Macroeconomic determinants of credit risk:
Evidence from the Eurozone

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Abstract

We propose and estimate several models controlling for firm-specific information, to examine the relation of macroeconomic variables with the probability of default of firms in the Eurozone. The novelty of our approach consists in capturing the informational value of macroeconomic factors on credit default prediction by using data from firms spanning eleven European countries; our panel data set covers 534 thousand firm-year observations. The results we obtain confirm that macroeconomic information strengthens the accuracy of models forecasting credit default of non-financial firms. With a negative effect on the probability of default, GDP growth stands out among the key macroeconomic predictors of default. Yet, we find compelling evidence that asymmetries exist within the Eurozone regarding the benign effects of GDP growth over credit risk; the reduction of the probability of default due to economic growth mostly occurs in economies more exposed to conditions of financial stress.

Key Words: Credit default; Macroeconomic effects; Crisis; Multi-period logit model; Eurozone.

JEL Classification: G01, G33; C41; E32

1 Introduction

Credit risk is traditionally modelled from a single country perspective. Behind this practice normally lies the prevalent significance of firm-specific factors over credit risk and the assumption that credit default forecasting models should be tailored to the cultural, business and economic specificities of the country to which each firm belongs. However, due to potential empirical evidence limitations, such approach may also inhibit the accurate measurement of the macroeconomic impact on credit risk. Besides, it also limits the comparison of credit risk between firms from different countries and in distinct macroeconomic contexts. For investors and creditors to firms in countries belonging to a common economic area, it may indeed make sense to standardize the credit risk assessment of those firms, controlling for each firm's specific information as well as the distinctive factors of the country it belongs to.

The literature on credit risk from a single country perspective or based on evidence from firms in the U.S. (Tian and Yu, 2017) is fertile. Altman (1968), Merton (1973), Ohlson (1980), Zmijewski (1984), Coats and Fant (1993), Shumway (2001), Campbell *et al*. (2008) provide major contributions to credit risk modelling approaches and point to some of the major firm-specific predictors of default. Extensions of their work currently include the effects of macroeconomic variables based on data from a single country (e.g., Bonfim, 2009; Bruneau *et al*., 2012). Still, to the best of our knowledge, there is a lack of investigation on firms' credit risk modelling backed by evidence from multiple countries.

We contribute to the literature and fill this gap by modelling the probability of default of firms throughout the Eurozone with an extensive set of firm-specific and macroeconomic potential drivers of credit default. The selection of a common economic area with a single currency – the Euro – allows a more straightforward analysis, as it removes the effects of foreign exchange rates fluctuations among the national currencies of different countries.

Our research aims to extend the knowledge on the fundamental determinants of credit risk and deepen the understanding of the relation between economic and credit cycles. A credit risk model based on empirical evidence from several countries, though more laborious, is also expected to be more proficient in capturing the sensitiveness in the relation between country-specific macroeconomic factors and credit risk than what otherwise may be achieved from the empirical evidence each country alone can provide. Consequently, should that perception be correct, the global accuracy of credit risk models improves. Moreover, the empirical evidence from multiple countries (a multi-country perspective) to model credit risk, controlling for macroeconomic variables, contributes to the consistent measurement of the portfolio's credit risk of creditors from different countries. In the case of banks, such measurement promotes the robustness of the stress testing exercises they might need to apply to their credit portfolios.

From the policymakers' point of view, the increased accuracy in identifying the macroeconomic variables to which credit risk is most sensitive, paves the way to conduct policies that prevent the emergence of unsustainable levels of non-performing loans (NPLs). Previous literature already underlined the dependence of financial stability in relation to credit risk control (e.g., Bonfim, 2009), as well as the usefulness of dynamically managing credit risk by assessing different default scenarios over multiple economic conditions (Koopman and Lucas, 2005). According to the European Systematic Risk Board (2019: 3), "authorities should develop early warning systems to monitor the risks of credit portfolio deterioration from a macroprudential perspective". Given such requirement, a broader knowledge on the interlink between key economic variables and credit risk is fundamental for bank supervisors to assess the extent to which the systems and risk policies banks maintain to measure and monitor credit risk are effective under distinct prospective economic scenarios. We hope that our approach contributes to extend that knowledge.

We use information of 48,714 firms and macroeconomic data of eleven Eurozone countries, from 2007 to 2017, corresponding to 534,835 firm-year observations. The results suggest that macroeconomic variables influence firms' credit default and significantly increase the prediction accuracy of credit risk models. We observe that an increase in the Gross Domestic Product (GDP) and inflation signals transverse declines in the probability of default. Conversely, by degrading firms' financing conditions, rising interest rates contribute positively to push up that probability. Still, the relation between macroeconomic variables and credit risk varies among the Eurozone countries. In our sample, economies more exposed to conditions of financial stress (Portugal, Italy, Ireland and Spain), despite revealing a higher level of credit risk, also confirm a larger effect on the reduction of the probability of default due to a positive GDP growth rate, comparatively to their peers in the sample. Such evidence confirms the remarkable relevance of economic growth in solving the NPL issue that is still affecting the profitability of some banking systems in Europe. It also reveals that potential economic downturns have asymmetric effects on credit risk around the Eurozone, which should be accounted for specially in the credit risk management of loan portfolios with foreign borrowers.

This study is organized as follows. In Section 2 we review the relevant literature on credit risk determinants and credit default prediction; the section ends with the formulation of the hypotheses under study. The methodology, sample and variables used in this research are described in Section 3. Section 4 construes and discusses the main estimated results. Robustness tests are presented in Section 5. The final section shows the concluding remarks.

2 Previous literature on credit default models

2.1 Default and bankruptcy

Credit risk is the potential inability of a debtor to pay loans, a customer to pay debts, or a counterparty to settle financial assets and financial liabilities. This is one of the most relevant financial risks whose effects extend to the causation of other risk types, such as the market risk (Hartman, 2010). Regardless of whoever is exposed to this type of risk, there is a likelihood of facing financial losses due to the occurrence of credit default, in which the debtor's bankruptcy stands out as an extreme scenario.

The use of credit default and of bankruptcy concepts to estimate credit risk models abound in the literature, with some approaches revealing a more legal focus whereas others are more related to accounting specificities.[1] For example, rather than using bankruptcy filings, Coats and Fant (1993) focus on the study of financial distress by using auditors' reports as an earlier warning of a firm reaching a distressful situation. Similarly, Ward and Foster (1997) suggest the use of credit default to model financial stress, whereas Tinoco and Wilson (2013) criticize the use of the legal concept of bankruptcy to model credit default prediction models. In the same line of thought, Chava and Jarrow (2004) model credit risk considering that credit default occurs when a company fails to meet at least one debt payment. Still, despite being different concepts, there are many correspondences between credit default and bankruptcy; both are mostly demonstrations of a company's financial distress, no matter the underlying causes.

2.2 Accounting and market-based models

Multiple factors allow the accurate detection of firms that in the future will be in credit default. The early identification of such factors is deemed as being essential to keep financial stability (Bonfim, 2009). This condition explains why the yearly number of publications related with credit risk models after the 2008 crisis more than doubled between 2008 and 2018, to over 700, according to data from the Web of Science.

The first seminal study is accomplished by Beaver (1966), using a univariate analysis to conclude that, up until five years prior to bankruptcy, failed firms showed significantly different

[1] For companies in the U.S., the legal definition of bankruptcy corresponds to situations falling in the chapters 7 and 11 of the United States Bankruptcy Code.

financial information relatively to those that survived. Later, Altman (1968) introduces the first multivariable approach to determine bankruptcy risk, based on a Multiple Discriminant Analysis (MDA) with five financial ratios.

A distinct but innovative approach to predict credit default is introduced by Merton (1973). Such approach establishes a link between the firm's credit default risk and its capital structure, considering the firm's equity as a call option on its assets. Under this market model approach, default occurs when the assets of the firm reach a very low market value compared to its debt value. The Merton distance to default is a special measure that results from this approach and has been widely used in the literature (e.g., Vassalou and Xing, 2004; Bharath and Shumway, 2008). An example of extensions of the market model approach of credit risk is discussed by Leppin and Reitz (2016), who investigate the impact of a changing market environment on the pricing of credit default swaps (CDS) spreads written on debt from EURO STOXX 50 firms. They find that CDS-pricing variables are time varying depending on current values of a set of variables such as the European Central Bank's composite index of systemic stress, the Sentix index for the current and future economic situation and the VStoxx, the latter two used as benchmarks for investors' market expectations and economic uncertainty.

A different methodology is proposed by Ohlson (1980), by using a logit model to predict bankruptcy based on four key determinants: i) company size; ii) financial structure or gearing; iii) performance; iv) and short-term liquidity. The Ohlson's approach departs from previous models by introducing at least three relevant features. Its output consists in a probability, the logit model is not restricted to be used in approximately normal distributions (contrary to Altman's MDA), and the model is applicable to non-listed firms (thus having a more universal use than Merton's model).[2]

The previous models mostly account for a single period, which eases their estimation and analysis. However, such simplicity may omit relevant factors and not consider properly non-bankrupt firms that are at risk, thus not controlling for the possibility of bias. Shumway (2001) introduces hazard models to predict bankruptcies and overcome the previous limitation. This type of models comes up as an extension of the classic logistic regression, but accounting for multiple periods, hence being considered dynamic logistic models. Hazard models can thus incorporate time-varying variables, as for instance macroeconomic variables, equal to all firms in a certain point in time but changing throughout time. Besides that, these models allow the

[2] Some noteworthy alternative econometric approaches to predict a firm's financial distress may be found in the probit regression, proposed by Zmijewski (1984), and in the use of neural networks proposed by Coats and Fant (1993).

utilization of a firm's age as potential explanatory variable. Moreover, according to Shumway (2001), they provide more efficient out-of-sample predictions, given their use of a larger quantity of observations (panel-data). Besides accounting variables, utilized in previous models, Shumway (2001) also considers market-based variables; he concludes that such variables allow enhanced prediction accuracy.

Campbell *et al*. (2008) apply similarly the hazard model, and equally explore the replacement of some accounting information, used in previous studies, by the corresponding market value. Under their approach, a broader definition of credit default, not limited to bankruptcy, is adopted. Besides the legal concept of bankruptcy, as defined in chapters 7 and 11 of the U.S. Bankruptcy Code, they consider as in default all firms with D ratings. Contrasting to Shumway (2001), Campbell *et al*. (2008) use firm-month observations obtaining over than one million observations. Other hazard models predicting credit default have been developed more recently, as seen in Tian and Yu (2017), who study default in different countries, specifically Japan, Germany, France and the U.K. The use of dynamic models to measure the credit quality of firms is also proposed by Tardelli (2017), who alternatively handles a filtering approach to achieve information about the probabilistic prediction of the population of firms and about the conditional distribution of firms' distance to default. The dynamics of credit default are also modelled by Centanni *et al*. (2017) by considering the effect from new firms joining the population, given that such firms enter the market and will interact with firms already in place. This last approach also emphasizes the influence of the fluctuation of macroeconomic variables on the existence of correlated changes in firms credit quality.

Most of the previous models employ as inputs different types of ratios and other firm-specific variables, namely liquidity, leverage, profitability, and activity ratios. According to the results in Altman (1968), Ohlson (1980) and Zmijewski (1984), higher liquidity levels allow a greater firm's ability to fulfil its short-term financial obligations, thus reducing the probability of default. Firms with higher returns on investment and profitability are also less likely to default. Activity indicators display a negative correlation as well with credit default. Conversely, firms with higher debt-to-equity ratios are more prone to default. Ohlson (1980) and Shumway (2001) also found evidence that company size is a relevant variable too. According to their results, larger companies are less likely to default.

2.3 Models using macroeconomic determinants

The effects of potential macroeconomic variables over credit risk - including GDP growth -, as well as those of firm-specific variables, have been analysed in several studies (e.g., Lis *et al*., 2001; Bangia *et al*., 2002; Lowe, 2002; Allen and Saunders, 2003; Koopman and Lucas, 2005; Hackbarth *et al*., 2006; Pesaran *et al*., 2006; Carling *et al*., 2007). For example, combining financial and macroeconomic variables and resorting to probit regressions, Bunn and Redwood (2003) investigate the factors with more influence on companies' default in the U.K. Controlling for firms' financial performance, they confirm that probabilities of default are significantly higher during economic downturns.

Liou and Smith (2007) point out multiple macroeconomic indicators as relevant predictors of credit default in industrial firms of the U.K., namely GDP, retail price index, consumer price index, interest rate, industrial production index and the stock market index. In turn, Harada and Kageyama (2011) study the default dynamics in Japan and find significance in macroeconomic variables (real GDP, GDP deflator, and the overnight interest rate). Similarly, Bruneau *et al*. (2012) conclude that macroeconomic variables add significant information to explain the bankruptcy rate of firms in France. According to the results they report, the probability of default decreases when the output gap and inflation increase; on the contrary, a decrease in that probability is observed when the exchange rate and long-term interest rates decrease as well.

Bonfim (2009) analyses the credit risk determinants in Portugal, based on probit and hazard approaches. She confirms that periods of high economic growth normally lead to an increase in credit granting, which later on generate an increase in default rates. Yet, the financial imbalances triggered by excessive risk taking in robust economic growth phases only materialises when economic growth slows down. The results she obtains suggest that GDP and loans growth rates are relevant determinants of credit risk, with the sources of such risk differing across industries.

Castro (2013) analyses the impact of the macroeconomic background to the banking system of a group of countries particularly described by unfavourable economic and financial conditions after the financial crisis of 2008 (Greece, Ireland, Portugal, Spain and Italy). To address the issue, instead of focusing on the individual risk of each creditor or developing a model of default prediction, he measures the effect of macroeconomic variables into the banks' global non-performing loans. Once again, GDP denotes a significant impact on credit risk, just like what is observed for the stock market index, housing prices and real exchange rate.

Based on evidence of non-financial corporate bond default rates over 150 years, Giesecke *et al*. (2011) similarly emphasize the relation between credit default and the macroeconomic framework. Their results suggest that stock returns, the volatility of stock returns, and changes in GDP are relevant predictors of default rates. Yet, other macroeconomic variables, such as inflation and the growth rates of consumption and industrial production do not emerge as statistically significant predictors of future default rates.

Overall, building on evidence from different countries and using alternative approaches, previous studies about default conclude that macroeconomic variables are indeed relevant for credit default prediction models. We envisage to extend the literature on a firm's credit default prediction by gauging the potential influence of macroeconomic variables in a multi-country framework, i.e., based on the joint empirical evidence from multiple countries, thus allowing for distinct macroeconomic backgrounds to be measured simultaneously. Accordingly, we define our first testable hypothesis:

H1: *Macroeconomic variables are relevant predictors of credit default in a multi-country framework*

Most studies investigating the influence of macroeconomic variables rely on evidence from a single country (Bunn and Redwood, 2003; Liou and Smith, 2007; Bonfim, 2009; Bruenau *et al*., 2012; Tinoco and Wilson, 2013; Daskalakis *et al*., 2017), or do not analyse the problem at a microlevel, per firm, but instead focus the issue of the banks' global non-performing loans (e.g., Castro, 2013). Nevertheless, the estimation of models of firms' credit risk based on the empirical evidence from multiple countries allows us to understand whether the marginal effects of macroeconomic drivers of credit risk are homogeneous across different countries.

For example, Ali and Daly (2010) document asymmetric reactions of firms' credit risks to macroeconomic shocks between Australia and USA. Using five-year credit default swap (CDS) Lee *et al*. (2016) conclude that institutional and informational channels capture effects beyond those associated with firm- and country-level fundamentals. Overall, they found that firm-level global asset and information connections are important mechanisms to delink firms from their sovereign and country risks. Schwaab, *et al*. (2017) investigate the dynamic properties of systematic default risk conditions for firms in different countries, industries, and rating groups. They found that macro and default-specific world factors are a primary source of default clustering across countries.

The heterogeneity of effects from the global financial crisis of 2008 within the Eurozone, where asymmetries have been found regarding NPLs among the banking systems in different countries, suggests that heterogeneous effects may indeed exist related with the country-specific macroeconomic drivers of credit risk.[3] Thus, our second hypothesis is the following:

H2: *The relation between macroeconomic variables and credit default is asymmetric across the Eurozone*

If credit risk relates differently with the macroeconomic settings of distinct countries, it may be reasonable to assume that relevant risk determinants exist as well in the different specificities between industries. Bunn and Redwood (2003), and Bonfim (2009) report evidence of significant differences in the credit risk drivers among distinct industries, while Altman and Sabato (2007) and Altman *et al*. (2010) draw attention to the relevance of industry-specific information to credit risk models. It seems therefore conceivable that the inclusion of economic sector in a multi-country framework of credit risk modelling promotes its prediction accuracy. Such framework should signal as well whether the same industries denote a similar credit risk in different countries. Consequently, our third and final hypothesis is:

H3: *The probability of default varies significantly across industries*

3 Methodology and data

3.1 Modelling framework

Similar to Shumway (2001), Campbell *et al*. (2008), Bonfim (2009), Tinoco and Wilson (2013) and Tian and Yu (2017), we employ a multi-period discrete choice model to estimate the probability of default. The aim is to assess the potential contribution of macroeconomic determinants to credit risk modelling, accounting for the evidence of multiple countries and controlling for the effects of firms' specific variables. We estimate a logistic regression model with panel data whose endogenous variable is a dummy denoting credit default ($Y_{it} = 1$, if the firm defaults in year t +1; $Y_{it} = 0$, otherwise), in line with Ward and Foster (1997), and Tinoco and Wilson (2013).

Accordingly, the probability of firm i being in default in $t + 1$, i.e. $P(Y_{it} = 1)$, abbreviately denoted as P_{it}, is determined in t, conditional to that firm being in non-default until then, by using the following logistic cumulative distribution function:

[3] Based on data from the Worldbank, we may confirm that the average NPL ratio of banks in European peripheral countries peaked at 14.8% in 2014, which is 4.1 times the same indicator in banks from core countries.

$$P_{it} = \frac{1}{1 + \exp\left[-\left(\alpha + \sum_{j=1}^{J} \beta_j X_{jit}\right)\right]} \quad (1)$$

where X_{jit} is the observation of independent variable j for firm i on year t; α and β_j are parameters.

For hypothesis testing purposes, we add macroeconomic and industry variables to Eq. (1). Denoting m_{kit} as the observation on year t of macroeconomic variable k for the country to which firm i belongs and defining D_{li} as industry dummy variables (1 = firm i belongs to industry l; 0 = otherwise), we adjust the previous conventional logit model:

$$P_{it} = \frac{1}{1 + \exp\left[-\left(\alpha + \sum_{j=1}^{J} \beta_j X_{jit} + \sum_{l=1}^{L} \gamma_l D_{li} + \sum_{k=1}^{K} \delta_k m_{kit}\right)\right]} \quad (2)$$

γ_l and δ_k are parameters, respectively reflecting the influences of industry and macroeconomic variables. As in the case of β_j, statistically significant positive estimates for γ_l and δ_k correspond to higher probabilities of default whenever the values of the related variables increase.

We do not reject the hypothesis H1 if $\exists\, k\colon \delta_k \neq 0$; the same applies to H3 if $\exists\, l\colon \gamma_l \neq 0$. Regarding γ_l, estimates statistically significant (or statistically different from zero) imply an effect additive to the intercept (or constant term). To test H2, we introduce a specific dummy variable (FS) to assess potential asymmetries in credit risk and in the related marginal effects of macroeconomic variables from different economic zones. FS = 1 stands for countries which had been under financial stress[4], namely Portugal, Italy, Ireland, and Spain, whereas FS = 0 represents the remaining countries.[5]

3.2 Data[6]

We retrieve firms' financial information from Amadeus, a Bureau van Dijk database. The data refers to non-financial firms from 11 countries that adopted the euro as their common currency (Eurozone) before 2002: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxemburg, Netherlands, Portugal and Spain. Due to a lack of data on firms' defaults, Greece

[4] According to data from the IMF (https://www.imf.org/external/datamapper), between 2007 to 2017 Portugal, Italy, Ireland, and Spain had a yearly average public debt in percent of GDP which exceeded by almost 44% the average of the remaining countries in the sample.

[5] Based on data from our sample, we note that financially stressed countries reveal an average default rate which is 2.73 times the correspondent average in the remaining countries.

[6] The data that support the findings of this study are available from the corresponding author upon reasonable request.

is not included. By selecting countries sharing the same currency, we remove the effects of foreign exchange rates fluctuations, allowing us to isolate the effects of other variables in a more direct manner. Likewise, such procedure also permits the assessment of the impact generated by a common monetary policy, shared by distinct countries, over credit risk. The data about country-specific macroeconomic variables is based on information reported from the European Central Bank, Eurostat and OECD.

Firms in our sample are either in default or non-default. Due to the conditional probability implied by Eq. (1) and in line with previous literature (e.g., Shumway, 2001; Hillegeist *et al*. 2004), firms with multiple defaults are classified as in default as early as the first observed default event occurs, and the eventual subsequent observations on such firms are eliminated from the sample.

To identify whether a firm is in default, we use information from Amadeus on the firms' status. In this sense, cases in default are those that change their status, from active without remarks to one of the following status: active (default of payment); active (insolvency proceedings); in liquidation; bankruptcy; dissolved (bankruptcy); dissolved (liquidation). Hence, although not too different from the concept of bankruptcy, our classification of default is somewhat more embracing.

Given the potential scarcity of complete financial information about small and medium enterprises, we impose a minimum firm size and require that selected cases have availability of financial data.[7] Accordingly, our sample of firms is composed by Public Limited Companies or Private Limited Companies:

- Not belonging to utilities;
- With total assets over 43 million euros in at least one of the last three years;
- With at least five years of available financial data.

Applying the previous sample selection criteria, our sample comprises 48,714 firms, of which 828 entered in default. With observations from 2007 to 2017, we achieve a panel data of 534,835 firm-years (Table 1). This data set contains a significant number of unlisted firms, as they represent most firms in the Eurozone.

[7] The definition of small and medium enterprises by the European Commission requires that maximum assets are 43 million euros.

Table 1
Distribution of firm-years per country

Country	Status		Total
	Non-default	Default	
Austria	27,908	10	27,918
Belgium	29,068	53	29,121
Finland	10,586	11	10,597
France	92,744	55	92,799
Germany	106,909	153	107,062
Ireland	3,422	8	3,430
Italy	88,281	351	88,632
Luxembourg	11,183	6	11,189
Netherlands	79,312	65	79,377
Portugal	14,807	32	14,839
Spain	69,787	84	69,871
Total	534,007	828	534,835

3.3 Variables selection

Based on previous studies and selected references, we choose potential firm-specific explanatory predictors of credit default, particularly financial metrics, as detailed in Table 2. We compute financial metrics from financial statements, given that most firms in our sample are not listed in a stock exchange. This means that an extension of our approach lies in the use of the market value of some financial indicators.

To test hypotheses H1 and H2, we draw from previous related literature the identification of potential macroeconomic predictors of default (Table 3). GDP growth is by far the most used variable in previous related studies, so we consider it a potentially relevant variable. Inflation may explain the different performance some firms reveal through their financial ratios. Liou and Smith (2007) refer to the unemployment rate as a generally accepted variable, but they don’t use it. Yet, as noted by Castro (2013), who finds evidence of the significance of the unemployment rate to determine credit risk, this variable affects firms’ demand and revenues, thus being an important barometer about a country economic strength. Therefore, we include it in the set of potential macroeconomic determinants.

Table 2
Potential financial determinants of credit default

Variable	Description	Author(s) / Source
EBITTA	Earnings Before Interest and Taxes (EBIT) / Total Assets	Altman (1968); Shumway (2001); Härdle *et al.* (2009); Tian and Yu (2017)
SATA	Sales / Total Assets	Altman (1968); Shumway (2001); Tinoco and Wilson (2013); Tian and Yu (2017)
TLTA	Total Liabilities / Total assets	Ohlson (1980); Shumway (2001); Campbell *et al.* (2008); Härdle *et al.* (2009); Tinoco and Wilson (2013)
NITA	Net Income / Total Assets	Ohlson (1980); Zmijewski (1984); Shumway (2001); Campbell *et al.* (2008)
WCTA	Working Capital / Total assets	Altman (1968); Ohlson (1980); Tinoco and Wilson (2013); Tian and Yu (2017)
SIZE	Logarithm of Total Assets	Tian and Yu (2017)
EBITINT	EBIT / Financial Expenses	Altman *et al.* (1977)
EBITDAINT	Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA) / Financial Expenses	Altman and Sabato (2007); Tinoco and Wilson (2013)
ORDEBT	Operating Income / Total Debt	Standard & Poor's (2006)
CFDEBT	Cash Flow / Total Debt	Standard & Poor's (2006)
EBITE	EBIT / Equity	Standard & Poor's (2006)
ORSA	Operating Income/Sales	Härdle *et al.* (2009); Tian and Yu (2017)
DTA	Total Debt / Total Assets	Härdle *et al.* (2009); Tian and Yu (2017)
CLSA	Short Term Liabilities / Sales	Tian and Yu (2017)
CLTL	Short Term Liabilities / Total liabilities	Härdle *et al.* (2009)

Additionally, our study weights the effects of two types of interest rates: the 10-year treasury bond yield and the banking loans rate to firms. We also use the EUR/USD exchange rate, to account for the effects of appreciation/depreciation of the Euro against the currency of the major trading partner of the Eurozone: the U.S.[8] Finally, given the asymmetries detected along the Eurozone crisis, started in 2009 amid concerns related with Greece's debt and public deficit, we define a binary variable (denoted as FS) that indicates whether a country within the Eurozone had been under financial stress (FS = 1).

[8] Likewise, we analyzed the influence of the state of the economy, as reflected in the stock market and the related investor sentiment and risk appetite, by including the main stock market index of each country. However, due to counterintuitive results from the economic point view, we withdraw this variable from the analysis.

Table 3
Potential macroeconomic determinants of credit default

Variable	Description	Author(s)
GDPG	Gross Domestic Product annual growth	Bunn and Redwood (2003); Liou and Smith (2007); Bonfim (2009); Harada and Kageyama (2011); Castro (2013)
INFLATION	Consumer price index annual change	Bonfim (2009); Bruneau *et al.* (2012); Castro (2013)
LIR	Interest rate on loans to non-financial companies (annual average)	Bonfim (2009)
PPI	Producer price index (annual average)	Liou and Smith (2007)
HPI	House price index (annual average)	Castro (2013)
UNEMPLOYMENT	Unemployment rate (annual average)	Castro (2013)
DCPS	Domestic credit to private sector provided by financial institutions (% GDP; annual average)	Bonfim (2009)*
LTIR	Long-term interest rate (10-year government bond yield; annual average)	Bonfim (2009)
EUR/USD	EUR/USD year's end exchange rate	Bonfim (2009)

* We adapt the assessment of loans to firms from Bonfim (2009), who uses Loans growth.

Table 4 shows that significantly higher mean profitability and return ratios (EBITTA and NITA), as well as mean interest coverage ratios (EBITINT and EBITDAINT), are observed in non-defaulted firms compared to firms that one year later turned out to be in default. Conversely, the latter group of firms is associated with notably greater means of variables measuring gearing (TLTA and DTA), confirming that firms in default were more indebted than the others.

Concerning variables related with liquidity (WCTA and CFDEBT), we do not find statistically significant difference in the means, although the means' difference in CFDEBT is statistically significant at 10%, pointing to higher liquidity (on average) in the non-defaulting group.

The empirical evidence regarding the relation of firms' size with later observed credit default is not consensual in the previous literature (Bonfim, 2009). For instance, Bunn and Redwood (2003) find that smaller firms have higher probability of default, while Bonfim (2009) observes that firms in default tend to be larger. In our sample, the average size of defaulted firms is lower than non-defaulted firms.

In our sample, means of GDPG, PPI and HPI are all greater in the defaulting group of firms, contrary to what is observed in LIR as well as in INFLATION, both lower in the same group. In turn, DCPS is, on average, lower in the defaulting group, in line with Bonfim (2009), suggesting that banks are more restrictive in granting loans when the economy slows down. As expected, UNEMPLOYMENT is higher in the default observations, in line with Castro (2013).

Table 4

Mean values in groups. This table shows the means of financial and macroeconomic variables across groups of firms, split according to being in default or in non-default. The Welch's *t*-test is used to assess the significance of differences between sample means. All variables are in decimals. SIZE is in logarithms, whereas indices are denoted as 1/100 of the index value. Significance of differences in means at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Variable	Non-default	Default	Difference in means
EBITTA	0.0391	-0.0994	0.1385 ***
SATA	1.0623	0.7174	0.3449 ***
TLTA	0.5848	0.9425	-0.3577 ***
NITA	0.0255	-0.1644	0.1899 ***
WCTA	0.1881	0.1973	-0.0092
SIZE	11.4258	10.9953	0.4305 ***
EBITINT	67.3210	-1.2968	68.6178 ***
EBITDAINT	118.9304	31.8143	87.1161 ***
ORDEBT	13.4476	5.3645	8.0831 ***
CFDEBT	2.6672	1.3453	1.3219
EBITE	0.1902	0.2272	-0.0370
ORSA	1.2387	1.5949	-0.3562 ***
DTA	0.3601	0.6219	-0.2618 ***
CLSA	5.9268	21.4371	-15.5103 ***
CLTL	0.6171	0.6914	-0.0743 ***
GDPG	0.0067	0.0114	-0.0047 ***
INFLATION	0.0149	0.0049	0.0100 ***
LIR	0.0269	0.0181	0.0088 ***
PPI	1.0273	1.0356	-0.0083 ***
HPI	0.9505	1.0217	-0.0712 ***
UNEMPLOYMENT	0.0918	0.1049	-0.0131 ***
DCPS	1.0191	0.9210	0.0981 ***
LTIR	0.0295	0.0180	0.0115 ***
EUR/USD	1.3121	1.1709	0.1412 ***

We observe that only 3 out of the 24 variables in Table 4 do not have a statistically significant difference in the means achieved in each group of firms: WCTA, CFDEBT and EBITE. We drop such variables in the multivariate analysis discussed along the next section.

4 Results

4.1 Pre-Estimation

To avoid imprecise estimates, wrong signal and excessive standard errors, we analyse the level of multicollinearity between the explanatory variables by using the Variance Inflation Factor (VIF). In line with Tinoco and Wilson (2013), we consider a high degree of multicollinearity when VIF is above 5. Consequently, for the estimation of the model we rule out the variables whose VIFs are above such reference: TLTA, EBITINT, EBITDAINT and LTIR.

Concerning the variables with acceptable VIFs, those reflecting information of similar type and with high correlations are not included simultaneously. This is the case of EBITTA (gross return on assets) and NITA (net return on assets), which are alternative measures of the firms' assets return. To circumvent the problem of potential bias of results (specially the standard errors of estimators), initially we use these variables in alternative models.

For estimation purposes, we follow Hosmer and Lemeshow (2013) in selecting all candidate variables with a *p*-value below 25% at the univariate analysis and below 5% at the multivariate analysis. We also winsorize the data at the first 1^{st} and 99^{th} percentile to suppress eventual disturbances in the results and reduce the effect of potential outliers. Our selection between fixed or random effects is based on the Hausman (1978) test. The results point to a rejection of the null hypothesis of correlation between the specific effects and the regressors; thus, a fixed effects model would be appropriate. However, due to the definition of the dependent dummy variable, the use of fixed effects in our sample removes all observations corresponding to non-defaulting firms. This is because the analysis of fixed effects requires a variation of the dependent variable of the subjects, as stated by Kleinbaum and Klein (2010). Hence, as there is no variation of the default status of a specific firm between distinct time points, it is not possible to estimate the coefficients using fixed effects. Consequently, like Bonfim (2009), who faced similar problems, we estimate the parameters using random effects.

Next, we randomly split the sample into two parts: 2/3 of the total number of cases serves for estimation purposes and the other 1/3 is used for validation. Therefore, 356,557 observations including 557 defaults are used for estimation, while 178,278 cases with 271 defaults correspond to validation.

4.2 Firm-specific financial determinants of credit risk

4.2.1 Base models

To test the hypotheses, we first estimate models that include firm-specific financial variables and afterwards add macroeconomic variables common to firms in the same country, all observations with a time varying nature. Table 5 contains the results of two models with firm-specific financial variables only, each comprising different measures of Return on Assets. Panel 5A shows estimates of a model including EBITTA, while panel 5B refers to NITA. Tables 6 through 8, report the results corresponding to alternative models estimated with additional information: i) type of industry; ii) macroeconomic variables; iii) type of industry and macroeconomic variables combined. Table 9 shows the estimates controlling for the region each firm belongs to, which allows us to conclude about our second hypothesis. Firms are classified in terms of industry in line with the North American Industry Classification System (NAICS), leading to 17 industries.

Table 5

Assessment of firm-specific financial variables. The dependent variable denotes the occurrence of a default event within 1 year after observing the exogenous. Panels 5A and 5B show estimates using EBITTA and NITA, respectively, as exogenous. Estimates and z-values (in parenthesis) in the table are obtained with random effects logistic regressions. Significance at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Variable	**Panel 5A**	**Panel 5B**
EBITTA	-10.850 ***	
	(-18.46)	
SATA	-0.482 ***	-0.497 ***
	(-5.42)	(-5.56)
SIZE	-0.105 *	-0.109 *
	(-2.03)	(-2.06)
DTA	3.076 ***	2.843 ***
	(13.55)	(12.24)
CLSA	0.003 **	
	(2.87)	
CLTL	1.631 ***	1.812 ***
	(6.91)	(7.64)
NITA		-7.800 ***
		(-18.31)
ORSA		0.077 *
		(2.18)
Intercept	-8.354 ***	-8.586 ***
	(-11,.82)	(-11.82)
Observations	199,776	194,582
Wald χ^2	640.65 ***	489.59***

On a multivariate perspective, we require that financial variables respect the 5% significance level in all models; variables of this nature not respecting this requirement were removed from the model. Based on the Wald null restrictions test, the models with financial variables only (Table 5) are strongly significant. The negative sign of the parameter estimates related with return on assets (EBITTA and NITA) confirm that higher profitably is, a priori, related with lower probabilities to default.[9] This is in line with Shumway (2001), as well as Tian and Yu (2017). The negative estimate for the coefficients of SATA indicate that less efficient firms, i.e. those with lower assets turnover, have higher probability to default. This result is in line with Tian and Yu (2017), but not with Shumway (2001). The negative sign of the estimate for the coefficient related to firms' size indicates that larger firms are related with lower prospects of default, supporting findings in Shumway (2001), and Bunn and Redwood (2003).

In line with the results in Zmijewski (1984), we confirm that gearing positively contributes to the probability of default, as shown by the positive sign of the coefficients estimates related

[9] Despite both measures of return are relevant, we opt to maintain NITA due to the better overall results related with this variable.

to DTA. The ability of a firm to pay its short-term liabilities based on sales is measured by CLSA, whose estimated positive coefficient signals that a lower value on this ratio denotes higher capacity to settle debts, similar to findings in Tian and Yu (2017). With a positive sign, the estimated coefficient of CLTL suggests that a firm with a higher proportion of short-term liabilities is more likely to fail to meet its financial commitments.

4.2.2 Inclusion of type of industry

Most empirical studies on credit risk confirm the importance of financial variables to predict default. However, the financial performance of each company and the respective default risk often depends on other circumstances that may explain why firms with similar financial indicators behave differently in terms of credit default. One of such circumstances, which justifies differences in financial variables not necessarily reflecting distinct performances, is the industry in which the firm operates. Previous studies (e.g., Bonfim, 2009; Altman *et al*., 2010), also incorporate differences at the industry level or industry-specific information to model credit risk. Hence, to control for industry effects over default, we add a categorical variable representative of the economic sector (Table 6). We choose manufacturing as the base category, in line with Bonfim (2007).

Table 6 reveals that with industry information the estimate for the coefficient of SIZE ceases to be statistically significant, suggesting that the industry may somehow be strong correlated with the average dimension of the firm; so, this variable was removed from the model. Firms belonging to the industry of water supply, sewers and waste management, as well as those in the construction and the industry of management of companies show significant differences with respect to the base industry; such differences in the probability of default support hypothesis H3. The positive sign of the coefficient related to construction denotes a higher probability to default, in line with Bunn and Redwood (2003), probably due to substantial activity fluctuations, high uncertainty and high competition within this sector.

Table 6

Model with financial variables and industry categorical variables. Estimates and z-values (in parenthesis) in the table are obtained with random effects logistic regressions. Significance at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Variable		
SATA	-0.389	***
	(-4.21)	
DTA	2.621	***
	(11.38)	
CLTL	1.635	***
	(6.85)	
NITA	-8.223	***
	(-20.1)	
ORSA	0.072	*
	(2.08)	
Agriculture, Forestry and Fisheries	0.720	
	(1.11)	
Mining	0.310	
	(0.39)	
Water and Waste Management	1.219	*
	(2.44)	
Construction	1.132	***
	(5.02)	
Wholesale and Retail Trade	0.155	
	(0.64)	
Transportation and Storage	-0.549	
	(-1.21)	
Hotels and Restaurants	0.220	
	(0.50)	
Information and Communication	-0.807	
	(-1.65)	
Companies Management	-0.690	*
	(-1.99)	
Real Estate	-0.038	
	(-0.13)	
Professional, Scientific and Technical Activities	-0.578	
	(-1.96)	
Administrative and Support Activities	-0.561	
	(-1.24)	
Health and Social Work	-1.040	
	(-1.02)	
Arts, Entertainment and Recreation	-0.283	
	(-0.45)	
Other Services	-0.298	
	(-0.28)	
Intercept	-9.472	***
	(-21.45)	
Observations	194,214	
Wald χ^2	749.56	***

4.3 Assessment of macroeconomic determinants

4.3.1 Base models

The results of Table 7 reflect how credit default relates with financial and macroeconomic variables together. All estimates for the coefficients of financial variables, except for the financial variables removed (CLSA), are statistically significant at the 1% significance level. Regarding macroeconomic variables, their significance supports the use of macroeconomic constraints to explain each firm's probability of default.

Table 7

Model with financial and macroeconomic variables. Estimates and z-values (in parenthesis) in the table are obtained with random effects logistic regression. Significance at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Variable	
SATA	-0.417 ***
	(-4.51)
SIZE	-0.215 ***
	(-3.53)
DTA	2.671 ***
	(11.90)
CLTL	1.306 ***
	(5.33)
NITA	-7.406 ***
	(-18.61)
GDPG	-31.632 ***
	(-5.89)
INFLATION	-75.667 ***
	(-6.80)
LIR	59.283 ***
	(3.83)
PPI	12.178 ***
	(3.91)
HPI	9.590 ***
	(7.08)
UNEMPLOYMENT	8.622 **
	(2.98)
DCPS	-5.378 ***
	(-8.10)
EUR/USD	-8.196 ***
	(-8.20)
Intercept	-14.936 ***
	(-4.08)
Observations	194,752
Wald χ^2	1,119.36 ***

The negative estimate of the coefficient linked to GDPG confirms that firms are in general less likely to default in benign macroeconomic scenarios. By stimulating more favourable business opportunities, a robust economy tends to reduce a firm's likelihood of default. Similar results may be found in Bunn and Redwood (2003), Bonfim (2009) and Harada and Kageyama (2011).

Our evidence supports the existence of co-cyclicality between credit risk and economic activity, in line with Koopman and Lucas (2005). Also related with an economic robust context, INFLATION shows a negative estimate for the coefficient as well, consistent with the results in Bruneau et al. (2012). Likewise, and in line with Bonfim (2009), LIR reveals a positive influence on the probability of default, confirming that higher debt servicing costs penalize firms' ability in meeting their financial commitments. In absolute terms, the estimated coefficient in this case is almost symmetrical to the one linked to INFLATION. Such close symmetry between both estimates seems to imply that credit default risk is insensitive to null real interest rates. Still, the ultimate appraisal regarding the effects from interest rates and INFLATION will depend on the combined influence of these variables with the effects of PPI and HPI over the probability of default, both positive in our sample.

Another significant contribution to the probability of default is detected in UNEMPLOYMENT, confirming expectations that fragile economic conditions, characterized by high levels of unemployment with negative impacts over firms' economic activity, stimulate credit risk. The level of credit granted and, consequently, the degree of restrictiveness in bank loans, is assessed by DCPS; we observe that the probability of default increases when lending is reduced, usually detected in economic downturns.

Opposite to Bonfim (2009), we find that the exchange rate is a statistically significant determinant of default. Our results confirm findings in Atanasijević and Božović (2016) that appreciations of the domestic currency generally reduce the likelihood of default, a signal of improved conditions of firms which are indebted in foreign currencies to pay their debts.

4.3.2 Inclusion of type of industry

Together with financial and macroeconomic variables, we now include dummies for the type of industry (Table 8), to assess industry specificities of credit risk. Variables revealing a *p*-value above 5% were again removed from the estimation process, the same being done to industries with no firms in default. In general, the estimates for the coefficients do not show striking differences in comparison to those in Table 7. Again, CLSA is not significant at 5%. Thus, like in the previous models, the results in Table 8 confirm the relevance of macroeconomic determinants. The only industry with meaningful differences relative to the base industry is Construction, which keeps its significance and positive relation with the probability of default.

Table 8

Model with financial, macroeconomic variables and industry categorical variables. Significance at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Variable		
SATA	-0.367	***
	(-3.75)	
SIZE	-0.180	**
	(-2.82)	
DTA	2.616	***
	(11.37)	
CLTL	1.301	***
	(5.30)	
NITA	-7.755	***
	(-19.08)	
Agriculture, Forestry and Fisheries	0.872	
	(1.32)	
Mining	0.580	
	(0.69)	
Water and Waste Management	1.154	**
	(2.25)	
Construction	1.326	***
	(5.85)	
Wholesale and Retail Trade	0.219	
	(0.89)	
Transportation and Storage	-0.483	
	(-1.07)	
Hotels and Restaurants	0.697	
	(1.60)	
Information and Communication	-0.443	
	(-0.91)	
Companies Management	-0.220	
	(-0.62)	
Real Estate	0.031	
	(0.11)	
Professional, Scientific and Technical Activities	-0.283	
	(-0.95)	
Administrative and Support activities	-0.200	
	(-0.44)	
Health and Social Work	-0.739	
	(-0.72)	
Arts, Entertainment and Recreation	0.032	
	(0.05)	
Other Services	0.300	
	(0.27)	
GDPG	-30.930	***
	(-5.78)	
INFLATION	-75.644	***
	(-6.78)	
LIR	59.35	***
	(3.81)	
PPI	11.830	***
	(3.83)	
HPI	9.037	***
	(6.70)	
UNEMPLOYMENT	5.247	*
	(1.79)	
DCPS	-5.041	***
	(-7.58)	
EUR/USD	-8.115	***
	(-8.06)	
Intercept	-14.65	***
	(-4.02)	
Observations	194,384	
Wald $\chi 2$	1,156.94	***

Therefore, regardless of the inclusion of type of industry, we find evidence supporting that macroeconomic variables determine the prediction of default in non-financial companies, as stated in hypothesis H1. The evidence towards macroeconomic influence over credit default is thus reinforced by the multi-country nature of the observations in our study.

To investigate the existence of distinct impacts of macroeconomic determinants between countries, we now introduce a new dummy variable that distinguishes whether a country belongs to the financially stressed group (FS = 1). Additionally, we estimate two types of models: one with interactions between macroeconomic determinants employed in the previous models and the new dummy, and another using the dummy without interactions. The results follow in Table 9.

Analysing coefficients of the FS dummy in the model without interactions (Panel 9A), we detect that, *ceteris paribus*, a firm in Portugal, Italy, Ireland or Spain is more likely to default than another firm with the same characteristics, but belonging to a country that had not been under financial stress. Moreover, the results in the same model indicate as well that the inclusion of the additive dummy absorbs the effects of some macroeconomic variables, particularly from GDPG, LIR, PPI and UNEMPLOYMENT, which become non-significant at the 5% level.

The model with the interactive dummy (Panel 9B) tells us that only GDPG has a significantly different effect between the two groups of countries. Specifically, we detect that GDPG stimulates reductions in the probability of default of firms in the financially stressed countries. In the case of firms in the non-stressed countries the evidence suggests that, although with a lower significance than in financially stressed countries, GDPG also influences credit risk, but positively. It seems that the more benign economic context that non-financial firms find in these countries allows them to assume higher risks during economic expansions, later reflected in higher default, compared to what happens in economic downturns.

Thus, we conclude that differences exist in the two groups of countries concerning macroeconomic influences on default, and accordingly we do not reject hypothesis H2. Yet, GDPG and DCPS seem to be the only macroeconomic determinants with a significantly distinct impact over credit default among the two groups.

Table 9

Models with a financial stress dummy without (Panel 9A) and with (Panel 9B) interactions. FS is a dummy denoting whether a country within the Eurozone had been under financial stress (FS = 1). FS = 1 corresponds to Portugal, Italy, Ireland and Spain; FS = 0 stands for the remaining countries in the sample. Significance at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Variable	Panel 9A	Panel 9B
NITA	-7.561 ***	-7.487 ***
	(-18.72)	(-18.46)
SATA	-0.371 ***	-0.3741 ***
	(-3.92)	(-3.93)
SIZE	-0.207 ***	-0.240 ***
	(-3.28)	(-3.69)
DTA	2.647 ***	2.701 ***
	(11.51)	(11.71)
CLSA	0.003 **	0.003 **
	(2.04)	(2.19)
CLTL	1.120 ***	1.145 ***
	(4.41)	(4.40)
GDPG	-19.790 **	24.923
	(-3.60)	(1.25)
INFLATION	-52.802 ***	-51.864
	(-4.68)	(-1.57)
LIR	15476	-54.052
	(0.90)	(-1.11)
PPI	9.958 **	-2.474
	(2.91)	(-0.39)
HPI	4.910 ***	5.818
	(3.66)	(1.26)
UNEMPLOYMENT	-2.357	-2.710
	(-0.68)	(-0.33)
DCPS	-3.773 ***	-2.336
	(-5.12)	(-1.90)
EUR/USD	-5.411 ***	-5.919 **
	(-5.22)	(-2.26)
FS	1.555 ***	-12.089
	(6.55)	(-0.93)
GDPG * FS		-42.865 *
		(-1.99)
INFLATION * FS		9.102
		(0.26)
LIR * FS		62.456
		(1.11)
PPI * FS		13.117
		(1.14)
HPI * FS		-2.202
		(-0.42)
UNEMPLOYMENT * FS		6.163
		(0.55)
DCPS * FS		-2.902
		(-1.37)
EUR/USD * FS		2.808
		(0.96)
Intercept	-11.770 **	0.552
	(-2.97)	(0,07)
Observations	194,752	194,752
Wald χ^2	1,154.93 ***	1,136.91 ***

5 Robustness check

5.1 Likelihood Ratio Test

This test compares two models, one (nested model) that contains a subset of the variables considered in the other (Chava and Jarrow, 2004; Bonfim, 2009; Bruneau *et al*. 2012). We define θ as a vector of parameters to be estimated, about which it is admitted a hypothesis (H_0) that, to some extent, restricts these parameters.

Defining $\hat{\theta}_U$ as the Maximum Likelihood Estimators of θ obtained without the restrictions of H_0, and $\hat{\theta}_R$ as the Maximum Likelihood Estimators applying the restrictions, with $\hat{L}_U$ and $\hat{L}_R$ being their respective likelihood functions, then the Likelihood Ratio is given by (Greene, 2012):

$$LR = \frac{\hat{L}_R}{\hat{L}_U} \tag{3}$$

and the test in its final form is given by:

$$LRT = -2\ln\left(\frac{\hat{L}_R}{\hat{L}_U}\right) \sim \chi^2(k) \tag{4}$$

where k is the number of parameters lost when moving to the model with restrictions. The null hypothesis in this case admits the superiority of the simpler model, i.e., the one containing simply the subset of variables; the hypothesis will be rejected if the value of the test overcomes the critical value of χ^2. In our study, comparing the models with and without macroeconomic variables, the null hypothesis corresponds to the use of the model without macroeconomic variables. We note that this test may only be correctly interpreted whenever the number of observations is the same in the two models being compared. Thus, to contrast the models in terms of the observations on which they are developed, we use solely the observations with non-missing data in any of the variables. To guarantee the same number of observations and avoid any potential bias, we use the same sample in the two models. Table 10 shows the results.

Comparing the model in Table 5 (Panel 5B) to the one in Table 7, we find statistical evidence to reject the null hypothesis that the nested model (5B) has a structure which makes it preferable to the "full model". Hence, this evidence supports the superiority of models with macroeconomic variables.

Table 10
Likelihood ratio test. Significance at the 0.1%, 1% and the 5% levels are respectively marked with ***, **, and *.

Comparison of models	LR χ^2	*p-value*
Table 5 (Panel 5B) vs Table 7	347.43	0.0000
Table 6 vs Table 8	337.24	0.0000
Table 7 vs Table 8	56.48	0.0000
Table 9 (Panel 9A) vs Table 5 (Panel 5B)	391.56	0.0000
Table 9 (Panel 9B) vs Table 5 (Panel 5B)	427.53	0.0000

Consistent with the results of the previous test, the model in Table 8 is also characterized by a better fit to the data than the corresponding model without macroeconomic variables (Table 6). Such fact suggests again that macroeconomic variables improve the quality of fit of models already accounting for financial variables and categorical variables, specifically the type of industry, reinforcing the non-rejection of our hypothesis H1.

The comparison of models in Tables 7 and 8, allows us to conclude about the influence of the type of industry. Even though the χ^2 is lower, when compared to the previous tests, there is statistical significance to state that more complete models, i.e., the ones considering financial and macroeconomic variables have their quality improved with the inclusion of type of industry. A similar remark is applied to the distinct impacts of macroeconomic determinants across distinct economic zones (Panels 9A vs 5B and 9B vs 5B).

5.2 AIC and BIC

The Akaike Information Criterion (AIC) (Akaike, 1974) and the Bayesian Information Criterion (BIC) (Schwarz, 1978) are particularly useful to compare models with different numbers of parameters (Hosmer and Lemeshow, 2013), and have been employed in the literature of default prediction (e.g., Bonfim, 2009; Tian and Yu, 2017). The first criterion evaluates the quality of the model to predict future values, whereas the second measures the cost of opportunity between the degree of adjustment of the model and its complexity. Generally, the smaller these indicators are the better tends to be the adjustment of the model (Mohammed *et al*., 2015).

The expressions of the two indicators are, respectively, given by:

$$AIC = -2\ln(L) + 2k \tag{5}$$

$$BIC = -2\ln(L) + 2\ln(N)\,k \tag{6}$$

where L is the maximum value of the likelihood function, N is the number of observations and k corresponds to the number of parameters.

These measures allow us to verify the goodness of fit of the model within the sample, and to compare the influence of different types of variables (Table 11). Although there is no test to compare the previous indicators (Hosmer and Lemeshow, 2013), Raftery (1995) indicates some references. Namely, a difference of 10 in the BIC of two models corresponds to a chance of 150 to 1 that the model with the smaller BIC has the better fit, which is a very strong likelihood.

Based on the values of AIC and BIC, we observe that among the models without macroeconomic variables (Table 5, Panels 5A and 5B), the results in Panel 5B reveal a better fit; the differences between values of BIC exceed 10. This suggests that models using net assets returns (NITA), thus accounting for the effects of interests and taxes on profitability, seem to be preferable to using instead gross return on assets (EBITTA) as predictor of credit default.

Table 11
Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

Model (panel)	AIC	BIC
Table 5 (panel 5A)	2,850.8	2,932.4
Table 5 (panel 5B)	2,829.1	2,910.5
Table 6	2,777.3	3,001.2
Table 7	2,497.7	2,660.6
Table 8	2,456.1	2,761.4
Table 9 (panel 9A)	2,455.6	2,643.3
Table 9 (panel 9B)	2,435.6	2,628.6

The evidence related to models with (Table 6) and without (Table 5, Panel 5B) the type of industry included is not so straightforward. When accounting for the industry type, we find that the BIC is greater, but the AIC is lower. We privilege in this case the ability of the model to predict future events of default, and thus we consider that the type of industry should be included in the model.

Regarding models with macroeconomic variables (Tables 7 and 8), we confirm a significant reduction in the values of AIC and BIC relatively to those revealed by our best alternative without macroeconomic influences included (Table 6), particularly with the introduction of the cross-section dummy (Table 9, Panels 9A and 9B). Overall, the results reinforce the evidence of the significance of macroeconomic determinants of defaults.

5.3 Receiver Operating Characteristics (ROC) – Discriminatory Power

Stein (2005) states that focusing solely on a cut-off point in a default prediction model is mostly inadequate. As each creditor has his own level of risk aversion and shows specific cost functions for different credit decision, the global discrimination capability of the models should be assessed for all possible cut-off points, i.e. for every credit decision.

To solve this problem, the literature (Chava and Jarrow, 2004; Tinoco and Wilson, 2013; Tian and Yu, 2017) usually considers the Receiver Operating Characteristics Curve (ROC). In practice, the ROC curve represents multiple cut-off points, denoting the trade-off between a higher proportion of true positives (correct predictions of payment default, also denoted as sensitivity) or a higher proportion of true negatives (correct predictions of non-defaults, also denoted as 1-specificity)

The area under the ROC curve (AUC) shows the capability of the prediction model to correctly assess the level of credit risk (Stein, 2007), and thus accurately discriminate between firms that will default and those that remain viable to pay their debts (Hosmer and Lemeshow, 2013). With an AUC of 0.5, the model is as good as a random classification; an AUC equal to 1 signals a perfect fit or discrimination.

The discriminatory power of the model is often expressed by the accuracy ratio (AR), an indicator related with the AUC (Englemann *et al.*, 2003). Such relation is formalized as follows:

$$AR = \frac{(1-\pi)(AUC-0.5)}{0.5(1-\pi)} = 2AUC - 1 \qquad (7)$$

where π is the *a priori* probability of default among all firms.

The AR analysis of the previous models relies on out-of-sample data, based only on a third of the initial sample, with the remaining two thirds employed for models' estimation purposes. Table 12 shows that the AUC and the AR of the model in panel 5A are both lower than the comparable indicators in Panel 5B. Such evidence seems to support again the use of NITA, instead of EBITTA. Nevertheless, the DeLong *et al*. (1988) test, applied to assess the significance of the difference between two or more AUCs (Table 13), points to no significant differences between the AUCs of these models. Even so, we underline that AUCs in our models only with financial variables compare favourably with the results in previous related literature (e.g., Tian and Yu, 2017).

Table 12
Area under the ROC curve and Accuracy Ratio

Model / Panel	AUC	AR
Table 5 (5A)	0.8708	0.7416
Table 5 (5B)	0.8741	0.7482
Table 6	0.8694	0.7388
Table 7	0.9128	0.8254
Table 8	0.9135	0.8270
Table 9 (9A)	0.9165	0.8288
Table 9 (9B)	0.9211	0,8366

Table 13
DeLong *et al*. (1988) test to compare AUCs*

Comparison of AUCs	p-value
Table 5 (5A vs 5B)	0.7012
Table 5 (5B) vs Table 6	0.5268
Table 5 (5B) vs Table 8	0.0100
Table 6 vs Table 8	0.0046
Table 7 vs Table 9 (9A)	0.4370
Table 7 vs Table 9 (9B)	0.2126

* Under the null hypothesis, the two areas are equal.

We may assess the results of the models without and with the type of industry included, by contrasting the indicators of models in Table 5 (Panel 5B) and Table 6. The AUC of model 5A exceeds the correspondent value in 5B, but the difference is not statistically significant to reject the null hypothesis that the areas are equal. We obtain the same conclusion when comparing the models in Panel 5B and in Table 6.

With the introduction of macroeconomic variables and the type of industry (Table 8), the AUC increases substantially, to more than 0.9, a relative change of about 5% versus the comparable model without macroeconomic information (Table 6). This improvement in discrimination against models without macroeconomic determinants corresponds to a statistical significance below 5%, allowing us to reject the null hypothesis that AUCs are equal. The evidence we obtain, therefore suggests that the inclusion of macroeconomic variables enhances significantly the global accuracy of credit default prediction.

Broadly speaking, the models with financial indicators, macroeconomic variables and industry dummies (Table 8), have a better discriminatory capability than those that only consider financial ratios and the type of industry (Table 6). According to the classification proposed by Hosmer and Lemeshow (2013), such models reveal an exceptional discriminatory power. Moreover, they offer complementary evidence to accept H1 and admit that macroeconomic variables improve the accuracy of credit default models, specifically those that consider multiple countries.

With respect to hypothesis H3, we already observed (Tables 6 and 8) that the inclusion of type of industry is significant, particularly the information about the construction industry. From Table 13, we detect that the DeLong *et al*. (1988) test applied to models without macroeconomic determinants (5B vs Table 6), does not provide evidence to admit that the type of industry adds relevant information. A similar conclusion applies to the cross-section dummy (Table 7 vs 9A and Table 7 vs 9B). However, the control for the type of industry in a prediction model combining financial and macroeconomic variables clearly allows an incremental discriminatory power.

6 Conclusion

The European economy was greatly affected by the financial crisis of 2008, which resulted in a significant increase in defaults and bankruptcies of firms worldwide. Our contribution envisages to explore the potential benefits that a multi-country approach, which measures the simultaneous empirical evidence from multiple countries, may bring to the study of macroeconomic determinants of credit risk.

To base conclusions, we analyse data from eleven Eurozone countries, including firm-specific financial information, industry type and macroeconomic variables of the country to which each firm belongs. The results we obtain suggest that the macroeconomic setting, as measured by the GDP growth rate, influences the probability of default of non-financial companies in the countries analysed. Nonetheless, we find some evidence that the influence of macroeconomic determinants over credit default is asymmetric and varies between countries. Particularly, the benign effect of GDP growth on credit default decreases is more pronounced in economic zones that are more exposed to situations of financial stress. In addition, we conclude that the industry type is relevant, but only to distinguish construction against the remaining industries.

The use of the joint empirical evidence from multiple countries to model credit risk offers relevant extensions of our results. Particularly interesting is the assessment of each country's political stability, ease of doing business, laws protecting creditors rights, as qualitative factors that may explain credit risk variations across different countries, beyond what is already described by firm's financial or even demographic determinants. Whether these are relevant determinants of default is an issue requiring further research.

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