Assessing the Credit Worthiness of Italian SMEs and Mini-bond Issuers

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Abstract

A number of innovations have been introduced in the last five years to counter the devastating impact of credit rationing in Europe, particularly from traditional bank lending. This is a major problem for the small and medium size firms' sector in Europe, which has also suffered from bank regulatory concerns of capital adequacy, heightened emphasis on default risk of bank counterparties and the general malfunctioning of credit extension and private sector growth. In Italy, some of these less traditional sources of funding for SMEs have started to become more popular and the development of the mini-bond market is a clear example. We believe "mini-bonds" can be a success in Italy as long as the market supplies an attractive risk/return tradeoff to investors as well as affordable and flexible financing for borrowers. Assessments of credit risk must be convincing and objective, providing complements to the traditional rating agency process. In this study, we develop a new innovative model to assess SMEs' creditworthiness and we test it on the companies that have issued mini-bonds so far. Our findings confirm that the amount of information asymmetry is still high in the market and is affecting the level of risk/return trade off potentially reducing the number of investors and small businesses that would be interested in using this new channel to fund their business growth.

JEL Classification: G21; G28

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Introduction

In the years following the last financial crisis, the credit transmission channel has been damaged as regards to the quantity, price, and distribution of credit. This is a major problem for the small and medium size firms' sector in Europe, which has also suffered from bank regulatory concerns of capital adequacy, heightened emphasis on default risk of bank counterparties and the general malfunctioning of credit extension and private sector growth. New regulatory requirements have forced banks to offload inventories of corporate and mid-market debt assets, and to scale back traditional lending for the foreseeable future. Banks are mandated to simplify their businesses and shrink balance sheets. In 2012, the International Monetary Fund estimated that European banks needed to reduce their asset base by $2.6 trillion. Being heavily reliant on traditional bank lending, small and medium-sized enterprises (SMEs), are confronted with difficult financing constraints in a deleveraging environment. This has been especially true in Italy.

A number of innovations have been introduced in the last five years to counter the devastating impact of credit rationing in Europe, particularly from traditional bank lending. For larger enterprises, especially in Northern Europe and the U.K., the high-yield, non-investment-grade bond market has grown from about €100 billion in 2010 to almost €500 billion by the end of 2015, with almost 700 different corporate issuers, of late. But, this market is only available to relatively large corporates. For smaller entities, and retail credit in particular, the internet-based "crowd-funding" market has shown considerable growth and promise, but still lacks regulatory scrutiny, size and sustainability issues persist in anticipation of continued tepid macroeconomic growth and a possible new economic downturn. In addition, non-bank market-based lending, or shadow-banking, from institutional lenders can improve the flow of credit to SMEs, but will not be sufficient, in our opinion, to provide wide participation to the varied types of SMEs across Europe.

Private debt is emerging as an important funding component for fast-growing, medium-sized companies, whose capital structure and competitive advantage have been seriously challenged by the new banking regulatory environment (Basle III) and the heightened globalization forces. Private debt comprises mezzanine and other forms of debt financing that comes mainly from institutional investors such as funds and insurance companies – but not from banks. In contrast to publicly listed corporate bonds, private debt instruments are generally illiquid and not regularly traded on organized markets. They originate in the UK and the USA, where they are an established form of funding and have long been used for financing growth and buyouts, but new initiatives are spreading across Europe.

The Emergence of Mini-bonds in Italy

To answer the call for wider credit accessibility for SMEs in Europe, a few countries have experimented with bond financing. For example, in Germany, the mechanism is called "Mittlestand-Anleihen Bonds," but its growth and impact has been mediocre, at best. In Italy, the market for SME bonds is known as "mini-bonds," and it is this market that we address in this report and suggest a critical ingredient to its eventual success.

Mini-bond is not a technical term: it is used in Italy to refer to debt securities (bonds) that can take advantage of a simplified issuing mechanism due to package of reforms in 2012[1]. The objective of the law was to facilitate access by SMEs and unlisted companies to capital markets. SMEs are defined as companies with less than 250 employees and annual turnover of no more than

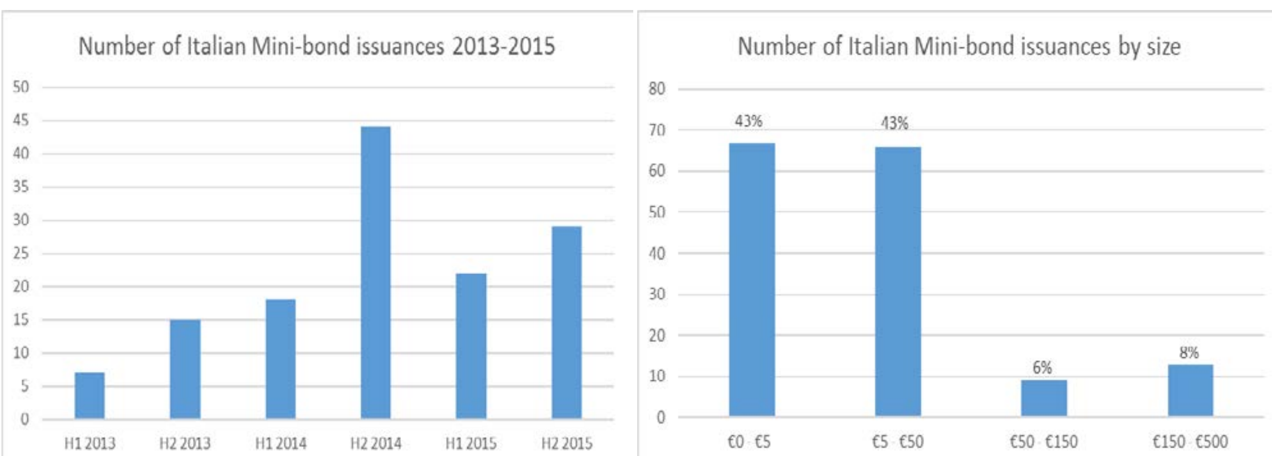
[1] Mini-bonds were introduced by Law Decree no. 83 of 22 June 2012 converted with Law 134/2012 (the so–called Decreto Sviluppo or Development Decree) as amended by Law Decree 179 of 18 October 2012 converted with Law 221/2012 (the Development Decree bis).

€50m. The corporate law reforms excluded Micro companies, i.e. businesses with less than 10 employees and annual turnover not exceeding €2m (EU recommendation 2003/361).

The new segment of the Extra-MOT market dedicated to listing of bonds, commercial paper, project finance bonds – whose trading is allowed only to professional investors – started in February 2013. The number of issuers as of the end of March 2016 is about 120 and the total amount of listed issuances since February 2013 is 160 (but only 134 mini-bonds are still outstanding) for a total issued amount of about €3.5bn. The vast majority (i.e. 86%) of the issuances has a size below €50m (see Figure 1).

Figure 1. **Italian Mini-bond market**

This graphs show the development of the Italian Mini-bond market from 2013 to 2015. Almost 90% of the issuances in these 3 years had a size less than €50m.



Source: Authors compilation of Mini-bonds listed on Borsa Italiana Extra MOT Pro platform.

Ingredients for a Successful Bond Market

Any financial market, if it will survive and provide an important function to economic growth, must provide proper incentives to issuers, investors and market intermediaries. The latter, through its underwriting, research and secondary-market trading operations, have always been crucial to financial market development. A good example is the growth of the high-yield/non-investment grade bond market in the U.S. and, of late, in Europe. The former now comprises over 2,300 firms with at least $1.6 trillion outstanding. And, as noted before, it is now about €500 billion in Europe. Can this innovation be extended to SMEs? Which is the potential size of this market?

According to a study published in late 2013 by the Cerved Group, there are approximately 35,000 Italian companies which are potentially eligible (annual turnover of between €5 and €250m) to issue Mini-bonds, mainly concentrated in the Northern part of the country. In Lombardy alone, out of a total of 15,308 companies, 11,187 (73.1%) would be eligible to issue mini-bonds.

We believe "Mini-bonds" can be a success in Italy as long as the market supplies an attractive risk/return tradeoff to investors as well as affordable and flexible financing for borrowers. As for the risk dimensions, the usual categories apply, namely, market, liquidity and credit risk. All bonds face these risks, but it is credit risk that is most critical for relatively unknown, smaller enterprises. Assessments of credit risk must be convincing and objective, providing complements to the traditional rating agency process. Indeed, the latter may not be available in many cases. It must be made absolutely clear to investors that defaults will occur over time and the loss from such events must be rigorously measured and then compared to the promised yields on firms and portfolios to determine their attractiveness.

The Z_I-Score SME Model[2]

To achieve the required risk assessment transparency, we suggest strongly that models be introduced and tested, built specifically to estimate default risk on Italian SMEs. Since the Min-bond market is very new, there does not yet exist data to include recovery rates on defaults nor any long-term market default rate statistics. We suggest, therefore, to concentrate on individual issuer

[2] These models were constructed by the authors in collaboration with the firm Classis Capital, SIM, S.p.A.

default probabilities, an area we have had considerable experience in and now focus upon for Italian SMEs (see Altman and Sabato (2005, 2007) and Altman et al. (2010)).

Model development

The main idea is compare the financial profiles of Italian SMEs, which have either defaulted or not in the past, in order to build a multivariate model for predicting the probability of default of those firms who have already, or could potentially, tap the mini-bond market for debt financing. The model(s) also can indicate the relative health of firms within specific sectors.

Based on a database extracted from AIDA, we assessed 15,452 active and 1,000 non-active Italian SMEs.[3] After cleansing this data, approximately 13% (2,032 companies) were not included due to missing information. The final sample included financial data on 14,420 Italian SMEs over the period 2004-2013 (see Figure 2).

Figure 2. **Development sample**

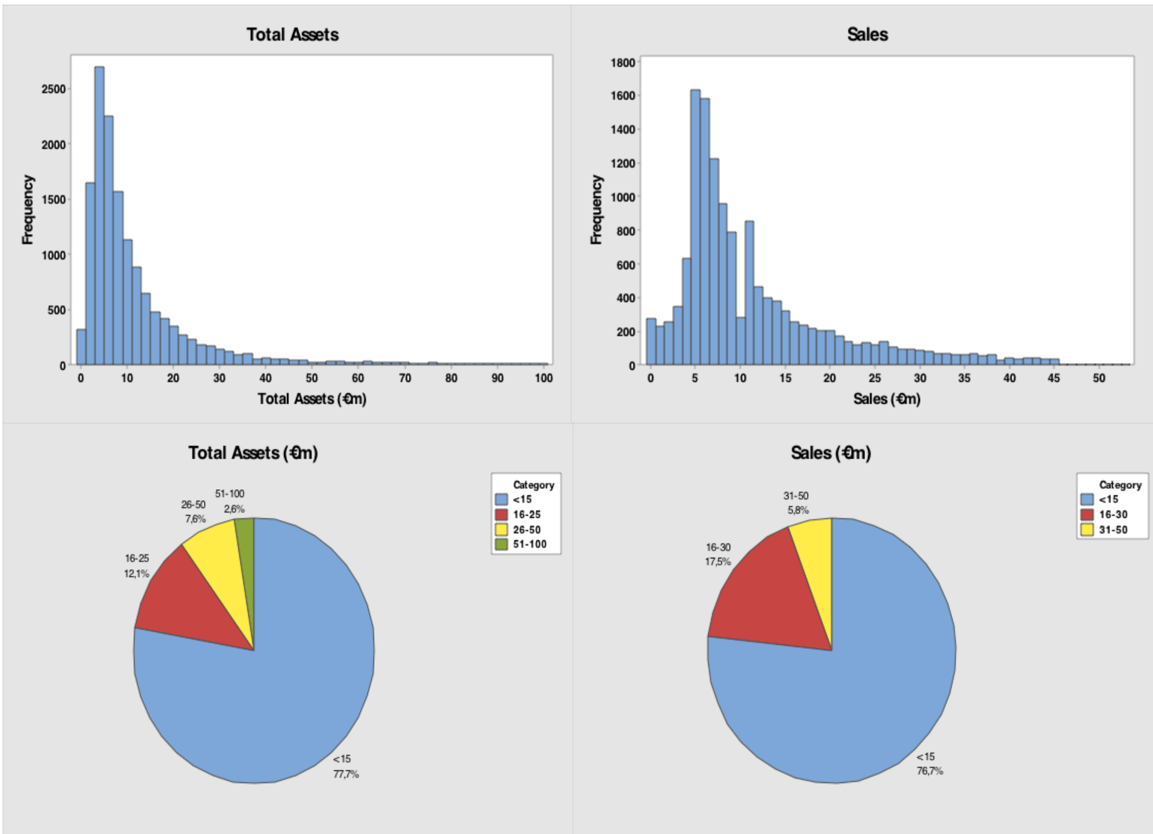
This table shows the structure of the Italian SME development sample. In the first and second row, the number and the percentage of non-defaulted and defaulted firms are shown.

	Number	Percentage
Non-defaulted firms	13,990	96.3%
Defaulted firms	520	3.7%
Total	14,510	100%

[3] AIDA is a database owned by Bureau Van Dijk and contains comprehensive information on companies in Italy, with up to ten years of history.

***Figure 3.* Distribution of total assets and sales in the Italian SME sample**

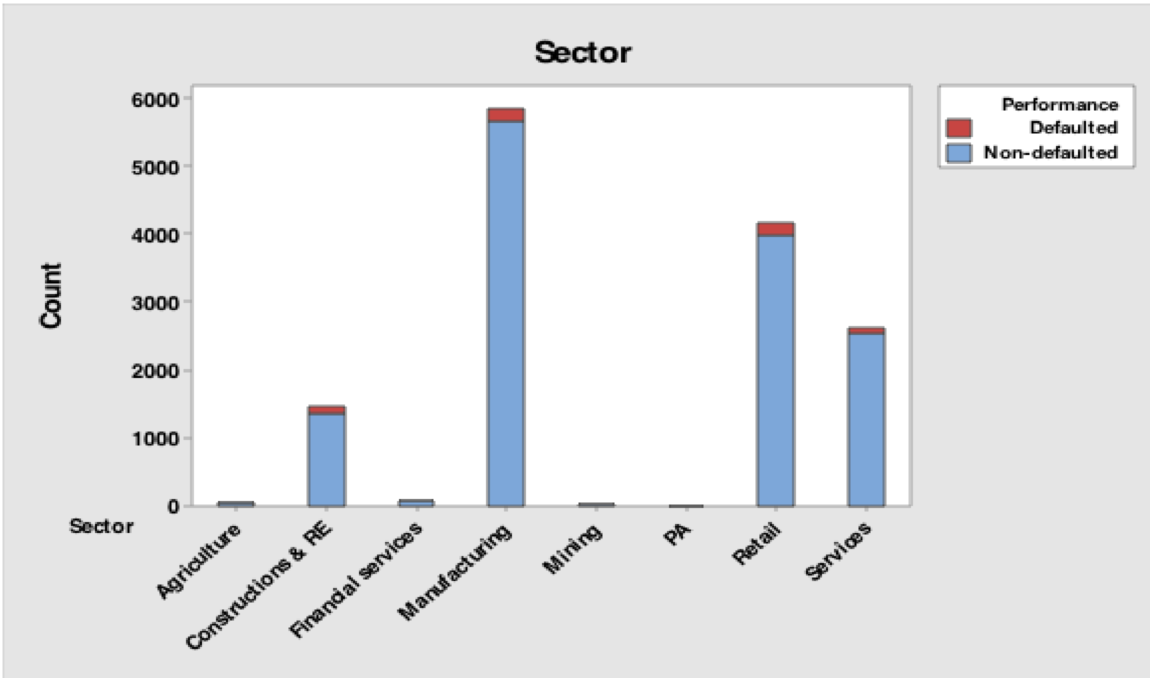
This figure shows the distribution of total assets and sales for the Italian SMEs included in our sample. More than 75% of the companies have total assets and sales less than €15m. This reflects the shape of the Italian SMEs that tend to be relatively smaller in size than the European average.



The breakdown by solvency status and size of Total Assets and Sales is given in Figure 3. Note that most firms had Total Assets between €1-30 million and Sales between €5-45 million. The number of employees ranges essentially between 5-150 and the business sectors are primarily in the (1) Manufacturing, (2) Retail, (3) Services, and (4) Construction and Real Estate groupings. The breakdown of defaults and non-defaults by Sector is given in Figure 4.

Figure 4. **Breakdown of defaulted and non-defaulted by sector of SME**

This graph shows the number of defaulted and non-defaulted companies for each of the available sector clusters.



Variable Selection

The next step in the model building process is to identify a number of variables that could be helpful indicators of firm credit worthiness. Consistent with a large number of studies, we choose five accounting ratio categories describing the main operating and financial aspects of a company's profile. As shown in Figure 5, these include measures of liquidity, profitability, leverage, coverage and activity. In some cases, statistical transformations are performed, such as logarithms, to enhance the predictive power and robustness of the individual variables and to reduce the impact of outliers.

Figure 5. **Original financial variables**

This table shows what variables have been used to calculate the ratios and indexes that have entered the final models.

Accounting Ratio Category	Selected Variables
Leverage	Short Term Debt/Equity (Book Value)
	Equity (Book Value)/Total Assets
	Short Term Debt/Total debt
	Short term debt/Total Assets
	Debt/EBITDA
	Net Debt/EBITDA
	Change in Short term debt in Last 2Y
	Total debt/Total Assets
Liquidity	Cash/Total Assets
	Current ratio
	Quick ratio
	Working Capital/Total Assets
	Tangible/Total assets
	Intangible/Total Assets
Profitability	Ebitda/Total Assets
	Net Income/Total Assets
	Return on Equity
	Retained Earnings/Total Assets
	Net Income/Sales
Coverage	Interest expenses/Sales
	Ebitda/Interest Expenses
	Ebit/Interest expenses
Activity	Sales/Total Assets
	Account Payable/Sales
	Account Receivable/Liabilities

Experience over the years by researchers in choosing appropriate variables has provided important guidance and has resulted in reduced outliers and more robust estimates. Next, we apply a statistical forward stepwise selection procedure to construct models for each of the four sectors, previously identified. The final choice of variables is determined by:

(1) Their individual statistical discrimination between the default and non-default groups.

(2) Their covariance with each other; we eliminate some variables which provide similar information to those already selected.

(3) Their accuracy levels on a multivariate basis, both in the original and test samples.

Model results

We utilize a logistic regression technique, whereby a forward step-wise variable selection method determined the final variable-set for each of the four sector models. The resulting models included a range of 6 to 8 variables, each subject to several transformations to enhance their predictive power. Each model was built on an original sample of 80% of the total sample, with holdout (secondary) samples for our test results on 20% of each of the defaulted and non-defaulted SME groups.

Based on data from one financial statement prior to default, we assess the Type I and Type II error rates for each major sector. The Type I error (Column 1 in Figure 6) measures the percentage of defaulted firms that are classified as non-default and the Type II error (Column 2) measures those firms classified as default but which did not default. The resulting overall Accuracy Rate (Column 3) is simply 1-Average Error Rate for the entire sample. Note that these results are based on both the original sample of defaulted and non-defaulted firms and just below, in parentheses, the "Holdout Samples" of firms not used to build the model but used to "test" the accuracy of the models on unbiased samples.

***Figure 6*. Accuracy tests of the four sectors for the SME default models**

This table shows the misclassification rates and the accuracy ratios of the four different models. The first column shows the type I error rate, i.e. the percentage of defaulted firms classified as non-defaulted. In the second column, the type II error rate is illustrated. This rate represents the percentage of non-defaulted firms classified as defaulted. The third column shows the average accuracy of the model, calculated as 1 minus the average of the two error rates. In the last column, the accuracy ratio, defined as the ratio of the area between the cumulative accuracy profile (CAP) of the scoring model being validated and the CAP of the random model, and the area between the CAP of the perfect model and the CAP of the random model, is shown. The values in the brackets result from the application of the different models on the hold-out sample.

	Type I error rate	Type II error rate	1- Average Error Rate	Accuracy ratio
Manufacturing Model	6.92% (8.23%)	26.57% (27.64%)	83.26% (82.07%)	93.08% (92.21%)
Retail Model	16.77% (18.54%)	27.78% (28.89%)	77.73% (76.29%)	83.23% (81.76%)
Services Model	12.05% (14.88%)	24.54% (26.43%)	81.70% (79.35%)	87.94% (84.12%)
Constructions and Real Estate	8.89% (10.12%)	26.02% (28.24%)	82.55% (80.82%)	91.11% (89.86%)

In addition, we list the Accuracy Ratio, which is defined in Figure 6. Note that the more critical Type I error ranged from as low as 6.92% (8.23% holdout test) for the manufacturing sector (our most important sector in terms of number of firms [see Figure 4]), to a higher error, but still impressive 16.77% (18.54% holdout) for the retail sector. The latter was the only sector with a lower than 80% overall accuracy *rate* but still had an acceptable accuracy *ratio* of over 80%. In general terms, our accuracy results were quite satisfactory in terms of predicting whether a firm was likely to default or not within one year.

Bond Rating Equivalents and Probabilities of Default

While it is useful to assess the accuracy ratio of a Default-Non-Default statistical model, the bi-variate result does not indicate the probability of and the expected timing of the default. These dimensions are critical for investors in terms of assessing the investment risk/return tradeoff and also are extremely helpful in providing an important metric for the relative health of firms across sectors and over time.

In order to provide additional measures of credit worthiness, we introduce the concept of Bond Rating Equivalents (BRE) and Probabilities of Default (PD). Our benchmarks for determining these two critical variables are comparisons to the financial profiles of thousands of companies rated by one of the major international rating agencies (Standard & Poor's) and the incidence of default given a certain bond rating when the bond was first issued. The latter is based on E. Altman's Mortality Rate Approach (Altman, *Journal of Finance*, 1989). The actual process is a three-step approach:

1. Build a credible and accurate credit scoring model.
2. Assign BREs to each firm based on its proximity to the Average Scores of the relevant bond ratings of constituent firms, as assigned by S&P (for each of the four sector models).
3. For mini-bonds issued in the last two years, utilize the most recent updated marginal and cumulative Mortality Rate Matrix (Figure 7) of actual Default Frequencies given the history of new issue defaults by original bond rating over the extended period 1971-2015.[4] For more seasoned issues, use the standard cumulative default rate matrices from the rating agencies.

Each firm's logistic credit score is first compared with the various average scores by S&P Bond Rating (based on the most recent annual data compilations). The resulting BRE is then assigned to the firm and referenced to the Default Probability Table found in Figure 7. As such, we can assign a one-year, two-year, three-year, etc. PD for each firm. Examples of the one-year and three-year PDs assigned to each BRE is given later in Figure 8.

[4] The latest Annual update can be found in E. Altman and B. Kuehne's "Default and Returns in the High-Yield Bond and Distressed Debt Market: The Year 2015 in Review and Outlook," NYU Salomon Center, February 10, 2016.

Figure 7. **Mortality Rates by Original Rating**

All Rated Corporate Bonds*

1971-2015

Years after Issuance

		1	2	3	4	5	6	7	8	9	10
AAA	Marginal	0.00%	0.00%	0.00%	0.00%	0.01%	0.02%	0.01%	0.00%	0.00%	0.00%
	Cumulative	0.00%	0.00%	0.00%	0.00%	0.01%	0.03%	0.04%	0.04%	0.04%	0.04%
AA	Marginal	0.00%	0.00%	0.21%	0.07%	0.02%	0.01%	0.01%	0.01%	0.02%	0.01%
	Cumulative	0.00%	0.00%	0.21%	0.28%	0.30%	0.31%	0.32%	0.33%	0.35%	0.36%
A	Marginal	0.01%	0.03%	0.12%	0.13%	0.10%	0.06%	0.02%	0.25%	0.08%	0.05%
	Cumulative	0.01%	0.04%	0.16%	0.29%	0.39%	0.45%	0.47%	0.72%	0.80%	0.85%
BBB	Marginal	0.33%	2.36%	1.26%	1.00%	0.50%	0.22%	0.26%	0.15%	0.15%	0.34%
	Cumulative	0.33%	2.68%	3.91%	4.87%	5.34%	5.55%	5.80%	5.94%	6.08%	6.40%
BB	Marginal	0.94%	2.02%	3.88%	1.97%	2.34%	1.51%	1.45%	1.12%	1.43%	3.13%
	Cumulative	0.94%	2.94%	6.71%	8.54%	10.68%	12.03%	13.31%	14.28%	15.51%	18.15%
B	Marginal	2.85%	7.72%	7.85%	7.80%	5.70%	4.48%	3.58%	2.08%	1.76%	0.77%
	Cumulative	2.85%	10.35%	17.39%	23.83%	28.17%	31.39%	33.85%	35.22%	36.36%	36.85%
CCC	Marginal	8.13%	12.43%	17.89%	16.32%	4.85%	11.65%	5.44%	4.84%	0.66%	4.28%
	Cumulative	8.13%	19.55%	33.94%	44.72%	47.40%	53.53%	56.06%	58.19%	58.46%	60.24%

*Rated by S&P at Issuance

Based on 2,903 issues

Source: Standard & Poor's (New York) and Author's Compilation

Assessing the SME Z_I-Score Model on Italian Mini-bond Issuers

We assessed the credit worthiness on a sample of 102 Italian mini-bond issuers that have issued mini-bonds in the last three years. Only a few companies (5) could not be analyzed due to lack of sufficient financial data. The size of the Mini-bond issuers' sample, registered and traded in the secondary market by **Borsa Italiana**, were slightly larger than the SME population that we used to construct the four sectors' credit scoring models. We therefore felt it appropriate to assess this mini-bond sample using our SME-derived models. We expect that an objective and rigorously determined model will be extremely helpful to investors and issuers and help promote secondary trading after issuance.

We now can observe the various metrics of mini-bond issuer credit worthiness. We apply the latest financial data available on 98 issuers and assess each firms' BRE and its associated one-year and three-year probability of default from Figure 8. We can observe the BRE distribution and their current yield, as given in Figure 9. It is not surprising, indeed expected, that the majority (almost 70%) of mini-bond issuers have non-investment grade financial profiles. This is to be expected amongst a list of SME, privately-held issuers. As such, over time, we can expect some defaults from this population, which is perfectly normal as long as it is consistent with expected returns. Comparisons between Italian mini-bond issuers and large corporate bond issuers in the United States is likely to find (as we did) a majority of SME issuers to be non-investment grade, or high-yield.

Figure 8. **One- and Three-Year PDs from Mortality Rate Table (Figure 6)**

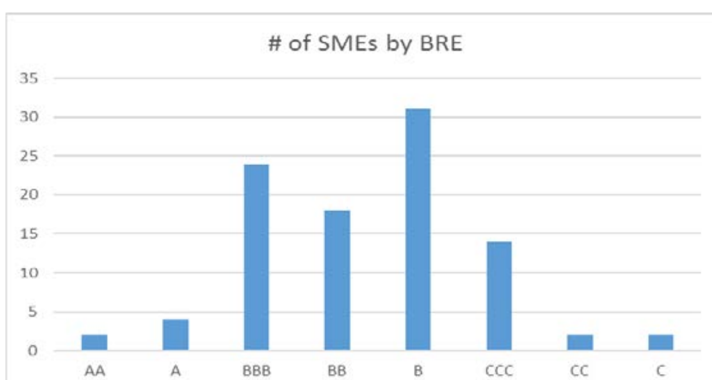
BRE	One-Year	Three-Year
AA	0.01%	0.10%
A	0.11%	0.16%
BBB	0.33%	3.91%
BB	0.94%	6.71%
B	2.85%	17.39%
CCC	8.13%	34.0%
CC	20.0%	50.0%
C	50.0%	70.0%

Source: E. Altman and B. Kuehne, 2016

Note also from Figure 9 that there does not appear to be any relationship between our models' credit risk assessment and the current yield to maturity of the mini-bond sample. This implies some market inefficiencies if our credit assessment is at all accurate and credible. We expect that greater transparency in risk assessment will enhance the market's appropriate risk-return tradeoff results.

Figure 9. **Results of the Z_I-Score SME Model on companies that have issued a mini-bond**

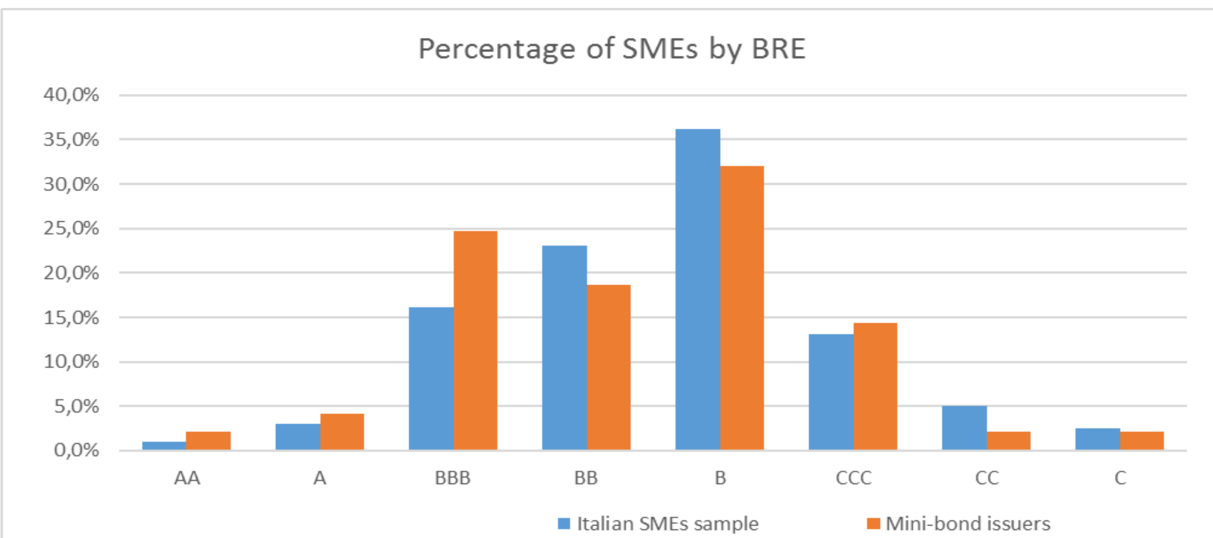
Bond Rating Equivalent	#SMEs	%SMEs	Avg. yield
AA	2	2%	0,057
A	4	4%	0,062
BBB	24	25%	0,065
BB	18	19%	0,055
B	31	32%	0,059
CCC	14	14%	0,065
CC	2	2%	0,03
C	2	2%	0,06



Source: Authors compilation of Mini-bonds listed on Borsa Italiana Extra MOT Pro platform.

Last, we look at the quality of the companies that have issued mini-bonds and compare it to the quality of the SMEs included in our development sample. Results show that the average quality of the mini-bond issuers is better than the one of the Italian SMEs included in our sample as we find a higher percentage of companies that have issued mini-bonds in the higher BRE bands (see Figure 10). Due to the relatively small size of the mini-bond sample compared to our development sample, we also assess whether the differences that we find are statistically significant. Our findings, reported in Figure 11, confirm the significance of our results for the BRE bands with the highest SMEs population (BBB, BB and B).

***Figure 10*. Comparison of distributions by BRE between companies that have issued a mini-bond and companies included in the Italian SME development sample.**



Source: Authors compilation of Mini-bonds listed on Borsa Italiana Extra MOT Pro platform and development sample

Figure 11. Difference in means test to assess the statistical significance of the differences in the two distributions.

	Mini-bond sample			Italian SMEs sample				
BRE	**#**	**MEAN1**	**ST DEV1**	**#**	**MEAN2**	**ST DEV2**	**p value**	**Significance**
AA	2	1403	564,89	149	1323	244,52	0,8409	
A	4	795	104,46	448	694	81,89	0,0539	*
BBB	24	515	97,14	2389	456	63,38	0,0032	***
BB	18	387	48,58	3434	427	51,92	0,0005	***
B	31	329	43,38	5376	352	47,14	0,0033	***
CCC	14	239	29,61	1941	255	23,76	0,044	**
CC	2	198	12,04	747	187	15,54	0,2128	
C	2	175	18,89	373	159	10,29	0,2229	

Conclusions

The SME Z_I-Score model is a powerful tool that provides an assessment of a company's risk profile based on the last two years of financial information. Based on four separate models, each specifically developed for a major industrial sector category, the family of Z_I-Score models successfully classified and predicted default or non-default on large samples of Italian SMEs. Utilizing creative transformations of standard financial ratio metrics and combining them with powerful statistical techniques, accuracy levels of at least 80% were achieved and these results were robust across the major business risk sectors, over the last decade.

The results from our models can be used to understand a company's creditworthiness relative to others in their grouping. While our method is not a traditional bond rating, international language of credit metrics is utilized. That is, a firm's Bond Rating Equivalent (BRE) and international default rate incidence for entities that have issued bonds are calibrated as to the expected default frequency for one year and three years after issuance. The results can also be generalized for any issuer, regardless of when its bonds were issued. The models' resulting analysis were applied to a meaningful sample of existing Mini-bonds in Italy that are listed on the

Borsa Italiana, in the hope that the added transparency of issuer credit risk profiles will enhance trading of the bonds in secondary markets, increase their liquidity and add to market efficiencies.

Other applications of the models are to risk-rank a portfolio of homogeneous companies in terms of their size and location, but different in their credit risk. Portfolio management of fixed income securities is difficult for any size firm, especially in the debt securities area, but when you add the small-firm dimension, most analysts need whatever rigorous tools are available to enhance their selection procedure. Finally, risk-profiles that are objective, even if highly negative for the firm being assessed, can be useful as well to the firm itself, and its management, for purposes of analyzing debt capacity, cash flow strength, growth possibilities and, yes, even to be used as a tool for financial sustainability and turnaround management.

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