A work project, presented as part of the requirements for the Award of a Master Degree in Economics from the NOVA – School of Business and Economics.

Determinants of Firm Failure in Portugal in 2010-2013

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A project carried out on the Master in Economics Program, under the supervision of:

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May 2017

Abstract

Firm failure is a cause and effect of economic recessions. Lower market demand can have enormous impact on firms' businesses. As some cannot rely on their activity to safeguard a source of income, others are constrained by their clients' inability to pay. Businesses may then collapse, contributing to job destruction, which in turn, can only further depressed economic conditions. Analysing firm failure determinants is therefore crucial. This work project proposes an analysis of financial-performance indicators on Portuguese firms during the 2010-2013 period. Variables analysed include impairment losses, short-term and long-term debt. These variables were analysed over different sub-samples to determine their effects on firm failure probability in specific contexts.

Keywords: Firm failure, Impairment losses, Logit model, Panel data

Acknowledgements: I would like to thank professor Pedro Brinca and doctoral student Miguel Ferreira for their encouragement and support throughout this project. To my parents and brother, who were always there for me; to my friends, for their never-ending patience. You all contributed to this project, with your reassurances and unwavering support.

1. Introduction

Economic crises are challenging occurrences to a company's business activity and stability. There are several factors which can hinder a firm's activity and may lead to its ultimate downfall. It is usually the case that, in times of recession, firms face more adversities, and sustaining their businesses may reveal itself to be a struggle.

Lower household confidence in the present, and even future, economic situation can have depressing effects on the demand for goods and services of an economy, not to mention households' increased indebtedness, which only adds to this unfavourable scenario. In the face of a lower demand, some companies will see their revenues decline; they might consider reducing the investment in the activity, and eventually may even fail to comply with their obligations towards financial institutions, or even suppliers. On another note, part of firms' accounts receivable may become irrecoverable, as customers are unable to meet their payment obligations. This will leave the firm in a precarious situation: it cannot reimburse the entities with which it has commercial or financial relations, since it cannot retrieve the payments for the goods sold and the services provided, while also not being able to generate other income, as the overall economic scenario is an unbecoming one. Moreover, companies in this situation, especially Small and Medium-sized Enterprises (SME), will ultimately find it more difficult to obtain credit from financial institutions. This situation is, in general, true for companies operating in most economies. The focus of this thesis is, however, on firms operating in the Portuguese economy.

The global economic and financial crisis of 2008-2009 would come to emphasise Portugal's macroeconomic imbalances, accumulated over the years. Budget and current account deficits, weak real Gross Domestic Product (GDP) growth were already a reality in pre-2008 recession years. Also, low interest rates, close to those of countries like Germany or France, had allowed for an increase in the country's indebtedness (both in the public and the private sectors). As the global crisis emerged, however, interest rates directed to Portugal started to reflect a certain credit risk, and it became more difficult for the country to obtain external financing, or even to attract foreign investment. This predicament had an enormous impact on the Portuguese economy, and demonstrated how unprepared the country was to endure the effects of such a shock.

All these factors combined, eventually led to the agreement of an Adjustment Programme, in 2011, between the Portuguese government, the European Commission, the European Central Bank (ECB) and the International Monetary Fund (IMF). This programme sought to restore the confidence of the international financial markets and to promote competitiveness and sustainable growth in the Portuguese economy.

The programme's implementation, combined with a global recession (or a rather slow recovery from it), led to a severe downturn as the country's real GDP annual growth registered an annual decrease of 4% in 2012, the lowest growth rate since 1975, according to OECD data.

Having had the recession an overall negative impact over the performance of firms, leading some to exit the market, the reverse is also true. These firms' failure also contributed to deepen the shock, as they generated high levels of job destruction. Indeed, job destruction was, according to the OECD, the main driver for the adjustments in labour input as a response to the crisis. Higher unemployment would in turn lead to lower demand, furthering the shock to economic activity.

It is thus relevant to study the factors determinant of a firm's collapse. This work project aims to contribute to that end, as it examines the effects some firm features, indicative of financial performance, may have on the probability of a firm closing during the period from 2010 until 2013. We will be analysing how the behaviour of these variables influence the probability of firm failure over the 2010-2013 period, and how this impact changes when considering only the case of SME and firms from capital-intensive and labour-intensive sectors, comparing those to the baseline case. Finally, we will be looking at how these variables affect the probability of firm failure over each one of the years under analysis, making a parallel with the Adjustment Programme (2011-2014) and its short-term consequences.

This work project is organized as follows. Section 2 includes an overview of existing literature on the topic. Section 3 comprises the methodology, data characteristics and model specification. Section 4 presents the results, as section 5 describes some weaknesses of the model. Finally, section 6 concludes.

2. Literary review

There are several papers in the literature searching for answers to the questions "Why do firms fail?", "Why do firms survive?". Some consider macroeconomic factors, some search for answers in firms' financial statements, while others look for firm characteristics and actions which can lead them to collapse.

One of determinants frequently studied is innovation and the role it plays on the probability of a firm's survival. There are those who regard it as a strong prospect for firm survival: Silviano Esteve Pérez et al. (2004) highlights the general importance of Research & Development (R&D) activities in a firm's competitiveness, and Helmers and Rogers (2010) regard the importance of innovation, as measured by published patents and trade-marks, in the survival of new firms in the UK.

Notwithstanding the above, Buddelmeyer, Jensen and Webster (2006) emphasize a characteristic of innovation: as it can both succeed or fail, it may also lead a firm to thrive or collapse. They propose a separation of innovation into two components: innovation capital, a stock variable representative of "successful" innovation, and innovation investment, a flow variable representative of “unsuccessful” innovation. Using a sample of Australian firms, they find that innovation capital can lower the probability of firm failure, but innovation investment increases said probability.

In addition to emphasising R&D as a mechanism for firm survival, Silviano Esteve Pérez et al. (2004) also takes into consideration the role a firm’s size and age can have on the probability of it closing doors. They find that, for a sample of Spanish manufacturing companies in the period 1990-1999, small and young firms are most likely to exit the market.

Also, in an analysis to Spanish firms, López-García and Puente (2006) studied the determinants of firm survival for a sample of firms of all business sectors, analysing, among other aspects, the effects that resorting to debt *versus* equity can have on the probability of firm failure. They find that holding debt can have beneficial effects and contribute to a firm’s survival but only up to a certain level, from which point onwards it increases the probability of a firm exiting the market.

Bottazzi, Grazzi, Secchi, and Tamagni (2010) follow other routes, as they distinguish several types of firm exit (voluntary liquidation, mergers, acquisitions or bankruptcy), focusing on the concept of firm default. They examine the impact both financial and economic variables can have on this occurrence in a panel of Italian manufacturing firms. Some of the financial variables include interest expenses, financial-debt-to-sales ratio and leverage; economic variables include size, growth and productivity.

Unlike Bottazzi et al. (2010), this thesis relies on the concept of firm failure as reported by statistical sources and focuses on the firms’ financial statements. It consists in an econometric analysis through the estimation of Logit models of firm failure probability. Like Bottazzi et al. (2010), the regressors are to some extent controlled for firm size, as they are scaled to the firm’s turnover.

Our model does not include variables such as productivity or R&D activities, as we focus on firm-level financial variables and attempt to ascertain if *per se* they produce effects on firm failure probability. On that note, a distinct perspective is offered through the consideration of impairment losses in accounts receivable in the estimated model.

The analysis was conducted on data from Portuguese firms from all sectors of business activity, from 2010 until 2013 which, as previously mentioned, encompasses part of the Adjustment Programme Period (2011-2014). The analysis performed can thus bring some insight into the determinants of firm failure over this period.

This work project was motivated by A. Carneiro et al. (2014), an analysis of three channels through which the Portuguese economic crisis impacted the labour market: the credit channel, the wage rigidity channel and the labour market segmentation channel. Nonetheless, this project's analysis was particularly motivated by the statistical evidence found on credit constraints having a significant impact over firm failure in the period 2006-2010.

3. Methodology

As this project aims to depict the factors affecting the probability of firm failure, the dependent variable presents itself as a binary variable. Thus, the dependent variable, y_{it}, will take on the value of 1 if a firm disappears in that year and 0 otherwise, being the respective probabilities p_i and $1 - p_i$.

The response variable, y_{it}, follows a Bernoulli distribution, which has a probability mass function given by:

$$f(y_{it}|X_{it}, c_i) = p_{it}^{y_{it}}(1 - p_{it})^{1-y_{it}}$$

As one wants to establish the effects the regressors have on the probability of a firm failing, the probability p_i is parameterized to depend upon the explanatory variables, their respective coefficients and time-invariant unobserved effects,

$$Pr(y_{it} = 1|X_{it}, c_i) = p_{it} = F(X'_{it}\beta + c_i)$$

Where X_{it} is a Kx1 vector of explanatory variables, β a Kx1 vector of coefficients and c_i an unobserved time invariant individual effect. This conditional probability will vary according to the F(.) function. If F(.) is a linear function, then we're in the presence of a Linear Probability Model (LPM). This specification holds one significant caveat: the predicted probability of y_{it} may not lie between 0 and 1, which can hamper economic reasoning and conclusions. Other specifications include the Probit and Logit models. These are non-linear models, for which the function F(.) is a cumulative distribution function, ensuring p_{it} takes values between 0 and 1, and thus overcoming a major LPM drawback. In the Probit model the cumulative distribution function used is that of the normal distribution, whereas in the Logit model it is the cumulative distribution function of the logistic distribution.

Since typically the dependent variable is not fully observed, these models can be construed around a latent variable y^*_{it}, unobserved, which is related to the observed variable, y_{it}, according to the following expression.

$$y_{it} = \begin{cases} 0, & if\ y^*_{it} \leq 0 \\ 1, & if\ y^*_{it} > 0 \end{cases}$$

Where y^*_{it} is given by $y^*_{it} = X'_{it}\beta + c_i + u_{it}$. The individual specific effect, u_{it}, has zero mean and is uncorrelated with all the regressors (strict exogeneity); in contrast, c_i is arbitrarily correlated with X_{it}. As u_i is assumed to have a symmetric density function, it follows that

$$Pr(y_{it} = 1) = Pr(y^*_{it} > 0) = Pr(X'_{it}\beta + c_i + u_{it} > 0) = Pr(u_{it} > -(X'_{it}\beta + c_i))$$
$$= Pr(u_{it} < X'_{it}\beta + c_i) = F(X'_{it}\beta + c_i)$$

Hence, depending on the chosen cumulative distribution function, one will have a Probit (normal distribution) or a Logit (logistic distribution) model.

3.1. Data and variables

The dataset was created by Statistics Portugal, or *Instituto Nacional de Estatística* (INE), and consists in annual data on all Portuguese firms engaging in the production of goods and/or services in the whole territory[1]. Excluded from this dataset are financial institutions, insurance companies and non-market-oriented entities, such as associations or public administration units.

The database has information on firms' financial and economic indicators, as it intends to provide a description of their economic and financial performance. Moreover, it includes demographic indicators, such as the year of birth and death of firms, the latter being the basis for our analysis in this project.

The data is obtained from *Informação Empresarial Simplificada* (IES) or, in English, Simplified Business Information, a thorough document containing a wide range of information about firms' business activities. It must be filled in and delivered by Portuguese firms every (fiscal) year.

The years in the dataset range from 2010 to 2013, and Table 1 provides a summary of the variables considered in the model.

[1] The dataset is known as *Sistema de Contas Integradas das Empresas* (SCIE), or in English, System of Integrated Business Accounts.

Table 1
Summary of data statistics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
LDebtLT_Turnover	579,914	-1.153	1.931	-14.904	13.435
LDebtST_Turnover	266,795	-2.008	2.045	-18.811	15.418
LIntExpenses_Turnover	728,209	-4.993	2.247	-18.522	12.251
LInvFA_Turnover	600,840	-3.377	2.071	-16.315	11.679
ImpAR_Turnover	1,255,851	0.032	21.251	-580.348	23,545.86
I_Death	4,419,057	0.163	0.369	0	1

Source: SCIE

The explanatory variables are: *LDebtLT_Turnover*, the logarithm of the ratio between outstanding long-term debt and turnover; *LDebtST_Turnover*, the logarithm of the ratio between outstanding short-term debt and turnover; *LIntExpenses_Turnover*, the logarithm of the ratio between interest expenses and turnover; *LInvFA_Turnover*, the logarithm of the ratio between investment in fixed assets and turnover; and *ImpAR_Turnover*, the ratio between impairment losses in accounts receivable and turnover.

The dependent variable is a binary variable (*I_Death*) which takes on the value 1 if the firm disappears (or "dies") in that year and 0 otherwise. This variable is defined by INE as follows. A firm is said to have died when its activity ceases to exist; this variable does not include firm closure by way of merger, majority acquisition, dissolution or restructuring within groups of companies. Also, firms that change its business activity are not considered to have "died".

To conclude, Table 2 summarizes the amount of firm failures over the years in percentage terms.

Table 2
Percentage of firm failures over the years

	Year				
I_Death	2010	2011	2012	2013	Total
0	84,67%	83,89%	82,05%	84,16%	83,72%
1	15,33%	16,11%	17,95%	15,84%	16,28%
Total	100,00%	100,00%	100,00%	100,00%	100,00%

Source: SCIE

The year with most firm failures was 2012, followed by 2011 and 2013, being 2010 the year with less firms ceasing activity.

3.2. Model Estimation

Probit and Logit models are non-linear models, and as such can be estimated through the Maximum Likelihood (ML) method. This estimation procedure finds the parameter estimates for which the likelihood function is maximum. This function is given by:

$$L = \prod_{t=1}^{T}\prod_{i=1}^{N}\left(F(X'_{it}\beta + c_i)^{y_{it}}\left(1 - F(X'_{it}\beta + c_i)\right)^{1-y_{it}}\right)$$

Maximizing the likelihood or the logarithm transformation of the likelihood is equivalent (since the logarithm is an increasing function), thus one can maximize the log-likelihood function to obtain the ML estimates. The log-likelihood function is specified as follows:

$$\mathcal{L} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(y_{it}\ln\left(F(X'_{it}\beta + c_i)\right) + (1 - y_{it})\ln(1 - F(X'_{it}\beta + c_i))\right)$$

The estimation procedure is achieved through an iterative process and as we will be working with a Logit model, the function F(.) takes the form of the cumulative distribution function of the logistic distribution.

When we are considering a fixed-effects Logit model, however, this estimation will produce inconsistent estimators for c_i and β. An alternative is Conditional Maximum Likelihood, which will be the method used in this work project. Even though they are accounted for, the time-invariant unobserved effects, c_i, are not involved in this estimation procedure, and as such an estimate for c_i cannot be computed. Further topics on the fixed effects model are described in the next section.

3.2.1. Model Specifications

The model under analysis was estimated by way of a Logit Regression with fixed effects.

The use of fixed effects allows us to control for invariable firm characteristics which are not included in the model (e.g. they can be difficult to measure, or even unobservable); these effects on the dependent variable will be accounted for, even though they cannot be estimated. This method is then a mechanism to avoid omitted-variable bias and endogeneity problems associated with time-invariant variables.

The use of fixed effects, however, poses some limitations on the model. Regressors must have a large variability within each firm, as the fixed effects estimation is based on within-firm differences as opposed to differences between firms. Also, observations of firms that do not die in any of the years under analysis (I_Death=0 for all four years) will be dropped in the estimation of the model. This may have some consequences over the results obtained, since the sample of firms will be reduced.

As we would like to analyse the effects of time-varying variables and control for firm characteristics (unchanged over time) that may affect firm failure probability, the option for fixed effects seems ideal. To ensure this was the most appropriate estimation method, we conducted the Hausman specification test, which indicated the preferred model to be Logit with fixed effects[2].

Moreover, cluster-robust standard errors were used. These control for unknown forms of heteroskedasticity (which may lead to inconsistent estimators), while also controlling for serial correlation within clusters – or firms.

[2] The performed Hausman specification test can be found in Appendix II.

Lastly, more than one Logit model was estimated. Even though the base model provides us with statistical evidence on the effects of the explanatory variables over firm failure probability for the whole sample, it remains relevant to analyse these same impacts for restricted groups of firms (or periods). This broadens the analysis and may bring light to certain firm behaviour that could influence a firm's decision to close.

3.2.2. Interpretation of results

In non-linear models, such as Probit or Logit, estimated coefficients cannot be directly interpreted as to their effect over the probability of firm failure. The marginal effect of a certain variable over the probability of firm failure is given by:

$$\frac{dP(y_{it} = 1)}{dX_{i,j}} = f(X'_{it}\beta + c_i)\beta_{i,j}$$

Where f(.) is the density function of the logistic regression. Since this function only assumes positive values, we can ascertain the direction of the marginal effect by looking at the sign of the coefficients. In Logit regressions with fixed effects, however, one cannot determine this marginal effect, as the estimation procedure does not provide an estimate of c_i (the unobserved time-invariant effect). However, we can resort to an alternative interpretation: the marginal effect of a regressor on the odds ratio –the ratio between the probability of firm failure and the probability of firm survival. In other terms,

$$OR = \frac{P(y_{it} = 1)}{P(y_{it} = 0)}$$

This ratio can be interpreted as a relative probability: for example, for an odds ratio of 1.2, a 1-unit increase in the explanatory variable generates an increase in the odds of firm failure or the relative probability of failure by 20%.

4. Results

The estimated model proposes to study the association between certain firm financial indicators and the probability of firm failure in a certain year. As previously mentioned, the dependent variable is a binary variable which takes on the value 1 if the firm disappears in that year and 0 otherwise[3]. The explanatory variables are transformations of the following performance indicators: annual revenue from sales and services provided (the company's turnover); the amount of outstanding debt (both short- and long-term debt) as of the end of the year; annual interest expenses; annual investment in fixed assets; and annual impairment losses in accounts receivable.

The firms in the dataset differ in size and, as such, an increase of 100 Euros in impairment losses in accounts receivable of a large firm is not equivalent to an increase by the same amount for a small or medium enterprise. To overcome this specificity, the chosen variables have been divided by the company's turnover, so that one can account for the company's business size. Hence, we'll be observing, for example, the effects of increases in the annual interest expenses over a year relative to the firm's turnover or, in other words, the increase in the interest payments-to-turnover ratio[4].

The results of the baseline model are presented in Table 3.

[3] Further information can be found in section 3.1. Data and variables.
[4] The full description of each variable can be found in section 3.1. Data and variables.

Table 3

Logistic Regression for the base model

	2010-2013	
	Coefficients	Odds Ratio
LDebtLT_Turnover	1.126***	3.084***
	(0.110)	(0.339)
LDebtST_Turnover	0.443***	1.557***
	(0.060)	(0.093)
LIntExpenses_Turnover	0.233***	1.262***
	(0.086)	(0.108)
LInvFA_Turnover	-0.658***	0.518***
	(0.066)	(0.034)
ImpAR_Turnover	2.094**	8.120**
	(1.019)	(8.271)
Observations	7,692	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: SCIE

As previously mentioned, one cannot infer on the marginal effects of each variable on the probability of firm failure directly through the coefficients. Nevertheless, conclusions can be drawn from the sign they present. As Table 3 suggests, increases in the ratios of debt (both long-term and short-term), interest expenses and impairment losses in accounts receivable to turnover are associated with an increase in the probability of firm failure[5]. As expected, an increase in the ratio of investment in fixed assets to the firm's turnover is associated with a decrease in the probability of a firm disappearing[6].

The Logistic regression also allows for an interpretation of the results using the concept of odds ratio, as suggested in section 3. Table 3 also presents the odds ratio for each explanatory variable.

[5] The first two statistically significant at the 1% level, the latter at the 5% level.

[6] Statistically significant at the 1% level.

As long as the other variables remain unchanged, an increase of 1% in the long-term debt-to-turnover ratio is expected to raise the odds of firm failure by 208%. If we consider an increase in 1% of short-term debt-to-turnover ratio, the relative probability of firm failure increases by 56%. We can then see that the effect of increases in long-term debt generate higher increases in the relative probability of firm failure than those in short-term debt.

There is another result that stands out, as a 1% increase in the registered losses in accounts receivable (to turnover) leads to a rise in the odds of a firm disappearing of 712%. To better analyse this case, one might want to consider the definition of an impairment in accounts receivable. Being accounts receivable the asset representing the amount of money owed by clients, an impairment results in a decrease in this asset's reported value; part of the money owed by clients can no longer be recovered, and the company must register this loss in their income statement.

Successive increases in this variable will thus leave the company in a perilous situation. Clients fail to comply with their obligations, not meeting the payments for services received, and companies are faced with significant losses, as their resources were employed into products and/or services, for which no compensation was provided. It is, therefore, to expect that an increase in impairment losses in accounts receivable would increase the probability of firm failure.

These results support recent evidence, since according to a survey conducted on a sample of Portuguese firms in 2014-2015[7], clients' inability to pay was one of the negative shocks that most affected firms during the economic crisis. This survey also refers to the effect of firms' size on their performance during the recession, which is discussed in the subsequent section.

[7] Survey conducted by Banco de Portugal.

4.1. Small and medium-sized enterprises

According to INE, 99.9% of Portuguese firms correspond to small and medium-sized enterprises. This can be observed in our dataset, as Table 7 in Appendix I summarizes.

Hence, the results of the regression on only small and medium-sized enterprises will not differ substantially from those of the base model, as can be confirmed in Table 4. Table 4 presents the logistic regression for three classifications of firms[8]: SME, small enterprises[9] and micro enterprises.

Table 4

Logistic Regression for different classifications of firms

	SME	Micro enterprises	Small enterprises
	Coefficients	Coefficients	Coefficients
LDebtLT_Turnover	1.132***	1.937***	0.713***
	(0.112)	(0.253)	(0.152)
LDebtST_Turnover	0.458***	0.756***	0.336***
	(0.061)	(0.117)	(0.089)
LIntExpenses_Turnover	0.215**	0.491**	0.259**
	(0.085)	(0.209)	(0.112)
LInvFA_Turnover	-0.663***	-1.848***	-0.366***
	(0.067)	(0.303)	(0.059)
ImpAR_Turnover	2.077**	10.069	3.216
	(1.012)	(9.834)	(2.004)
Observations	7,627	4,864	1,787

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: SCIE

The main difference between these three regressions is that the effect of impairment losses in accounts receivable is no longer statically significant when we consider only small enterprises or only micro enterprises. The sample sizes are significantly reduced in comparison to the regression on SME, which may be why no statistical association could be found between the

[8] The adopted definition of small and medium-sized enterprises is detailed in Appendix I.

[9] Even though the classification of a small enterprise does not exclude micro enterprises, in this analysis we will consider both definitions to be mutually exclusive.

variables. In theory, one would expect a positive relation, as smaller firms usually have scarce sources of income and thus rely more on expected client payments. Moreover, initiating litigation processes to receive respective payment can be costly for smaller companies. Even though this theory seems to be supported by the data on SME, one cannot conclude on the relation between firm failure and impairment losses for the small and micro enterprises cases.

In other respects, in Table 4, as was the case for the base model (Table 3), one observes that rises in the long-term and short-term debt-to-turnover ratios will increase the probability of firm failure.

Essentially, regarding firms' debt levels (both short-term and long-term debt), one can consider two different standpoints. On one hand, financial institutions want to safeguard their investments. They would prefer not to grant credit to firms without a dependable source of revenue or assets to serve as collateral, as there is a higher risk these firms won't be able to reimburse the loan and make the respective interest payments. In this case, we are referring not only to financially unstable firms, but also start-ups or small firms, which typically have a restrictive capacity to self-financing, and as such resort to credit to expand and/or improve their business.

On the other hand, firms with a stable source of income, with steady client bases (usually, large firms) may not need to resort to credit as much as other firms, since they have other ways of financing themselves (e.g. by raising equity capital, returns from investments made, among others).

The data seems to support this last argument, as those who most require bank financing are the ones that may not meet the best prerequisites for loan application: in Tables 3 and 4 we can see that higher debt-to-turnover ratios originate increases in the probability of firm failure.

The results are in line with data on Portuguese[10] and European Union[11] firms' indebtedness levels: SME are found to be more leveraged than larger firms and to rely more on bank financing. Furthermore, the above-mentioned survey finds that access to external financing, or the lack thereof, was considered the third most crucial factor affecting the performance of Portuguese firms during the recession.

Although this analysis does not consider debt-level effects, i.e. initial debt levels and the different effects that may arise for low-debt level firms *versus* high-debt level firms, it still remains indicative of the effects higher debt have on a firm's business activity and overall performance in the market.

4.2. Capital Intensity

Firms operating in capital-intensive sectors will usually be required to make large investments and, consequently, they may be more leveraged. This can potentially generate differences in the effects of the variables under analysis over firm failure probability, when comparing firms in capital-intensive and non-capital-intensive sectors. Further analysis was then conducted.

A firm is considered to be capital-intensive the higher the ratio between capital required and labour required for its activity. As mentioned, usually capital-intensive industries will involve large initial investments, especially in fixed assets. In contrast, labour-intensive sectors require substantial amounts of workforce.

In the analysis performed capital intensity was defined as follows. The firms' fixed assets (by the end of the year) were used as measure for capital and the number of workers (by the end of the year) were considered as measure for labour. The capital-to-labour ratio was then computed for each sector, being the different sectors classified according to the first two digits of their

[10] Data from Banco de Portugal.
[11] Data from ECB.

Classificação das Atividades Económicas (CAE), the Portuguese industry classification, which categorises the different economic sectors present in the Portuguese economy.

To decide which sectors were considered capital intensive and which were considered labour intensive, the median of the capital-to-labour ratio for the whole sample was found. Firms belonging to a sector with a capital-to-labour ratio above the median (of the whole sample) were classified as being capital intensive and those belonging to a sector with a ratio below the median as labour intensive.

The regression results are described in Table 5, which includes the regressions for both capital- and labour-intensive firms and the respective odds ratios.

Table 5

Logistic Regression for capital- and labour-intensive firms

	Capital Intensive	Labour Intensive	Capital Intensive	Labour Intensive
	Coefficients	Coefficients	Odds Ratio	Odds Ratio
LDebtLT_Turnover	0.915***	1.343***	2.498***	3.831***
	(0.115)	(0.198)	(0.286)	(0.758)
LDebtST_Turnover	0.292***	0.602***	1.339***	1.826***
	(0.080)	(0.091)	(0.107)	(0.167)
LIntExpenses_Turnover	0.151*	0.349**	1.163*	1.418**
	(0.082)	(0.175)	(0.096)	(0.248)
LInvFA_Turnover	-0.446***	-0.925***	0.640***	0.396***
	(0.064)	(0.135)	(0.041)	(0.054)
ImpAR_Turnover	3.479**	1.365	32.428**	3.914
	(1.642)	(0.956)	(53.233)	(3.741)
Observations	3,064	4,628	3,064	4,628

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: SCIE

Results show that for both capital-intensive and labour-intensive sectors increases in the debt-to-turnover ratios increase the probability of firm failure. The effect is more prominent in the labour-intensive case, as increases in 1% of the long-term and short-term debt-to-turnover ratios increases the odds of firm failure by factors of 3.831 and 1.826, respectively – higher than 2.498 and 1.339, the case for capital-intensive firms.

It is worth mentioning that even though capital-intensive firms are usually highly leveraged, as investments in equipment may require large sums of capital, their assets serve as collateral, which may be one of the reasons the impact of debt-to-turnover increases on the probability of firm failure is lower than in the labour-intensive firms' case. Nonetheless, in both cases there is a positive association between the variables.

Another significant result lies on the effect increases in fixed assets investment (to turnover) have over a firm's failure probability. As expected, an increase in investment leads to a reduction in the relative probability of firm failure. However, the effects over said probability are lower in magnitude for the capital-intensive sector. This result may reflect the fact that higher investment in fixed assets also mean higher depreciation costs every year. And as capital-intensive industries already support excessive costs in this respect, further investment (to turnover) will decrease, but by a lower factor, the relative firm failure probability.

It is also important to stress that our sample is mainly comprised of small and medium-sized enterprises, so much so that, of all the capital-intensive observations, 99.83% correspond to SME[12]. Therefore, the effects for small and medium-sized enterprises discussed in the previous section also play a role in this analysis.

Moreover, the increases in impairment losses in accounts receivable has a high (positive) impact on the probability of firm failure for capital-intensive firms, as can be seen in an odds ratio of

[12] To confirm this distribution still holds when the regression analysis is made, as observations can be dropped in the process, a logistic model considering only capital-intensive firms that are SME, as well as a logistic model considering only capital-intensive firms that are not SME were estimated. The former yielded similar results to the case in Table 5, the number of observations totalling 3,048, as the latter could not be estimated with only 14 observations available. The regression output can be found in Appendix III.

32.428. In what concerns the labour-intensive firms, no conclusion can be drawn as the variable is not statistically significant[13].

4.3. Annual analysis

Lastly, we look at the effects the explanatory variables have on the probability of firm failure over the years under analysis. Table 6 includes the results for the base model, as well as for each year individually.

Table 6

Logistic Regression for the base model and each year individually

	2010-2013	2010	2011	2012	2013
	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
LDebtLT_Turnover	1.126***	0.201***	0.187***	0.063	0.193***
	(0.110)	(0.016)	(0.022)	(0.043)	(0.033)
LDebtST_Turnover	0.443***	-0.028*	0.051**	0.211***	0.059**
	(0.060)	(0.015)	(0.022)	(0.048)	(0.028)
LIntExpenses_Turnover	0.233***	0.206***	0.061**	0.100*	0.009
	(0.086)	(0.016)	(0.025)	(0.057)	(0.033)
LInvFA_Turnover	-0.658***	0.718***	0.252***	0.002	0.138***
	(0.066)	(0.018)	(0.018)	(0.029)	(0.023)
ImpAR_Turnover	2.094**	-3.468***	0.199	0.499	-0.830
	(1.019)	(0.892)	(0.236)	(0.335)	(0.733)
Constant		-3.082***	2.327	-5.014***	-4.496***
		(0.142)	(0.000)	(0.198)	(0.111)
Observations	7,692	39,355	26,695	22,366	22,813

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: SCIE

As one considers the relation between the independent variables and the dependent variable over each year, some of the results change in comparison to the base model. One feature in the output above stands out: the number of observations is higher for each year than it is for the base model. The reason is that in the base model, when, within each firm, there is no variability

[13] When saying that the "variable is not statistically significant", we mean to say that we fail to reject the null hypothesis that the coefficient associated to the variable is equal to zero.

over the years in the dependent variable, i.e. the firm did not disappear in 2010-2013, those groups of observations are dropped. The fixed effects model looks for determinants of variability within a firm, and as such, when there is no variability, there is nothing to analyse.

Considering the above, the base model then determines the effects which over the four years most contributed to the failure of firms (as measured within each firm), while the annual models concentrate in the effects that, over that year, contributed to the disappearance of firms (as measured between firms). The analyses differ, but some common ground can be found.

The effect of increases in the debt ratios over the probability of firm failure are still positive for both long-term and short-term debt in the years 2011 and 2013, as are the effects of interest rate expenses in 2010, 2011 and 2012.

Even though Portugal registered a 1.4% growth rate in 2010, the period under analysis was mostly a picture of low growth and profound economic recession; real GDP growth registered annual rates of -1.8%, -4% and -1.1% in 2011, 2012 and 2013, respectively[14].

In May 2011, the Adjustment Programme was initiated. One of the programme's goals was fiscal consolidation, as the country had registered systematic budget deficits over the years and, in 2010, its public debt reached 96.2% of GDP, the 4th highest in the European Union (according to Eurostat).

The measures adopted to achieve budgetary discipline, the distrust from international financial markets, and the consequent credit constraints, along with a reduced domestic market demand and high unemployment levels, led the country's GDP to contract more than expected, leaving the economy under a deep recession.

[14] According to OECD Data.

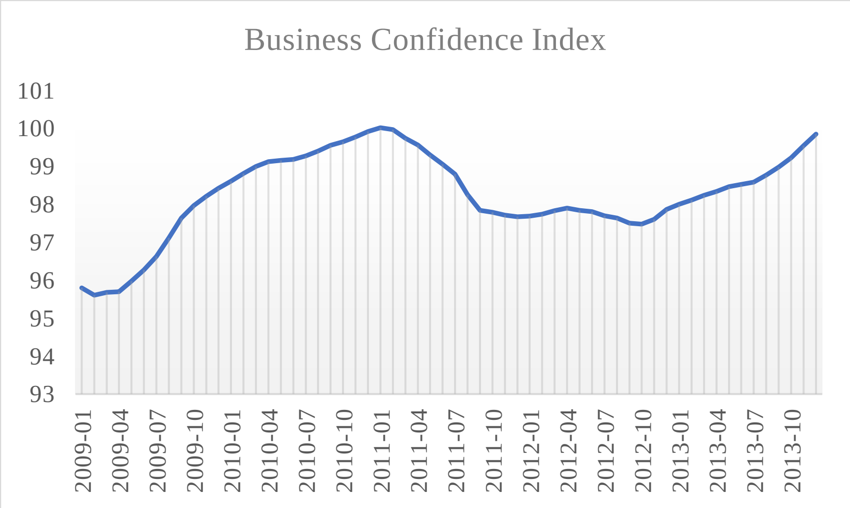
An interesting result is that of increases in short-term debt-to-turnover ratio in 2012, the year of lowest GDP growth. Short-term debt, in this context, must be repaid within a year and, as the recession deepened in 2012, we can observe in the regressions' odds ratios (Appendix IV) that increases in short-term debt (to turnover) have an increasing effect over the probability of firm failure which is higher than that of other years.

All things considered, and as previously suggested, highly indebted firms, especially small and medium-sized enterprises, can be vulnerable during recession periods. Reduced market demand and high debt levels can destroy a firm's business; with obligations to meet, and insufficient revenue to allow it, the probability of bankruptcy increases.

This leads us to the effect of impairment losses in accounts receivable. The impairment losses-to-turnover ratio is not statistically significant for three of the four years under analysis, being its coefficient statistically different from zero in 2010, when it presents a negative sign. It seems that during this year, increases in the ratio of impairment losses to turnover should decrease the probability of firm failure, in contrast to the result obtained for the whole period. As the year with the highest GDP growth rate of the period under analysis, and as the year with less percentage of firm failures (see Table 2), one can argue that there could have been some level of firms' confidence in a recovery. As OECD data reveals, enterprises showed positive expectations regarding their businesses' performance in the immediate future. Graph 1 presents the Business Confidence Index over the years under analysis.

Graph 1

Business Confidence Index



Source: OECD

As firms envision economic prospects to improve, after the 2009 recession (when GDP growth registered an annual decrease of 3%), they expect higher future revenues, and this may be one of the reasons increases in impairment losses would not lead to higher probability of firm failure. In line with this argument, there's the effect of increases in short-term debt-to-turnover ratio, as it exhorts a lowering effect in the probability of firm failure.

However, other effects may be present, and one cannot make further conclusions on this matter. Also, the baseline model results remain valid, as increases in impairment losses (over turnover) have a positive effect on firm failure probability over the four years under analysis.

5. Weaknesses of the model

The fixed effects regression model estimation imposes several constraints on a model. As aforementioned, one of those is the loss of observations in the analysis. Moreover, the dataset has missing values for some firms regarding the variables of interest in the model. Even though there are thousands of observations on the initial dataset (millions for some variables), the final model only considers 7.692 observations. A model with more observations will always be preferable, as the results for the sample will then better represent those of the population.

Additionally, if data on firms' age were available, the performed analysis could also have been conducted for a restricted sample comprised of start-up firms. It would have been interesting to compare this model's results with those of the examined cases – capital-intensive firms and small and medium-sized enterprises.

Finally, the data considered for this analysis covered only four years, a brief period. It would have been interesting to perform a more thorough comparative analysis: the period 2011-2014, the years of the Adjustment Programme, *versus* the period 2007-2010, and analyse the studied effects in the years after the global recession but before the agreement for the Adjustment Programme *versus* the years of the Adjustment Programme.

6. Conclusion

High firm failure levels can have damaging effects over an economy, especially during times of economic recession. Overall lower demand and credit constraints pose challenges to firms. Those which cannot overcome these obstacles, close and contribute to further job destruction, which in turn will only aggravate the overall economic activity.

Therefore, it is of the utmost importance to investigate the determinants behind these firm failure occurrences. These elements can then provide some guidance to the best practices for firms to follow, as they strive to improve their businesses.

This project's main result focuses on the effect of impairment losses over firm probability failure. The analysis shows that increases in impairment losses in accounts receivable will increase the probability of firm failure. This result is sustained by recent data, as firms confirm client's inability to pay as one of the main adversities faced during the recession.

Capital-intensive industries typically rely heavily on debt to initiate, but also maintain, their business activity. Results show that increases in their debt-to-turnover ratios are associated with increases in the probability of failure; this is also true for labour-intensive firms, and the effects over the relative probability (odds ratio) are found to be higher for the latter. Also, as the sample is comprised mostly of SME, these results reflect firm's size effects.

Further analysis was conducted regarding the behaviour of the model's determinants over the years. Some important results from the baseline model carry over to this analysis, even though some variables behave somewhat differently. It is worth noticing that although annual analysis can provide some insight into the effects these variables have on the firm failure probability, the study of within-firm determinants of firm failure differ from that of "between-firm" determinants (considered in annual analyses).

The results obtained in this work project are to some extent comparable to those in A. Carneiro et al. (2014). As the latter discerns the effect of higher interest rates on the probability of firm failure, our analysis focuses instead on the effects of annual interest payments-to-turnover ratio and outstanding debt-to-turnover ratios over the same probability. Even though the variables differ, the analysis comes to the same conclusion, as credit constraints are found to take a significant part in increases of firm failure probability.

On the other hand, this work project analyses the association between failure and other variables of interest, for which the results were summarised above.

Improvements could be made to this project's analysis, as further research could consider, for example, including a variable to control for debt levels, as this would allow for a discerning of the effect increases in debt have for low debt-level *versus* high debt-level firms, refining thus the impact debt can have over a firm's failure probability. Moreover, analysing the effects of these variables on start-up companies' failure probability could shed some light into the differences between these two groups of firms (start-ups and non-start-ups), and the factors that may determine their ultimate collapse.

7. Appendixes

Appendix I

Table 7

SME in the sample

SME		Frequency	Percentage
	0	4,591	0.10
	1	4,414,466	99.90
Total		4,419,057	100.00

Source: SCIE

According to the European Commission, a firm is considered to be a small and medium-sized enterprise when its turnover is equal, or lower, than 50 million euros (or its balance sheet total does not exceed 43 million euros) and its staff headcount falls below 250. A micro enterprise will have a turnover below or equal to 2 million euros (or a balance sheet total also below 2 million euros) and a staff headcount lower than 10. A small enterprise (not including those classified as micro) has a turnover between 2 and 10 million euros (or a balance sheet ranging in the same interval) and a staff headcount between 10 and 50.

Appendix II

Hausman specification test

$H_0: the\ preferred\ model\ is\ a\ random\ effects\ model$

$H_1: the\ preferred\ model\ is\ a\ fixed\ effects\ model$

Table 8

Hausman Specification Test

	Coefficients			
	(b)	(B)	(b-B)	
	fixed	random	Difference	S.E.
LDebtLT_Turnover	1.126	0.193	0.934	0.075
LDebtST_Turnover	0.443	0.096	0.347	0.051
LIntExpenses_Turnover	0.233	0.083	0.150	0.064
LInvFA_Turnover	-0.658	0.297	-0.955	0.043
ImpAR_Turnover	2.094	-0.099	2.193	1.041

b is consistent under H_0 and H_1

B is inconsistent under H_1 and efficient under H_0

Test:

chi2(5) = 522.83

Prob>chi2=0.0000

Source: SCIE

Appendix III

Table 8

Logistic Regression for SME that are capital intensive

	Capital Intensive
	Coefficients
LDebtLT_Turnover	0.922***
	(0.115)
LDebtST_Turnover	0.288***
	(0.080)
LIntExpenses_Turnover	0.146*
	(0.082)
LInvFA_Turnover	-0.440***
	(0.064)
ImpAR_Turnover	3.465**
	(1.627)
Observations	3,048

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: SCIE

Appendix IV

Table 9

Logistic Regression for the base model and each year individually

	2010-2013	2010	2011	2012	2013
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
LDebtLT_Turnover	3.084***	1.222***	1.206***	1.065	1.213***
	(0.339)	(0.020)	(0.027)	(0.046)	(0.040)
LDebtST_Turnover	1.557***	0.972*	1.053**	1.235***	1.061**
	(0.093)	(0.014)	(0.024)	(0.059)	(0.030)
LIntExpenses_Turnover	1.262***	1.228***	1.063**	1.106*	1.009
	(0.108)	(0.020)	(0.026)	(0.063)	(0.034)
LInvFA_Turnover	0.518***	2.050***	1.287***	1.002	1.148***
	(0.034)	(0.037)	(0.023)	(0.029)	(0.027)
ImpAR_Turnover	8.120**	0.031***	1.220	1.647	0.436
	(8.271)	(0.028)	(0.288)	(0.552)	(0.320)
Constant		0.046***	0.048***	0.007***	0.011***
		(0.007)	(0.005)	(0.001)	(0.001)
Observations	7,692	39,355	26,695	22,366	22,813

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: SCIE

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