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Modeling hard and soft facts for SMEs: Some international evidence

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Abstract

This paper asks how well the use of quantitative and qualitative variables can improve the assessment of companies' creditworthiness and how this result can be influenced by the economic and financial peculiarities of countries. We harden qualitative variable measures to model soft information aimed at scoring microfirms, small, and medium-sized firms. The structural survey covers Germany, Italy, and the UK in a sample of about 17 thousand companies observed during the financial crisis. Soft facts are determined within the balanced scorecard framework in order to find out the impact of customers, business processes, learning and growth, and financial perspectives. Our findings show that credit models integrating soft variables optimize the risk estimation, but estimates are country-specific and should be tailored to the characteristics of each economic system.

1 | INTRODUCTION

The financial crisis of 2008–2009 stimulated economists' and managers' interest in the identification of the major drivers to explain the resilience of companies in turbulent markets. According to an old argument (Holling, 1973), resilient firms are able to maintain a high level of functioning when shocked. Azadegan and Jayaram (2018) echo this view by arguing that resilience is a process, whereby steps can be taken before the disaster to build resilience capacity. In this paper, we identify the qualitative and quantitative drivers that allow banks to identify this resilience and, specularly, the risk that microfirms, small, and medium-sized enterprises (MSMEs) may fail.

Credit risk models have frequently been built using primarily quantitative information, based on past business performance and past behavior. On the one hand, these estimates are retrospective; on the other hand, pro-cyclicality in the banking system is intensifying (Kashyap & Stein, 2004). The financial crisis that began in 2007 and the rigidity of the Basel II principles have highlighted the limitations of a credit approach that is overly focused on quantitative information (transaction approach). These limits have been materialized in credit crunch phenomena, especially with regard to the small and medium-sized enterprises (SMEs) (Bocchi & Lusignani, 2004), and have led to the modest predictive reliability of banks' lending models.

Our research aims to demonstrate that quantitative variables can usefully be combined with strategic variables to make insolvency forecasts for companies more reliable and how this contribution varies across countries based on the economic and financial features of different national systems.

A number of researchers (Brunner, Pieter, & Weber, 2000; Grunert, Norden, & Weber, 2005; Morales, Sacasas, & Munter, 2000) show that some qualitative data are typically forward-looking, such as financial projections, future management plans and objectives, and statements of future economic performance. As demonstrated by numerous studies (Godbillon-Camus & Godlewski, 2005; Grunert et al., 2005; Lehmann, 2003), the qualitative information acquired through a relational approach with fund borrowers can overcome the problems of information opacity and the problems that SMEs faced more accurately during the credit crunch phase. In addition, this approach also serves to mitigate the pro-cyclical behavior of banks. More precisely, more favorable information amplifies the bargaining power of borrowers, and as a result, SMEs may have greater availability of credit and lower costs (Grunert & Norden, 2012; Howorth & Moro, 2012).

In the economic literature, there is evidence that supports the growing importance of the use of soft information within the bank credit approval process (Agarwal & Hauswald, 2010; Bartoli, Ferri, Murro, & Rotondi, 2013, Gabbi et al., 2019). In addition, some studies confirm that the banks that have focused their development policies on traditional business areas and relationship banking logic have been less affected by the 2007 financial crisis: These banks use not only back "concrete" financial data, but also soft and forward-looking information (Beccalli, Bongini, & Patarnello, 2009).

The asymmetric information puzzle is particularly relevant for SMEs because of the inherent difficulty in estimating and determining their fair value (Stein, 2002). This is an important issue in many countries where the number of SMEs accounts for a large percentage of total enterprises. These companies do not usually provide any reliable quantitative information and, in some countries, most of them are not obliged to record their data in the profit and loss account and accounting. According to Petersen and Rajan (2002), banks should assess the credit quality of these companies by trying to transform the large sets of non-binding information that affect their value into quantitative terms. According to Tingting (2011), the cost of collecting non-binding information induces banks to maintain a long-term relationship with customers and to reduce pro-cyclicality.

Although reliable information on SMEs is rare and costly for financial intermediaries, a single bank relationship (Hernández-Cánovas & Koëter-Kant, 2010) is more likely when a trustee relationship is established to gather soft information. As a result, the bank's ability to obtain qualitative and strategic data from borrowers becomes crucial (Baas & Schrooten, 2006).

Regulators have focused on this issue, requiring the use of qualitative variables to classify undertakings. The Basel Committee on Banking Supervision (2005) states that banks should take qualitative facts into account in their internal rating approaches. According to the Banca d'Italia (2006), "the rating represents the assessment, for a given time horizon, of the ability of the assigned or potential debtor to meet his contractual obligations, carried out on the basis of all quantitative and qualitative information reasonably accessible and expressed in ordinary terms." In addition, control systems and auditors are required to verify the final individual ratings generated by the models, the completeness of the factors considered, and the procedures for processing objective qualitative information. Most models based on internal rating (IRB) are still constructed on the basis of debtors' financial statements and past conduct, with the consequent risk of a retroactive rating.

Consequently, the question of whether credit institutions can best estimate a firm's rating with forecasting variables is mainly related to policy and management implications.

However, the problem cannot be tackled without considering the profound differences that exist between economic and industrial systems at the level of individual countries. In our study, while considering three industrialized European countries (Germany, Italy, and the UK), we highlight peculiarities that we expect to be captured in a different way from the qualitative variables that can be used in credit risk management models and in building portfolios (Gabbi, 2005).

More precisely, our objective is to verify whether some characteristic elements of the industrial fabric of the countries considered are intercepted by the soft variables, allowing a more effective estimate of the credit risk.

Most empirical evidence (OECD and EU) shows that in Germany and the UK, R&D orientation is greater than in Italy (Arrighetti & Ninni, 2012). The same applies to the graduation rate of corporate managers, which can be seen as a proxy for managerial skills. On the contrary, Italy prevails in the degree of relational intensity with the banking system and in the diversification of business (EU, 2012).

A relevant issue is closely related to the ability to process soft facts: According to Petersen (2004), the implicit assumption is that not all useful information is summarized in the numbers. Some of the relevant data are qualitative and require judgment. It cannot be accurately reduced to a number.

In our paper, we suggest a concrete and valid approach to hardening qualitative variables, unlike the use of discretionary variables (i.e., Keasey & Watson, 1987) or with uncertain scores (i.e., Grunert et al., 2005). The paper shows an efficient integration process of a rating based on "traditional" quantitative variables with a wide set of qualitative, fundamentally organizational, and strategic information capable of capturing the company's prospective dynamics. The analysis is based on three countries, Germany, Italy, and the UK, where we collected both hard and soft data to compare the benefit in terms of credit analysis and, more importantly, how soft variables differently explain the credit risk in countries characterized by heterogeneous industrial features.

The research is structured as follows: Section 22 describes the data and sampling design of our research and shows the methodology for estimating the default of companies using quantitative and qualitative variables; Section 33 illustrates our empirical results; and Section 44 concludes.

2 | DATA AND METHODOLOGY

The database covered 17,248 microfirms (MFs) and small and medium-sized enterprises (SMEs) observed in three large European countries: Germany, Italy, and the UK, respectively. In all the cases, data cover the period from 2008 to 2015, the most critical years for the downturn of the European economic cycle. Companies are defined as MFs and SMEs following the EU recommendation 2003/361. The main factors determining whether an enterprise is an SME are staff headcount and turnover. The thresholds are for the turnover (MF $\leq$ € 2m; SME $\leq$ € 50m) and staff headcount (MF $<$ 10; SME $<$ 250). The default rate is the percentage of enterprises that have gone into default. In total, 706 firms failed (Table 1).

The three countries selected show different contribution of microfirms and SMEs to employment in the non-financial business sector: 53% in the UK, 63% in Germany, and 79% in Italy, with a EU average of 67% (EU Commission, 2017). The contribution to value added was a bit lower but with a similar order: 53% in the UK, 54% in Germany, and 68% in Italy, and a EU average of 57%. Nevertheless,

TABLE 1 Database features

Country	Good companies	Bad companies	Total # of companies	Default rate
Germany	5,718	160	5,878	2.72%
Italy	7,621	431	8,052	5.35%
UK	3,203	115	3,318	3.47%
Total	16,542	706	17,248	4.09%

Note: Our database counts 17,248 companies distributed in three countries (Germany, Italy, and the UK) as shown in the table. Companies are microfirms and small and medium-sized enterprises (SMEs), defined following the EU Recommendation 2003/361. The main factors determining whether an enterprise is an SME are staff headcount and turnover. The thresholds are for the turnover (microfirms ≤ € 2m; SME ≤ € 50m) and staff headcount (microfirms < 10; SME < 250). The default rate, that is, the percentage of enterprises that have gone into default, is 4.09%

the birth rate of SMEs in the period 2010–2014 recorded a reverse trend: +12.7% in the UK, +7.9% in Germany, and + 6.8% in Italy. The EU average was 9.7%.

Our database is characterized by two kinds of variables: on the one side, the rating based on hard fact, estimated through an IRB approach, validated by the national banking regulators; and on the other side, the qualitative variables (Table 2) collected through a questionnaire, submitted to firms and assessed by the relationship manager of the bank.

Besides the fact that the soft information tends to be forward-looking, the rationale for the use of this database is that qualitative variables are not provided by any external source and the default monitoring process is more accurate when delegated to a financial firm.

The basic framework that inspired the choice of qualitative variables is the balanced scorecard (BSC) introduced by Kaplan and Norton (1992). The BSC suggests the evaluation of firm strategy from (a) customers, (b) business processes, (c) learning and growth, and (d) financial perspectives.

The customers' perspective focuses on the firm's ability to meet customer's needs. An efficient quality management system aims to offer better products and services while improving process efficiency (Flynn, Schroeder, & Sakakibara, 1995; Kaynak, 2003; Samson & Terziovski, 1999). This perspective is captured and made explicit in our work with the "the business diversification" (MANU_DIS) and the "market pattern and perspectives" (MKT_EXP).

The internal process perspective aims to improve core processes. The firm should optimize key business processes such as product innovation, the distribution process, and the after-sales service. In this sense, the "management experience" (TM_EXP), the "product diversification" (PROC_FLEX), and the "organizational model" (ORG_DES) are the variables which make this perspective explicit. Business diversification can be realized following two different strategies: (a) related business or (b) unrelated business. The first enables the transfer of skills, technical knowledge, or other competitive ability among different businesses, along with cost reduction through combining related operations. The second strategy allows the firm to share risk among different sectors and stabilize firm profitability through the business cycle (Thompson, Strickland, & Gamble, 2007).

The learning and growth perspective relates to the firm's attitude in setting goals of improvement regarding its ability to carry out the processes that create value for customers and other stakeholders. The strategic vision is fundamental because it focuses the firm on quality, process reengineering, and the constant challenge with best performers, which should lead to relevant increases in operational effectiveness (Porter, 2001). Moreover, the predisposition for a continuous business improvement process is essential due to intense competition in the reference market: In the absence of innovation in a competitive market, the firm is bound to spurt out from the market itself (Casu & Girardone, 2010; Hicks, 1989). This perspective is approximated by the variables "strategic vision" (VISION) and "competition intensity" (CO_CO) and the “research & development” (R&D).

The financial perspective looks at the financial equilibrium that is considered in order to observe whether the firm is able to ensure an adequate financial coverage at all times (Hamilton & Fox, 1998).

TABLE 2 Strategic and business variables

BSC perspective	Variable name	Focus of the variable	Qualitative answers
Internal process	PROC_FLEX	Process flexibility	a – the company's business is divided into several sectors b – the company's business is focused on one sector but with flexible processes c – the company's business is focused on one sector and with inflexible processes
Customers	MANU_DIS	Manufacturing diversification	a – high diversification of customers b – quite diversified customers c – little diversified customers
Internal process	TM_EXP	Management experience	a – top managers have an experience of more than 10 years b – top managers have an experience between 5 and 10 years c – top managers have an experience of less than 5 years
Learning	VISION	Strategic vision	a – the strategic vision of the company is excellent: clear long-term goals b – the strategic vision of the company is good: good long-term goals c – the strategic vision of the company is satisfactory d – the strategic vision of the company is poor
Internal process	ORG_DES	Organizational design	a – the organization of the company is efficient and well structured b – the organization of the company is sufficiently structured and key positions covered c – the organization of the company is inadequate with some key positions being uncovered
Customers	MKT_EXP	Market expectations	a – the market where the company operates is expected to rise b – the market where the company operates is expected to slowdown c – the market where the company operates is expected to be flat d – the market where the company operates is expected to decline
Learning	R&D	Research and development	a – the company considers investments in R&D crucial for the growth b – the company does not believe that investments in R&D are crucial for the growth
Learning	CO_CO	Competition and contestability	a – the market where the company operates is highly competitive and contestable b – the market where the company operates is relatively competitive and contestable c – the market where the company operates is less competitive and contestable

(Continues)

TABLE 2 (Continued)

BSC perspective	Variable name	Focus of the variable	Qualitative answers
Financial	BANK_LOAN	Relations between the firm and the banking system	a – the relationship between the company and the banking system is excellent; no credit tensions b – the relationship between the company and the banking system is good; some overdrafts c – the relationship between the company and the banking system is sufficient; some precarious situations have been experienced d – the relationship between the company and the banking system is critical; some non-authorized overdrafts have been experienced
Financial	CRED_TREND	Credit requirements and firm growth	a – the credit need is expected to be in line with the firm dynamics b – the credit need is not expected to be in line with the firm dynamics

Note: This table shows the scorecard category (first column) and the variables (second column) we used to calibrate the soft facts model to estimate the credit risk. The name of the variable is the same used within the text. Every single variable focuses on a strategic dimension (third column) to explain the excellence or the critical issue of a company. The last column lists the answers for every question.

Since our sample consists of SMEs, the financial aspect concerns the relationship with the bank considering that, in bank-oriented systems, credit availability is a signal of liquidity and soundness appreciated within both the real and the financial environment (Castelli, Dwyer, & Hasan, 2006). The financial perspective is examined by the "borrowing requirements trend" (CRED_TREND) and "relations with the banking system" (BANK_LOAN) variables.

In these models, the dependent variable is a dummy assuming value 1 if the firm defaults and value 0 otherwise. Every question represents an independent variable in each model that will be applied afterward. Our questions were codified in order to attribute a numerical value to each answer given. To eradicate any element of discretion about the numerical value of each answer of the questionnaire, we calculated their values in the following way. Firstly, in reference to each question, we have divided the sample of firms into subgroups, so that each answer corresponds to one subgroup. Secondly, for each subgroup, where each company for a certain question gave the same answer, we estimated the average default ratio in each country. Finally, the “distance” of each answer is the average default ratio of the subgroup less the average default ratio for the country database (Table 3).

We applied the logit regression to estimate the probability that the dependent variable takes the value 1 (in our analytical case, this is equivalent to the event that the firm defaulted) explained by a vector of independent variables (the questions in the questionnaire whose answers are explained in Table 1).

$$\mathrm{DEFAULT}_t = \alpha + \beta * \mathrm{QUANT}_{i,t-1} + \gamma * \mathrm{QUAL}_{i,t-1} + \varepsilon$$

In the above equation, subscript i denotes the borrower and t denotes the year. In this regression, we control for important financial and behavioral features (QUANT) selected by the bank in its IRB model, and strategic features (QUAL) that may explain the credit risk. Our estimates based on three different equations: first, the default explained only by hard facts (Model 1); second, the default explained by only qualitative variables (Model 2); and finally, the default explained by the whole independent variables, both quantitative and qualitative ones (Model 3).

TABLE 3 Hardening qualitative variables

	Germany				Italy				UK			
Variables	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
PROC_FLEX	−2.4	−0.9	16.6		0.5	−0.3	0.9		−1.6	−0.1	5.9	
MANU_DIS	−0.2	−0.3	3.5		−1.4	1.9	5.7		−1.7	−0.5	28.1	
TM_EXP	−0.5	3.0	13.2		−0.6	3.4	16.3		−0.7	3.5	18.9	
VISION	−2.3	−1.0	1.6	24.4	−4.7	−2.1	7.5	32.1	−2.3	−1.1	4.2	18.5
ORG_DES	−1.4	0.6	23.2		−2.8	2.0	31.2		−1.5	2.2	22.3	
MKT_EXP	−0.7	−0.5	1.4	5.4	−1.0	−0.7	1.5	6.5	−0.5	−0.5	1.3	4.8
R&D	−1.6	2.3			0.2	−0.1			−1.6	2.6		
CO_CO	1.2	−0.8	−0.5		0.2	0.0	−2.6		1.3	−1.1	0.9	
BANK_LOAN	−2.4	−1.8	6.2	13.0	−4.9	−3.1	9.4	30.6	0.0	−1.6	1.3	8.6
CRED_TREND	−0.8	12.4			−1.4	22.7			−0.5	9.7		

Note: This table shows the "distance" of answers from the sample average default ratio shown in Table 1 and indicated with a, b, c, and d. Values in percentage. The first column lists all the soft variables: PROC_FLEX is the productive diversification; MANU_DIS is the business diversification; TM_EXP captures the management experience; VISION denotes the strategic vision; ORG_DES denotes the organizational structure; MKT_EXP indicates the trend of the reference market; R&D indicates whether or not the firm invests in research and development; CO_CO is the competition intensity; BANK_LOAN explores the relations with the banking system; and CRED_TREND shows the trend of the borrowing requirements. Values show the average default ratio of the groups of firms by country in relation to answers given for each question.

The last model will be subsequently analyzed separating qualitative variables by the BSC perspectives, that is, customers (Model 3a), business processes (Model 3b), learning and growth (Model 3c), and financial perspectives (Model 3d).

3 | RESULTS

Our findings are structured to compare the accuracy of hard, soft, and mixed models for each country. Then, we estimate the first- and second-type errors to further appreciate the ability of the models to classify borrowers.

The comparison of the two default estimation models based on quantitative variables (Model 1) and qualitative and strategic variables (Model 2), respectively, offers significant results from the risk management perspective compared by countries (Table 4).

The first significant result is that of Model 1, which estimates credit risk using quantitative and behavioral variables. In all countries considered, the variable QUANT is relevant and highly significant, but for Italy, it is more decisive than in the case of Germany and the UK. If this result is combined with Model 2, the contribution of the soft variables (QUAL), which is higher for German and British enterprises, becomes even more significant.

With regard to the overall contribution of qualitative variables to detect the default probability is extremely high. Comparing the pseudo-R^2, all the QUAL estimates outperform the QUANT ones. The result is more relevant for credit risk estimates in Germany and the UK. This is consistent with the evidence that the companies of these countries, if compared with Italy, show a greater orientation to research and development, as well as elements of managerial competence.

In the estimates in Table 4, it is particularly clear that the R&D variable is the one that contributes most to the explanation of the variability between enterprises in different countries. The companies that develop better products and/or advanced technologies are expected to gain market shares and so higher profits (Del Monte & Papagni, 2003). Empirically, a number of studies demonstrated how R&D investments positively affected firms' efficiency and growth (Hall & Mairesse, 1995, Harhoff, 1998 and Wakelin, 2001).

By contrast, in the risk estimates of Italian enterprises the R&D variable is not statistically significant. This result is consistent with the dimension "skills and innovation" of the SBA profile (Figure 1). Moreover, according to Eurostat, the national share in EU-28 of researchers working in companies assesses that 23% works in Germany, 14% in the UK, and only 9% in Italy (German Trade, 2018).

With regard to internal controls, PROC_FLEX appears to be significant only in Germany. This may be explained with the highly diversified German economy proved also by the foreign direct investments targeting 29 different sectors, one of the highest in Europe. Our findings confirm that diversification strategies of single companies, when pursued by SMEs, allow firms to originate new combinations of functions–technologies for new products and/or new market segments (Penrose, 1959).

The performance of the reference market (MKT_EXP) is not significant for all the countries we study, in both Model 2 and Model 3. This finding may be explained for the systemic impact that it generates on the SMEs. Our result may also be interpreted in terms of market union impact: Germany, Italy, and the UK show SBA profile which is almost similar and close to the EU average.

The ability to diversify often requires a significant managerial quality (TM_EXP), which in our analyses is statistically significant for all the three countries. The ability to diversify often requires a significant managerial quality (TM_EXP), which in our analyses is statistically significant for all the three countries. The factor that changes between countries is the coefficient of regression, which is

TABLE 4 Logit regression – quantitative versus qualitative variables

	Model 1 (only QUANT)			Model 2 (only QUAL)			Model 3 (both QUANT and QUAL)		
Variables	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**
Constant	−4.124 (0.102) ***	−3.578 (0.068) ***	−3.689 (0.112) ***	−5.172 (0.184) ***	−3.719 (0.0814) ***	−4.167 (0.153) ***	−5.387 (0.195) ***	−3.955 (0.0873) ***	−4.366 (0.164) ***
QUANT	13.27 (0.922) ***	19.17 (0.883) ***	10.92 (1.116) ***				7.916*** to1.072	9.629*** to0.824	7.815*** to1.379
PROC_FLEX				14.98 (1.112) ***	4.629 (11.55)	0.867 (4.513)	15.49 (1.174) ***	5.866 (12.14)	1.983 (4.586)
MANU_DIS				11.13 (7.981)	8.669 (2.537) ***	9.409 (0.807) ***	12.11 (8.426)	6.881** (2.702)	9.292 (0.826) ***
TM_EXP				9.582 (3.044) ***	7.861 (1.667) ***	10.19 (1.867) ***	8.947 (3.264) ***	7.126 (1.761) ***	9.958 (1.902) ***
VISION				4.959 (1.325) ***	2.897 (0.679) ***	5.223 (2.474) **	5.269 (1.409) ***	2.367 (0.738) ***	4.615 (2.548) *
ORG_DES				0.848 (1.713)	1.568 (0.907) *	4.533 (2.25) **	0.874 (1.882)	1.824 (0.979) *	4.649 (2.387) *
MKT_EXP				−1.323 (4.98)	2.432 (2.63)	−0.216 (7.034)	−1.961 (5.411)	1.825 (2.864)	−1.24 (7.642)
R&D				22.81 (5.623) ***	25.13 (45.06)	16.13 (5.529) ***	21.66 (5.821) ***	18.62 (47.59)	16.00 (5.653) ***
CO_CO				19.0 (10.09)*	23.45 (13.82)*	20.97 (9.44) **	13.72 (10.62)	27.85 (14.96) *	16.63* (9.64)
BANK_LOAN				16.91 (1.578) ***	8.745 (0.377) ***	9.638 (2.736) ***	12.59 (1.758) ***	6.999 (0.424) ***	3.639 (3.087)
CRED_TREND				7.759 (1.913) ***	3.242 (0.659) ***	5.146 (3.351)	5.781 (2.067) ***	2.415 (0.719) ***	4.058 (3.464)
Obs.	5,878	8,052	3,318	5,878	8,052	3,318	5,878	8,052	3,318
Pseudo-R^2	0.180	0.234	0.100	0.425	0.318	0.295	0.469	0.372	0.327
LR chi^2	264.494	786.411	99.994	624.453	1,069.44	294.804	689.238	1,250.61	327.086
Prob > chi^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	−602.163	−1,287.83	−449.638	−422.184	−1,146.315	−352.233	−389.791	−1,055.73	−336.092

Note: The table reports the estimates of the logit regressions. The dependent variable is a dummy with value 1 if the firm is in default, zero otherwise. The table shows the coefficients and statistics used to assess their significance. Model 1 estimates firms' default running only the quantitative variables (QUANT). Model 2 estimates firms' default running the qualitative facts (QUAL). Model 3 estimates firms' default running all the explanatory variables (both QUANT and QUAL). Statistics to evaluate the goodness of fit of the regression are the likelihood ratio (LR), chi-squared, and pseudo-R^2.
*, **, and *** denote a statistical significance at the 10, 5, and 1 percent levels, respectively; the standard error is in brackets.

higher in the case of the UK and lower for Italy. This result captures an element that emerges from the level of education in SMEs. In the UK, 42% have a high level of education (degree or higher), in Germany 48%, and in Italian only 25% (EU Commission, 2017).

Business diversification (MANU_DIS) is expected to increase the value for shareholders when compared with a concentrated strategy. Its contribution to the credit risk models is significant especially for the UK. A similar result emerges with the efficiency of the company's organization (ORG_DES). According to Corbett and Rastrick (2000), "the efficiency within organizational structure may play a positive role for the success of a firm. Moreover this helps to build an organizational culture, consistent with the strategy, and the competitive environment." Our findings are consistent with the dimension "responsive administration" estimated above the EU average for the UK.

With regard to learning and growth, "the firm strategic vision underlies the focus on quality, process reengineering, constant challenge with best performers, which should lead to relevant increases in operational effectiveness" (Porter, 2001). Moreover, as argued by Miles, Snow, Meyer, and Coleman (1978), "a good management quality affects the firm culture spreading values in which employees can believe, communicating and institutionalizing them through the daily behaviour." We capture this dimension through the variable VISION which appears to be highly significant and more sensitive for SMEs, whose capability to be resilient in larger and more sophisticated markets requires a stronger strategy. The VISION variable is very significant for all countries in Model 2, and only for the UK is it slightly less relevant, reflecting the entrepreneurship dimension in the SBA review. The above-average figure in the UK shows that this variable is particularly useful for identifying the most risky companies, especially in Germany and Italy.

Albeit, according to Porter (1989), "a fundamental determinant of a firm's profitability is the attractiveness of the industry," affecting the choice to establish the firm competitive strategy (Grant, 1996), our results tend to be less useful to explain the credit risk for banking institutions lending money to microfirms and SMEs. This factor appears to be relatively low for all the EU companies and with a small variance.

With regard to the financial scorecard, we selected two variables (BANK_LOAN and CRED_TREND, respectively). In bank-oriented systems, credit availability is a signal of liquidity and soundness appreciated within both the real and the financial environment. Castelli et al. (2006) show the advantages of a stable relationship between bank and borrowers. A good relations between the firm and the banking system is fundamental for the resilience of both microfirms and SMEs , especially during critical periods.

The firm financial equilibrium regards its ability to ensure at all times an adequate financial coverage. This implies that the goods and services production process cannot be implemented unless it is financially supplied in an efficient and balanced way (Hamilton & Fox, 1998). Our variable (CRED_TREND) captures the capability to balance in- and outflows.

All these results are consistent with the evidence of the access to financial markets recorded by the SBA profile. Only the UK companies have an easier access than the average. This explains why both BANK_LOAN and CRED_TREND are significant for German and Italian companies, especially in Model 3.

As regards Table 5, we compare the contribution to explain the probability of default of the four categories of the balance scorecard. More specifically, we run four regressions classifying companies with QUANT and all the QUAL variables by scorecard category.

If we compare the four perspectives of the balance scorecard, we get results that are significantly different by country. The most accurate model for Germany is the one based on the financial perspective. For Italy, the preferred model is the internal control perspective. Finally, for the UK it is that of the customer perspective.

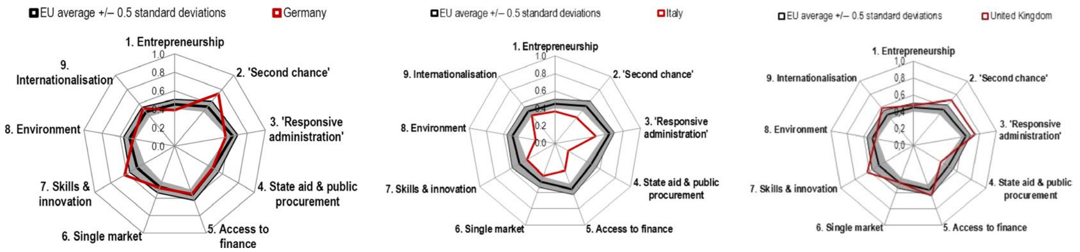

FIGURE 1 Small business facts. The figure shows the SME Performance Radar used by the European Commission to monitor and assess countries' progress in implementing the Small Business Act (SBA) on a yearly basis. The SBA focuses on key performance indicators and national policy developments related to the SBA's policy dimensions. Compared to EU average, the three plots assess the 2017 position of Germany, Italy and UK, respectively.
Source: European Commission, 2017

Since the models are oriented toward discriminating against companies on the basis of probability of default, this result not only appears relevant for operational purposes, but allows us to highlight how the most significant factors are strongly conditioned by the peculiarities of each economic and industrial system.

In particular, for Germany, the intensity that SMEs have with the banking system is decisive, even more so than Italian companies. This is explained on the one hand by the low market orientation of small firms. But in Germany, the Hausbank model strongly affects the stability of businesses: those that do not have a strong relationship with their reference bank, are more likely to be in difficulty, and do not have, like Italian entrepreneurs, the same ease to develop multi-bank relationships.

In the case of Italy, the companies that are most likely to be resilient even in the critical phase that we have analyzed are those that present the greatest efficiency in terms of organizational, production, and managerial processes. This is clearly a factor that explains the robustness of businesses better than others, in a system that rewards these dimensions compared to other countries where these variables are more common.

Finally, the British companies that best withstand the tensions of periods of crisis are those that develop the strongest characteristics of market orientation and are most sensitive to the perspective of the customer. Also in this case, a peculiarity of the national economic system emerges, which distinguishes itself from the more continental European ones by a tendency to the market. Those who are more fragile on this dimension also show a higher probability of default.

To assess the accuracy of our estimates, we also take into consideration the classification errors relating to the two sample groups for the methodologies we applied. A first-type classification error occurs when a default firm is classified as a performing firm; conversely, a second-type classification error occurs when a performing firm is classified as a firm in default.

Table 6 shows the errors of classification of some of the most relevant contributions within the literature in our field of analysis, selected in order to evaluate the use of qualitative variables in credit risk management. The papers we selected are relevant for our research because of their seminal contribution within the credit risk management literature (Altman, 1968), the use of qualitative variables along with hard facts (Altman, Sabato, & Wilson, 2008; Grunert et al., 2005; Keasey & Watson, 1987), and the analysis of a sample of Italian SMEs that is comparable with our dataset (Pederzoli & Torricelli, 2010).

To conduct this analysis, we considered as threshold the average PD for each country. Firms with a PD lower than the threshold level were classified as performing, and on the contrary, firms with a PD

TABLE 5 Logit regression – balance scorecard models

	Model 3a—customers' perspective			Model 3b—internal process perspective			Model 3c—learning and growth perspective			Model 3d—financial perspective		
Variables	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**
Constant	−3.628 (0.0705)***	−4.190 (0.107)***	−4.108 (0.142)***	−3.643 (0.0709)***	−4.924 (0.156)***	−3.905 (0.127)***	−3.671 (0.0724)***	−4.529 (0.132)***	−3.911 (0.131)***	−3.897 (0.0844)***	−4.503 (0.131)***	−3.748 (0.117)***
QUANT	18.59 (0.881)***	13.05 (0.94)***	10.44 (1.205)***	17.81 (0.885)***	12.56 (1.006)***	9.598 (1.157)***	16.81 (0.88)***	11.53 (0.937)***	9.147 (1.171)***	10.09 (0.835)***	7.657 (0.908)***	8.506 (1.195)***
MANU_DIS	11.83 (2.447)***	22.36 (7.118)***	10.21 (0.758)***									
MKT_EXP	11.62 (2.439)***	17.49 (4.261)***	13.22 (6.36)**									
PROC_FLEX				11.57 (11.48)	16.75 (1.098)***	12.43 (4.166)***						
TM_EXP				7.767 (1.64)***	10.45 (2.89)***	10.30 (1.657)***						
ORG_DES				6.741 (0.716)***	9.405 (1.402)***	9.724 (1.522)***						
VISION							6.714 (0.548)***	9.177 (0.93)***	9.591 (1.684)***			
R&D							22.65 (45.28)	33.52 (5.298)***	24.53 (5.095)***			
CO_CO							26.61 (14.59)*	23.17 (9.367)**	16.99 (8.757)*			
BANK_LOAN										7.618 (0.408)***	14.74 (1.482)***	9.237 (2.672)***
CRED_ TREND										3.570 (0.665)***	7.952 (1.6***	9.666 (2.802)***
Observations	8,052	5,878	3,318	8,052	5,878	3,318	8,052	5,878	3,318	8,052	5,878	3,318
Pseudo-R^2	0.246	0.196	0.256	0.261	0.389	0.181	0.273	0.280	0.164	0.357	0.280	0.127

(Continues)

TABLE 5 (Continued)

	Model 3a—customers' perspective			Model 3b—internal process perspective			Model 3c—learning and growth perspective			Model 3d—financial perspective		
Variables	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**	**Germany**	**Italy**	**UK**
LR chi2	827.181	287.917	255.371	878.125	570.981	180.638	918.456	411.025	163.713	1,199.807	410.882	126.858
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	−1,267.444	−590.451	−371.950	−1,241.973	−448.919	−409.316	−1,221.807	−528.897	−417.778	−1,081.132	−528.969	−436.206

Note: The table reports the estimates of Model 3, run separating qualitative variables by the BSC perspectives, that is, customers (Model 3a), business processes (Model 3b), learning and growth (Model 3c), and financial perspectives (Model 3d). The dependent variable is a dummy with value 1 if the firm is in default, zero otherwise. The table shows the coefficients and statistics used to assess their significance. Statistics to evaluate the goodness of fit of the regression are the likelihood ratio (LR), chi-squared, and pseudo-R^2.

*, **, and *** denote a statistical significance at the 10, 5, and 1 percent levels, respectively; the standard error is in brackets.

TABLE 6 Classification errors in the previous literature

Authors	Methodology	Type I error ratio	Type II error ratio	Correct classification rate
Altman (1968)	Discriminant analysis Z-score of Altman	28.00	6.00	83.00
Keasey and Watson (1987)	LG with financial ratios only, IS	23.30	23.30	76.70
	LG with non-financial information only, IS	24.70	24.70	75.30
	LG with financial ratios and non-financial information, IS	17.80	17.80	82.20
	LG with financial ratios only, OS	70.00	20.00	55.00
	LG with non-financial information only, OS	30.00	40.00	65.00
	LG with financial ratios and non-financial information, OS	20.00	50.00	65.00
Grunert et al. (2005)	Probit regression with only quantitative factors	55.81	4.25	69.97
	LR with quantitative and qualitative factors	41.86	4.25	76.95
Altman and Sabato (2007)	LG with logarithm-transformed predictors	11.76	27.92	80.16
	LG with original predictors	21.63	29.56	74.41
	LR Z-score of Altman	25.81	29.77	72.21
	MDA model with logarithm-transformed predictors	30.12	29.84	70.02
Pederzoli and Torricelli (2010)	LG model with cutoff of 0,6%	14.47	31.82	76.86
	LG model with cutoff of 1%	31.58	17.37	75.53
	LG model with cutoff of 5%	87.37	0.10	56.27
	LG model with cutoff of 10%	87.37	0.03	56.30
Altman et al. (2010)	LG model z-scores of Altman (1968) with only quantitative variables (OS)	24.00	27.00	74.50
	LG model *z*-scores of Altman (1968) with qualitative variables (OS)	24.00	25.00	75.50
	LG model *z*-scores of Altman (1968) with new quantitative variables (OS)	23.00	27.00	75.00
	LG model *z*-scores of Altman (1968) with new quantitative and qualitative variables (OS)	20.00	24.00	78.00

Note: Abbreviations: IS, in sample; LG, logit regression; LR, linear regression; OS, out of sample; PR, probit regression.
This table compares some relevant contributions to credit risk estimates, based on quantitative, qualitative, or blended databases. Some of the qualitative variables are strategic factors. The first column shows the authors and the year of publication of their work. The second column shows the statistical methods used to determine the correct classification errors specifying the type of analysis and data used (financial, non-financial, or both types). The last two columns show the type I and type II error ratios, respectively. All values are percentage.

higher than the threshold were classified as non-performing. We also report the correct classification rate (Table 7) as the average between the correct classification rate of performing firms (complementary to one of the first-type error) and the correct classification rate of default firms (complementary to one of the second-type error).

Comparing our findings (Table 7) with the selected literature (Table 6), we observe that both the type I and the type II errors of our estimates appear to prevail over the average of the outcomes of the literature which emerges from quantitative (and backward looking) variables.

TABLE 7 Error estimation

Models	Germany			Italy			UK		
	Type I error ratio	Type II error ratio	Correct classification rate	Type I error ratio	Type II error ratio	Correct classification rate	Type I error ratio	Type II error ratio	Correct classification rate
Model 1 (only QUANT)	30.0%	11.7%	79.2%	40.4%	4.8%	77.4%	49.6%	9.2%	70.6%
Model 2 (only QUAL)	15.0%	13.0%	86.0%	25.1%	11.0%	82.0%	30.4%	11.2%	79.2%
Model 3 (both QUANT and QUAL)	6.3%	19.3%	87.2%	23.9%	10.0%	83.1%	26.1%	9.9%	82.0%
Customers' perspective	32.5%	15.9%	75.8%	27.6%	10.8%	80.8%	36.5%	6.8%	78.4%
Internal process perspective	21.9%	9.7%	84.2%	28.8%	8.7%	81.3%	31.3%	13.1%	77.8%
Learning and growth perspective	23.8%	18.6%	78.8%	28.1%	8.8%	81.6%	25.2%	25.9%	74.5%
Financial perspective	22.5%	13.5%	82.0%	25.1%	8.9%	83.0%	46.1%	14.9%	69.5%

Note: This table shows the ratios of the two types of classification errors and the correct classification rate in both the sample and out-of-sample analysis. The type I error ratio is the percentage of default firms classified as performing firms by the logit model, while the type II error ratio is the percentage of performing firms classified as default firms by the model. The correct classification rate is determined as the average between the correct classification rate of performing firms (complementary to one of the first-type error ratio) and the correct classification rate of default firms (complementary to one of the second-type error ratio). The discriminating cutoff corresponds to the threshold for each country. Firms with a PD lower than the threshold level were classified as performing, and on the contrary, firms with a PD higher than the threshold were classified as non-performing.

The analysis of errors for our models (Table 7) shows more clearly that models based on qualitative variables dominate those based only on quantitative variables. This applies to all countries, in terms of both type I errors and the classification rate. It tends to worsen type II error, but typically, when estimating full models (Model 3, both QUANT and QUAL), this size also improves.

Models based on the individual perspectives of the balanced scorecard are not particularly robust in terms of errors. Although they are therefore distributed differently in terms of results aimed at estimating the credit risk of microfirms and SMEs in the three countries, a more complete vision, which takes into account all the qualitative parameters analyzed, appears to be advantageous in order to optimize the final result.

More precisely, if we consider the higher costs of type I errors compared with type II errors, the benefit of the use of qualitative facts appears to be robust enough to sustain the cost of their collection (Cornée, 2017).

Our results allow us to highlight the advantage of using models that incorporate qualitative variables (Model 2) and integrate quantitative variables with soft facts (Model 3).

We simulated a portfolio of 10,000 companies and loans to each of them for 1,000 euros/sterling. Applying the standard recovery rate provided by the Basel Committee for the IRB foundation model (50%) and assuming a spread on loans of 2%, it is possible to quantify the loss in the case of type I errors and the opportunity cost in the case of type II errors. The simulation does not take into consideration the asset correlation among firms (Gabbi & Vozzella, 2013). We find the economic impact of the different credit risk models estimated in this paper (Table 8).

Applying these assumptions to the three countries and to the results obtained with the estimated models, we find that the country with the greatest benefit is the United Kingdom, thanks to the best balance of results between the reduction of non-performing loans and the reduced effect on opportunity costs for the misclassification of performing companies.

4 | CONCLUSIONS

The implications of our findings are, firstly, that qualitative information features often generate databases that are difficult to reconcile with orthodox models based essentially on quantitative data. We introduced an innovative solution to harden the soft data, based on a credit risk indicator, such as the probability of default. This allows managers, for both non-financial and financial firms, to determine the main drivers that will enable them to calibrate the credit exposure according to a set of strategic variables that are coherent with the balanced scorecard theory.

A comparison between the three countries analyzed (Germany, Italy, and the UK) shows that the qualitative variables selected and measured, as described above, contribute decisively to classifying microfirms and SMEs for the purposes of assessing credit risk. In particular, the estimated models make it possible to make a robust estimate of the risk of insolvency for companies in different countries. A particularly original result, when compared to the most common literature and practical applications, is the contribution of soft information. This result tends to reverse the general use of qualitative variables as relatively marginal compared to quantitative and behavioral variables in credit risk management models. This result is even more relevant when considering the different "cost" related to errors of type I and II. In particular, since the cost of type I errors is the loss given default while type II errors generate an opportunity cost that can be approximated with the spread applied to loans, our results show how the use of soft variables and in particular their integration in risk

TABLE 8 Simulation for credit portfolio applying credit risk models with quantitative and qualitative variables

	Germany	Italy	UK
Default rate	2.72%	5.35%	3.47%
# non-performing firms (NPF)	272	535	347
Type I error ratio Model 1 (QUANT only)	30.0%	40.4%	49.6%
# NPF classified as performing	82	216	172
Non-performing exposure classified as performing	82,000	216,000	172,000
Loss given default (LGD) of Model 1	41,000	108,000	86,000
Lower LGD with Model 2 (QUAL only)	20,500	41,000	33,500
Lower LGD with Model 3 (QUANT + QUAL)	32,500	44,000	40,500
Type II error ratio Model 1 (QUANT only)	11.70%	4.80%	9.20%
# performing firms classified as non-performing	1,138	454	888
Potential performing exposure classified as non-performing	1,138,000	454,000	888,000
Opportunity cost with Model 1	22,760	9,080	17,760
Higher opportunity cost with Model 2 (QUAL only)	−2,540	−11,740	−3,860
Higher opportunity cost with Model 3 (QUANT + QUAL)	−14,800	−9,860	−1,360
Overall benefit using Model 2 instead of Model 1	17,960	29,260	29,640
Overall benefit using Model 3 instead of Model 1	17,700	34,140	39,140

Note: This table simulates a portfolio of 10,000 companies and loans for 1,000 euros/sterling for each country. We applied the recovery rate provided by the Basel Committee for the IRB foundation model (50%). This means that all the times the model makes an error of type I, the economic loss is 50% of the exposure. We also assume that banks get a profit on loans of 2% (approximately the spread applied to credit). The consequence is that all the times there is an error of II type, the opportunity cost is 2% of the exposure that the bank missed to provide the misclassified good borrower. Non-percentage values are in euros/pounds.

management models with quantitative variables allows a structural reduction in losses, albeit with some significant differences between countries.

These peculiarities by country modify the contributions and the statistical significance of the variables in the estimated models. In particular, each country analyzed allows us to highlight how the most resilient companies to the crisis were those that showed the greatest ability to strengthen the most critical factors in the country: the banking relationship in Germany, the internal organization in Italy, and market orientation and customer orientation in the UK. These findings confirm some of the typical managerial characteristics of companies, especially microfirms and small, in the various countries considered.

The policy implications of our research affect also the regulatory approach for banking institutions. Financial regulators, when asked to validate internal rating models (IRB) introduced by the Basel framework, should check the robustness of forecasting methodologies applied following the process we suggest—this should also drive risk managers to integrate their quantitative rating models with soft facts. The review of internal models should seriously consider our results, which could benefit both banks and firms.

Finally, within the Capital Markets Union (CMU) framework recently proposed by the European Commission, where a new kind of securitization process should be introduced following the criteria of simplicity and transparency (STS securitizations), it is expected that qualitative drivers along with the quantitative variables will be incorporated. Our paper suggests that the rating of loans traded in financial markets can be successfully calibrated and monitored.

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