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"Determinants of Default: Empirical Evidence from Portuguese Small and Medium-Sized Manufacturing Firms"

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Dedicated to my Family

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Resumo:

Estudos prévios focam-se, essencialmente, em analisar o risco de crédito na perspectiva do banco, quando investigam a relação entre o cliente e este. Contrariamente, este paper pretende desenvolver um modelo de credit scoring que possa ser usado pelas Pequenas e Médias Empresas (PMEs) e que melhore o seu conhecimento sobre o risco de incumprimento. Usando dados de 1260 PMEs Portuguesas que operam no sector transformador durante o período de 1998 a 2006, os resultados do modelo mostram que a probabilidade de cumprimento no próximo ano é uma função crescente da rentabilidade, liquidez, cobertura e actividade e uma função decrescente do endividamento. Tendo em conta os factores qualitativos, os resultados indicam que as pequenas empresas e empresas com apenas uma relação bancária têm uma elevada probabilidade de incumprimento. A análise dos factores de qualidade de gestão e de propriedade mostram que as empresas onde o proprietário é simultaneamente o gestor e empresas não familiares são mais seguras financeiramente em termos de probabilidade de cumprimento.

Abstract:

Previous studies focus on modelling credit default in the bank perspective when analysing the bank-customer relationship. Inversely, this paper aims to develop a credit scoring model that could be used by SMEs, and that improves their knowledge about their default risk. Using data of 1260 Portuguese Manufacturing SMEs, over the period of 1998-2006, the results show that the probability of non-default is an increasing function of profitability, liquidity, coverage and activity, and a decreasing function of leverage. Concerning qualitative factors, the results report that smaller firms and firms with just one bank relationship have a higher probability of default. The analysis of management quality and ownership factors demonstrate that firms where the owner is at the same time the manager and non-family firms are more financially secure in terms of the Probability of Non-Default. Moreover, the performance and qualitative measures for the model developed show that the model is accurate.

JEL Classification: C10; G21; G33.

Keywords: Probability of default; SMEs; Credit Scoring Models; Logistic Regression.

1. Introduction

Small and medium-sized enterprises (SMEs) play a fundamental role in the economy of many countries all over the world (Saurina and Trucharte, 2004; Altman and Sabato, 2005). According to Craig et al. (2007) they are an incubator of economic growth, a place where innovation occurs and new ideas become economically viable business enterprises. Therefore, SMEs make a significant contribution to the Gross Domestic Product (GDP) and to the sustainability of the employment levels. In 2007, for European Union (EU) members, the percentage of SMEs was about 99%, producing two-thirds of the total jobs in the private sector (Audretsch et al., 2009). In Portugal, they have a weight of 99.6% in the business structure, creating 75.2% of private employment and making more than half of business (56.4%) (IAPMEI, 2008). Thanks to the simple structure of SMEs, they can respond quickly to changing economic conditions and meet local customers' needs, growing sometimes into large and powerful corporations or failing in a short time (Altman and Sabato, 2005).

But, for growing into large and powerful corporations, SMEs need to obtain financial funds. In this sense, the vast majority of small businesses rely on commercial banks as their primary loan lenders (Berger and Udell, 1998; Wu et al., 2008), since equity financing is hardly a viable alternative. This happens because the equity market for small firms is not well developed, most owners/managers lack the experience and expertise to obtain equity financing and raising equity is rather costly and therefore inefficient for smaller financing volumes (Blumberg and Letterie, 2008).

Nevertheless, sometimes financial institutions hesitate to lend funds to SMEs due to lack of credible information about them (Baas and Schrooten, 2006; Berger and Frame, 2007; Craig et al., 2007; Blumberg and Letterie, 2008). Most SMEs are relatively young, have little or no credit history (Craig et al., 2007), and face some difficulties signalling their qualities to commercial banks in order to obtain financial funds (Steijvers and Voordeckers, 2009; Wu et al., 2008; Okura, 2009). These difficulties are classic information asymmetries between borrowers and lenders (Farinha and Santos, 2002; Craig et al., 2007; Vos et al., 2007) which may give rise to credit rationing, adverse selection and moral hazard problems (Steijvers and Voordeckers, 2009). According to Petersen and Rajan (1994) the causes of those problems may be more prominent when firms are younger and small. So, capital market imperfections exist and limit the availability of finance to small firms (Love, 2003; Cowling, 2009).

In order to solve market imperfections, firms can develop a relationship lending with lenders (Ogawa and Suzuki, 2000; Jacobson et al., 2005; Baas and Schrooten, 2006; Steijvers and Voordeckers, 2009). Normally this relationship is characterized by a Housebank which can be defined as the first and sometimes the only lender to a firm (Elsas and Krahnen, 1998; Farinha and Santos, 2002; Behr and Güttler, 2007, Neuberger et al., 2008). Though, the Housebank can lead to hold-up problems. In other words, the lender can monopolize firms' information and changes loan interest rates, which will not reflect the real loan risk (Farinha and Santos, 2002; Neuberger et al., 2008). In order to solve the hold-up problems, firms can decide on multiple bank relationships (Farinha and Santos, 2002). But this situation will imply higher interest rates as the new lender doesn't have credible information about the borrower (Behr and Güttler, 2007).

Thus, instead of developing relationships lending, the SMEs can initial a transaction lending (Neuberger et al., 2008; Wu et al., 2008). The use of a transactional lending technology like credit scoring models is relatively new, but is a growing practice in the area of SMEs lending. The adoption of scoring models as management tools has significantly altered the way banks deal with their SMEs loan portfolio. This is an important issue nowadays because of the introduction of the New Basel Capital Accord (Basel II) (Glennon and Nigro, 2005). Under the Basel II, banks are able to compute the minimum capital requirements using an Internal Ratings Based (IRB) approach which is founded on the most sophisticated credit risk internal models (Dietsch and Petey, 2002). In line with Haber (2007) most banks choose to implement the IRB approach, because it is in their interest to assess the credit risk of their customers as precisely as possible.

The adoption of Basel II in EU was made by the publication of Directives 2006/48/EC and 2006/49/EC, June 14, that changed the Directives 2000/12/EC and 93/6/EC, respectively. These Directives were transposed to the Portuguese law entered into force in 2007. Since the adoption of the new regulatory framework was optional in 2007, its implementation by the majority of Portuguese banks only took place in 2008 (Antão and Lacerda, 2008).

Currently, another relevant issue is the global financial crisis and the “collapse” of financial system which took place in the second half of 2008. This situation is followed by an economic slow-down or even recession in some Member States of EU. Consistent with Audretsch et al. (2009), this crisis can have an adverse effect on SMEs access to bank financing. The firms with the weakest financial structure and lower credit rating, like SMEs, suffer the most. Remembering that SMEs are more dependent on external sources of finance, it is expected that the current financial crisis have a strong impact on this type of firms. According to Banco de Portugal (2010), in the first quarter of 2010, the criteria for lending to non-financial firms have become more rigorous, increasing the degree of contraction and focusing in the long-term credit and in the SME segment.

Based on above arguments, the objective of this paper is to develop a logit scoring model for the prediction of the probability of default by Portuguese SMEs. Commonly, researchers focus on the bank’s behaviour when analysing the bank-customer relationship. This paper pretends to do the opposite that is helping SMEs creating an adequate credit scoring model. Thus, the main contribution of this paper is to help SMEs to gain knowledge about their default risk, which can be used to approximate their risk adequate cost of debt. This knowledge is likely to lead to a detection of hold-up problems that SMEs might be confronted with their bank relationships. Further it allows them to monitor their bank’s pricing behaviour and it reduces information asymmetries between lenders and borrowers. To assess a distress prediction model this paper uses a logit regression technique on panel data to estimate a one-year default prediction model. The objective is to modelling credit risk for SMEs separately from large corporate. Thus, data of 1260 Portuguese SMEs operating in manufacturing sector over the period of 1998-2006 was collected.

The results show that the probability of non-default within the next year is an increasing function of profitability, liquidity, coverage and activity, and a decreasing function of leverage. Concerning qualitative factors, the results report that smaller firms and firms with just one bank relationship have a higher probability of default. Moreover, the results also show that firms that have more collateral to pledge to the bank have a lower probability of default. The analysis of management quality and ownership factors showed that firms where the owner is at the same time the manager and non-family firms are more financially secure in terms of the Probability of Non-Default. Concerning to predictive factors, the results reported by the variable Failure Score show that firms with a higher probability of end activity with loss over the next twelve months have a higher probability of default. The results of the variable Paidex show that when the average delay of payments is lower than 30 days, the probability of Non-Default is higher. Moreover, the performance and qualitative measures for the model developed show that the model is accurate.

The paper is organized as follows. Section 2 discusses theoretical background about credit rationing and relationship lending and The New Basel Capital Accord (Basel II). Section 3 provides a description of dataset, methods and variables. Section 4 discusses the results. Section 5 concludes with a summary of the main findings and the limitations of the study as well as prospects for further investigations.

2. Literature Review

2.1. Credit Rationing and Relationship Lending

Bank loans are the most widely used form of small and new business financing. Although, the exchange relationship between lenders and borrowers often suffers from market imperfections, such as, information asymmetries (Stiglitz and Weiss, 1981; Craig et al., 2007; Freel, 2007; Blumberg and Letterie, 2008; Steijvers, 2008; Cowling, 2009). These information asymmetries occur because the lenders have little and no reliable information about the default risk of the applicants (Afonso and Aubyn, 2002). According to Carling and Lundberg (2005) the degree of information asymmetry is lower if the bank has good knowledge about the local market on which a potential borrowing firm acts and if bank knows more about the firm’s ability to perform an investment, its board and its human capital.

Nevertheless, smaller firms often have difficulties to signal their qualities to financial institutions in order to obtain bank finance (Blumberg and Letterie, 2008; Steijvers, 2008; Steijvers and Voordeckers, 2009). Smaller firms are mainly non listed firms, not followed by analysts and lacking any audited financial statements. Moreover, these firms are not always willing to release any information since it is a time-consuming (costly) occupation. Normally the quality of the data provided by small business owners for review by banks is often poor due to a lack of management experience or staff capable to produce useful information (Berger and Udell, 1998; Cziráky et al., 2005; Berger, 2006; Blumberg and Letterie, 2008; Wu et al., 2008). This dilemma is the so called opacity problem (Berger and Frame, 2007; Neuberger et al., 2008).

This information asymmetry between bank and SMEs could be so severe that could lead to credit rationing (Stiglitz and Weiss, 1981; Trovato and Alfò, 2006; Craig et al., 2007; Steijvers and Voordeckers, 2009). According to Steijvers (2008) the credit rationing is one of the most important examples of market failure in our modern economy. It can be defined as the situation where the demand for loans exceeds supply at the prevailing interest rate (Stiglitz and Weiss, 1981; Afonso and Aubyn, 2002; Cziráky et al., 2005; Steijvers and Voordeckers, 2009). This means that loans are allocated by some mechanism other than price (Craig et al., 2007). The rationing of demand may be achieved in two ways: either borrower does not receive the full amount of credit they have applied for (the so called “type I rationing”) or some of the borrowers are simply turned down (“type II rationing”) (Afonso and Aubyn, 2002).

Especially in markets where it is difficult to distinguish between good and bad credit risks, these capital market imperfections result in a supply lack of financial funds, so it is conceivable that the demand for credit may exceed the supply in equilibrium (Craig et al., 2007; Blumberg and Letterie, 2008)**.** If there is an excess demand for bank funds it should be expected that banks raise loan price (the interest rate) to equate demand for loans with supply, thus increasing profits. But it is well known that in the normal course of bank lending this do not happen (Afonso and Aubyn, 2002; Steijvers, 2008; Cowling, 2009). They do not have an incentive to raise the interest rates when demand exceeds supply. As pointed out by Steijvers (2008:4) “the bank-optimal interest rate is the equilibrium interest rate since at any interest rate above the bank-optimal interest, the expected return for the bank increases at a slower rate than the interest rate and will even decrease after a certain interest rate is exceeded”.

Consequently, some borrowers that will not receive bank credit are willing to pay a higher interest rate. If the bank accepted this higher interest rate this means that higher riskier borrowers are attracted. This is the adverse selection effect (Steijvers, 2008; Steijvers and Voordeckers, 2009). It is a consequence of different borrowers having different probabilities of repaying their loan (Craig et al., 2007). In another words, the adverse selection effect means that the borrower quality is ex ante undetectable by the lending bank which gives the firm an unfair advantage. Sequentially, banks will not accept the higher interest rate because higher risk lending is not expected to be rewarded with higher return. On the other hand, if banks raise the interest rate, the borrowers will prefer higher riskier projects, which mean that the return of the bank will decrease again. This is the moral hazard effect (Cowling and Mitchell, 2003; Steijvers and Voordeckers, 2009). These arguments suggest that the demand will not equal the supply and that the banks will prefer to ration credit due to adverse selection and moral hazard problems.

The expected return to the bank obviously depends on the probability of repayment, so the bank would like to be able to identify borrowers who are more likely to repay. But it is difficult to identify such borrowers (Craig et al., 2007). The relationship lending might serve as a mechanism to mitigate informational asymmetries and thus solving the credit rationing problem (Ogawa and Suzuki, 2000; Jacobson et al., 2005; Baas and Schrooten, 2006; Steijvers and Voordeckers, 2009). It is often considered as the most appropriate lending technique for collecting information on SMEs, since reliable information on these type of firms is rare and costly (Elsas and Krahnen, 1998): the firm and the bank enter in a long-term relationship that assures the firm’s access to credit and gives the bank access to information about the firm (Baas and Schrooten, 2006). The relationship lending is mainly based in soft information or qualitative data which takes significant time to accumulate and it’s not easily observed (Berger, 2006; Berger and Frame, 2007; Wu et al., 2008). This lending technology addresses the problem of SMEs’ information opacity (Neuberger et al., 2008; Steijvers and Voordeckers, 2009; Wu et al., 2008).

Relationship lending with long-term commitment and informational monopoly by the lender has some relationship with the so-called Housebanking. Normally small firms have an exclusive outside financier, their Housebank. It can be defined as the premier lender to a firm. It has more relevant and timelier information than other bank and is more committed to its client, enlarging their role as financier if the firm faces unexpected and temporary difficulties. Nevertheless, the information monopoly of the Housebank potentially poses a risk for the borrower, since it is informationally captured by the lender and might lose future benefits of an improved creditworthiness (Elsas and Krahnen, 1998; Farinha and Santos, 2002; Behr and Güttler, 2007, Neuberger et al., 2008). In the case of repeated lending, the Housebank can extract profits, practicing a higher, not fair, interest rate. This situation can occur because, during the relationship lending, the bank accumulates privileged information about the firm quality which other potentials lenders doesn't have access to it. If the borrowers try to get financing from another bank it will be refused because they assume that it is a bad quality firm since it could not get financing by the Housebank. Therefore, long-term bank relationship could lead to hold-up problems (Farinha and Santos, 2002; Neuberger et al., 2008). The main concern is that the firm will reduce their investment and thus lower profits (Mahrt-Smith, 2006). As a result, the bank relationship may become costly because sub-optimal investments in a relationship.

Initiating a second bank lending relationship could be an optimal solution to the potential hold-up problem. According to Neuberger et al. (2008) firms choose multiple banking relationships in order to obtain financial services at more competitive terms than at their Housebank, which exerts monopoly power in highly concentrated markets. But the new lender doesn't have the same information about the borrower as the Housebank. This situation leads to a higher default risk assumed by the new lender and consequently higher interest rates for the borrower. These are typically switching costs that firms may be confronted when initiating a new relationship lending. Along with Behr and Güttler (2007: 208), "the borrower will not obtain the "fair" rate of interest - that is, the risk adequate cost of debt - either from her Housebank or from a new lender".

Beyond relationship lending the bank customer relationship can be also characterized by transaction lending which is based primarily on “hard” quantitative data and is focused on informationally transparent borrowers (Neuberger et al., 2008; Wu et al., 2008). In line with Berger and Udell (2002) transactions lending technologies are distinguished primarily by the source and type of information used like financial ratios for financial statement lending; the quantity and quality of the available collateral; usually accounts receivable and inventory for asset-based lending; and the financial condition and history of the principal owner of the firm for small business credit scoring. Therefore, only SMEs with sufficient hard information available generally receive transactions credit from banks (Berger, 2006). Similar to capital market investors that rely on external credit ratings provided by rating agencies, banks assign internal credit ratings to evaluate the creditworthiness of their borrowers. In both cases, ratings can be interpreted as a screening technology that is applied to alleviate asymmetric information problems between borrowers and lenders. Internal credit ratings for corporate borrowers are an aggregated valuation procedure of various financial and non-financial factors (Grunert et al., 2005).

Nowadays, the transaction lending technologies are an important issue, not only for external credit ratings but also as an internal tool for banks because of the introduction of the New Basel Capital Accord (Basel II) (Butera and Faff, 2006). Concerns have been raised that the Basel II will change the way banks analyse credits, introducing new credit risk management techniques, like credit scoring models, and possibly reducing the lending activity toward SMEs (Altman and Sabato, 2005). Credit scoring models are generally developed by lenders for the purpose of ranking the population by relative credit quality similar to the way ratings developed by the rating agencies (Glennon and Nigro, 2005). So, any business owner seeking bank financing needs to overcome the hesitation and doubts of banks (Blumberg and Letterie, 2008) creating its own internal rating models and analysing their probability of default. Thus, if a firm knows its own creditworthiness, this could lead to a fair treatment of SMEs by lenders, possibly reducing the loan interest rate and having an impact on the weight average cost of capital.

2.2. The New Basel Capital Accord (Basel II)

Basel II is a regulatory framework for the banking sector, which objective is to align regulation with best practices in credit risk management (Haber, 2007) and to provide banks with an incentive to invest in more sophisticated risk measurement and management capabilities (Herring, 2007). It consists of three Pillars: Pillar I, Minimum Capital Requirements (credit risk, operational risk, market risk); Pillar II, Supervisory Review Process, and Pillar III, Market Discipline (Mohanty, 2008).

In Pillar 1 of the Basel II, the rules to calculate bank capital requirements for each of the different segments are clearly explained. The banks can use the Standardized Approach (RSA) and the Internal Ratings-Based Approach (IRB) (the Foundation (FIRB) or the Advanced (AIRB)), to calculate capital requirements (Altman and Sabato, 2005; Jacobson et al., 2005; Haber, 2007; Herring, 2007; Jarrow, 2007; Mohanty, 2008). With the IRB approach, banks are able to personalize the capital requirement calculation, building their own models in order to estimate Probabilities of Defaults (PDs) (with the FIRB) or even Expected Loss Given Defaults (LGDs), Exposure at Default (EAD) and Maturity (M) (with the AIRB) for each client (Altman and Sabato, 2005; Jacobson et al., 2005; Herring, 2007; Jarrow, 2007). In this sense, the majority of banks choose to implement the AIRB, because it is in their interest to assess the credit risk of their customers as precisely as possible.

Along with the Basel II banks will have to categorize exposures into five broad classes of assets with different underlying risk characteristics: corporate, sovereign, bank, retail, and equity exposures (Jacobson et al., 2005). The probability of default is defined to be the one year long term average default probability. Default is defined for wholesale and retail exposures in Basel II. A wholesale exposure is a credit exposure to a company, individual or government entity, and a retail exposure is a credit exposure to an individual or small business managed as part of a portfolio of similar exposures (EU, Directive 2006/48/EC). A wholesale exposure defaults if either the bank determines the borrower in unlikely to pay or the borrower is at least 90 days past due on a coupon or principal payment. A retail exposure defaults if it is 120 days past due (unless it is a revolving retail exposure, then it must be 180 days past due) (Jarrow, 2007).

According Basel II retail credit and loans to SMEs will receive a different treatment than corporate loans and will require less regulatory capital for given default probabilities. The main reasons for this differential treatment is that small business loans and retail credit are generally found to be less sensitive to systematic risk and the assumption that the loans maturities are shorter (Jacobson et al., 2005). Nevertheless, the New Basel Accord assumes that the smaller an obligor, the greater its probability of default (Saurina and Trucharte, 2004). So, banks are able to consider SMEs as retail or as corporate entities, considering the total exposure. If total exposure is under 1 million, SMEs can be classified as retail but at the same time the exposure must be managed as a retail exposure, on a pooled basis (Fabi et al., 2004; Saurina and Trucharte, 2004; Altman and Sabato, 2005; Claessens et al., 2005; Jacobson et al., 2005; Haber, 2007).

According to Altman and Sabato (2005) the New Basel Capital Accord will encourage banks to update their internal systems and procedures so as to be able to manage SMEs on a pooled basis through the use of a scoring, rating or some other automated decision system. The same authors pointed out that access to bank financing is likely to become easier and possibly cheaper, since larger banks will find SME lending more profitable. Berger and Frame (2007) came to the same conclusion. They analysed the potential effects of the small business credit scoring on credit availability and they find that banking organizations that implement automated decision systems (such as scoring systems) increase small business credit availability. Some authors like Berger (2006) and Kolari and Shin (2006) conclude that small business lending has a strong positive effect on bank profitability. Divergent from this opinion are Saurina and Trucharte (2004) and Dietsch and Petey (2004) that finding that lending to SMEs is riskier than to large corporations.

Taking into account these different results, the introduction of Basel II remains an important issue nowadays. Since SMEs play a fundamental role in the economy and with the Basel II banks are able to create their own credit scoring models, it is very important that SMEs gains knowledge about their default risk, being better prepared to their relationships with the bank.

3. Empirical Analysis

3.1. Data Set

A panel dataset of Portuguese SMEs for the period of 1998-2006 was constructed from AMADEUS, and from a database required to Dun & Bradstreet (D&B). The first one is a database managed by Bureau Van Djik (BVD) which includes standardized annual accounts (consolidated and unconsolidated) for approximately 9 millions of companies through Europe, including Eastern Europe. D&B is a leader provider of business information for risk management, sales and marketing, and supply management decisions. The selected period is due to the fact that de database AMADEUS only have information available from 1998 to 2006.

This paper focuses on Portuguese SMEs for several reasons. Portugal has a financial system dominated by the presence of financial intermediaries, mostly banks (Bonfim et al., 2009). Thus the relationships between lenders and borrowers are characterized by relationship lending. In this context, SMEs are confronted with relatively harsh credit constraints (Baas and Schrooten, 2006) because they suffer from information asymmetries problems. They do not have certified audited financial statements to yield credible financial information on a regular base and usually do not have publicly traded equity or debt (Wu et al., 2008). Further, most SMEs are managed by only one manager who owns all the shares (Blumberg and Letterie, 2008). So, they are characterized by a lack of credible information (Berger and Frame, 2007) having difficulties to signal their qualities. Another reason is the fact that the small business sector is an incubator of economic growth, being responsible for the creation of majority of private employment and contribution to GDP (Saurina and Trucharte, 2004; Craig et al., 2007). As a SME classification, this study employs the definition established in the European Commission

Recommendation of 6 May 2003 (2003/361/EC)[1] and at the same time the one defined in the Basel II[2].

Consistent with Dragos et al. (2008), the selection of the sample should be the first step when estimating firm's probability of default once it can cause classification and estimation biases. To avoid this problem this paper focuses only on one sector, the manufacturing sector (NACE, Section C), more specifically the manufacture of Food Products (NACE, Division 10) and the Manufacture of Beverages (NACE, Division 11). According to Antão e Lacerda (2008), this sector is characterized by a higher default rate. One possible explanation is due the fact that the manufacturing sector is a capital intensive one which means that requires more investment and once report larger financing obstacles (Beck et al., 2006). Nevertheless, these sub-sectors are the major producers of essential goods and represented 13.6% in total manufacturing in 2008 (INE, 2008). In 2004, these enterprises accounted 16% of turnover and 13% of GVA in manufacturing industry (AEP, 2007). To control the survivor bias effect, active and inactive firms were selected According with Butera and Faff (2006) the balance sheet data used must be at least one or two previous to the data on which the probability of default is assessed. Once observing this assumption and eliminating firms with too many missing and inconsistent data (e.g. total assets are different from total shareholders plus liabilities), at this point the sample of this study comprises an unbalanced panel data of 1260 Portuguese SMEs for the period between 1998 and 2006.

To get information about the default rate of the selected sample the data was submitted to D&B. Data on defaults are difficult to access because they refer to rare events and the data is prepared by the entities which themselves are the source of information. Central banks have only recently begun to make some efforts in order to copulate a practical loan default data, following the recommendations of the New Basel Capital Accord. The final sample consists on a pooled panel data with 375 default and 2121 non defaulted observations

[1] According to the European Commission Recommendation (2003/361/EC) the category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million.

[2] The New Basel Accord only considers the value of annual turnover (EUR 50 million) (Saurina and Trucharte, 2004).

corresponding to a default rate of 15% during the period 1998-2006.[3] Table 1 presents the results.

Table 1

Construction of the data set for the Portuguese Manufacturing Firms

	Defaults	Non-Defaults	Total	% Default
1998	9	112	121	7.44%
1999	2	90	92	2.17%
2000	5	102	107	4.67%
2001	5	100	105	4.76%
2002	6	116	122	4.92%
2003	11	122	133	8.27%
2004	3	137	140	2.14%
2005	113	541	654	17.28%
2006	221	801	1022	21.62%
Total Observations	375	2121	2496	15.02%

This table shows the construction of the data sample for the Portuguese Manufacturing firms for the period 1998-2006. In the first column, the different years are depicted. The second column shows the number of defaulted observations and the third column the number of non-defaulted observations. The column four shows the total number of observations. The last column shows the percentage of defaulted for each year and for total observations.

3.2. Methods and Variables

3.2.1 Methods

This paper uses the logit regression to analyse the predictors of default by Portuguese manufacturing SMEs. According to Lacerda and Moro (2008), the logit model is commonly used since its score is calibrated as probability of default (PD). Additionally, the logit model allows working with disproportional samples and do not require restrictive assumptions (Altman and Sabato, 2007) that is, it does not oblige the assumption of multivariate normality of the data (Butera and Faff, 2006)[4].

[3] In order to keep the confidentiality, when we receive the sample from D&B we could not identify the enterprises. So, we just could classify the number of default observations.

[4] The seminal works in the field of default predictions studies were Beaver (1966) and Altman (1968), who developed univariate and multivariate analyses, respectively. Specifically, Altman (1968) combined five financial ratios in a linear way with weights to produce what he called the *Z*-score model. This technique was applied to default prediction studies for a long time for some other authors. Nevertheless, the model has been criticized because it assumes the normality and the equality of the variance-covariance matrices for defaulting and non-defaulting companies. Considering this criticism, Ohlson (1980) applies the logistic model to analysing the default probability.

The logit model takes the form:

$$Y = \log it\ (\mathrm{p(x)}) = \ln \frac{\mathrm{p(x)}}{1 - \mathrm{p(x)}} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \quad (1)$$

where *P(x)* is the probability that a firm non-defaulted ($p = Prob(Y=1)$); $\frac{p}{1-p}$ is the "*odds ratio*"; ln [$\frac{p}{1-p}$] is *p logit*; β_0 is the coefficient of the constant term; $\beta_{(1,\ldots,n)}$ is a vector of coefficients of the independent variables; $x_{(1,\ldots,n)}$ is a vector of independent variables; and ε is the error term that is log-normally distributed by assumption.

3.2.2. Variables

3.2.2.1 Dependent variable

The dependent variable is the Probability of Non-Defaulted (P-NDF) that takes the value of one if the firm non-defaulted and zero otherwise. This study uses as dependent variable the P-NDF in order to have positive slopes and intercept since the higher the final logit score, the higher the probability that a firm will not default (Altman and Sabato, 2007).

3.2.2.2 Independent Variables

As independent variables, this study comprises at the same time financial (quantitative) and non financial (qualitative) factors, because financial ratios are mostly backward looking point in time measures. This assumption is consistent with Basel II IRB (BIS, 2006) approach and, according to Lehmann (2003) and Grunert et al. (2005), the combined use of those variables leads to a significantly more accurate default prediction than the single use of financial or non-financial factors. Appendixes B and C show the definition and statistics of all variables.

In line with previous studies[5], this study selected six accounting ratio categories: profitability, solvency, liquidity, leverage, coverage, and activity. According to Beaver et al. (2005) and Grunert et al. (2005), profitability is expected to be a critical element in the analysis of the probability of default because it is a key indicator of firms' ability to pay. Profitability is negatively related to credit risk (Doumpos et al., 2002). More profitable firms are able to generate larger cash-flows with their activity, and may face lower funding costs. Related to this point this study introduces the solvency category in order to measure the capacity of a firm to generate internal funds (e.g., Cánovas and Solano, 2006). Another important area in this field is the liquidity of a firm. Firms having enough liquid assets are in better liquidity position and are more capable of meeting their obligations (Doumpos et al., 2002; Grunert et al., 2005). The leverage ratios are classic indicators of financial risk. High values of these ratios indicate a high default probability (Carling and Lundberg, 2005) since firms have to generate more income to meet their obligations and repay their debt (Doumpos et al., 2002). This study also uses the coverage ratios as higher levels of these ones implies lower levels of financial leverage and thus a lower probability of default. Furthermore, this study comprises activity indicators. These ratios allowed to measure the effectiveness of investment in a given category of assets (Butera and Faff, 2006; Altman and Sabato, 2007).

For each one of the categories it was selected a number of financial ratios (see Appendix A) as being most used in relevant studies. This study uses a forward stepwise selection procedure for each one of the categories in order to identify (statistically) which financial indicators are better discriminators between "default" and "non-default" firms. Then the model is performed only with the selected ratios. For this study, the significant level is set at 20% (e.g., Altman and Sabato, 2007). Table 2 presents the results. All ratios have the expected sign and the Wald Test for each of the predictors is statistically significant.

[5] For example: Beaver (1966); Altman (1968); Doumpos et al. (2002); Altman and Sabato (2005); Beaver et al. (2005); Carling and Lundberg (2005); Grunert et al. (2005); Butera and Faff (2006); Cánovas and Solano (2006); Altman and Sabato (2007); Behr and Güttler (2007); Cánovas and Solano (2007); Lacerda and Moro (2008); Bonfim et al. (2009) and Fidrmuc and Hainz (2009) among others.

Table 2

Model Developed with Financial Ratios

	Coefficient and Wald Test	Standard Error
Profitability = Profit (Loss) before Taxation / Total Sales	17.429**** (52.714)	2.401
Solvency = Cash Flow / Total Assets	4.880**** (10.192)	1.529
Liquidity = (Current Assets – Short Term Liabilities) / Total Assets	2.778**** (35.647)	0.465
Leverage = Debt / Total Assets	-11.571**** (126.536)	1.029
Coverage = Operating Profit / Interest Paid	0.038**** (9.14)	0.013
Activity = Sales / Total Assets	0.194* (1.787)	0.145
Constant	10.819**** (161.064)	0.853

This table shows the model developed using the financial ratios to predict the probability of non-default. The parameters are estimated by maximum likelihood method. Wald statistics are in parentheses. ****Significant at 1%; ***Significant at 5%; **Significant at 10%; *Significant at 20%.

Relatively to size, Saurina and Trucharte (2004) and Jacobson et al. (2005) show that the smaller an obligor, the greater its probability of default. This assumption is consistent with the Basel II (BIS, 2006). Moreover, Dietsch and Petey (2004) distinguished three categories of SMEs: the small or very small ones, in which the default risk is lower than in the medium-size SMEs; the medium-size SMEs that are riskier, on average; and the largest SMEs, where credit risk is lower. Thus, they concluded that on average, the PDs tend to vary with size. In the model developed, this study uses the natural logarithm of total annual turnover as a measure of firm's size[6]. Concerning to the variable size, this study expects a positive sign between size and the P-NDF.

Due to acknowledge 'liabilities of newness', younger firms are less likely to successfully access credit than older firms (Freel, 2007). Consistent with Glennon and Nigro (2005), new firms are statistically more likely to default than established firms, as they are generally more information opaque, making it more difficult to judge the relative

[6] The Basel II only considers total annual turnover as a measure of firm's size (BIS, 2006).

creditworthiness of those firms. To analyse this relationship this study employs four dummies variables considering four categories of age (see Berger and Udell, 2002).

For collateral this study uses the ratio of Total Tangible Fixed Assets under Total Assets (Farinha and Santos, 2002; Bonfim et al., 2009). This is an important issue due to the introduction of the New Basel Capital Accord. According to Steijvers and Voordeckers (2009), it is expected that collateral based lending will occur more often because the risk of lending should be align to the amount of capital a bank has to hold. Thus, a collateralized loan represents less risk regarding the recovery of the loan and thus less equity has to be reserved by the bank (BIS, 2006). In this sense, only good risk borrowers will be willing to put up collateral against a loan, as they feel confident that they will not default and lose their assets. So, a positive sign between collateral and the P-NDF is expected.

Since one objective of this study is to reduce the information asymmetries between SMEs and banks it is important to analyse how the opaqueness of a firm influences its probability of default. Farinha and Santos (2002) use the ratio between intangible assets under total assets as a proxy for firm’s opaqueness. Consistent with Neuberger et al. (2008), industries with a large share of physical assets (e.g., manufacturing) tend to be less opaque than industries with more intangible assets (e.g., services, trade). Thus, this study uses the ratio of tangible assets under total assets to measure the firm’s opaqueness. If this ratio is higher (near 1) this means that the firm has lower intangible assets and that it is less opaque.

Usually, to overcome the opacity problem, main small and younger firms rely on a close bank-customer relationship, having only a low number of lending relationships. Although, a single bank relationship is most efficient when a firm borrows once, due to information monopoly by the lender, which can lead to hold-up problems. These problems may be reduced by multiple bank relationships. So, consistent with Bolton and Scharfstein (1996), multiple bank relationships signal higher borrower quality. Other authors like Bhattacharya and Chiesa (1995), Yosha (1995), and Carletti (2004), agree that firms with valuable information prefer fewer creditors (but more than one) to keep some private information (for instance, Bonfim et al. (2009), concluded that Portuguese SMEs borrows from two banks on average). In this sense, this study uses the number of bank relationships as a measure of borrower quality and two dummy variables ($Bank_1$ and $Bank_2$) are created to analyse the referred effect.

Another important issue is that SMEs are normally owner–managed and the owner-managers generally possess general rather than specific expertise (Wu et al, 2008). This is an important topic because, when the owner is at the same time the manager, the information opacity of these firms is higher. According to Schäfer (2003), owner-managed enterprises represent a higher statistical risk. However, in cases where the ownership and management are separated, managers may invest in projects that benefit their own personal interests, rather than developing projects that can contribute to improve company performance. These are typically agency problems between managers and owners (Serrasqueiro and Nunes, 2008). One way to overcome this problem is centring decision-making on company owners or having more than one manager specialized in a given area. To measure these effects this study employs the variable $Ownership_1$, a dummy variable that takes the value 1 if the business owner is at the same time the manager and 0 otherwise; and the variable $Ownership_2$, also a dummy variable that takes value 1 if the company has more than one manager and 0 otherwise. To analyse the effect of a family on firm P-NDF, this study defines the variable Family Firm, a dummy variable that takes the value one if the company is controlled and usually managed by multiple family members (Shanker and Astrachan, 1996). Normally this type of enterprises faces a higher level of commitment to the managerial project for the reason that the subsistence of the family depends on the success of the firm (Brokaw, 1992). Behr and Güttler (2007) concluded that a single owner, in this situation a family, can be more disposed to provide the firm with new equity in an attempt to avoid a loan default. Cabrera-Suárez et al. (2001) argue that family firms are more hesitant to invest in risky projects. This could be interpreted in two different ways. On one hand, firms could miss growth opportunities, which could mean a higher probability of default; and on the other hand, family firms does not assume risky projects which could lead to a lower probability of default. So, this study does not predict the expected sign between the variable family firms and the P-NDF.

Additionally, this study also employs predictive indicators provided by D&B[7]. Thus, to analyse the level of risk associated with the company's financial capacity this study uses the variable Rating; the variable Failure Score measures the probability of a firm ends activity with loss over the next twelve months; and the variable Paidex is an indicator that measures the average delay of payments from a company in the domestic market (days beyond the credit granted).

4. Results

4.1. Univariate Analysis

Appendix C shows measurements and descriptive statistics of Probability of Non-Default and Probability of Default firms. Defaulted firms have a lower mean of profitability, solvency, liquidity, coverage and activity ratios and a higher mean of leverage ratio than non-defaulted firms. Firms that have a higher mean ratio between tangible fixed assets and total debt are non-defaulted firms, which mean that these firms are able to pledge more collateral to the bank than defaulted firms.

For non-default and for default observations the majority of the firms have more than sixteen years, corresponding to 60% and 51% of the total sample, respectively. Regarding the size, the non-default firms are bigger. The mean value for size is 14, 301€ for Non-Defaulted Firms and 13, 813€ for defaulted firms. The sample also shows that 74% of non-defaulted firms and 68% of defaulted firms have more than one bank relationship. Both for non-defaulted and defaulted firms, in the vast majority of the firms the owner is at the same time the manager and they have more than one manager. Also, they are characterized for being mostly family firms.

For rating predictive indicator the sample shows that only 21% of observations for non-defaulted firms have a higher commercial transaction risk. For defaulted firms this value is 51%. Concerning Failure Score, both defaulted and non-defaulted firms have a higher

[7] Berger and Frame (2007) analyse the use of small business credit–scoring models by U.S. commercial banks. They conclude that to improve the model, it should be used at the same time information collected directly from the firm and business data provided by a commercial credit bureau (in this study, D&B).

percentage (91% and 80%, respectively) of firms which the probability of ends activity with loss over the next twelve months is higher. Although, the mean value for Failure $Score_2$ for defaulted firms is higher than for non-defaulted firms.

4.2. Logistic Regression

Table 3 present the results of the logit regression. Appendix D shows the matrix of correlations. Regarding financial variables the results show that financial ratios have the expected sign that is, positive relation between P-NDF and the Profitability, Solvency, Liquidity, Coverage and Activity predictors and a negative relation between P-NDF and Leverage indicator. For the variable Collateral the results shows a significant positive sign which indicates that more collateral a firm has to pledge to the bank, the higher the P-NDF.

Concerning the variable opaqueness the coefficient reports a negative sign indicating that SMEs with a higher ratio between Tangible fixed Assets and Total Assets have a lower P-NDF. This is an unexpected result. In line with Neuberger et al. (2008), industries with large tangible assets tend to be less opaque, and consequently should report a lower probability of default. Nevertheless, one possible explanation is that these firms could suffer from liquidity constraints, especially in short term.

Relating to Size, the results indicate that the P-NDF is higher when the firm’s size increases but this result is not significant at all. Butera and Faff (2006) report a similar result. Related to the Age, all dummies variables are statistically significant and report the expected sign. Thus, the firms that have between zero and ten years old influence negatively the P-NDF, indicating that smaller and younger firms are financially more constrained.

For the variable number of bank relationships, the results show that firms with just one bank relationship have a higher probability of default. This result are in line with Neuberger and Räthke (2009) and suggests that firms with more than one bank relationship have a lower risk of default and face lower hold-up problems. Thus, these firms are higher quality firms.

Table 3

Estimated Model

	Coefficient and Wald Test	Standard Error
Financial Ratios		
Profitability	20.341****	8.848
	(5.285)	
Solvency	7.833	9.020
	(0.7541)	
Liquidity	7.523****	3.103
	(5.880)	
Leverage	-12.668*	9.210
	(1.892)	
Coverage	0.435****	0.153
	(8.127)	
Activity	2.600****	1.188
	(4.793)	
Collateral	17.167**	10.613
	(2.617)	
Opaqueness	-27.178****	13.900
	(3,823)	
Size	0.702	0.588
	(1.427)	
Age		
Age1	-4.647****	2.200
	(4.461)	
Age2	-2.008**	1.266
	(2.513)	
Age3	2.537***	1.344
	(3.563)	
Number of Bank Relationships		
Bank1	-2.338**	1.565
	(2.230)	
Management Quality and Ownership		
Ownership1	4.389****	1.893
	(5.373)	
Ownership2	0.125	1.714
	(0.005)	
Family Firms	-2.329***	1.364
	(2.915)	
Predictive Indicators		
Rating1	0.159	1.733
	(0.008)	
Failure Score1	3.807****	1.594
	(5.705)	
Paidex2	3.312**	2.137
	(2.403)	
Paidex3	9.990****	3.739
	(7.138)	
Paidex4	41.774	277238946.832
	(0.000)	
Paidex5	47.875	197274381.485
	(0.000)	
Paidex6	4.651****	1.787
	(6.773)	
Constant	-2.525	12.153
	(0.043)	

This table shows the results of model developed using all the variables (financial and non-financial) to predict the probability of non-default. The parameters are estimated by maximum likelihood method. Wald statistics are in parentheses.

****Significant at 5%; ***Significant at 10%; **Significant at 15%; Significant at 20%.

Regarding the management quality and ownership the variable $Ownership_1$ shows a positive and statically significant coefficient that is when business owner is at the same time the manager the P-NDF is higher. This result suggests that the agency problems between owners and managers have a high weight in the probability of default for SMEs. Indeed, the subsistence of the owner depends on the success of the firm which means that he will avoid taking any decision that put the firm in risk. But when the firm is classified as a family firm, the results indicate that the probability of default is higher. One possible explanation relies on family differences and role conflict that can lead to behaviour that is not in the best interest of the firm. Moreover, family firms normally do not invest in risk projects losing good opportunities to grow into large and powerful firms (e.g., Kets de Vries (1993); Cabrera-Suárez et al., 2001).

The predictive indicator $Rating_1$ is not significant but positively influences the P-NDF. The Failure Score indicator is also positively related to P-NDF. Thus, the results show that firms with lower probability of end activity with loss over the next twelve months have a higher P-NDF. Concerning Paidex indicator and as expected, the results show a positive sign between $Paidex_6$ and P-NDF that is firms for which the average delay of payments is lower than 30 days the P-NDF is higher. In turn, the variables $Paidex_2$ and $Paidex_3$ also show a positive sign, suggesting that that a firm can have a higher average delay of payments and the probability of default is lower. One possible explanation for this result is due the small number of observations for these variables (see Appendix C).

4.3. Validation Results

This section presents diagnostic and performance measures related to the model estimated. To evaluate the quality of the forecast, this study uses the Receiver Operating Characteristic Curve (ROC). The model is better the larger the area under the curve is[8].

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[8] The better the model is at discriminating, the closer the curve is to the top left of the chart and the larger the area which varies from 0 to 1 depending on the discriminatory ability of the model. The area under the curve has probabilistic significance and indicates the probability of any non defaulting firm selected at random from the population will have a higher estimated score than any other defaulted firm, also randomly selected. See Engelman et al. (2003) for more details.

Thus, the estimation provides by the study here reports 99% which means that the results are accurate (Appendix E shows the diagnostic plot of ROC Curve). To measure the accuracy of the model, this study calculates the Type I (2.55%) and Type II (12.20%) error rates.[9] To calculate these percentages, the study here assumes an arbitrary cut-off rate of 50% of the population.[10]

To examine the joint predictive ability of all the independent variables in the model, this study analyses the Omnibus test of Model Coefficients. The p-value related to the model estimated (Table 3) of this test is found to be statistically significant (p-value=0). Thus, there is an adequate fit of the data to the model or at least one of the covariates is significantly related to the response variable. Next, the study here also considers the Cox & Snell's R^2 and the Nagelkerke R^2 as a goodness of fit measures. The first one has a similar interpretation of multiple R-squared based on the log likelihood for the baseline model. Although, its maximum is usually less than 1. The Nagelkerke R^2 test is a modification of the Cox and Snell's R^2 coefficient to assure that it can vary from zero to one. This test will normally be higher than Cox and Snell's R^2 but will tend to run lower than the corresponding OLS R^2. For the model estimates, Cox and Snell's and Nagelkerke measures are 0.461 and 0.840, respectively, which gives statistically robustness to the results estimated.

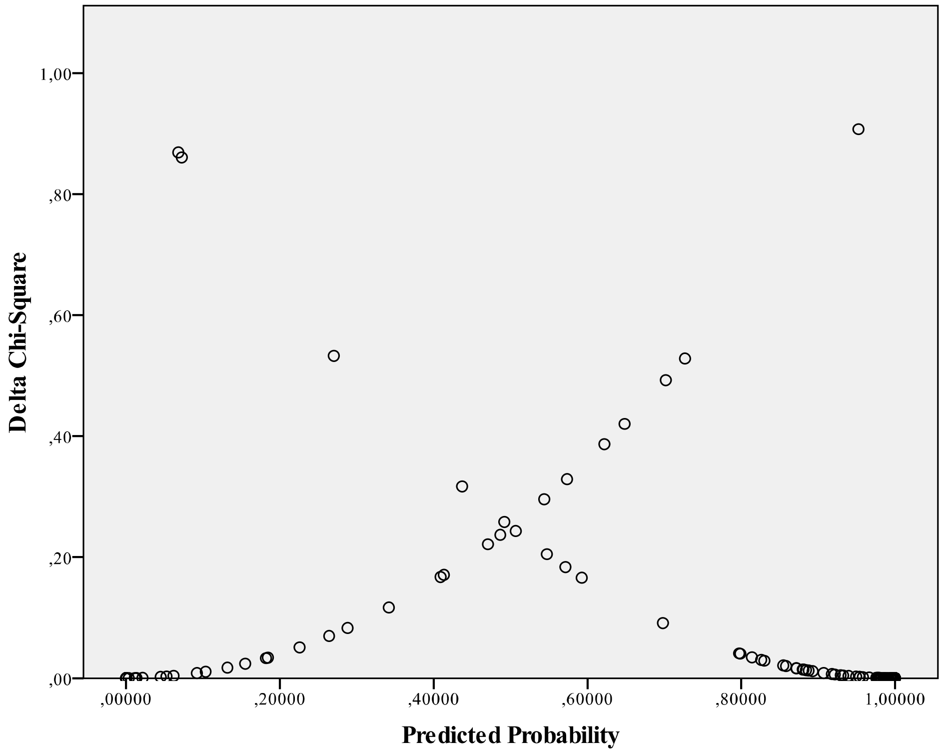
To test if the model estimated adequately describes the data, this study employs the Hosmer-Lemeshow Test, also called the chi-square test. The result of the Hosmer-Lemeshow is not statistically significant (pvalue=0,993), which means that the study here applies an appropriate statistical technique. Furthermore, and as suggested by Altman and Sabato (2007), the study here also analyses the delta chi-square versus probability of default as diagnostic plot to confirm the result of the Hosmer-Lemeshow test. Because the plot looks like an "X", the performance of the model estimated is good. The following plot shows the results.

[9] Type I error is the percentage of observations classified as ''non-default'' but which actually did default. Type II error is the percentage of observations classified as ''default'' that actually did not default (Grunert et al, 2005).

[10] This means that all firms with a forecasted probability of non-default greater than 0.5 will be considered as non-defaults while all firms with a lower forecasted probability of non-default will be assumed to be default (Lehmann, 2003).

Plot 1

Diagnostic Plot of Delta Chi-Square versus Predicted Probability



The plot shows an approximation of the square residuals versus fitted values.

4.4. Robustness Sample

According to Lehmann (2003), the accuracy of the model estimated increases, if the sample comprises 1/3 of default observations and 2/3 of non-default observations. Thus, to validate the results the model from Table 3 was estimated using a sample of 300 defaulted observations and 600 non-defaulted observations. The results in terms of coefficients, Wald Test and Standard Errors are similar as for the initial sample and are presented in Appendix F. Table 4 summarizes the results in terms of diagnostic and performance measures of the initial sample and the robustness sample.

Table 4

Diagnostic and Performance Measures for Initial Sample and Robustness Sample

	Initial Sample	Robustness Sample
Type I Error Rate	2.55%	2.64%
Type II Error Rate	12.20%	12.20%
-2 Log likelihood	56.24	56.18
Cox & Snell R Square	0.46	0.46
Nagelkerke R Square	0.84	0.84

The Type I and Type II error rates for the robustness sample are similar to initial model. The Cox & Snell's R^2 and the Nagelkerke R^2 have the same values. The likelihood ratio (-2LL) of the best-fitted model is minimal for the robustness sample. The Hosmer-Lemeshow is also not statistically significant (pvalue=1). The area under the ROC curve is also 99% like the initial model. Thus, we might conclude that the initial model leads to an accurate prediction of default.

5. Conclusion

Usually banks hesitate to provide credit to SMEs which means that they suffer from limited access to financial resources. Often this behavior is due to SMEs having difficult to signaling their qualities. These are typically asymmetric information problems between SMEs and banks. To avoid these problems SMEs can develop a relationship lending or a transaction lending with the bank. The use of a transactional lending technology like credit scoring models is a growing practice in the area of SMEs lending in particular with the publication of the New Basel Capital Accord in June 2004. This document at its most sophisticated IRB approach allows banks to employ its own estimates of the Probability of Default, the Expected Loss Given Default (LGD), the Exposure at Default (EAD) and Maturity, as inputs in the regulatory model that determines the risk-weight.

Many studies focus on modeling credit default in the bank perspective when analyzing the bank-customer relationship. This paper pretended to do the opposite that is to develop an adequate credit scoring model that could be used by SMEs. The objective is to improve the knowledge of Portuguese SMEs about their default risk. Using a panel data from a representative sample of Portuguese SMEs, operating in Manufacturing of Food and Beverages, this paper develops a logit scoring model for the prediction of default. First the study here analyses a complete set of financial ratios. Following a stepwise procedure the ratios that best explained the probability of default were selected. Then, to perform the scoring model this study uses at the same time the financial ratios selected and other non-financial indicators. The results show that the probability of non-default within the next year is an increasing function of profitability, liquidity, coverage and activity, and a decreasing function of leverage. Concerning qualitative factors, smaller firms and firms with just one bank relationship have a higher probability of default. This result is consistent because normally smaller firms have a lower number of bank relationships. Moreover, the results show that firms that have more collateral to pledge to the bank and firms where the owner is at the same time the manager and non-family firms have a lower probability of default. Additionally, firms with lower probability of end activity with loss over the next twelve months and when their average delay of payments is lower than 30 days, have a higher probability of non-default. Sustain in the results of the ROC Curve and the Type I and Type II error rates, the study here concludes that the model developed is accurate.

The main contribution of this paper is related to the model developed that it is a model which specially focuses on SMEs side. The model pretends that SMEs are well informed when they are going to get financing from commercial banks and "discuss" the interest rate in order to reduce information asymmetries and to avoid that SMEs are credit rationing. Moreover, SMEs can recognize if the bank is applying a fair interest rate. Nevertheless, other factors such as the duration of the relationship banking, loan maturity, information about the firm's owner (e.g., age and education), the presence of past credit problems and firm's market position are some forward looking indicators that could improve the model. Furthermore, future research should apply the model taking into account that under the Basel II SMEs can be considerer as retail or corporate entities.

APPENDIXES

Appendix A

Selection of Financial Ratios

Category	Ratios Examined	Financial Ratios selected under a Stepwise Procedure	Financial Ratios Entered in the Model
Profitability	Profit (loss) before Taxation / Total Sales	Profit (loss) before Taxation / Total Sales	
	EBITDA/Total Assets	EBITDA/Total Assets	Profit (loss) before Taxation / Total Sales
	EBIT/Total Assets	EBIT/Total Assets	
	Gross Profit / Total Assets		
	EBIT/Total Assets		
Solvency	Cash Flow /Total Assets	Cash Flow /Total Assets	
	Capital/Total Liabilities		Cash Flow /Total Assets
	Capital/Total Assets	Capital/Total Assets	
Liquidity	(Current Assets-Short-Term Liabilities) / Total Assets	(Current Assets-Short-Term Liabilities) / Total Assets	
	(Current Assets- Stocks)/Current Liabilities	(Current Assets- Stocks)/Current Liabilities	(Current Assets-Short-Term Liabilities) / Total Assets
	Cash/Total Assets		
	Current Assets / Current Liabilities		
	Cash/Current Liabilities	Cash/Current Liabilities	
	Working Capital /Total Assets	Working Capital /Total Assets	
Leverage	Debt/Total Assets		
	Short Term Debt/ Total Liabilities		
	Total Liabilities/Total Assets	Debt/Total Assets	Debt/Total Assets
	(Long-term debt + loans)/Total Liabilities		
	Interest Paid/Total Bank Debt		
	(Non-Current Liabilities + Loans)/Capital		
Coverage	Operating Profit (loss) /Interest Paid	Operating Profit (loss) /Interest Paid	
	Net profit / Interest Expenses		
	EBITDA/Interest Expenses	EBITDA/Interest Expenses	Operating Profit (loss) /Interest Paid
	EBIT/Interest Expenses		
	Retained Earnings/Total Assets	Retained Earnings/Total Assets	
	Financial Expenses / Total Bank Debt		
Activity	Sales/Total Assets		
	Sales/Stocks	Sales/Total Assets	Sales/Total Assets
	Sales/Current Assets		
	Interest Expensive / Total Liabilities		

This table shows the procedure of selection of the financial ratios that entered in the model. The first column describes the category of each ratio. The second column shows the candidate financial ratios. The third column presents the ratios selected after a forward stepwise procedure applied to each category. The column four shows the financial ratios entered in the final model.
EBIT – Earnings before interests and taxes.
EBITDA – Earnings before Interests, Taxes, Depreciations and Amortizations.

Appendix B

Definition of Variables

Variables	Definition
Dependent Variable	
Probability of Non-Defaulted (P-NDF)	Dummy that takes value 1 if borrowers non-default and 0 otherwise.
Independent Variables	
Financial Ratios	
Profitability	Profit (loss) before taxation / Turnover
Solvency	Cash Flow / Total Assets
Liquidity	(Current Assets-Short-term liabilities)/ Total Assets
Leverage	Debt / Total Assets
Coverage	Operating Profit (loss) / Interest Paid
Activity	Sales / Total Assets
Collateral	Tangible Fixed Assets / Total Debt
Opaqueness	Tangible Fixed Assets / Total Assets
Size	Natural logarithm of Total Annual Turnover
Age	
Age_1	Dummy that takes value 1 if the company has between zero and five years old, and 0 otherwise.
Age_2	Dummy that takes value 1 if the company has between six and ten years old, and 0 otherwise.
Age_3	Dummy that takes value 1 if the company has between eleven and fifteen years old, and 0 otherwise.
Age_4	Dummy that takes value 1 if the company has more than sixteen years old, and 0 otherwise.
Number of Bank Relationships	
$Bank_1$	Dummy that takes value 1 if the company works with just one bank, and 0 otherwise.
$Bank_2$	Dummy that takes value 1 if the company works with two or more banks, and 0 otherwise.
Management Quality and Ownership	
$Ownership_1$	Dummy that takes value 1 if the business owner is at the same time the manager, and 0 otherwise.
$Ownership_2$	Dummy that takes value 1 if the company has more than one manager, and 0 otherwise.
Family Firms	Dummy that takes value 1 if the company is a family one, and 0 otherwise.
Predictive Indicators	
$Rating_1$	Dummy that takes value 1 if the company commercial transactions risk is lower, and 0 otherwise.
$Rating_2$	Dummy that takes value 1 if the company commercial transactions risk is higher, and 0 otherwise.
Failure $Score_1$	Dummy that takes the value 1 if the probability of a firm ends activity with loss over the next twelve months is lower and 0 otherwise.
Failure $Score_2$	Dummy that takes the value 1 if the probability of a firm ends activity with loss over the next twelve months is higher and 0 otherwise.
$Paidex_1$	Dummy that takes value 1 if the firm average delay of payments is unsatisfactory or placed in collection, and 0 otherwise.
$Paidex_2$	Dummy that takes value 1 if the firm average delay of payments is 180 days or more, and 0 otherwise.
$Paidex_3$	Dummy that takes value 1 if the firm average delay of payments is 90 days , and 0 otherwise.
$Paidex_4$	Dummy that takes value 1 if the firm average delay of payments is 60 days, and 0 otherwise.
$Paidex_5$	Dummy that takes value 1 if the firm average delay of payments is 30 days, and 0 otherwise.
$Paidex_6$	Dummy that takes value 1 if the firm average delay of payments is 15 days, and 0 otherwise.
$Paidex_7$	Dummy that takes value 1 if the firm average delay of payments is satisfactory or cash, and 0 otherwise.
$Paidex_8$	Dummy that takes value 1 if the firm average delay of payments is advanced or discounted, and 0 otherwise.

Appendix C

Statistics of Probability of Non-Default and Probability of Default

Panel A: Probability of Non-Default

	N	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
Dependent Variable	2121	1	1	2121	1.000	0.000	0.000		
Independent Variables									
Financial Ratios									
Profitability	2082	-0.831	0.549	-4.979	-0.002	0.099	0.010	-2.471	15.988
Solvency	2087	-2.405	0.795	166.515	0.08	0.125	0.016	-3.799	78.078
Liquidity	2119	-4.077	0.949	-97.724	-0.046	0.418	0.175	-2.139	13.301
Leverage	1814	0.051	5.014	1341.130	0.739	0.388	0.150	3.849	29.42
Coverage	1485	-79.730	928.850	46484.400	31.303	107.308	11514.957	5.096	28.461
Activity	2098	0,001	14.375	3349.384	1.596	1.185	1.405	2.627	13.996
Collateral	1814	0.000	7.505	1313.901	0.724	0.648	0.420	3.678	22.805
Opaqueness	2116	0.000	0.955	902.486	0.427	0.223	0.050	0.150	-0.842
Size	2098	5.572	17.904	30004.324	14.301	1.385	1.917	0.118	0.363
Age									
Age_1	2113	0	1	221	0.105	0.306	0.094	2.586	4.692
Age_2	2113	0	1	289	0.137	0.344	0.118	2.116	2.479
Age_3	2113	0	1	334	0.158	0.365	0.133	1.876	1.521
Age_4	2113	0	1	1269	0.601	0.490	0.240	-0.411	-1.833
Number of Bank Relationships									
$Bank_1$	1920	0	1	507	0.264	0.441	0.194	1.071	-0.853
$Bank_2$	1920	0	1	1413	0.736	0.441	0.194	-1.071	-0.853
Management Quality and Ownership									
$Ownership_1$	2083	0	1	1310	0.629	0.483	0.233	-0.534	-1.716
$Ownership_2$	2083	0	1	1784	0.856	0.351	0.123	-2.035	2.142
Family Firms	1888	0	1	1508	0.799	0.401	0.161	-1.491	0.224
Predictive Indicators									
$Rating_1$	2090	0	1	1651	0.790	0.407	0.166	-1.425	0.030
$Rating_2$	2090	0	1	439	0.210	0.407	0.166	1.425	0.030
Failure $Score_1$	2091	0	1	426	0.204	0.403	0.162	1.472	0,168
Failure $Score_2$	2091	0	1	1665	0.796	0.403	0.162	-1.472	0,168
$Paidex_1$	500	0	1	2	0.004	0.063	0.004	15.764	247.484
$Paidex_2$	500	0	1	11	0.022	0.147	0.022	6.537	40.897
$Paidex_3$	500	0	1	11	0.022	0.147	0.022	6.537	40.897
$Paidex_4$	500	0	1	19	0.038	0.191	0.037	4.847	21.582
$Paidex_5$	500	0	1	18	0.036	0.186	0.035	4.996	23.057
$Paidex_6$	500	0	1	156	0.312	0.464	0.215	0.814	-1.343
$Paidex_7$	500	0	1	274	0.548	0.498	0.248	-0.193	-1.970
$Paidex_8$	500	0	1	9	0.018	0.133	0.018	7.273	51.095

Panel B: Probability of Default

	N	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
Dependent Variable	375	0	0	0	0.000	0.000	0.000		
Independent Variables									
Financial Ratios									
Profitability	368	-0.958	0.112	-39.300	-0.107	0.146	0.021	-2.500	8.607
Solvency	370	-0.807	1.573	-0.581	-0.002	0.155	0.024	2.019	31.441
Liquidity	375	-2.799	0.786	-140.232	-0.374	0.45	0.202	-1.592	5.230
Leverage	327	0.385	4.355	341.715	1.045	0.449	0.202	3.864	20.039
Coverage	342	-79.440	990.91	82.730	0.242	68.710	4721.095	12.296	162.689
Activity	374	0.003	7.706	530.816	1.419	1.199	1.437	1.984	5.626
Collateral	327	0.002	2.192	182.729	0.559	0.318	0.101	0.847	2.960
Opaqueness	374	0.002	0.947	194.088	0.519	0.239	0.057	-0.316	-0.837
Size	374	9.007	17.256	5165.949	13.813	1.243	1.545	0.177	0.739
Age									
Age_1	366	0	1	68	0.186	0.389	0.152	1622	0.636
Age_2	366	0	1	48	0.131	0.338	0.114	2194	2.831
Age_3	366	0	1	62	0.169	0.376	0.141	1.77	1.139
Age_4	366	0	1	188	0.514	0.500	0.250	-0.055	-2.008
Number of Bank Relationships									
$Bank_1$	312	0	1	100	0.321	0.467	0.218	0.773	-1.412
$Bank_2$	312	0	1	212	0.679	0.467	0.219	-0.773	-1.412
Management Quality and Ownership									
$Ownership_1$	363	0	1	239	0.658	0.475	0.226	-0.671	-1.559
$Ownership_2$	363	0	1	291	0.802	0.399	0.159	-1.519	0.310
FamilyFirms	337	0	1	268	0.795	0.404	0.163	-1.47	0.162
Predictive Indicators									
$Rating_1$	364	0	1	177	0.486	0.500	0.250	0.055	-2.008
$Rating_2$	364	0	1	187	0.514	0.500	0.250	-0.055	-2.008
Failure $Score_1$	364	0	1	31	0.085	0.280	0.078	2.985	6.947
Failure $Score_2$	364	0	1	333	0.915	0.280	0.078	-2.985	6.947
$Paidex_1$	61	0	0	0	0	0	0		
$Paidex_2$	61	0	1	4	0.066	0.250	0.062	3.599	11.324
$Paidex_3$	61	0	1	1	0.016	0.128	0.016	7.810	61
$Paidex_4$	61	0	0	0	0	0	0		
$Paidex_5$	61	0	1	4	0.066	0.250	0.062	3.599	11.324
$Paidex_6$	61	0	1	25	0.410	0.496	0.246	0.376	-1.923
$Paidex_7$	61	0	1	27	0.443	0.501	0.251	0.237	-2.011
$Paidex_8$	61	0	0	0	0	0	0		

Appendix D

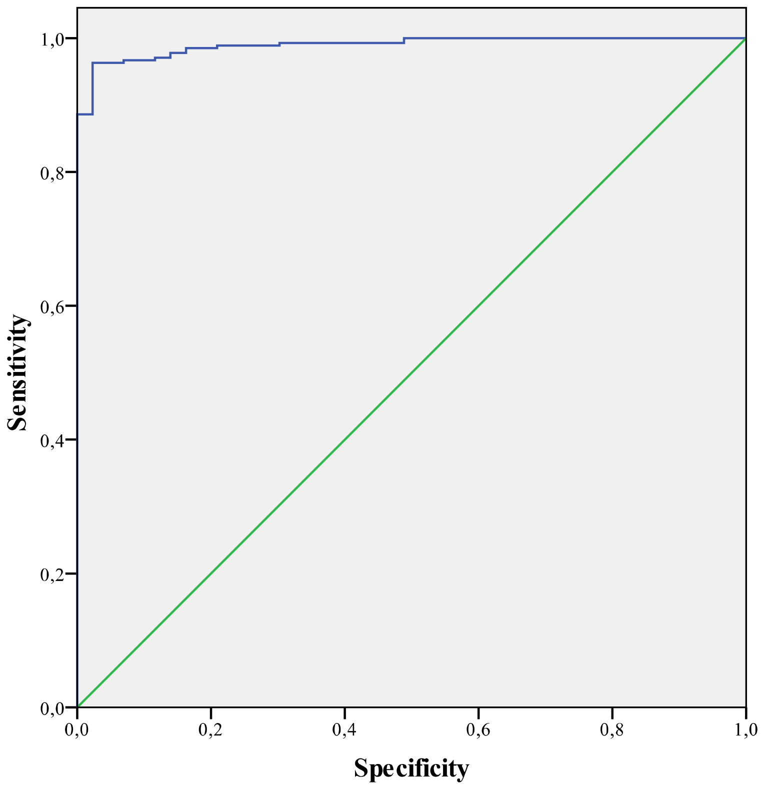
Matrix of Correlations

	Profitability	Solvency	Liquidity	Leverage	Coverage	Activity	Collateral	Opaqueness	Size	Age_1	Age_2	Age_3	$Bank_1$	$Ownership_1$	$Ownership_2$	Familyfirms	$Rating_1$	Failure $Score_1$	$Paidex_2$	$Paidex_3$	$Paidex_4$	$Paidex_5$	$Paidex_6$
Profitability	1.000																						
Solvency	-0.385	1.000																					
Liquidity	0.317	-0.085	1.000																				
Leverage	0.159	-0.232	0.299	1.000																			
Coverage	-0.044	0.041	0.573	-0.115	1.000																		
Activity	-0.072	0.153	0.572	-0.151	0.766	1.000																	
Collateral	0.240	-0.143	0.590	0.662	0.510	0.352	1.000																
Opaqueness	-0.209	0.061	-0.559	-0.552	-0.581	-0.408	-0.975	1.000															
Size	0.010	0.144	0.245	-0.004	0.366	0.160	0.269	-0.339	1.000														
Age_1	-0.187	-0.060	-0.378	0.122	-0.453	-0.365	-0.213	0.262	-0.139	1.000													
Age_2	0.013	-0.292	-0.347	-0.095	-0.386	-0.294	-0.261	0.296	-0.092	0.446	1.000												
Age_3	0.373	-0.119	0.399	-0.090	0.433	0.308	0.251	-0.300	0.419	-0.275	-0.002	1.000											
$Bank_1$	-0.101	0.062	-0.120	0.320	-0.239	-0.225	-0.016	0.090	-0.116	-0.026	-0.055	-0.195	1.000										
$Ownership_1$	0.135	0.062	0.582	-0.030	0.736	0.619	0.475	-0.576	0.602	-0.424	-0.370	0.520	-0.265	1.000									
$Ownership_2$	0.240	-0.132	0.163	-0.026	-0.132	0.033	-0.123	0.209	-0.312	0.008	0.261	0.110	0.158	-0.194	1.000								
Familyfirms	-0.173	0.124	-0.466	-0.148	-0.470	-0.402	-0.485	0.526	-0.261	0.310	0.159	-0.296	0.204	-0.591	0.159	1.000							
$Rating_1$	-0.062	-0.164	0.307	0.350	0.199	0.148	0.306	-0.314	0.246	-0.084	-0.146	-0.032	0.170	0.366	-0.231	-0.396	1.000						
Failure $Score_1$	0.127	-0.069	0.383	-0.383	0.504	0.454	0.078	-0.120	0.051	-0.621	-0.255	0.389	-0.282	0.381	0.239	-0.194	-0.143	1.000					
$Paidex_2$	-0.030	0.061	0.384	0.010	0.382	0.379	0.293	-0.334	0.326	-0.214	-0.148	0.140	-0.057	0.414	-0.145	-0.233	0.426	0.205	1.000				
$Paidex_3$	0.206	0.120	0.696	-0.040	0.650	0.659	0.408	-0.471	0.477	-0.393	-0.370	0.515	-0.305	0.758	0.077	-0.283	0.253	0.482	0.454	1.000			
$Paidex_4$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000		
$Paidex_5$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
$Paidex_6$	0.000	0.162	0.502	-0.247	0.558	0.654	0.234	-0.296	0.056	-0.496	-0.365	0.426	-0.243	0.526	0.071	-0.063	-0.122	0.540	0.301	0.667	0.000	0.000	1.000

For definition of variables see Appendix B.

Appendix E

Receiver Operating Characteristic Curve (ROC) for Estimated Model



This plot shows that the results for the model estimated are accurate as the area under the curve is 99% with an asymptotic significance at 0%.

Appendix F

Estimated Model for Robustness Sample

	Coefficient and Wald Test	Standard Error
Financial Ratios		
Profitability	20.376****	8.849
	(5.302)	
Solvency	7.795	8.997
	(0.751)	
Liquidity	7.503****	3.094
	(5.880)	
Leverage	-12.478*	9.247
	(1.821)	
Coverage	0.431****	0.153
	(7.928)	
Activity	2.577****	1.188
	(4.704)	
Collateral	17.120**	10.568
	(2.625)	
Opaqueness	-27.050****	13.844
	(3.818)	
Size	0.683	0.594
	(1.324)	
Age		
Age_1	-4.625****	2.198
	(4.425)	
Age_2	-2.007**	1.265
	(2.517)	
Age_3	2.520***	1.345
	(3.513)	
Number of Bank Relationships		
$Bank_1$	-2.314**	1.568
	(2.178)	
Management Quality and Ownership		
$Ownership_1$	4.349****	1.891
	(5.286)	
$Ownership_2$	0.140	1.713
	(0.007)	
Family Firms	-2.312***	1.363
	(2.877)	
Predictive Indicators		
$Rating_1$	0.151	1.722
	(0.008)	
Failure $Score_1$	3.784****	1.596
	(5.623)	
$Paidex_2$	3.284**	2.133
	(2.372)	
$Paidex_3$	9.921****	3.734
	(7.060)	
$Paidex_4$	41.055	192849724.598
	(0.000)	
$Paidex_5$	47.410	160510463.963
	(0.000)	
$Paidex_6$	4.641****	1.781
	(6.792)	
Constant	-2.389	12.126
	(0.039)	

This table shows the robustness model developed using all the variables (financial and non-financial) to predict the probability of non-default. The unknown parameters are estimated by maximum likelihood. Wald statistics are in parentheses.
****Significant at 5%; ***Significant at 10%; **Significant at 15%; * Significant at 20%.

REFERENCES

AEP – Associação Empresarial de Portugal (2007): *Sector Agro-Alimentar*, http://www.aeportugal.pt/.

AFONSO, A. and AUBYN, M. ST. (2002): "Credit Rationing and Monetary Transmission: Evidence for Portugal", *SSRN Working Paper Series*, Rochester.

ALTMAN, E. I. (1968): "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", *The Journal of Finance*, 23 (4): 589-609.

ALTMAN, E. I. and SABATO, G. (2005): "Effects of the New Basel Capital Accord on Bank Capital Requirements for SMEs", *Journal of Financial Research*, 28 (1/2/3): 15-42.

ALTMAN, E. I. and SABATO, G. (2007): "Modelling Credit Risk for SMEs Evidence from the U.S. Market", *ABACUS*, 43 (3): 332-357.

ANTÃO, P. and LACERDA, A. (2008): "Avaliação dos Requisitos de Capital sob Basileia II: o Caso Português", *Relatório de Estabilidade Financeira 2008 – Banco de Portugal*: 207-228**.**

AUDRETSCH, D.; HORST, R.; KWAAK, T. and THURIK, R. (2009): "First Section of the Annual Report on EU Small and Medium-sized", *EIM Business & Policy Research*: 1-46.

BAAS, T. and SCHROOTEN, M. (2006): "Relationship Banking and SMEs: A Theoretical Analysis", *Small Business Economics*, 27: 127-137.

BANCO DE PORTUGAL (2010): "Inquérito aos Bancos sobre o Mercado de Crédito, Resultados para Portugal", Estudos Económicos, http://www.bportugal.pt/pt-PT/EstudosEconomicos/Publicacoes/IBMC/Publicacoes/Results_abr10_p.pdf.

BIS – BANK FOR INTERNATION SETTLEMENTS, BASEL COMMITTEE ON BANKING SUPERVISION (2006): "International Convergence of Capital Measurements and Capital Standards – A Revised Framework": 1-333.

BEAVER, W. H. (1966): "Financial Ratios as Predictors of Failure", *Journal of Accounting Research*, 4: 71-102.

BEAVER, W. H.; McNICHOLS, M. F. and RHIE, J. W. (2005): "Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy", *Review of Accounting Studies*, 10: 93-122.

BECK, T.; DEMIRGÜÇ-KUNT, A.; LAEVEN, L. AND MAKSIMOVIC, V. (2006): "The determinants of financing obstacles", *Journal of International Money and Finance*, 25: 932-952.

BEHR, P., AND GÜTTLER, A. (2007): "Credit Risk Assessment and Relationship Lending: An Empirical Analysis of German Small and Medium-Sized Enterprises", *Journal of Small Business Management*, 45 (2): 194-213.

BERGER, A. N. (2006): "Potential Competitive Effects of Basel II on Banks in SME Credit Markets in the United States", *Journal of Financial Services Research*, 29 (1): 5-36.

BERGER, A. N. and FRAME, W. S. (2007): “Small Business Credit Scoring and Credit Availability”, *Journal of Small Business Management*, 45 (1): 5-22.

BERGER, A. N. and UDELL, G. F. (1998): “The Economics of Small Business Finance: The roles of private equity and debt markets in financial growth cycle”, *Journal of Banking & Finance*, 22 (6-8): 613-673.

BERGER, A. N. and UDELL, G. F. (2002): “Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure”, *The Economics Journal*, 112: F32-F54.

BHATTACHARYA, S. and CHIESA, G. (1995): “Proprietary information, financial intermediation, and research incentives”, *Journal of Financial Intermediation*, 4: 328-357.

BLUMBERG, B. F. and LETTERIE, W. A. (2008): “Business Starters and Credit Rationing”, *Small Business Economics*, 30: 187-200.

BOLTON, P. and SCHARFSTEIN, D. (1996): “Optimal debt structure and the number of creditors”, *Journal of Political Economy*, 104: 1-25.

BONFIM, D.; DAI, QINGLEI and FRANCO, F. (2009): “The number of bank relationships, borrowing costs and bank competition”, *Working Paper – Banco de Portugal*, Portugal.

BROKAW, L. (1992): “Why Family Firms Are Best”, *Inc.* 14 (3): 72-81.

BUTERA, G. and FAFF, R. (2006): “An integrated multi-model credit rating system for private firms”, *Review of Quantitative Finance and Accounting*, 27: 311-340.

CABRERA-SUÁREZ K.; SAÁ-PÉREZ, P D. E. and GARCIA-ALMEIDA, D. (2001): “The Succession Process from a Resource and Knowledge-Based View of the Family Firm”, *Family Business Review*, 14(1):37-46.

CÁNOVAS, G. H., and SOLANO, P. M. (2006): “Banking Relationships: Effects on Debt Terms for Small Spanish Firms”, *Journal of Small Business Management*, 44 (3): 315-333.

CÁNOVAS, G. H., and SOLANO, P. M. (2007): “Effect of the Number of Banking Relationships on Credit Availability: Evidence from Panel Data of Spanish Small Firms”, *Small Business Economics*, 28: 37-53.

CARLETTI, E. (2004): “The structure of bank relationships, endogenous monitoring, and loan rates”, *Journal of Financial Intermediation*, 13: 58-86.

CARLING, K., and LUNDBERG, S. (2005): “Asymmetric information and distance: an empirical assessment of geographical credit rationing”, *Journal of Economics and Business*, 57: 39-59.

CLAESSENS, S.; KRAHNEN, J. and LANG, W. W. (2005): “The Basel II Reform and Retail Credit Markets”, *Journal of Financial Services Research*, 28 (1/2/3): 5-13.

COWLING, M. and MITCHELL, P. (2003): “Is the Small Firms Loan Guarantee Scheme Hazardous for Banks or Helpful to Small Business?”, *Small Business Economics*, 21 (1): 63-71.

COWLING, M. (2009): “The role of loan guarantee schemes in alleviating credit rationing in the UK”, *Journal of Financial Stability*, 30: 1-9.

CRAIG, B. R.; JACKSON III, W. E. and THOMSON, J. B. (2007): “Small Firm Finance, Credit Rationing, and the impact of SBA-Guaranteed Lending on Local Economic Growth”, *Journal of Small Business Management*, 45 (1): 116-132.

CZIRÁKY, D.; TISMA, S. and PISAROVIC, A. (2005): “Determinants of the Low SME Loan Approval Rate in Croatia”, *Small Business Economics*, 25: 347-372.

DIETSCH, M. and PETEY, J. (2002): “The credit risk in SME loans portfolios: Modelling issues, pricing, and capital requirements”, *Journal of Banking & Finance*, 26: 303-322.

DIETSCH, M. and PETEY, J. (2004): “Should SME exposures be treated as retail or corporate exposures? A comparative analysis of default probabilities and asset correlations in French and German SMEs”, *Journal of Banking & Finance*, 28: 773-788.

DOUMPOS, M.; KOSMIDOU, K.; BAOURAKIS, G. and ZOPOUNIDIS, C. (2002): “Credit risk assessment using a multicriteria hierarchical discrimination approach: A comparative analysis”, *European Journal of Operational Research*, 138: 392-412.

DRAGOS, C.; DRAGOS, S. and DUMITRU, A. (2008): “Financial Scoring: a literature review and experimental study”, *Economic and Business Review for Central and South – Eastern Europe*, 10 (1): 53-68.

ELSAS, R., and KRAHNEN, J. P. (1998): “Is Relationship Lending Special? Evidence from Credit-File Data in Germany” *Journal of Banking & Finance*, 22 (10/11): 1283-1316.

ENGELMAN, B.; HAYDEN, E. and TASCHE, D. (2003): “Measuring the Discriminative Power of Rating Systems”, *Discussion Paper 01, Deutsche Bundesbank Research Center*.

EUROPEAN UNION, *Commission Recommendation* No. 2003/361/EC in Official Journal of the European Union, of 20 May 2003.

EUROPEAN UNION, *Council Directive* No. 93/6/EEC in Official Journal of the European Union, of 15 March 1993.

EUROPEAN UNION, *Directive of the European Parliament and of the Council* No. 2000/12/EC in Official Journal of the European Union, of 20 March 2000.

EUROPEAN UNION, *Directive of the European Parliament and of the Council* No. 2006/48/EC in Official Journal of the European Union, of 14 June 2006.

EUROPEAN UNION, *Directive of the European Parliament and of the Council* No. 2006/49/EC in Official Journal of the European Union, of 14 June 2006.

FABI, F.; LAVIOLA, S. and REEDTZ, P. M. (2004): “The treatment of SMEs loans in the New Capital Accord: some evaluations”, *Banca Nazionale del Lavoro Quarterly Review*, 57 (228): 29-70.

FARINHA, L. A. and SANTOS, J. A. C. (2002): “Switching from single to multiple bank lending relationships: determinants and implications”, *Journal of Financial Intermediation*, 11 (2): 124-151.

FIDRMUC, J. and HAINZ, C. (2010): “Defaults Rates in the Loan Market for SMEs: Evidence from Slovakia”, *Economic Systems*, 34 (2): 133-147.

FREEL, M. S. (2007): “Are Small Innovators Credit Rationed?”, *Small Business Economics*, 28: 23-35.

GLENNON, D. and NIGRO, P. (2005): “An analysis of SBA Loan Defaults by Maturity Structure”, *Journal of Financial Research*, 28 (1/2/3): 77-111.

GRUNERT, J.; NORDEN, L. and WEBER, M. (2005): “The role of non-financial factors in internal credit ratings”, *Journal of Banking & Finance*, 29: 509-531.

HABER, G. (2007): “Basel II: International Competition Issues”, *Atlantic Economic Journal*, 35: 383-389.

HERRING, R. J. (2007): “The Rocky Road to Implementation of Basel II in the United States”, Atlantic *Economic Journal*, 35: 411-429.

IAPMEI – Instituto de Apoio às Pequenas e Médias Empresas e ao Investimento (2008): *Sobre as PME em Portugal*, http://www.iapmei.pt.

INE – Instituto Nacional de Estatística (2008): *Empresas em Portugal 2008*, http://www.ine.pt.

JACOBSON, T.; LINDÉ J. and ROSZBACH, K. (2005): “Credit Risk Versus Capital requirements under Basel II: Are SME loans and Retail Credit Really Different?”, *Journal of Financial Services Research*, 28 (1): 43-75.

JARROW, R. A. (2007): “A Critique of Revised Basel II”, *Journal of Financial Services Research*, 32: 1-16.

KETS DE VRIES, M. (1993): “The Dynamics of Family Controlled Firms: The Good and Bad News”, *Organizational Dynamics*, 21(3): 59-71.

KOLARI, J. W. and SHIN, G. H. (2006): “Assessing the Profitability and Riskiness of Small Business Lenders in the Banking Industry”, *SSRN Working Paper Series*, Texas.

LACERDA, A. and MORO, R. (2008): “Analysis of the Predictors of Default for Portuguese Firms”, *Workingpaper n. º 22 – Banco de Portugal*, Portugal.

LEHMANN, B. (2003): “Is it Worth the While? The Relevance of Qualitative Information in Credit Rating”, *SSRN Working Paper Series*, Germany.

LOVE, I. (2003): “Financial Development and Financing Constraints: International Evidence from the Structural Investment Model”, *Review of Financial Studies*, 16 (3): 765-791.

MAHRT-SMITH, J. (2006): “Should Banks Own Equity Stakes in their Borrowers? A Contractual Solution to Hold-Up Problems”, Journal *of Banking and Financing*, 30: 2911-2929.

MOHANTY, S. K. (2008): “Basel II: Challenges and Risks”, *Academy of Banking Studies Journal*, 7 (2): 109-130.

NEUBERGER, D.; PEDERGNANA, M., and DÖPPNER, S. R. (2008): “Concentration of Banking Relationships in Switzerland: The Result of Firm Structure or Banking Market Structure?”, *Journal of Financial Services Research*, 33: 101-126.

NEUBERGER, D. and RÄTHKE, S. (2009): “Microenterprises and multiple bank relationships: the case of professionals”, *Small Business Economics*, 32: 201-229.

OGAWA, K. and SUZUKI, K. (2000): “Demand for Bank Loans and Investment under Borrowing Constraints: A Panel Study of Japanese Firm Data”, *Journal of the Japanese and International Economies*, 14: 1-21.

OHLSON, J. A. (1980): “Financial Ratios and the Probabilistic Prediction of Bankruptcy”, *Journal of Accounting Research*, 18 (1):109-131.

OKURA, M. (2009): “Firm Characteristics and Access to Bank Loans: Na Empirical Analysis of Manufacturing SMEs in China”, *International Journal of Business and Management Science*, 1 (2): 165-186.

PETERSEN, M. A., and RAJAN, R. G. (1994): “The Benefits of Lending Relationships: Evidence from Small Business Data”, *The Journal of Finance*, 49 (1): 3-37.

SAURINA, J. and TRUCHARTE, C. (2004): “The impact of Basel II on Lending to Small- and Medium-Sized Firms: A Regulatory Policy Assessment Based on Spanish Credit Register Data”, *Journal of Financial Services Research*, 26 (2): 121-144.

SCHÄFER, D. (2003): “The New Basel Capital Accord and its Impact on Small and Medium-sized Companies”, *Economic Bulletin*, 40 (6): 209-214.

SERRASQUEIRO, Z. S., and NUNES, P. M. (2008): “Performance and Size: empirical evidence from Portuguese SMEs”, *Small Business Economics*, 31: 195-217.

SHANKER, M. C. and ASTRACHAN, J. H. (1996): “Myths and Realities: Family Businesses’ Contribution to US Economy **-** A Framework for Assessing Family Business Statistics”, *Family Business Review,* 9(2):107-123.

STEIJVERS, T. (2008): “Existence of Credit Rationing for SMEs in the Belgian Corporate Bank Loan Market”, *SSRN Working Paper Series*, Belgium.

STEIJVERS, T. and VOORDECKERS, W. (2009): “Collateral and credit rationing: a review of recent empirical studies as a guide for future research”, *Journal of Economic Surveys*, 23 (5): 924-946.

STIGLITZ, J. and WEISS, A. (1981): “Credit rationing in markets with imperfect information”, *American Economic Review*, 71 (3): 393-410.

TROVATO, G. and ALFÒ, M. (2006): “Credit Rationing and the Financial Structure of Italian Small and Medium Enterprises”, *Journal of Applied Economics*, 9 (1): 167-184.

VOS, E.; YEH, A. J.; CARTER, S. and TAGG, S. (2007): “The happy story of small business financing”, *Journal of Banking & Finance*, 31: 2648-2672.

WU, J.; SONG, J. and ZENG, C. (2008): “An empirical evidence of small business financing in China”, *Management Research News*, 31 (12): 959-975.

YOSHA, O. (1995): “Disclosure costs and the choice of financing source”, *Journal of Financial Intermediation*, 4: 3-20.