market. In essence, Mark Twain (1894) deftly reminds us of why is so important to help these agents: because courage is not the absence of fear, but the resistance to fear, the mastery of fear.

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A Appendix

A.1 Data Appendix

Orbis and *Quadros de Pessoal* share the following variables: 1) location, given by NUT-II nomenclature; 2) 5-digit industry CAE code; 3) year of inception; 4) month of inception; 5) share capital; 6) annual sales; and 7) number of employees. Observations were matched if the initial five variables coincided and the values observed for the annual sales deviated less than 1%. The number of employees was used as a check variable. This method is based on Card et al. (2016). However, the procedure in the present paper was adapted to be stricter, as deviations could impact the results obtained. Card et al. (2016) analyzed a sample with 301 417 firms and thereby equipped the procedure with more flexibility by allowing observations to match using only two common variables, and not considering the inception month. The present study was able to cross 3 558 observations, corresponding to 25.27% of the firms provided in *Quadros de Pessoal*. Active dormant and dissolved merged or took-over firms were dropped given the difficulty to interpret the context that led to the respective status. Observations with missing values were also dropped. The final sample was composed of 2 847 observations.

A.2 Figures

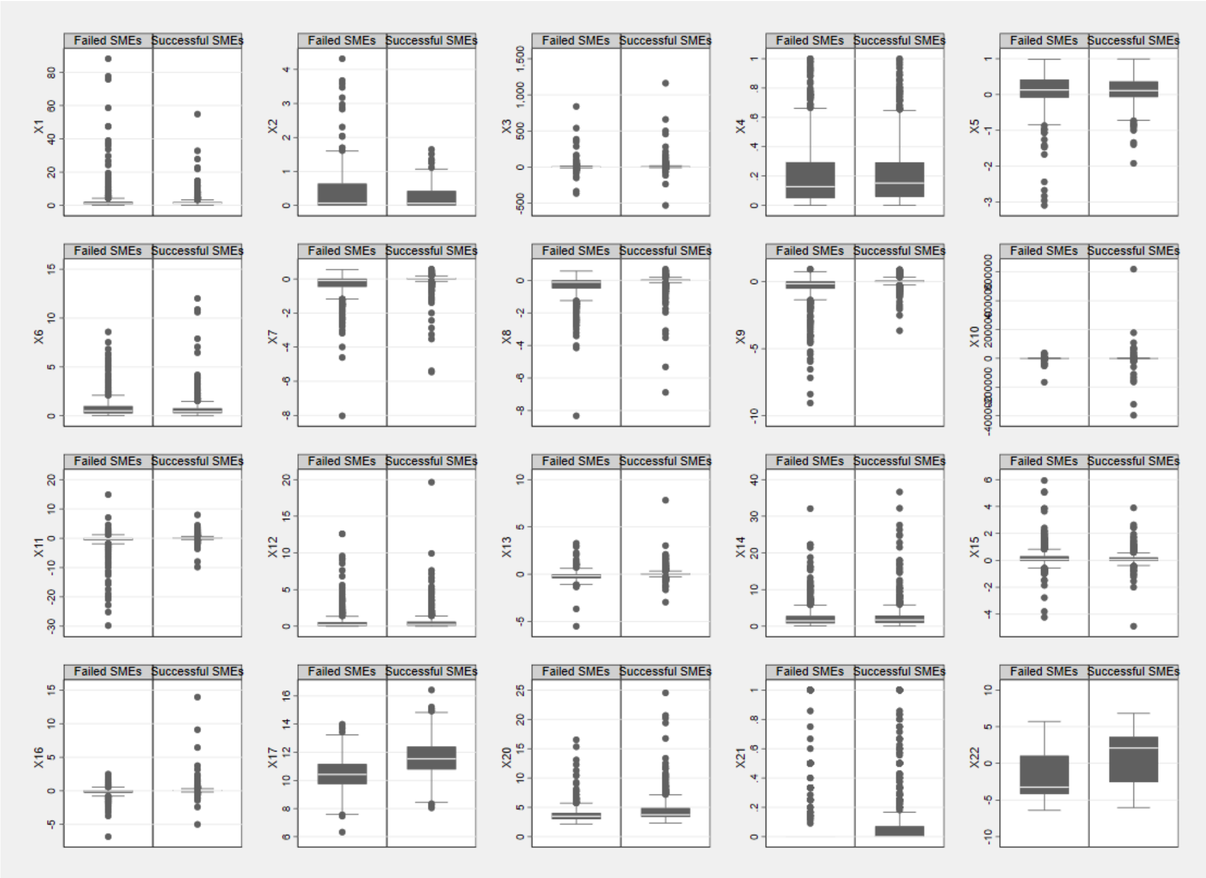


Figure A.1: Box plots of failed and successful SMEs for each regressor. Binary independent variables are not analyzed due to the lack of variation. The identification of the variables is done through the respective ID, which can be consulted in Table 1.

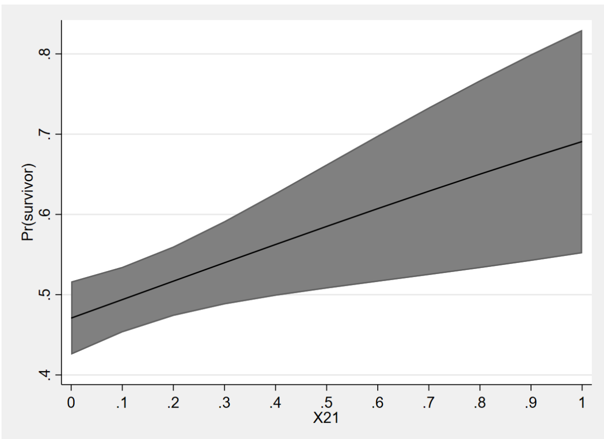
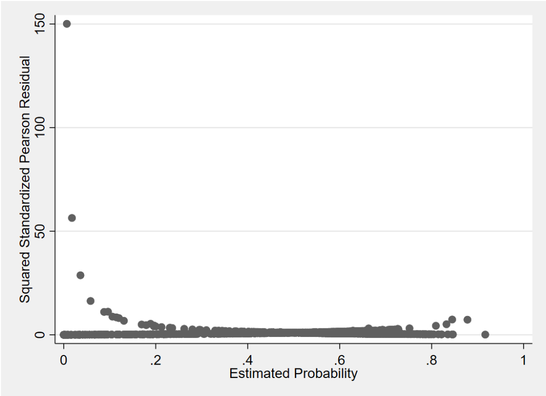
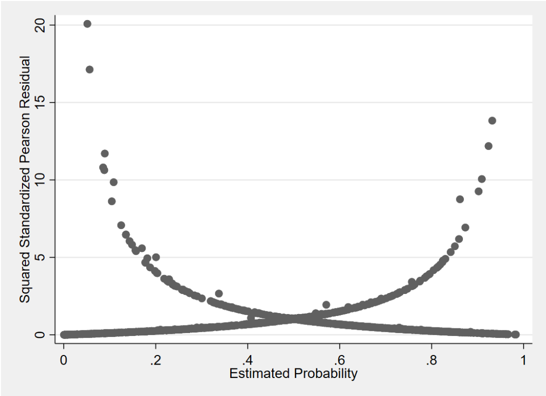


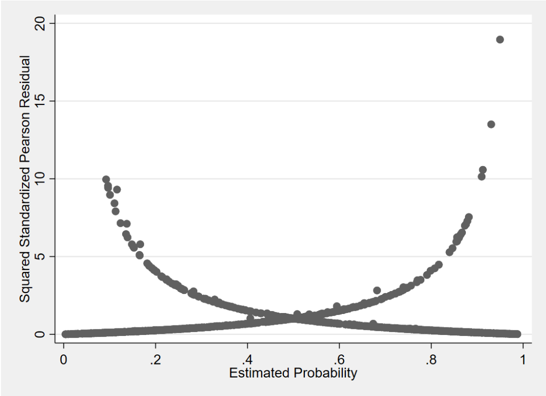
Figure A.2: Estimated probability for different proportions of graduated employees with 95% confidence intervals. All other factors are assumed to be at the respective means.



(a) Model I

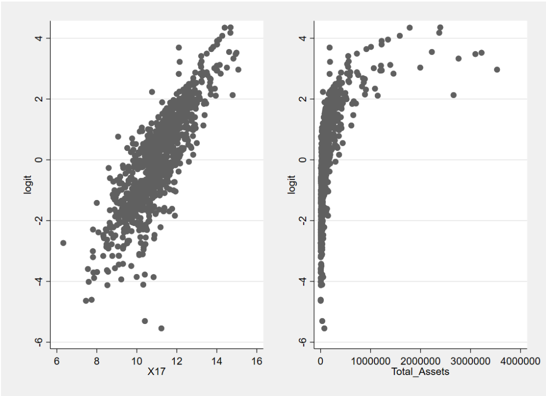


(b) Model II

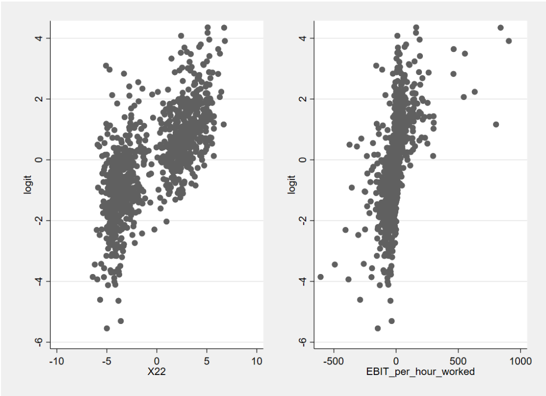


(c) Model III

Figure A.3: The squared standardized Pearson residuals versus estimated probabilities. Models with non-financial predictors reduced the variability observed in the traditional financial model.



(a) Total Assets



(b) EBIT per hour worked

Figure A.4: The non-linearity of total assets and EBIT per hour worked with the logit. Both variables were logarithmized, which is a common practice, as observed in Altman and Sabato (2008). The EBIT per hour worked posed the additional obstacle of exhibiting negative values, thus not permitting the direct application of the natural logarithm, as done to Total Assets. Instead, a log-modulus transformation was employed, based on the findings by Trigueiros and Sam (2016) that this delivers more accurate, robust and balanced prediction models.

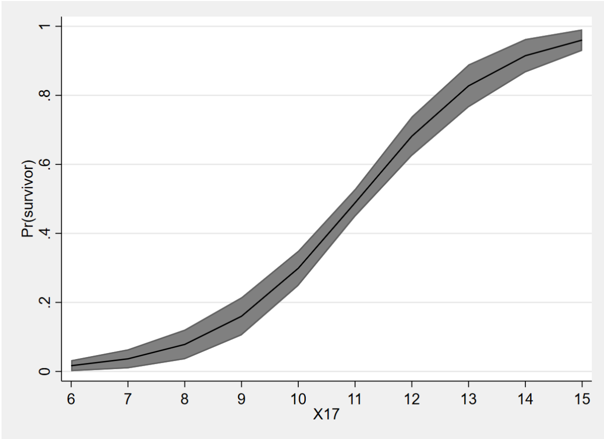


Figure A.5: The estimated probability of being a successful SME by the end of the fifth year after inception for different initial sizes, holding other factors at the respective means, with 95% confidence intervals. There are particular gains to be collected at intermediate levels.

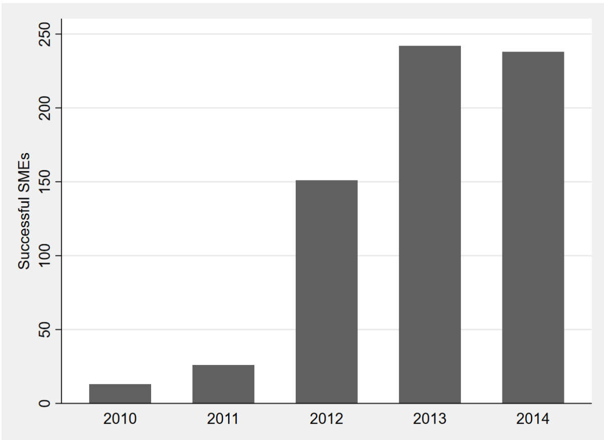


Figure A.6: The number of successful SMEs per inception year. The number is clearly reduced in 2010 and 2011, corresponding to the beginning of the Portuguese financial crisis, suggesting the presence of external determinants.

A.3 Tables

ID	Failed SMEs		Successful SMEs	
	Mean	Median	Mean	Median
X1	2.864	1.099	2.056	1.263
X2	0.362	0.067	0.237	0.061
X3	4.271	-0.133	9.613	2.394
X4	0.207	0.127	0.216	0.152
X5	0.108	0.130	0.124	0.110
X6	0.839	0.502	0.715	0.452
X7	-0.346	-0.088	-0.041	0.021
X8	-0.375	-0.109	-0.054	0.013
X9	-0.457	-0.162	0.001	0.025
X10	-1 523.042	-18.968	-296.506	2.474
X11	-0.803	-0.194	0.128	0.064
X12	0.612	0.207	0.588	0.252
X13	-0.197	-0.164	0.060	0.015
X14	2.462	1.457	2.711	1.707
X15	0.182	0.073	0.127	0.060
X16	-0.178	-0.009	0.130	0.055
X17	10.439	10.423	11.595	11.536
X18	0.549	1.000	0.506	1.000
X19	0.242	0.000	0.200	0.000
X20	3.774	3.462	4.463	3.721
X21	0.073	0.000	0.117	0.000
X22	-1.819	-3.252	0.984	2.090

Table A.1: Descriptive statistics: the mean and median values for failed and successful SMEs. The results shall be interpreted carefully due to skewed distributions and extreme observations. The ID remits to the predictors described in Table 1.

ID	Predictor	Type
X1	Current Assets / Current Liabilities	Leverage
X3	Current Liabilities / Equity	Leverage
X4	Cash / Total Assets	Liquidity
X5	Working Capital / Total Assets	Liquidity
X8	EBIT / Sales	Profitability
X9	EBIT / Total Assets	Profitability
X11	Cash Flow / Current Liabilities	Coverage
X13	Net Income / Total Liabilities	Coverage
X14	Sales / Total Assets	Activity
X16	Equity / Sales	Activity
X17	LN(Total Assets)	Non-Financial
X18	Binary Predictor = 1 if Sole Proprietorship by Shares	Non-Financial
X19	Binary Predictor = 1 if Lisbon Metropolitan Area	Non-Financial
X20	Total Wage / Total Hours Worked	Non-Financial
X21	Employees with Higher Education / Total Employees	Non-Financial
X22	Log-Modulus(EBIT / Total Hours Worked)	Non-Financial

Table A.2: The final list of financial and non-financial predictors divided by type. Financial metrics were reduced to two per type in order to tackle potential multicollinearity issues, according to the respective accuracy ratios, following Altman and Sabato (2008).

Model	Failure in... (%)				
	1-year	2-years	3-years	4-years	5-years
Cut-off = 0.5					
I	64.41	60.83	58.72	43.68	48.94
II	77.97	80.83	66.97	62.07	61.70
III	77.97	84.17	74.31	64.37	69.15
Cut-off = 0.75					
I	98.31	99.17	99.08	98.85	98.94
II	93.22	96.67	92.66	90.80	93.62
III	94.92	97.50	92.66	93.10	92.55

Table A.3: The predictive accuracy of each model for failed SMEs analyzed by the year of failure since inception, in the training sample.

ID	X1	X3	X4	X5	X8	X9	X11	X13	X14	X16	X17	X18	X19	X20	X21	X22
X1	1.000															
X3	-0.033	1.000														
X4	-0.023	-0.023	1.000													
X5	0.241	0.007	-0.314	1.000												
X8	-0.029	0.062	0.132	0.100	1.000											
X9	0.077	0.050	0.056	0.314	0.544	1.000										
X11	-0.397	0.027	0.137	-0.032	0.409	0.332	1.000									
X13	0.070	0.021	0.184	0.151	0.460	0.553	0.468	1.000								
X14	-0.073	-0.034	0.192	-0.151	0.162	-0.098	0.083	0.030	1.000							
X16	0.014	0.026	0.046	0.105	0.583	0.400	0.250	0.201	-0.007	1.000						
X17	-0.003	0.058	-0.195	0.106	0.270	0.472	0.167	0.235	-0.231	0.280	1.000					
X18	-0.016	0.011	0.046	0.042	0.019	0.024	-0.008	0.021	0.014	-0.022	-0.178	1.000				
X19	0.071	-0.010	0.044	-0.037	-0.023	-0.035	-0.008	0.011	0.031	-0.044	0.018	-0.048	1.000			
X20	-0.041	-0.014	-0.047	0.001	0.060	0.068	0.037	0.016	-0.081	0.214	0.392	-0.139	0.140	1.000		
X21	-0.007	0.022	-0.026	0.025	-0.079	-0.025	-0.032	0.030	-0.077	0.040	0.129	-0.104	0.084	0.346	1.000	
X22	-0.004	0.037	0.121	0.155	0.595	0.501	0.431	0.596	0.105	0.319	0.360	-0.004	-0.030	0.104	-0.003	1.000

Table A.4: Cross-correlation between all predictors included in Model III. The ID remits to the predictors described in Table 1.

Group by decile	Estimated Probability	Observed 1	Expected 1	Observed 0	Expected 0	Total
1	0.1183	7	6.2	87	87.8	94
2	0.2125	18	15.7	76	78.3	94
3	0.2940	27	23.9	67	70.1	94
4	0.4092	34	32.8	60	61.2	94
5	0.5116	32	43.3	61	49.7	93
6	0.6080	47	52.6	47	41.4	94
7	0.7000	66	61.6	28	32.4	94
8	0.7784	74	69.7	20	24.3	94
9	0.8665	80	77.6	14	16.4	94
10	0.9874	84	85.7	9	7.3	93

Table A.5: The Hosmer-Lemeshow table. The training sample is divided into deciles according to the estimated probability. Expected values are calculated based on the average estimated probability within each decile and compared to the observed values.

	Observed
Hat	1.001***
	(14.16)
Hat sq	0.009
	(0.22)
Constant	-0.012
	(-0.12)
Observations	938

Exponentiated coefficients; z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Regressing the observed outcomes on the estimated probabilities and estimated probabilities squared. In a correctly specified model, predicted values are statistically significant and squared values should not have much predictive power.

Model	Failure in... (%)				
	1-year	2-years	3-years	4-years	5-years
Cut-off = 0.5					
I	65.22	59.09	55.32	41.03	50.00
II	91.30	84.09	68.09	61.54	66.67
III	95.65	81.82	76.60	71.79	70.83
Cut-off = 0.75					
I	91.30	97.73	100.00	97.44	93.75
II	100.00	95.45	95.74	87.18	89.58
III	100.00	95.45	97.87	87.18	87.50

Table A.7: The predictive accuracy of each model for failed SMEs analyzed by the year of failure since inception, in the validation sample.