J. Account. Public Policy 29 (2010) 517–532

Contents lists available at ScienceDirect

J. Account. Public Policy

journal homepage: www.elsevier.com/locate/jaccpubpol

Accounting and non-accounting determinants of default: An analysis of privately-held firms ☆

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ABSTRACT

We model default with novel loan data maintained by the Portuguese Central Bank for 31,025 accounts of privately-held firms that include 30 accounting ratios and non-accounting information on size, age, industry and geographic regions. Interest costs to gross income, number of days in payables and receivables have a positive and significant influence on the probability of default. Financial and asset coverage, the investment ratio, return on equity and investment, solidity, variation in gross income and working capital to total assets are negatively related to default. Interest costs to gross income, solidity and working capital to total assets show larger marginal influence on the probability of default compared to return on investment, financial coverage, days in payables, days in receivables, and return on equity. Asset coverage, investment ratio and variation in gross income show relatively low marginal influence. While size influences default positively, age influences default negatively. The analysis of the joint influence of size and accounting ratios shows that size significantly alters the relation and the magnitude of the marginal influence of the accounting ratios on default. Our findings also indicate that industry and geography influence default. Besides assessing default in privately-held firms, our study identifies the important role of non-accounting information on default prediction and the practical significance of assessing the marginal influence of predictors instead of the

☆ We benefited from detailed comments made by Andrew Clare, Carl Lins, Christine Wiedman, Duane Kennedy, Peter Wysocki, Phil Molyneux, Raj Aggarwal, Sarkis Khoury, Steve Fortin, two anonymous reviewers and the editors. The views stated herein are those of the authors and are not necessarily the views of the London School of Economics, Harvard University, or the European Central Bank.

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doi:10.1016/j.jaccpubpol.2010.09.009

classical coefficients. The factors we find as influencing default can be used as early warning signals in policies underlying supervision, and the default probabilities in the assessment of financial pressures in the corporate sector.

1. Introduction

Default prediction has become a matter of escalating interest to banking systems particularly in the light of the global financial crisis. Default is universally defined unlike bankruptcy which as another form of corporate failure is specific to a country's legal and financial frameworks (Boritz et al., 2007). It thus justifies independent study with the benefit of enabling the generalization of insights from findings to wider institutional contexts.

The Revised International Capital Framework (Basel II) promotes the adoption by banks of the Internal Rating-Based Approach when calculating minimum capital requirements. The basic intent of the internal rating approach is to be more sensitive to the risk of the key elements that determine asset quality and therefore to the potential economic losses of a portfolio. In this regard, banks themselves must assess the probability of a borrower defaulting on future credit obligations. Whilst default models have general applicability, their risk assessment implication relate to the ultimate borrowers and consequently to the financial system under study. Central banks in many countries are making efforts to develop models adapted to their specific requirements and data collection and availability (Altman and Sabato, 2005 – Italy; Bardos, 1998 – France; Saurina and Trucharte, 2004 – Spain). Our study is consistent with these efforts.

Over the past several years, banks have developed sophisticated models to assess credit risk arising from business loans. Most banks adopt credit risk capital, risk adjusted return on capital and other complex models to evaluate the risks of borrowers entering into default. The commercial benchmark models (JP Morgan's Credit Metrics, McKinsey's Credit Portfolio View and Moody's KMV amongst others) have been introduced as alternatives to measure credit risk and act as industry standards (Westgaard and Wijst, 2001). However, commercially available models generally use data for listed firms, which impose serious constraints on the generalization of the results to the specific context of privately-held firms.

The risk of firms entering into default is described in terms of a measure of expected loss (anticipated annual credit loss) and unexpected loss (volatility of credit loss). Expected loss is a function of expected default probability (forward looking probability of default), loan equivalent exposure (amount outstanding) and severity (amount lost as a percentage of the loan equivalent exposure or one minus the recovery rate). Expected default frequency is the probability that the customer or counterparty will default (see for example Chacko et al., 2006). Banks generally classify customers into rating groups to guide credit decisions on limit facilities, pricing and provisioning. Large firms are often rated by specialist agencies whereas small firms and retail customers need to be rated internally by a grading system. Internal rating systems need benchmarks to improve their quality and ensure correct calibrations against the overall financial system (Engelmann et al., 2003).[1] The aforementioned commercial models can be used as benchmarks but mostly for listed firms. For privately-held firms, estimates provided by central banks may be more appropriate although specialist agencies are expending significant resources to provide similar benchmarks.

We assess the accounting and non-accounting determinations of default for private firms with a unique proprietary sample maintained by the Central Bank of Portugal that contains information on 31,025 accounts covering the period 1997–2003. Specifically we build on the established literature on corporate failure and examine the influence of 30 accounting ratios as well as other characteristics including age, size, industry and geographical location on default. We regard loan default as defined in Basel II making our results amenable to generalization to a wide range of institutional contexts. In Section 2 we discuss the prior literature and theoretical concepts and practices that are currently

[1] Credit scores and ratings can be derived from default probabilities quite easily but the reverse is more complex and much less accurate (Siddiqi, 2006; Glantz and Mun, 2008).

documented in the corporate failure literature. In Section 3 we describe the data used in the analysis. In Section 4 we present the model and the estimation procedure. We discuss the results in Section 5 and the conclusions and policy implications in Section 6.

2. Determinants of default

Concepts such as default and credit risk are closely associated with the Basel II framework. This framework consists of three pillars: minimum capital requirements, supervisory review of an institution's internal assessment process and capital adequacy and effective use of public disclosure to strengthen market discipline as a complement to supervisory efforts. The Accord in place utilizes the concept of capital ratio that is calculated by dividing an institution's capital by the measure of risk it faces (referred to risk-weighted assets). The risk faced by financial institutions is aggregated in three types: credit, market and operational risk. The Accord clearly recognizes that it is the credit risk that matters most for the majority of banks. Following Basel II guidelines, a number of attempts have been made in the last few years to develop internal assessment models to measure credit risk. These models and risk predictions have drawn on accounting and finance theory also used to explain bankruptcy or legal failure and corporate failure more generally. However, unlike these later concepts, default as defined in Basel II is a universal concept making findings amenable to generalization over wide institutional contexts.

Corporate failure plays an important role in accounting and finance theory (see for example Ward and Foster, 1997). The theory advocates that owners can abandon firms and transfer ownership to debt holders and ensure a lower limit (zero) in the payoff of equity. Limited liability conventions lower the downside risk whilst retaining the upside potential and creating an option-like payoff structure with the associated incentives for taking risk (Bhimani and Ncube, 2006; Hillegeist et al., 2004). In this context, default is endogenously related to capital structure. Firms default on their obligations to banks if the market value of their assets falls below a certain critical level determined by the respective credit risk model a framework that is the basis of JP Morgan's Credit Metrics and Moody's KMV models. The inputs required for these models, in particular the market data that is available for listed firms, limits its usefulness for the purpose of estimating default probabilities of privately-held firms which is the focus of the present study. The broader corporate failure literature developed for non-listed firms is more appropriate here.

Bankruptcy is a widely studied form of corporate failure. But bankruptcy definitions are specific to the country associated with the failure prediction model and the corresponding legislation on what constitutes bankruptcy. Thus, the determinants of bankruptcy cannot be generalized across all forms of failure and contexts, and studies in the area tend to be country-specific (e.g., Franks et al., 1996 – US, UK and Germany; Laitinen and Kankaanpää, 1999 – Finland; Westgaard and Wijst, 2001 – Norway).

The corporate failure literature has also been extended to encompass financial distress (Keasey and Watson, 1991; Hill et al., 1996). Firms experiencing financial distress may never face legal failure. These specific models are structurally embedded in the dated bankruptcy prediction models (Beaver, 1966; Karels and Prakash, 1987) and their contextual applications generate different implications depending on the question under study (Kolari et al., 2002; Rashad and El-Sheshai, 1980). But the general consensus is that scholars should develop models for different types of corporate failures that are specific to the country contexts wherever required and meet end user needs (Platt and Platt, 2002; Peat, 2007).

Firms face corporate failure (broadly encompassing bankruptcy and other forms of distress) when realized operational profits or realized plus expected operational profits are less than debt obligations (Wilcox, 1971). Scott (1981) concludes that if current operating profits accurately predict future financial status, then past and present operational profits should be good indicators of failure. Empirical studies that predict corporate failure generally include some theoretically determined cash flow variables in their models. Besides cash flow related variables, studies also use some measure of both short and long-term debt, earnings and liquidity (see for example Dambolena and Khoury, 1980). The extensive scholarly research on corporate failure posits and confirms relevant propositions about the influence of accounting ratios but an important problem is yet to be resolved: there is still no agreement on which accounting ratios are good predictors of default and why.

Models developed to predict corporate failure often use annual accounting information mainly because these are objective measures based on publicly available information. Models constructed on the basis of accounting ratios implicitly assume that financial statements are sufficient to predict default. A relatively less explored line of inquiry is the assessment of the influence of non-accounting information to capture influences that are not detectable in the accounting statements (Ohlson, 1980), which is particularly relevant in the context of predicting default in privately-held firms. Non-accounting information should unveil at least some of the opacity of financial statements. Examples of possible non-accounting variables are size and age of the firm. Both size and age are associated with safer cash flows. Compared to small and young firms, large and older firms have more bargaining power in debt restructuring. Large and older firms also have more managerial resources making them less susceptible to idiosyncratic shocks.

A related line of inquiry looks into whether the risk of corporate failure is non-diversifiable or diversifiable. It is argued that if this risk is not diversifiable, it should be priced accordingly in capital markets (see for example Denis and Denis, 1994); whereas if it is diversifiable, it can be reduced through portfolio management (see for example Asquith et al., 1994).

The study of corporate failure has also been spurred by the development of new techniques for estimating and reporting results. Early endeavours used multivariate discriminant analysis (MDA) to predict bankruptcy through the use of accounting ratios of matched samples of bankrupt and non-bankrupt firms (Beaver, 1966; Altman, 1968). Subsequently, logit and probit models also gained acceptance (Ohlson, 1980; Zmijewski, 1984). These models have been embraced by both academics and practitioners and are widely used by banks to predict corporate failure (Westgaard and Wijst, 2001). The empirical literature increasingly shows advanced logit structures like multinomial logit (Johnsen and Melicher, 1994) and particularly non-IID models, such as mixed logit (Jones and Hensher, 2004; Hensher and Jones, 2007). Other extensions that aim to determine the time to bankruptcy and the associated probabilities of firms going bankrupt include duration models. Lee and Urrutia (1996) and Shumway (2001) formulate duration models with time-dependent covariates and perceive them as equivalent to simple logistic models. Nevertheless, the complementary use of both models and advanced structures are promising areas for future research.

Other techniques such as recursive partitioning (Frydman et al., 1985), genetic algorithms (Varetto, 1998); multidimensional scaling (Mar Molinero and Ezzameli, 1991), catastrophe theory (Gregory et al., 1991), neural networks (Tam, 1991), multicriteria decision-making (Zopounidis and Doumpos, 1999) and rough sets (Dimitras et al., 1999) have also been applied to the study of bankruptcy and corporate failure. This extensive research on the application of new techniques is reviewed by Dimitras et al. (1996).

The corporate failure literature encompasses definitions that range from bankruptcy to financial distress. Most models are structurally embedded in the older bankruptcy literature. These studies are generally country-specific and focus on listed firms for which data is readily available. These studies have been successful in several respects, but important concerns remain particularly in terms of the lack of agreement over which accounting variables are good predictors of different types of failure, the sample size, the country coverage and the inter-industry and inter-regional validity of the results. In addition, the studies largely use accounting ratios to predict failure. There is also no consensus over which method to use to predict failure: MDA is more appropriate when the objective is to discriminate failed and non-failed firms. Logit and probit models are more appropriate when the objective is hypothesis testing.

We contribute to the literature in several ways. First, we use a large data set on defaults relating to privately-held firms enabling us to extend the findings for listed firms. This legal form is commonly observed in continental Europe and less so in countries following the Anglo-Saxon system. Unlike bankruptcy for example that is country-specific because of the legal definition that governs this situation, default is universally defined making findings amenable to generalization to both the European continent and the Anglo-Saxon world. We use actual loan data to predict default because default estimates from other forms of corporate failure can be misleading: firms entering into default may never reach bankruptcy. Second, we use both accounting and non-accounting variables and their interaction to predict default thus broadening the framework for assessing default in particular and corporate failure in general with its disproportionate focus on accounting ratios. Finally, we assess the marginal influence of variables on the probability of default, an approach not commonly taken in the literature but reflecting the correct method for assessing the influence of independent variables on the probability of failure in non-linear models of the type we use.

3. The data

3.1. Sources and selection

Data on defaults are difficult to access because they refer to odd events and the data is prepared by the entities that are the sources and users of information. The situation is challenging across many countries as there may be no legislation stipulating an official depository of such data. Central banks have only recently begun allocating significant resources for the compilation of usable loan default data, following the Basel supervisory committee's recommendations.

We use a comprehensive set of accounting and non-accounting data for privately-held firms compiled at the Central Bank in Portugal. By law, these companies are obliged to file their annual financial statements. Companies like Dun & Bradstreet and Mope provide information on these companies and their solvency status (i.e., whether they are bankrupt or non-bankrupt) but not on their credit status, thus making the central bank data the only credible source for estimating default probabilities.

The central bank data sample allows access to not only the credit status but also approximately 30 accounting ratios, size in millions of euros, date of set-up and the industry and geographic code on 31,025 observation points over the period 1997–2003. This enables us to use a large data set to assess the influence of both accounting ratios and non-accounting information on default. Since these firms are non-listed, we are unable to assess the influence of trailing (stock and index) returns and volatility on default (Duffie et al., 2007).

The data contains information on credit granted by Portuguese credit institutions and includes indicators on the credit status of each loan (used in this study to define each loan as defaulted or non-defaulted) and the aforementioned accounting ratios and non-accounting information. The central credit register defines a firm as defaulted at time "t" when any exposure in the Central Credit Register for that firm at time "t" is in default. We also consider alternative thresholds at 2% and 5% of the total exposure to test the definition of default, not taking residual events into account. As such, the unpaid amount is not considered unpaid if it is less than 2% or 5% of the total credit drawn down. The study relates accounting data for the year before "$t-1$" to the credit status of the firm in year "t". Default events in the central bank credit register are defined as credit losses associated with any delay in payments longer than 90 days or with a distressed restructuring involving the forgiveness or postponement of principal amounts or interest due by financial institutions as determined in Basel II (BIS, 2005, p. 96).

At this time we are unable to discriminate firms with 'doubtful' or 'reasonably doubtful' loans. Thus we cannot estimate default probabilities for firms that are perhaps moving toward default or that can be 'reasonably' expected to default. We also do not have information on the number of days in arrears, i.e. whether payments are less than 90 days in arrears but more than 30 or 60 days in arrears.

We removed the firms from our sample which have zero assets; negative sales and negative gross income and debt; and total exposure lower than €100,000. In alignment with previous studies, some observations were deleted (outlier and missing values). As the study uses the final accounts reported for each firm, all the accounts reported up to a default are defined as accounts for solvent firms. Only the last account of a defaulted firm is characterized as a default account using all available accounts from the firm under study to strengthen the estimation results.

3.2. Description

The contents of this data set are illustrated in Table 1. Of the 31,025 accounts 1700 relate to firms that entered into default, representing 5.48% of the total. Table 2 shows the distribution of defaults by industry breakdown (PRIMARY, MANUFACTURING, CONSTRUCTION, TRADE, HOSPITALITY, TRANSPORT AND COMMUNICATION, and OTHER). The highest average default frequency is in TRANSPORT

Table 1
Defaults and accounts 1997–2003.

	Number of defaults	Number of accounts	Default frequency
1997	–	5676	–
1998	308	6523	5.43%
1999	299	5612	4.58%
2000	262	4392	4.67%
2001	334	4440	7.60%
2002	253	4382	5.70%
2003	244	–	5.57%
Total	1700	31,025	5.48%

Table 2
Defaults by industry 1998–2003.

Industry	1998 (%)	1999 (%)	2000 (%)	2001 (%)	2002 (%)	2003 (%)	Total (%)
PRIMARY	3.50	5.41	4.83	7.73	7.69	6.56	5.70
MANUFACTURING	6.74	5.48	5.06	7.65	6.61	5.95	6.17
CONSTRUCTION	5.26	4.69	5.53	8.61	5.75	7.03	5.81
TRADE	3.44	2.49	3.33	6.04	3.67	4.14	3.77
HOSPITALITY	5.41	5.66	5.00	8.82	5.00	6.52	6.00
TRANSPORT	8.22	8.38	6.55	14.09	11.06	10.58	9.52
OTHER	11.36	6.52	2.94	9.20	5.42	3.92	5.95
Total	5.43	4.58	4.67	7.60	5.70	5.57	5.48

AND COMMUNICATIONS (9.52%) followed by HOSPITALITY (6.00%) while the lowest is in TRADE (3.77%) followed by the PRIMARY sector (5.70%). Table 3 shows the variation in default across different geographical areas (NORTH, LISBON, CENTER, ALENTEJO, ALGARVE, AZORES and MADEIRA). MADEIRA (6.98%) followed by AZORES (6.61%), the two autonomous regions, experienced the highest average default rates. ALGARVE (4.48%) and the CENTER (4.97%) experienced the lowest default rates. These variations in the industry and geography indicate the need to control default models with these variables.

The discussion of the theory in Section 2 does not produce explicit content for predicting default. The theoretical underpinnings suggest variables in such models should relate to the properties of cash flows in combination with debt obligations and liquidity. Without explicit agreement over which ratios should be used to predict default, we use a large number of ratios available in the central credit register in combination with a search technique described in the next section. The accounting ratios in our data set are listed in Table 4.

Table 3
Defaults by geographical region 1998–2003.

Geography	1998 (%)	1999 (%)	2000 (%)	2001 (%)	2002 (%)	2003 (%)	Total (%)
NORTH	4.81	4.34	4.78	7.54	6.11	5.79	5.40
LISBON	6.05	5.36	4.75	8.22	5.52	6.56	5.97
CENTER	5.09	4.06	4.41	6.64	5.78	4.27	4.97
ALENTEJO	5.70	4.93	4.55	10.10	3.54	7.84	5.95
ALGARVE	7.69	5.63	2.29	3.96	3.81	3.36	4.48
AZORES	10.67	6.41	9.59	4.08	4.08	1.85	6.61
MADEIRA	9.41	3.23	4.00	14.86	6.90	3.39	6.98
Total	5.43	4.58	4.67	7.60	5.70	5.57	5.48

The Nomenclature of Territorial Units for Statistics (NUTS) is a geo-code standard for referencing the administrative division of countries for statistical purposes. The standard was developed by the European Union.

Table 4
Accounting and non-accounting ratios in the data set.

Explanatory variables	Definition
Accounting variables	
AUTONOMY	Equity/total net assets
CASH TO DEBT	(Gross income plus depreciation)/total debt
DAYS IN PAYABLES	(Total trade credits and advances received/(purchases of goods for resale, raw materials, secondary and consumables + supplies and external services)) × number of days
DAYS IN RECEIVABLES	(Total trade credits and advances granted/turnover) × number of days
DEBT RATIO	Financial debt/(shares and other equity)
FINANCIAL COVERAGE	Net results before financial costs/financial costs
ASSET COVERAGE (FIXED)	Stable resources/fixed assets
ASSET COVERAGE (TOTAL)	Stable resources/total assets
INTEREST COSTS	Interest costs/gross income
INVESTMENT RATIO	Total investments/gross income
LIQUIDITY	Current assets/current liabilities
LIQUIDITY ACID-TEST	(Cash + marketable securities)/current liabilities
QUICK RATIO	(Current assets – stocks)/current liabilities
RETURN ON EQUITY INVESTED (GROSS)	(Gross income + interest costs)/(fixed assets + stocks + total trade credits – total supplies and external services)
RETURN ON EQUITY INVESTED (NET)	Gross income/(fixed assets + stocks + total trade credits – total supplies and external services)
RETURN ON EQUITY	(Gross income + interest costs + tax)/shares and other equity
RETURN ON INVESTMENT	(Gross income + interest costs + tax)/total assets
RETURN ON SALES	(Gross income + interest costs + tax)/sales
SELF-FINANCING COVERAGE	Self-financing/gross income
SELF-FINANCING RATIO	Self-financing/total investments
SOLIDITY	Shares and other equity/total assets
SOLVABILITY	Ordinary shareholders' fund/capital used
STOCKS/WORKING CAPITAL	Stocks/(stocks + total trade credits – total supplies and external services)
STOCK TURNOVER	Stocks/total assets
ASSET TURNOVER	Sales/total assets
VAR. GROSS INCOME	Change in gross income (t; $t-1$)/gross income (t)
VAR. OUTPUT	Change in output (t; $t-1$)/output (t)
VAR. TURNOVER	Change in turnover (t; $t-1$)/turnover (t)
WORKING CAPITAL/TOTAL ASSETS	(Stocks + total trade credits – total supplies and external services)/total assets
WORKING CAPITAL/SALES	(Stocks + total trade credits – total supplies and external services)/sales
Non-accounting variables	
SIZE	Total assets (in the base 10 logarithms)
AGE	Firm age (in years)

To give an indication of the differences between defaulting firms and non-defaulting firms with respect to these variables, the average ratios for the 1997–2002 data are presented in Table 5, broken down by default in 1998–2003. Additionally, we include two non-accounting variables AGE (in years) and SIZE (in million euros). These two variables are generally considered to be associated with safer cash flows. Finally, we include dummy variables to capture specific industry and region effects. The distribution of these variables, broken down by default in 1998–2003 over default and non-default firms, is presented in Table 6.

4. Empirical method

4.1. Model specification

The corporate failure literature is largely inconclusive as to which ratios should be used in models to predict default. It is therefore difficult to reformulate the theoretical insights in the form of hypotheses, specify an empirical model, estimate the model's coefficients, and test whether the sign and

Table 5
Properties of default – non-default sample financial ratios.

Ratio	Non-default sample 1998–2003	Default sample 1998–2003
AUTONOMY	26.64%	10.18%
CASH TO DEBT	81.50%	8.20%
DAYS IN PAYABLES	97.02	170.36
DAYS IN RECEIVABLES	103.02	151.53
DEBT RATIO	89.35%	86.73%
FINANCIAL COVERAGE	1.48	1.15
ASSET COVERAGE (FIXED)	2.09	1.43
ASSET COVERAGE (TOTAL)	74.54%	66.57%
INTEREST COSTS	11.05%	15.36%
INVESTMENT RATIO	58.69%	31.94%
LIQUIDITY	55.01%	17.03%
LIQUIDITY ACID-TEST	14.04%	3.12%
QUICK RATIO	26.35%	22.54%
RETURN ON EQUITY INVESTED (GROSS)	12.03%	5.53%
RETURN ON EQUITY INVESTED (NET)	5.29%	−3.36%
RETURN ON EQUITY	18.10%	16.66%
RETURN ON INVESTMENT	7.44%	4.85%
RETURN ON SALES	10.04%	6.64%
SELF-FINANCING COVERAGE	15.94%	−8.21%
SELF-FINANCING RATIO	39.08%	7.34%
SOLIDITY	24.48%	10.49%
SOLVABILITY	2.32	2.58
STOCKS/WORKING CAPITAL	51.77%	55.39%
STOCK TURNOVER	23.93%	19.96%
ASSET TURNOVER	0.93%	0.64%
VAR. GROSS INCOME	29.47%	25.01%
VAR. OUTPUT	16.06%	12.05%
VAR. TURNOVER	22.98%	15.93%
WORKING CAPITAL/TOTAL ASSETS	17.02%	9.95%
WORKING CAPITAL/SALES	4.12%	3.25%

Table 6
Default and non-default sample non-accounting ratios.

Average figures 1997–2002	Non-default 1998–2003	Default 1998–2003
SIZE	6.13	6.15
AGE	17.55	15.97
PRIMARY	4.46%	4.65%
MANUFACTURING	38.40%	43.53%
CONSTRUCTION	16.10%	17.12%
TRADE	32.79%	22.18%
HOSPITALITY	0.80%	0.88%
TRANSPORT	4.86%	8.82%
OTHER	2.59%	2.82%
NORTH	41.58%	40.94%
LISBON	24.54%	26.88%
CENTER	24.25%	21.88%
ALENTEJO	4.69%	5.12%
ALGARVE	2.33%	1.88%
AZORES	1.20%	1.47%
MADEIRA	1.41%	1.82%

significance of the coefficients lead to rejecting or not rejecting the propositions. We thus use the accounting ratios listed in Table 4 in combination with the stepwise search technique that selects the ratios that predict default for our data (see for example Greene, 2000).

4.2. Estimation procedure

The purpose of the investigation is to determine the accounting ratios and non-accounting information that influence default in privately-held firms and estimate the default probabilities. The analytical technique needs to allow for a binary dependent variable, the selection of the accounting ratios and non-accounting information and generate these probabilities. The requirement of an outcome in terms of probabilities inhibits the use of classification techniques (such as MDA and neural networks) as they do not produce probabilities. The binary dependent variable precludes usual regression analysis and the linear probability model as an important problem with these techniques is that linear functions are unbounded, whilst probabilities are bounded (0–1). Logit and probit models become the obvious candidates for the multivariate regression analysis of our binary dependent variable (both models return values between 0 and 1 also allowing the use of a search technique and generation of probabilities of default). It is difficult to distinguish between logit and probit statistically as both models are very similar and rarely lead to different qualitative conclusions. Econometric theory does not resolve the question of which of the two to choose (Greene, 2000). Without decisive arguments in favor or against, we use logit (see also Westgaard and Wijst, 2001).

In the logit model the probabilities are transformed in such a way that they cease to be bounded: the upper bound is eliminated by changing the probability p to the odds ratio $p/(1-p)$ and the lower bound is eliminated by the logarithm of the odds ratio: $\ln(p/(1-p))$. These are easier to interpret than the coefficients in classical regression analysis. The logit also enables the estimation of how much the event probability changes when a given predictor is changed by one unit, i.e. the marginal effect. The marginal effect is defined as the partial derivative of the event probability with respect to a predictor. It equals $p_{\mathrm{i}}\,(1-p_{\mathrm{i}})b$, where p_{i} is the event probability at the i^{th} setting of the predictors, and b is the coefficient. The marginal effect measures the expected instantaneous change in the dependent variable as a function of a change in the independent variable when all the other coefficients are kept constant. We compute the marginal effect at each observation and then calculate the sample average of individual marginal effects to obtain the overall marginal effect for each predictor.

We use the data described above to estimate a logit model for the probability of a firm entering into default based on accounting ratios and non-accounting information from the previous year. The logit model formulated here contains a two-state dependent variable (state 1 = default, state 0 = non-default). The independent variables (Tables 4–6) are selected through the stepwise procedure. The model is estimated using maximum likelihood procedure. We use stratified random sampling to create partitioned data sets. We estimated the model from the training set with 80% partition in terms of default events and test this model on a validation out-of-sample set with the remaining 20% of default events. The training set was used for preliminary model fitting. The validation data set was used to monitor and tune the model weights during estimation and also for model assessment.

5. Empirical findings

5.1. Parameter estimates

The results of the logit analysis outlined in the previous section are summarized in Table 7. We report the coefficient estimates, their estimated standard errors and test statistics[2] for the null that each coefficient is equal to 0, and the odds ratio and marginal effect.

The table shows that the stepwise procedure selects 11 accounting ratios and the 2 non-accounting variables at the 1% level of significance and some industry and geographic dummies. We can observe from the estimation that FINANCIAL COVERAGE, ASSET COVERAGE (FIXED), INVESTMENT RATIO, RETURN ON EQUITY, RETURN ON INVESTMENT, SOLIDITY, VAR. GROSS INCOME and WORKING CAPITAL/TOTAL ASSETS are negatively related to default, i.e. an increase in these ratios reduces the probability of default. On the other hand, DAYS IN RECEIVABLES, DAYS IN PAYABLES, and INTEREST COSTS/GROSS INCOME are positively related to default. In terms of non-accounting variables, SIZE is positively re-

[2] Wald Chi-squares calculated by dividing each coefficient by its standard error and squaring the result.

Table 7
Estimation results logit model.

Parameters	Estimates	SE	Wald Chi-squares	*p*-Value	Exp (B)	Marginal effect
Accounting variables						
DAYS IN PAYABLES	0.527	0.046	128.68	0.000	1.694	0.022
DAYS IN RECEIVABLES	0.444	0.046	92.83	0.000	1.559	0.021
FINANCIAL COVERAGE	−0.664	0.072	84.08	0.000	0.515	−0.028
ASSET COVERAGE (FIXED)	−0.156	0.029	29.26	0.000	0.855	−0.007
INTEREST COSTS/GROSS INCOME	2.530	0.261	94.07	0.000	12.547	0.121
INVESTMENT RATIO	−0.132	0.030	18.98	0.000	0.877	−0.006
RETURN ON EQUITY	−0.311	0.122	6.44	0.011	0.733	−0.012
RETURN ON INVESTMENT	−0.699	0.254	7.61	0.009	0.497	−0.029
SOLIDITY	−1.229	0.133	85.19	0.000	0.293	−0.058
VAR. GROSS INCOME	−0.201	0.083	5.86	0.016	0.818	−0.008
WORKING CAPITAL/TOTAL ASSETS	−0.789	0.231	11.68	0.001	0.454	−0.041
Non-accounting variables						
SIZE	0.308	0.066	21.83	0.000	1.360	0.013
AGE	−0.014	0.003	27.16	0.000	0.986	−0.001
Industry dummies						
PRIMARY	−0.418	0.135	9.53	0.002	0.658	−0.010
TRADE	−0.301	0.089	11.46	0.001	0.740	−0.004
TRANSPORT	0.804	0.108	55.46	0.000	2.235	0.043
Geographic dummies						
CENTER	−0.268	0.083	10.50	0.001	0.765	−0.008
AZORES	0.551	0.200	7.62	0.006	1.735	0.020
	−4.213	0.412	104.60	0.000	0.015	
Intercept						
−2 Log likelihood	8811					
Likelihood ratio Chi square	1727		Pr > Chi Sq	0.000		
	Training	Validation				
N	24,818	6207				
Root mean squared error	0.2116	0.2154				
Misclassification rate	0.0514	0.0525				

lated to default and AGE is negatively related to default. In terms of industry dummies, PRIMARY and TRADE are negatively related to default and TRANSPORT is positively related to default. In geographic dummies, CENTER is negatively related to default and AZORES is positively related to default.

As there is no easy way to interpret the coefficients in the logit model, we use the odds ratio and the marginal effects in conjunction with the coefficient estimates.[3] For continuous variables (for example FINANCIAL COVERAGE), we subtract 1 from the odds ratio and multiply by 100. This gives the percentage change in the odds for each 1-unit increase in the independent variable. For example, an increase in the ratio of net results before financial costs over financial costs (FINANCIAL COVERAGE) of 1-unit decreases the odds of default by $(0.515 - 1) \times 100 = 48.50\%$. For binary variables, for example TRADE that takes 1 if the firm is in this sector and 0 if it is not, the odds ratio of 0.740 tells us that the predicted odds for default of clients in this sector are 0.740 times the predicted default for clients in the remaining sectors.

We also use the marginal effect to estimate how much the event probability changes when a given predictor is changed by one unit. For continuous variables, for example FINANCIAL COVERAGE, the marginal effect of −0.028 indicates that an increase of 1-unit in the ratio of net results before financial costs over financial costs decreases the probability of default by 0.028, holding all else constant. For

[3] In a linear probability model, a coefficient of 0.5 expresses that the predicted probability of the event increases by 0.5 for every 1-unit increase in the explanatory variable. The logit model assumes a non-linear relation between the probability and the explanatory variables. The change in the probability for a 1-unit increase in an independent variable varies according to the starting point. Therefore, the odds ratio and marginal effects can prove useful in conjunction with the sign of the coefficient estimates.

binary variables, for example TRADE that takes 1 if the firm is in this sector and 0 if it is not, the marginal effect of −0.004 indicates that the probability of default for clients in this sector is 0.004 less than other sectors. We focus our analysis on the marginal effects.

The principal findings of this study relate to the accounting ratios that explain default. INTEREST COSTS/GROSS INCOME, SOLIDITY and WORKING CAPITAL/TOTAL ASSETS have the largest marginal effects, 0.121, −0.058 and −0.041, respectively. Large interest costs mean that a significant amount of the earnings before interest and tax is absorbed in payments associated with debt servicing, leaving less room to retain and distribute dividends and increasing the probability of default. For the firms under study, a 1-unit change in the interest costs to gross income increases the probability of default by 0.121. The level of capital is also relevant since it is related not only to the level of debt, but also to the capacity of the firm to absorb losses. A high solvency ratio, measured through equity as a ratio of total assets, indicates the firm's ability to finance assets with own equity reducing the dependence on external finance. Thus, a 1-unit change in the solvency ratio reduces the probability of a privately-held firm entering into default by 0.058. A larger proportion of working capital in relation to the total asset base signifies the availability of funds to meet short-term commitments: a change in 1-unit in this ratio reduces the probability of default of these firms by 0.041.

The accounting ratios that show relatively low marginal influence on the probability of default are RETURN ON INVESTMENT (−0.029), FINANCIAL COVERAGE (−0.028), DAYS IN PAYABLES (0.022), DAYS IN RECEIVABLES (0.021), and RETURN ON EQUITY (−0.012). The ratios that show very low marginal influence on the probability of default include VARIATION IN GROSS INCOME (−0.008), FIXED ASSET COVERAGE (−0.007) and the INVESTMENT RATIO (−0.006).

In terms of non-accounting variables, SIZE is positively related to default: a change in 1-unit of the asset base increases the probability of default by 0.013. That is, privately-held firms with assets to guarantee repayments are more willing to enter into default. AGE is negatively related to default as would be expected but its marginal effect on the probability of default is −0.001: a 1-unit change in the age decreases the probability of default by 0.001. These two findings suggest non-accounting information may provide useful content for default prediction models.

In order to further assess the influence of accounting and non-accounting variables we estimated 22 models in which we interacted each of the non-accounting variables, SIZE and AGE, with the accounting variables. The interaction of AGE with the accounting variables is not reported here as it did not change the results. Table 8 reports the 11 models involving the interaction of SIZE with the accounting variables. We find that DAYS IN PAYABLES (−0.104), DAYS IN RECEIVABLES (−0.035), and INTEREST COSTS/GROSS INCOME (−0.578), are significantly related to default. The interaction variables (with SIZE) DAYS IN PAYABLES (0.020), DAYS IN RECEIVABLES (0.009), FINANCIAL COVERAGE (–0.028), INTEREST COSTS/GROSS INCOME (0.114), SOLIDITY (–0.051), and WORKING CAPITAL/TOTAL ASSETS (−0.037) are significantly related to default.

In the interactive estimations, the individual influence of DAYS IN PAYABLES (−0.104) and DAYS IN RECEIVABLES (−0.035) on default indicate that the larger the number of days in payables and days in receivables, the lower the probability of default. However, the joint influence of SIZE × DAYS IN PAYABLES (0.020) and SIZE × DAYS IN RECEIVABLES (0.009) suggests that the larger the size of the firm and the number of days in payables and days in receivables, the greater the probability of default. Surprisingly, INTEREST COSTS/GROSS INCOME (−0.578) appears negatively related to default, i.e. an increase in interest costs to gross income reduces the probability of default. This relation is again different from the one observed in the estimations without the interaction variables. The joint influence of SIZE × INTEREST COSTS/GROSS INCOME (0.114) is positive implying that an increase in interest costs to income increases the probability of default. Large firms with assets to guarantee loan repayment can opt to default unlike firms without assets and loans guaranteed with personal liability. The interactive variables SIZE × FINANCIAL COVERAGE (–0.028), SIZE × SOLIDITY (−0.051) and SIZE × WORKING CAPITAL/TOTAL ASSETS (−0.037) are also significantly related to default indicating considerable influence of these specific accounting variables in large firms. The broader conclusion of these findings is that accounting and non-accounting variables jointly can offer more insights into the explanation of default and corporate failure in general but surprisingly this approach has been precluded in previous studies.

Table 8
Interacting accounting and non-accounting variables.

Parameters	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11
Accounting variables											
DAYS IN PAYABLES	−0.104**	0.021**	0.021**	0.021**	0.021**	0.022**	0.022**	0.021**	0.020**	0.021**	0.021**
DAYS IN RECEIVABLES	0.022**	−0.03*5	0.022**	0.022**	0.023**	0.021**	0.021**	0.022**	0.022**	0.022**	0.022**
FINANCIAL COVERAGE	−0.027**	−0.027**	0.145	−0.027**	−0.026**	−0.028**	−0.028**	−0.027**	−0.027**	−0.027**	−0.027**
ASSET COVERAGE (FIXED)	−0.007**	−0.007**	−0.007**	0.022	−0.007**	−0.007**	−0.007**	−0.007**	−0.007**	−0.007**	−0.007**
INTEREST COSTS	0.120**	0.120**	0.117**	0.120**	−0.578**	0.120**	0.121**	0.119**	0.116**	0.118**	0.119**
INVESTMENT RATIO	−0.006**	−0.006**	−0.006**	−0.006**	−0.006**	0.013	−0.006**	−0.006**	−0.006**	−0.006**	−0.006**
RETURN ON EQUITY	−0.011	−0.011	−0.013	−0.011	−0.013	−0.012	0.017	−0.011	−0.012	−0.011	−0.011
RETURN ON INVESTMENT	−0.027	−0.028	−0.025	−0.028*	−0.025	−0.029	−0.029	0.157	−0.026	−0.028	−0.028
SOLIDITY	−0.058**	−0.058**	−0.060**	−0.059**	−0.058**	−0.058**	−0.058**	−0.059**	0.245	−0.058**	−0.059**
VAR. GROSS INCOME	−0.008	−0.008	−0.008	−0.008	−0.007	−0.008	−0.008	−0.008	−0.008	0.102	−0.008
WC/TOTAL ASSETS	−0.050*	−0.048*	−0.047*	−0.050*	−0.050*	−0.041**	−0.041**	−0.049*	−0.049*	−0.049*	0.176
Non-accounting variables											
SIZE	−0.014	0.001	0.044**	0.018**	−0.005	0.014**	0.013**	0.013**	0.019**	0.013**	0.016**
AGE	−0.001**	−0.001**	−0.001**	−0.001**	−0.001**	0.001**	0.001**	−0.001**	−0.001**	−0.001**	−0.001**
Interaction											
SIZE × DAYS IN PAYABLES	0.020**										
SIZE × DAYS IN RECEIVABLES		0.009**									
SIZE × FINANCIAL COVERAGE			−0.028**								
SIZE × ASSET COVERAGE (FIXED)				−0.005							
SIZE × INTEREST COSTS					0.114**						
SIZE × INVESTMENT RATIO						−0.003					
SIZE × RETURN ON EQUITY							−0.005				
SIZE × RETURN ON INVESTMENT								−0.030			
SIZE × SOLIDITY									−0.051**		
SIZE × VAR. GROSS INCOME										−0.018	
SIZE × WC/TOTAL ASSETS											−0.037*

* Significant at the 1% level.
** Significant at the 0.1% level.

5.2. Prediction, classification and validation

The analysis of the goodness of fit in logit estimation is quite problematic because the observations of the dependent variable are restricted to 0 and 1 while the estimates are the probabilities or odds. Further, although R^2 measures are available, they are difficult to interpret. We obtain a dimension of the predictive power of the model by applying the model to the validation hold-out sample. The hold-out sample consists of 5866 non-defaulting firms and 341 defaulting firms. The results are displayed separately in Table 9 for the groups of defaulting and non-defaulting firms. The estimated average default probability for the default sample is almost twice that of the non-default sample. The variations in the estimated default probabilities of the non-defaulting firms are also lower than those in the default probabilities of the defaulting sample. It can be observed that some non-defaulting firms have a very high default probability (maximum of 85.43%) and some defaulting firms have very low default probabilities (minimum of 0.01%). These results indicate a strong relationship between default and the variables used in the model.

Table 10 summarizes the overall classification and the two types of error for different cut-off points to analyze the degree to which firms are correctly classified into one of two categories: defaulting or non-defaulting, an essential phase in estimating the prediction efficiency of the model. It can be observed that using a cut-off level of 0.03, the model correctly classifies 70.5% (i.e. 1 − 29.5%) of the defaulting-firms as defaulting. That is, type I error is 29.5%. The model also correctly classifies 75% (i.e. 1 − 25.0%) of the non-defaulting-firms as non-defaulting. That is, type II error is 25%. The proportion of overall correct classification is 74.8%. The low cut-off level of 0.03 reflects the fact that we are not using a matched sample of defaulting and non-defaulting firms (and a cut-off level of 0.5) as is usual in the bankruptcy literature. The overall correct classification is similar to other studies and remains stable for different and higher cut-off points around the average default rate (5.48%, in Table 1).

We use the characteristic receiver operating curve to assess the model's predictive ability which helps complement the classification table in more general terms: a number of score thresholds are considered which equal the estimated scores of the population studied; for each estimated score, the curve links the percentage of correctly classified defaulting firms to the percentage of incorrectly classified non-defaulting firms. The area below the curve provides a good measure of the model's discriminating capability. The better the model is at discriminating, the closer the curve will be 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 larger the area under the curve or the closer the trade-off function to both axes, the better the model's performance. The area below indicates the probability that any defaulting firm

Table 9
Descriptive statistics for non-default and default validation hold-out-sample.

Predicted EDF	Non-default	Default
N	5866	341
Mean default rate	5.33%	11.63%
SD	5.42%	12.20%
Minimum default rate	0.00%	0.01%
Maximum default rate	84.19%	83.48%
99% percentile	27.41%	68.89%
95% percentile	13.38%	38.48%
50% percentile	4.05%	7.99%
5% percentile	0.81%	2.08%

Table 10
Error classification for validation hold-out-sample.

Cut-off	Type I	Type II	Correct
0.06	36.1	31.0	68.7
0.04	29.7	29.1	70.9
0.03	29.5	25.0	74.8

Table 11
Area under the ROC-curve.

	N	Area	Std. error	95% Confidence interval	
				Lower	Upper
Total sample	31,025	0.764	0.007	0.751	0.777
Partial sample period (1998–2000)	17,811	0.779	0.009	0.761	0.796
Partial sample period (2001–2003)	13,214	0.761	0.009	0.743	0.778
Training data set	24,818	0.782			
Validation data set	6207	0.753			

picked at random from the population will have an estimated score which is greater than that of any other non-defaulting firm selected at random. This is 76.4% for the basic model under study and 75.3% for the validation dataset as can be observed from Table 11.

6. Conclusions

Default prediction is receiving significant attention from policy-makers as the global financial crisis unfolds. Unlike the widely studied topic of bankruptcy, another form of corporate distress that depends on the country in which it occurs and the corresponding legislation concerning company failure, default is universally defined but surprisingly less studied in the literature, especially in the case of privately-held firms.

We model default with novel loan data maintained by the Portuguese Central Bank for 31,025 accounts of privately-held firms that include 30 accounting ratios and non-accounting information on size, age, industry and geographic regions. Our theoretical framework is structurally embedded in the classical corporate prediction literature but our findings can be generalized because, unlike bankruptcy, default is universally defined. Due to the lack of theoretical consensus on which variables best predict default, we use a search technique that selected eleven accounting ratios and two non-accounting variables that best predicts default for our data. The less evident results relate to the non-accounting variables. The relation between the size of the firm and default is extensively positive, and although the relation between age and default is negative as expected, it shows a very small marginal influence on default. Further analysis shows that the interaction of accounting ratios with the non-accounting information alters the relation between the accounting ratios and default. These findings suggest that applying results obtained for listed firms with market data and using only accounting ratios to predict default for privately-held firms can mislead investors and external stakeholders, which consequently affects policy and regulatory options. Our study highlights the need to extend the foundations laid in this paper in one clear direction that is missing in the literature – to the methodical study of the influence of other non-accounting information such as the auditors' going concern valuation, the liability status of firms and corporate diversification amongst others on default jointly with accounting data. This approach is likely to provide useful substance for predicting default (and also other forms of corporate failure) and guiding credit decisions on limit facilities, pricing and provisioning.

The Basel Committee on Banking Supervision is recommending central and commercial banks to model and estimate default probabilities with specific country or bank portfolios. Monetary authorities in many countries are now developing prediction models for corporate failure. In general, models are not standard as they are adapted to fit the specific requirements of the central bank and the stage of the data assembling process. Whilst our effort is theoretically driven towards the assessment of default in privately-held firms that have not received attention despite their growing importance in many economies, our study can also be viewed as a contribution to the development of country specific models in light of Basel II. Consequently, commercial banks can use the findings as a benchmark to improve the quality of their internal risk-assessment models and to ensure correct calibrations against the overall financial system. Our findings can also be used as early warning signals by banking supervisors across institutional contexts populated predominantly by privately-held firms. The default probabilities can be used as synthetic indicators of the overall pressure in the corporate sector.

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