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Using Prior Payment Behavior Variables for Small Enterprise Default Prediction Modelling

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Abstract

This study aims to verify the potential of combining prior payment behavior variables and financial ratios for SE default prediction modelling. Logistic regression was applied to a sample of 980 Italian SEs in order to calculate and compare two categories of default prediction models, one exclusively based on financial ratios and the other based also on company payment behavior related variables. The main findings are: 1) using prior payment behavior variables significantly improves the effectiveness of SE default prediction modelling; ii) the longer the forecast horizon and/or the smaller the size of the firms which are the object of analysis, the higher the improvements in prediction accuracy that can be obtained by using also prior payment behavior variables as default predictors; iii) SE default prediction modelling should be separately implemented for different size groups of firms.

Keywords: bankruptcy, company payment behaviour, default prediction models, financial ratios, small enterprises

1. Introduction

Company default prediction models and processes have been largely analysed in the literature (e.g., Aaron, Nainggolan, & Trinugroho, 2017; Altman, 1968, 1993, 2004; Altman, Brady, Resti, & Sironi, 2005; Altman & Sabato, 2005; Beaver, 1966; Blum, 1974; Figini, Savona, & Vezzoli, 2016; Grice & Ingram, 2001; Gupta, 2014; Huijuan, 2015; Ohlson, 1980; Pindado, Rodrigues, & De la Torre, 2008; Traczynski, 2017). Nevertheless, some relevant limitations characterize the large majority of studies.

First of all, most authors use only financial ratios calculated on the last published financial statements as default predictors. This approach limits the predictive capacities of the developed models because a company's last published financial statements regard its past results while bankruptcy prediction should look at its future. Furthermore, firms not rarely tend to postpone the accounting emergence of their financial and/or economic unbalances, thereby postponing also the translation of a firm's crisis into weak financial ratios. As a consequence, official financial statements and financial ratios (which are based on these statements) tend to give a representation of a firm's financial health that is out-of-date and therefore of little use for effective default prediction processes.

Second, most of the studies analyse large firms and very rarely focus on small and medium sized enterprises (SMEs) as their specific object of prediction. However, SEs have their own specific characteristics (e.g. they are generally riskier and show a lower asset correlation with each other than larger firms; Dietsch & Petey, 2004) and their default prediction models should therefore be designed separately from that of larger firms (Altman & Sabato, 2007). Edmister (1972) analysed a sample of 562 SMEs, and by applying a multivariate discriminant analysis, developed a SME default prediction model based on 18 financial ratios. More recently, other authors developed default prediction models based on financial ratios and specifically designed for SMEs (e.g. Altman & Sabato, 2007; Ciampi, 2017b; Ciampi & Gordini, 2013; Pompe & Bilderbeek, 2005). For example, Altman and Sabato (2007) analysed a sample made up of 2,010 US SMEs in the period 1994-2002, and, by applying logit regression, found that designing default prediction models separately for differently sized firms reduces the capital requirements of banking institutions as established by Basel Capital Accord. Nevertheless, default prediction modelling based only on financial ratios tends to be ineffective, particularly in the case of SMEs, whose accounting data and financial statements are normally less transparent and articulated compared to those produced by larger firms (Berger & Frame, 2007). From this it follows that SME bankruptcy prediction models should not only be specifically designed for this category of firms, but they should also be based on further default predictors, other than financial ratios.

Third, the prediction models which have been proposed in the literature show a significant reduction of accuracy rates when moving from a one-year forecast period to longer (two or more years) horizons (Du Jardin & Severin, 2011).

Aiming to face these shortcomings, this study hypotheses that, as shown by the empirical evidence, the payment history of a firm may be used to predict its future payment behaviours (e.g. Back, 2005), and that consequently default prediction modelling can increase its effectiveness if it is based also on a company's previous payment behavior related variables, which are expected to compensate for the low predictive capacity of financial ratios.

This study analyses a sample of 980 Italian small enterprises (SEs), defined, following Basel Capital Accord, as firms with a turnover below 5 million Euro. Applying logistic regression, a first model at one, two and three-year forecasting horizons was designed using two categories of default predictors: previous payment behavior variables and financial ratios. The effectiveness of this model was then compared to that of a second model, which was designed using only financial ratios as predictive variables.

In the next two sections a literature review is presented and the research hypotheses are proposed. In the fourth section, the sample object of analysis, the proposed predictive variables, and the research method are described. Finally, the research results are presented and discussed, and the conclusions proposed.

2. Review of the Literature

Many authors have proposed a large number of different default prediction models, using different statistical methods (Gepp & Kumar, 2012), different forecasting horizons, and different samples (Balcaen & Ooghe, 2006); and obtaining very different results in terms of prediction effectiveness (Du Jardin & Severin, 2011).

Altman (1968) analysed a sample of 66 firms (33 defaulting and 33 non-defaulting) and, by applying a multivariate linear discriminant analysis, selected the following financial ratios as best default predictors: Working Capital/Total Assets, Retained Earnings/Total Assets, Earnings Before Interest and Taxes/Total Assets, Market Capitalization /Total Debt and Sales/Total Assets. Ohlson (1980) applied logistic regression to a sample of 2,163 firms (2,058 non-defaulting and 105 defaulting) and nine financial ratios calculated on accounting data between 1970 and 1976.

More recently different methodologies and techniques for default prediction have been applied, such as support vector machines (e.g., Shin, Lee, & Kim, 2005), genetic algorithms (Back, Laitinen, & Sere, 1996; Etemadi, Rostamy, & Dehkordi, 2009), artificial neural networks (Ciampi & Gordini, 2013; Fletcher & Gross, 1993; Lacher, Coats, Sharma, & Fant, 1995; Tam & Kiang, 1992; Wilson & Sharda, 1994; Zhang, Hu, Patuwo, & Indro, 1999), hazard models (Shumway, 2001), case based forecasting, and dynamic event-history analysis (Dowell, Shackell, & Stuart, 2011).

A review of the existing bankruptcy prediction methodologies was recently proposed by Sun, Li, Huang and He (2014), who outlined the need for new and more anticipatory modelling methods, better able to cope with real-world applicability.

Indeed, some significant weaknesses can be identified in the large majority of the studies which are present in the literature (e.g., Aaron et al., 2017; Altman, 1968, 1993, 2004; Altman et al., 2005; Altman & Sabato, 2005; Beaver, 1966; Blum, 1974; Figini et al., 2016; Grice & Ingram, 2001; Gupta, 2014; Huijuan, 2015; Ohlson, 1980; Pindado et al., 2008; Traczynski, 2017).

A first weakness is connected to the fact that these studies use only financial ratios calculated on the last published financial statements as predictive variables and are consequently based on the past results of a firm while default prediction regards its future. Berger and Udell (1995) found that SEs with longer and closer banking relationships benefit from lower interest rates and are required to produce fewer guarantees, thanks to the qualitative information which banking institutions can obtain through these relationships. Nevertheless, only a few contributions have used non-accounting based variables for company default prediction modelling, such as data regarding the timeliness of financial reporting (Peel & Peel, 1988), subjective evaluations of shareholders and directors (Sarac, 2010), firm age and industry (Grunert, Norden, & Weber, 2005), macroeconomic data (Hol, 2007), and geographical location (Buehler, Kaiser, & Jaeger, 2012). An even lower number of studies has used non-accounting information to develop bankruptcy prediction models specifically designed for SMEs. Keasey and Watson (1987) found that using non-financial variables, such as the number of and change in directors, the existence of loans secured on the firm's assets and reporting lags improves the SE failure prediction accuracy compared to using only financial ratios. Dowell et al. (2011) analysed a sample of 227 young Internet small and medium sized firms and, by applying an event-history analysis, found that for highly financially distressed SMEs, CEO power, small sized boards and board independence reduce a firm's default probability. Altman, Sabato and Wilson (2010) found that regulatory compliance and "event" data (such as those referred to legal actions by creditors, company filing histories, comprehensive audit report/opinion data) compensate for the limited accounting data produced by non-listed SMEs. Ciampi (2015) analysed a sample of 934 Italian SEs and, by applying logistic regression, found that some corporate governance variables (owner concentration, CEO duality and the number of outside directors) significantly improve SE default prediction accuracy rates. Ogane (2016) analysed a sample of 2,667 unlisted SMEs incorporated in Japan between April 2003 and December 2009. He applied survival models and found a positive correlation between the number of correspondent financial institutions for SMEs at the first settlement of accounts and subsequent SME bankruptcy. Ciampi (2017a, 2018) analysed two samples of Italian SEs (with a turnover below 5 million Euro), and, by applying logistic regression, found that both corporate social responsibility orientation characteristics (2018) and management characteristics (2017a) significantly improve SE default prediction accuracy rates. Apart from these few contributions, the subject of using non-accounting variables for SME default prediction modelling still remains a largely unexplored field of research. Duarte, Gama and Gulamhussen (2017) analysed confidential financial data referred to more than five thousand loans granted to SMEs by a major commercial bank operating in Portugal and found that the joint effect of collateral and low credit score was positively associated with SME bankruptcy, while the joint effect of collateral and high credit score was negatively associated with SME default.

A further limitation that characterises the existing literature is the significant decline in prediction accuracy rates when moving from a one-year forecast horizon to a longer horizon: from a one-year horizon to a three-year horizon the decline is on average 15% (Du Jardin & Severin, 2011).

Based on the empirical evidence that shows that previous payment patterns of a firm may give useful information about its future payment behavior (e.g., Back, 2005) and aiming to fill the above-mentioned gaps, this study hypothesizes that accuracy rates increases if default prediction models are designed by using not only financial ratios but also prior payment behavior related variables, which are expected to compensate for the low predictive power of accounting data.

3. Research Hypotheses

The reliability of financial statements on which financial ratios are based has been recently called into question, especially after the 2008 global financial crisis that brought unorthodox accounting practices back to the centre of the scientific debate (Sarac, 2010). Furthermore, in addition to being usually available several months after the end of the financial year (in Italy normally 6 months), the last approved financial statements do not give any information about the strategic plans of the firms.

Laitinen (1999), by applying both a logistic regression analysis and a linear regression analysis, designed prediction models based on both financial ratios and non-financial variables and demonstrated that non-accounting variables related to payment behaviors and properties of the responsible persons of a firm had a higher predictive capacity compared to financial ratios. Back (2005) analysed a sample of 3,199 firms and, by applying multinomial logistic regression, found that variables related to a firm's prior payment behavior (payment delays and payment disturbances) significantly improved default prediction accuracy.

Turetsky and McEwen (2001) found a positive correlation between a firm's payment delays and default. Wilson, Summers, and Hope (2000) found that using also prior payment behavior variables as default predictors increases accuracy compared to using only accounting data.

Based on these considerations, the first research hypothesis is the following:

H1: When SE default prediction modelling is based also on prior payment behavior related variables, prediction accuracy will be significantly higher compared to prediction modelling based only on financial ratios.

Considering that the lack of transparency of financial statements and accounting data tends to get more pronounced as the size of the firm decreases (Berger & Frame, 2007), using only financial ratios as predictive variables is likely to have a stronger negative impact on default prediction accuracy rates the smaller the firm size is. The second research hypothesis is therefore the following:

H2: The smaller the size of the firms which are the object of analysis, the higher the improvements in prediction accuracy that can be obtained by using also prior payment behavior variables as default predictors.

Furthermore, it is reasonable to expect that designing prediction models separately for different size groups has a positive impact on default prediction accuracy rates (Ciampi, 2017b). Consequently:

H3: Applying logistic regression separately for different size groups increases default prediction accuracy rates compared to calculating predictive functions on the aggregate sample.

Most of the studies consider default as the result of a sudden and fast event (Du Jardin & Severin, 2011) and consequently aim to optimise prediction accuracy rates over a one-year forecast period. Furthermore, the prediction models developed in the existing literature show a significant decline in accuracy rates when moving from a one-year forecast horizon to a longer horizon: Blum's (1974) one year before failure and three years before failure prediction model showed accuracy rates of 95% and 70% respectively, Altman, Eom and Kim's (1995) model of 97.1% and 69.7%, Sharma and Mahajan's (1980) model of 91.7% and 73.9%. Considering that a company's financial statements are usually available several months after the end of the financial year (in Italy normally 6 months) and that a certain amount of time is also necessary to analyse and reclassify these statements, as well as load all the relevant items in the rating systems, a year-ahead prediction is actually a rather useless exercise (in other words, when the prediction has been made, the time available to take the decisions suggested by that prediction has run out). This is all the more true when a banking institution needs to decide about granting a medium or long-term loan, which by its nature has to be repaid over a period much longer than a year.

The transition from the occurrence of symptoms of a company's weaknesses to bankruptcy very often requires a significant period of time, during which the company's financial health becomes progressively, but not immediately, worse (D'Aveni, 1989; Laitinen, 1991): for example, this transition might be conditioned by the efforts of the management team and/or the majority shareholder to contrast a deterioration process which is, however, irreversible.

Prior payment behaviors may have a higher predictive value than financial ratios in anticipating the future payment patterns of the firm not only because they offer a more up-to date financial picture of the firm itself but also because they may negatively (positively) affect a company's reputation and, consequently, induce financial institutions to claim back (confirm) already granted loans and/or to refuse (grant) new loans. As a consequence, it is reasonable to expect that designing prediction models based also on a company's prior payment behavior related variables is likely to have a stronger positive impact on default prediction accuracy rates the longer the forecasting horizons are.

The fourth research hypothesis is therefore the following:

H4: The longer the forecast horizon, the higher the improvements in prediction accuracy that can be obtained by using also prior payment behavior variables as default predictors.

4. Research Methodology

4.1 The Analysed Sample

The population object of this study was made up by all manufacturing firms with a turnover below 5 million Euro operating in Central Italy.

Table 1. The training sample composition in 2014 (percentage values)

	Firms Defaulting (in 2015)	Firms Non-Defaulting (in 2015)
BUSINESS SECTOR		
Food	13.7	17.3
Clothing	27.9	26.4
Wood products	11.7	8.3
Chemical products	6.4	6.9
Metallurgy	9.6	8.9
Mechanical machines	18	18.9
Electronic and optical machines and tools	12.7	13.8
REGION OF CENTRAL ITALY		
Abruzzo	7.2	5.4
Emilia Romagna	22.6	23.2
Lazio	22.1	22.5
Liguria	10.7	11.9
Marche	8.5	8.4
Toscana	18.5	21.7
Umbria	10.4	6.9
SIZE (TURNOVER IN EURO)		
Size group 1 (below 1.0 million)	33.6	34.4
Size group 2 (1.0-2.5 million)	28.5	28.9
Size group 3 (2.5-4.0 million)	17.9	16.1
Size group 4 (4.0-5.0)	20.0	20.6

In line with the main literature (e.g., Altman, 1968; Beaver, 1966; Edmister, 1972; Fulmer, Moon, Gavin, & Erwin, 1984; Pindado & Rodrigues, 2004; Pompe & Bilderbeek, 2005; Zenzerović, 2009) the sample analysed in this study was built using a "matched-pairs" approach. A training sample made up of 980 companies was used to design default prediction models. This training sample was made up of two sub-samples, both extracted from the Cerved Database, which includes financial records of all the Italian firms which are obliged to issue annual financial statements. The first one consisted of 440 firms located in Central Italy, operating in the manufacturing industry, whose turnover was below 5 million Euro, which defaulted during the year 2015, were regularly operating between 2012 and 2015, had regularly published financial statements during the period 2012-2014 and had one or more outstanding credit facilities from the "cooperating banking group" (Note 1) in each of the years comprised in the period 2012-2014. The second sample was made up of 440 firms, with the same characteristics, but which did not default during the year 2015.

The defaulted firms were extracted from the reference population through a stratified sampling method based on size (measured by 2014 turnover), geographical location (region of Central Italy in which the firm was located), and business sector. The not defaulted firms were selected using the same method, with the aim to replicate the structure of the defaulted firms in terms of location, size, and business sector.

The structure of the training sample analysed in this study is shown in Table 1.

Table 2. Financial ratios in the firms of the training sample: 2014 mean and median values

	Defaulting firms		Non-defaulting firms	
Financial ratios	Mean	Median	Mean	Median
Cash Flow/Total Debts	0.039	0.042	0.093	0.088
Rod = Interest Expense/Total Debts	0.051	0.053	0.032	0.033
Interest Expense /Bank Loans	0.059	0.063	0.038	0.039
Bank Loans/Turnover	0.982	0.081	0.411	0.414
Net Financial Position /Turnover	-0.245	-0.221	-0.094	-0.096
Total Debts/Equity	8.796	9.013	3.899	2.976
Financial Debts/Equity	7.011	6.990	2.980	2.991
Total Debts/EBITDA	7.021	7.101	4.098	4.102
Acid Test Ratio	0.499	0.502	0.911	0.899
Roi = EBIT/Net Operative Assets	-0.202	-0.213	0.657	0.701
Ros = EBIT/Turnover	-0.332	-0.339	0.603	0.599
Value Added/Turnover	0.166	0.0159	0.301	0.289
Ebitda/Turnover	0.059	0.058	0.134	0.138
Interest Expense/Ebitda	0.609	0.616	0.141	0.139
Value Added/Number of Employees	0.592	0.603	1.30	1.31

Note. Ebit = operat. revenue – operat. expenses + not operat. income;
Ebitda = Ebit + depreciation + amortization; Acid Test Ratio: (Current Assets - Inventories)/Current Liabilities.

Median and mean 2014 values assumed in the two training sub-samples by each financial ratio analysed in this study are shown in Table 2. In line with expectations, the non-defaulting firms show a much higher level of profitability with regard to both Roi (+0.657 against -0.202) and Ros (+0.603 against -0.332), a much lower cost of debts (average Interest Expense/Total Debts ratio is 0.032 for non-defaulting firms and 0.051 for defaulting firm), a much lower level of indebtedness with regard to both Financial Debt/Equity ratio (2.980 against 7.011) and Total Debts/Equity ratio (3.899 against 8.796), and a much better situation regarding liquidity (average Acid Test Ratio is 0.911 for non-defaulting firms and 0.499 for defaulting firm).

A holdout sample was used to verify the prediction accuracy of the models developed in this study. This sample consisted of 380 companies located in Central Italy, operating in the manufacturing industry, whose turnover was below 5 million Euro, which regularly operated between 2011 and 2013, had regularly published financial statements during the period 2011-2013 and had one or more outstanding credit facilities from the "cooperating banking group" (Note 1) in each of the years comprised in the period 2011-2013. It was made up of 190 firms which defaulted during the year 2014 and 190 firms which did not default during the same year and it was extracted from the CERVED Database using the same method used for the training sample (stratified sampling method based on size in terms of 2013 turnover, geographical location, and business sector).

4.2. Predictive variables

In this study the default/non-default event, defined as the formal beginning of legal proceedings for debt recovery (bankruptcy, forced liquidation, etc.), represents the dependent variable, which takes a value of 0 for non-defaulted companies and 1 for defaulted firms.

Two categories of default predictors (independent variables) were the object of analysis: previous payment behaviors and financial ratios.

The 15 financial ratios shown in Table 3 were initially considered potential default predictors (Altman, 1968, 1993; Altman, Haldeman, & Narayanan, 1977; Altman et al., 2005; Altman & Sabato, 2005; Beaver, 1966; Blum, 1974; Crouhy, Galai, & Mark, 2001; Edmister, 1972). These ratios were calculated using the financial statements (present in the CERVED database) for each financial year from 2012 to 2014 for firms in the training sample, and from 2011 to 2013 for firms in the holdout sample.

Table 3. Initial set of financial ratios

X1	Cash Flow/Total Debts
X2	Rod = Interest Expense/Total Debts
X3	Interest Expense /Bank Loans
X4	Bank Loans/Turnover
X5	Net Financial Position /Turnover
X6	Total Debts/Equity
X7	Financial Debts/Equity
X8	Total Debts/Ebitda
X9	Acid Test Ratio
X10	Roi = Ebit/Net Operative Assets
X11	Ros = Ebit/Turnover
X12	Value Added/Turnover
X13	Ebitda/Turnover
X14	Interest Expense/Ebitda
X15	Value Added/Number of Employees

Note. Ebit = operat. revenue – operat. expenses + not operat. income;
Ebitda = Ebit + depreciation + amortization;
Acid Test Ratio: (Current Assets - Inventories)/Current Liabilities.

Only the ratios selected at least by three of the six selection methods used by Du Jardin (2010), and applied using data from the training sample referring to the 2014 financial year, were chosen and used for the development of prediction models (Table 4).

Table 4. Financial ratios selected to develop default prediction model

FINANCIAL RATIOS	P-VALUE
Bank Loans/Turnover	0.000
Cash Flow/Total Debts	0.001
Roi = Ebit/Net Operative Assets	0.000
Interest Expense/Ebitda	0.001

Note. Ebit = Revenue - Operating Expenses;
Ebitda = Ebit + Depreciation + Amortization.

Table 5 shows the initial group of company prior payment behavior variables analysed in this study.

Table 5. Prior payment behavior variables selected to develop default prediction model

VARIABLES	DESCRIPTION/MEASURE
Past due and/or overdrawn exposures for more than 60 days	Presence (value of 1) or absence (value of 0), at the end of the reporting year, of bank loans past due and/or overdrawn for more than 60 days*
Past due and/or overdrawn exposures for more than 60 days/Turnover	Value of bank loans past due and/or overdrawn for more than 60 days at the end of the reporting year divided by turnover referred to the same year
Past due and/or overdrawn exposures for more than 60 days/Ebitda	Value of bank loans past due and/or overdrawn for more than 60 days at the end of the reporting year divided by Ebitda referred to the same year
Past due and/or overdrawn exposures for more than 60 days/Cash flow	Value of bank loans past due and/or overdrawn for more than 60 days at the end of the reporting year divided by cash flow referred to the same year
Past due and/or overdrawn exposures for more than 60 days/Bank loans	Value of bank loans past due and/or overdrawn for more than 60 days at the end of the reporting year divided by total bank loans
Past due and/or overdrawn exposures for more than 60 days/Financial debts	Value of bank loans past due and/or overdrawn for more than 60 days at the end of the reporting year divided by total financial debts
Number of annual payment delays exceeding 60 days	Number of bank loan payment delays a firm had during the reporting year
Number of annual non-remedied payment delays exceeding 60 days	Number of bank loan payment delays a firm had during the reporting year which were not remedied by the end of the same year
Number of cumulative payment delays exceeding 60 days	Number of bank loan payment delays a firm had from the beginning of 2012 (for firms in the training sample) or 2011 (for firms in the holdout sample) to the end of the reporting year
Number of cumulative non-remedied payment delays exceeding 60 days	Number of bank loan payment delays a firm had from the beginning of 2012 (for firms in the training sample) or 2011 (for firms in the holdout sample) to the end of the reporting year which were not remedied by the end of the same year

Note. *Dummy variable.

The "cooperating banking group" (Note 1) made available data related to these variables for each financial year from 2012 to 2014 for firms in the training sample, and for each financial year from 2011 to 2013 for firms in the holdout sample.

Only the prior payment behavior variables selected at least by three of the six selection methods used to choose financial ratios (and applied using data from the training sample referred to the 2014 financial year) were used for the development of prediction models (Table 6).

Table 6. Initial group of prior payment behaviors variables

PRIOR PAYMENT BEHAVIORS VARIABLES	P-VALUE
Past due and/or overdrawn exposures for more than 60 days/Turnover	0.000
Past due and/or overdrawn exposures for more than 60 days/Ebitda	0.001
Number of cumulative non-remedied payment delays exceeding 60 days	0.001

Note. Ebitda = Ebit + depreciation + amortization.

4.3 Statistical methods

Many different traditional and non-traditional methodologies have been proposed in literature with the aim of developing company default prediction models and processes such as logistic regression analysis (Ohlson, 1980), multivariate discriminant analysis (Altman, 1968; Altman et al., 1977; Blum, 1974; Deakin, 1972; Edmister, 1972; Rosenberg & Gleit, 1994), back-propagation neural network (Tam, 1991), and artificial neural networks (Zhang et al., 1999; Ciampi & Gordini, 2013). Though multivariate discriminant analysis has represented the most frequently used method, it has also revealed several weaknesses, especially in the cases of not linear and not normally distributed independent variables (Karels & Prakash, 1987; Ohlson, 1980) and binary (default/non-default) dependent variables (Altman & Saunders, 1996). Therefore, in this study the logistic regression analysis was used. Two prediction models were built, one designed using both financial ratios and payment behavior variables as predictive variables (Model 2); the other designed using only financial ratios (Model 1). Both Model 1 and Model 2:

a) were developed using data from the training sample referring to the years 2012, 2013 and 2014, i.e.

respectively one, two and three years before the default/non-default event;

b) were then assessed by making use of data from the holdout sample (referring to the years 2011, 2012 and 2013), with the aim of testing their prediction accuracy one, two and three years before the default/non-default event.

The independent variable (default/non-default) was regressed on the four financial ratios indicated in Table 4, the three payment behavior related variables indicated in Table 6, and the following control variables: firm age (measured by the number of years since the firm was established), firm location (six dummy variables referred to the region of Central Italy in which the firm was located: Liguria, Marche, Toscana, Abruzzo, Emilia Romagna, Lazio, Umbria; "Umbria" was used here as the reference category), business sector (six dummy variables referred to the sector in which the firm operated: wood products, clothing, metallurgy, chemical products, mechanical machines, electronic and optical machines and tools, food; "food" was used as the reference category); family ownership (a dummy variable with a value of 1 if the majority of shares was owned by members of the same family, 0 otherwise), CEO-duality (a dummy variable with a value of 1 for companies in which the CEO was also the chair of the board of directors, 0 otherwise), and degree of overlap between ownership and management (measured in function of the share of the firm's capital owned by management team members as follows: 1: 0%; 2: >0%<25%; 3: >25%<50%; 4: >50%<75%; 5: >75%).

5. Research findings

5.1 Findings

Both Model 1 and Model 2: 1) were initially developed at an aggregate level (i.e. using data referred to the aggregate training sample) and then separately designed for each of the four turnover size groups shown in Table 1 (below 1.0 million, 1.0-2.5 million, 2.5-4.0 million, 4.0-5.0 million); 2) were designed in order to predict default/non default at forecast horizons of one, two, and three years; 3) were assessed by testing their prediction accuracy on the holdout sample.

The results of regressing the dependent variable referring to the year 2015 on financial ratios referred to the 2014 financial year (i.e. at one-year forecast horizon), as well as on the control variables (firm business sector, age, and geographic location, CEO-duality, family ownership, and level of overlap between management and ownership) are shown in Table 7.

The results of regressing the default/non-default event (still referred to the year 2015) on both financial ratios and payment behavior variables (still referred to the 2014 financial year), as well as on the same control variables are shown in Table 8.

Table 7. Model 1 at one-year forecast horizon: logistic regression coefficients

	Aggregate Sample	Size 1	Size 2	Size 3	Size 4
INTERCEPT	-3.78**	+2.64**	+4.23*	-1.32*	+2.34**
INDEPENDENT VARIABLES					
Financial Ratios					
Bank Loans/Turnover	+4.34**	+3.54**	+3.76*	+5.78**	+4.01*
Cash Flow/Total Debts	-4.23**	-3.78**	-7.32**	-3.98*	-7.61*
Roi = EBIT/Net Operative Assets	-8.23*	-7.45**	-11.52*	-8.23**	-9.43**
Interest Expense/EBITDA	+6.90**	+8.65**	+6.04**	+9.56*	+14.31**
Control Variables					
CEO duality	-3.05*	-1.67*	-3.78*	-2.67*	-2.90*
Management-Owner	+3.56	+1.67	+4.78	+2.89	+0,89
Firm age	-0.89	-2.54	-1.56	-3.67	-2.69
Firm family ownership	-1.56	-0.45	-2.01	+1.67	-1.09
Abruzzo	+1.45	+1.78	-0.98	+3.21	-1.67
Emilia Romagna	+3.54	+2.53	+1.89	-3.23	-2.45
Lazio	+1.83	+1.21	+2.45	-0.85	+3.77
Liguria	-0.34	-1.56	-2.54	-3.92	-2.89
Marche	+3.21	+3.89	+4.78	+3.72	+1.72
Toscana	-0,72	-1.18	-2.45	-3.21	+0.98
Clothing	-3.56	-2.67	-3.89	-2.78	+0,32
Wood products	+1.45	+1.32	+0.98	+0,43	+2.21

Chemical products	+1.33	+2.67	+2.12	+1.56	+2.67
Metallurgy	-2.51	-2.09	-3.56	-4.67	-1.97
Mechanical machines	+1.45	+1.49	+2.67	+1.43	+2.56
Electronic and optical machines and tools	-3.54	-2.41	-2.00	-1.32	-4.67

Note. *Significant at 5 percent. **Significant at 1 percent. VA = Value Added.

Table 8. Model 2 at one-year forecast horizon: logistic regression coefficients

	Aggregate Sample	Size 1	Size 2	Size 3	Size 4
INTERCEPT	-1.34**	-2.67*	+2.43**	-1.21**	-2.09**
INDEPENDENT VARIABLES					
Financial Ratios					
Bank Loans/Turnover	+2.98**	+1.99**	+4.32**	+4.56*	+4.51**
Cash Flow/Total Debts	-3.21**	-2.78*	-3.91**	-4.89**	-3.90**
Roi = EBIT/Net Operative Assets	-3.89**	-4.87**	-6.89**	-3.32*	-7.86**
Interest Expense/EBITDA	+5.76**	+4.34**	+3.82**	+3.90**	+9.54*
Payment Behavior Variables					
Past due and/or overdrawn exposures for more than 60 days/Turnover	+2.45**	+3.21*	+3.89**	+4.32*	+4.78**
Past due and/or overdrawn exposures for more than 60 days/Ebitda	+2.43**	+3.78**	+2.64**	+4.78*	+4.89*
Number of cumulative non-remedied payment delays exceeding 60 days	+3.98**	+4.32**	+7.54**	+4.21**	+6.90**
Control Variables					
CEO duality	-2.23*	-2.45**	-1.89*	-3.54*	-0,97*
Management-Owner	+1.56	+3.76	+2.51	+5.99	+3.71
Firm age	-1.54	-3.32	-2.87	-4.51	-3.50
Firm family ownership	-2.43	-3.31	-1.20	+2.50	-4.72
Abruzzo	-0.98	+2.32	-1.43	+4.21	+4.23
Emilia Romagna	-1.23	+1.32	+2.09	-2.62	-3.90
Lazio	+4.32	+3.05	+1.54	+4.32	+1.53
Liguria	-1.36	-2.43	-1.73	-2.53	+4.56
Marche	+4.43	-0.08	-1.34	+2.41	+2.74
Toscana	-2.56	-2.78	-3.61	-2.53	-1.11
Clothing	-1.54	-4.32	-2.11	-1.94	-1.87
Wood products	+2.43	+1.89	+2.56	+2.89	+4.32
Chemical products	+0.21	+1.59	+3.31	+2.50	+4.00
Metallurgy	-2.43	-3.45	-2.11	-3.93	-0.98
Mechanical machines	+3.54	+2.11	+0.45	+2.67	+1.81
Electronic and optical machines and tools	-0,32	-0.87	+0.45	+1.32	-2.56

Note. *Significant at 5 percent. **Significant at 1 percent.

For both the logistic functions: 1) the coefficients of all the default predictors were always found to be significant at conventional levels, and all signs were in line with expectations; 2) the coefficients of all the control variables were always found to not be significant at conventional levels, except for CEO duality, which was found significantly and negatively associated with company default, in contrast to the findings of the literature regarding large firms (e.g., Argenti, 1976; Hambrick & D'Aveni, 1992; Mallette & Fowler, 1992), but in line with the results referred to SEs (Ciampi, 2015). These results give a first clear confirmation that along with financial ratios also payment behavior variables represent useful bankruptcy predictors when the objects of analysis are SEs.

The same results (the coefficients of all the default predictors were always found to be significant at conventional levels, and all signs were in line with expectations; the coefficients of all the control variables were always found to not be significant at conventional levels, except for CEO duality (which was found significantly and negatively associated with company default) were found for both Model 1 and Model 2 logistic regression functions when calculated to predict failure at forecast horizons of two and three years.

Table 9 shows the results of the assessment of the two prediction models developed at an aggregate level (i.e. on the aggregate training sample) and at one-year forecast horizon.

Table 9. Test on holdout sample of Model 1 and Model 2 calculated on the aggregate sample and at one-year forecast horizon

Model	Observed state		Predicted State (%)		Firms correctly classified (%)
			1	0	
Model 2	Defaulting firms	1	81.0	19.0	80.4
	Non-defaulting firms	0	20.2	79.8	
Model 1	Defaulting firms	1	76.5	23.5	74.2
	Non-defaulting firms	0	28.1	71.9	

The "Observed State 1" lines indicate the percentages of correctly classified defaulting firms ("Predicted State 1" column), i.e. 81.0% for Model 2 and 76.5% for Model 1, and the percentages of wrongly classified defaulting firms ("Predicted State 0" column; type I error), i.e. 19.0% for Model 2 and 23.5% for Model 1. The "Observed State 0" lines indicate the percentages of wrongly classified non-defaulting firms ("Predicted State 1" column; type II error), i.e. 20.2% for Model 2 and 28.1% for Model 1, and the percentages of correctly classified non-defaulting firms ("Predicted State 0" column), i.e. 79.8% for Model 2 and 71.9% for Model 1.

Model 2 shows an increase in prediction accuracy rate of more than 6%, with a type I error reduction of 4.5% and a type II error reduction of 7.9%, thus confirming H1. These findings are in line with financial ratios being based on accounting data that are normally 12-18 months old, and therefore offering a much less up-to-date picture of the firm's financial health than payment behavior variables. These results are also coherent with SEs being less subject to pressure for accountability from their stakeholders and the financial community compared to larger firms as well as with SEs' financial statements being very often produced mainly for tax purposes.

Table 10 shows the results of the assessment (based on the holdout sample) of the prediction capacity of Model 1 and Model 2 separately developed for each size sub-samples at a one-year forecast horizon.

Table 10. Test on holdout sample of Models 1 and 2 separately calculated for each size sub-sample and at one-year forecast horizon

	Model 2 correctly classified firms (%)	Model 1 correctly classified firms (%)	Model 2 versus Model 1: accuracy increase (%)
Size 1	83.1	74.2	8.9
Size 2	83.7	74.7	9.0
Size 3	83.1	75.4	7.7
Size 4	83.5	75.8	7.7
Total	83.4	75.0	8.3

Model 2 shows higher prediction accuracy rates for all size sub-samples, thus further confirming H1. Furthermore, the difference in prediction accuracy between Model 2 and Model 1 rises as firm size gets smaller (7.7 for both size group 3 and size group 4; 8.9 and 9.0, respectively for size group 1 and 2), thus confirming H2. As a consequence, when firm size changes, Model 2 tends to be more stable compared to Model 1. Finally, the results shown in Table 10 confirm H3 as they demonstrate that for both Model 1 and Model 2 separately applying logistic regression to different size groups allows to obtain higher accuracy rates than calculating predictive functions on the aggregate sample. Banking institutions should therefore design different default prediction models for different size groups of firms, as well as update these models when the dimensional composition of their client base changes significantly. The increases in prediction accuracy obtained by the model based also on payment behavior variables compared to the model based only on financial ratios (H1), as well as the fact that this increase rises as a company's size decreases (H2) are consistent with the fact that financial statements produced by SEs are typically more opaque and less articulated than those of larger firms (Berger & Frame, 2007); they are also consistent with the fact that SEs have low contractual power towards their counterparts, which consequently have a significant influence on their strategic behaviors and financial results (this influence may for example mean that one year financial ratios may get worse because an important customer has imposed lower selling prices or an important supplier has forced the firm to accept higher purchase prices).

The differences in the prediction accuracy rates obtained by Model 1 and Model 2 at the three forecast horizons object of this study are shown in Table 11. The overall prediction accuracy rates of Model 2 remain higher compared to those given by Model 1 at all the three forecast horizons and for all the four firm size groups, thereby further confirming H1.

Table 11. Test on holdout sample of Models 1 and 2 separately calculated for each size sub-sample at forecast horizons of one, two, and three years (prediction accuracy percentage rates)

	Years before the event (default/non-default)		
	1	2	3
MODEL 2			
Size group 1 (below 1.0 million)	83,1	81,6	79,5
Size group 2 (1.0-2.5 million)	83,7	82,3	80,4
Size group 3 (2.5-4.0 million)	83,1	81,9	80,3
Size group 4 (4.0-5.0)	83,5	82,5	81,0
Total sample	**83,4**	**82,1**	**80,3**
MODEL 1			
Size group 1 (below 1.0 million)	74,2	71,4	68,2
Size group 2 (1.0-2.5 million)	74,7	71,5	66,0
Size group 3 (2.5-4.0 million)	75,4	72,9	69,0
Size group 4 (4.0-5.0)	75,8	73,9	70,6
Total sample	**75,0**	**72,4**	**68,5**
DIFFERENCES BETWEEN ACCURACY RATES			
Size group 1 (below 1.0 million)	8,9	10,2	11,3
Size group 2 (1.0-2.5 million)	9,0	10,8	14,3
Size group 3 (2.5-4.0 million)	7,7	9,0	11,3
Size group 4 (4.0-5.0)	7,7	8,6	10,4
Total sample	**8,4**	**9,7**	**11,8**

In line with H2, also at forecast horizons of two and three years, the difference in prediction accuracy between Model 2 and Model 1 increases as firm size gets smaller: from 8.6% for size group 4 to 10.2% for size group 1 at a two-year horizon, and from 10.4% for size group 4 to 11.3% for size group 1 at a three-year horizon. As a consequence, even at forecast horizons longer than one year, when firm size changes, Model 2 tends to be more stable compared to Model 1. Most importantly, the difference in prediction accuracy between Model 2 and Model 1 increases as the forecast horizon gets longer (from 8.4% at a one-year horizon, to 9.7% at a two-year horizon, to 11.8% at a three-year horizon), thereby confirming H4. When the forecast horizon changes, Model 2 tends consequently to be more stable compared to Model 1. These results are consistent with the fact that a SE's financial weakness rarely translates immediately into weak financial ratios: it may, for example, happen that the emergence of a new fiercer competitor and/or the loss of an important competitive advantage have their full impact on a firm's financial statements one or two years after these events have happened. These findings are also consistent with the propensity of firms, especially smaller ones, to postpone the accounting emergence of their financial weaknesses, thereby enlarging the delay with which a company's weakness translates into weaker financial ratios. In this connection, the findings of this study confirm that financial statements and financial ratios (which are based on financial statements) represent out-of-date information whose availability may prove tardy and therefore of little value for an effective SE bankruptcy prediction.

5.2 Robustness Tests

A second holdout sample and a different period of time (2013-2016) were the object of analysis in order to assess the robustness of the findings of this study. Holdout sample 2 was made up of 540 firms located in Central Italy, operating in the manufacturing industry, whose turnover was below 5 million Euro, which regularly operated between 2013-15, had regularly published financial statements during the period 2013-2015 and had one or more outstanding credit facilities from the "cooperating banking group" (Note 1) in each of the years comprised in the period 2013 and 2015. It consisted of 270 firms which defaulted during the year 2016 and 270 which did not default during the same year and was extracted from the CERVED Database making use of the same criteria used to select holdout sample 1 (stratified sampling method based on 2015 turnover, geographical location and business sector).

The "cooperating banking group" (Note 1) made available data related to payment behavior variables for each financial year from 2013 to 2015, while financial ratios were calculated using the financial statements, present in the CERVED database, for each financial year from 2013 to 2015.

This exercise of robustness verification gave confirmation to all our findings in that:

1) compared to Model 1, Model 2 showed a significant increase in prediction accuracy both when prediction functions were calculated on the aggregate training sample and when they were separately designed for each size group of firms; 2) the difference in prediction accuracy between Model 2 and Model 1 increased as firm size got smaller, with the consequence that when firm size changed, Model 2 confirmed to be more stable compared to Model 1; 3) applying logistic regression to different size groups separately for both Model 1 and Model 2 allowed to obtain higher accuracy rates than calculating predictive functions on the aggregate sample; 4) at all the three forecast horizons the overall prediction accuracy rates of Model 2 remained higher compared to those given by Model 1 and the difference in prediction accuracy between Model 2 and Model 1 increased as firm size got smaller; 5) the difference in prediction accuracy between Model 2 and Model 1 increased as the forecast horizon got longer, with the consequence that when the forecast horizon changed, Model 2 was more stable compared to Model 1.

6. Conclusions

This study aimed to verify the potential of using prior payment behavior variables for SE default prediction modelling.

Applying logistic regression to a sample of 980 Italian small companies, a SE default prediction model was developed using both prior payment behavior variables and financial ratios as default predictors. The accuracy rates of this model were then compared to those of a second model based only on financial ratios.

This study contributes to the existing literature as follows. First, it finds that using prior payment behavior variables significantly improves the effectiveness of SE default prediction modelling, thereby confirming that payment behavior variables compensate the fact that the translation of a SE financial bad (good) condition into weak (strong) financial ratios normally takes a significant period of time, which is also conditioned by the tendency of firms, especially smaller ones, to postpone the accounting emergence of financial weaknesses.

Second, consistent with smaller firms producing far more opaque and less articulated accounting data than large firms, this study demonstrates that the smaller the size of the firms, the higher the improvements in prediction accuracy that can be obtained by using also prior payment behavior variables as default predictors, with the consequence that when the size of the firm changes, the prediction accuracy of the models based also on prior payment behavior variables are much more stable compared to those of models based only on financial ratios.

Third, it confirms that banking institutions should design different default prediction models for different size groups of firms, as well as update their models when the dimensional composition of their client base changes significantly.

Fourth, it finds that the longer the forecast horizon which is object of analysis, the higher the improvements in prediction accuracy that can be obtained by using also prior payment behavior variables as default predictors; and that when the forecast period changes, the prediction accuracy of the models based on both the categories of predictive variables is much more stable compared to that given by models based only on financial ratios. These results are consistent with the fact that the transition from the appearance of the first symptoms of financial weakness to weak financial ratios normally takes a rather long period of time, during which the crisis grows progressively but does not deteriorate immediately. Relying only on financial ratios may consequently represent an ineffective approach, particularly in the case of SEs, whose scarce contractual power make their financial results highly dependent upon the behavior of their counterparts, thereby reducing the predictive power of their financial ratios, especially when forecast horizons are longer than one year.

This research has three main limitations. First, all the firms object of analysis operate in the manufacturing industry. As a consequence, the findings of this study cannot be generalized to firms operating in other sectors, such as service firms.

Second, this study analyses firms operating in a specific geographical context (Central Italy), which has its own specific institutional, economic and industrial characteristics. The results of this research cannot consequently be generalized to firms operating in different economic and industrial systems.

Third, the developed default prediction models continue to show significant classification errors (both Type I and Type II errors). Hence, the need to further enlarge the range of default predictors used is vital, by also including qualitative characteristics, such as those related to strategic behaviors and plans, knowledge creation processes and strategies (Ciampi, 2008), and organizational structures.

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Notes

Note 1. “Cooperating banking group” is defined as the banking group (whose name is not disclosed for reasons of confidentiality) which collaborated with this study by making data available related to the company’s previous payment behavior variables described in Section 4.2.

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