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Probability of Corporate Bankruptcy over Two Periods of Crisis (2007-2010 vs 2019-2022): Application to Italian Manufacturing SMEs Using a Three Years Rating Model

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Abstract

Predicting corporate insolvencies over the last three years is more complex than in the past. An empirical analysis of a sample of 2,823 SMEs operating in Northern Italy in the manufacturing sector, shows that the logistic function created to discriminate the firms that became insolvent after three years, has a lower level of accuracy when it's built over the last period of crisis (2019-2022). The companies that entered into default status in 2022, therefore, had, three years earlier, a greater volatility of the averages of financial ratios such as to induce greater misclassifications in a hypothetical statistical forecasting model. The study compares the global financial crisis during years between 2008-2012, which had the highest peak of insolvency in 2010/2011, with the current global crisis that began with the COVID19 pandemic and has continued with the war in Ukraine and related problem of price increases. The analysis aims to detect the differences between firms of 2019 that became insolvent in 2022 compared to a previous crisis period (2007-2010).

Keywords: manufacturing SMEs, bankruptcy prediction, rating model, model accuracy, Covid19 crisis

1. Introduction

During the 2008-2009 period the productivity of Italian companies decreased. At the same time net incomes were declined against the financial requirement that increased first, and over-indebtedness subsequently. These same dynamics can be read in the financial statements of firms during the following years: 2020, 2021 and 2022. There may be important similarities in the economic and monetary aspects of the 2008 financial crisis and the current global crisis, which began with the Covid-19 pandemic and continued with the effects on the prices of raw materials due to the outbreak of the war in Ukraine and the consequent inflationary pressures. The most obvious differences, however, are precisely in the causes and recovery times. The crisis of 2007-2008, born from internal and purely financial reasons, slowed down the world economy and presumably spread over a longer period than the current crisis, which was caused by external factors. Due to this different starting point, ECB Economists and local politicians, with the support of Istat investigations and empirical research, predict a more rapid recovery but only if, and when, the circulation of the virus is less intense and there are no other relevant causes, such as the energy crisis or the high inflation developed from the end of 2021 to today.

Among the major differences, again, between the two world crises, it is necessary to specify that the first, which began as early as the second half of 2007, was a financial liquidity crisis that affected all the banks influencing the offer of bank loans. The recession hit practically the whole world with effects that lasted until 2012. In this period, to avoid a systemic crisis, several international banks were saved worsening the public debt of several countries and generating a vicious circle that was difficult to reverse, especially in the short time. The current crisis, however, was fought immediately by injecting new liquidity, from banks and governments, before there was the need or urgency to remedy the lack of financial availability.

There is a persistent effort to use a rating model developed for firms in different economies or time, even if it is well known that the assumptions operated for fitting the initial models are undoubtedly not effective anymore. So, the purpose of this study starts from these premises: apply the insolvency forecasting model built in the period 2007-2010 to the firms of 2019, in order to ascertain whether the characteristics of insolvent companies have remained similar and whether it is still possible to use a single forecasting model. The objective to develop two forecasting models, using 64 financial ratios on two balanced samples of 2,823 companies (including 200 firms that became insolvent after three years), is replicated for the sample of firms of 2007 and 2019.

This study aims to answer the following questions:

- Have the characteristics of insolvent companies changed over time?
- Is it possible to identify the insolvent firms three years before default during the last crisis period?
- What is changed in firms when comparing two crisis periods? Are all crises the same?
- Is it possible to use just a single model to forecast firms that will become insolvent over time?

The secondary purpose, however instrumental to demonstrate the main objective, is the detection of firms that did not record the past-due (insolvency) during the pandemic period, and to identify their specific peculiarities, despite they have similar characteristics to the companies that statistically experienced the default in previous periods. In this sense, also the opposite hypothesis opens up: the counterparties that have unexpectedly become insolvent, are not only companies with different characteristics, but there is also the possible reverse phenomenon. These firms, potentially high-risk companies, go through unscathed the current situation of crisis.

The paper is structured in six chapters. The paragraph following the introduction presents a quick review of recent studies on the effects of the current global crisis on the solvency of firms. The third paragraph describes the hypotheses of the work, the sample, the data and the variables used. After a description of the methodology adopted, the fifth paragraph illustrates the results of the empirical analysis, while the final paragraph contains some conclusive considerations.

2. Literature Review

It is now generally accepted that the economic and financial crisis caused by the Covid-19 pandemic, and its results, is different from the past crises. In recent years, many researchers have explored these dissimilarities, focusing primarily on the changed role of government authorities.

Some statistical studies have focused on the importance of public involvement, as a mitigation of the major consequences of the crisis, alternatively demonstrating the number of companies that would have failed (Gourinchas et al. 2022) or, on the contrary, the firms that merely delayed the emergency situation. (Dorr et al. 2022). Iyer and Simkins (2022) examined the specific economic impacts induced by the pandemic and, more generally, by the Covid-19 crisis, demonstrating the fundamental role of governments in mitigating the harmful consequences. Ferreiro and Serrano (2021) deepened the analysis by comparing economies in recession before and after the implementation of government policies while Hale et al. (2020) and Haroutunian et al. (2021) described the effects of monetary policies undertaken by international authorities.

The Italian Government's initiatives, aimed at protecting company liquidity through temporary moratoriums on financial amortizations, loan extensions or new loans with Public Guarantees (Gonzalez-Uribe & Wang, 2021), have undoubtedly proven to be very effective, especially in the short term (Core & De Marco, 2021). On the other hand, we still don't have a perfect idea of the long-term implications for firms or, more generally, for the Italian business context, leading us to assume that there will be a tailwind of greater insolvencies over time.

The extraordinary injection of liquidity directly to firms, replacing the financial flows deriving from ordinary commercial activity, leads to a general increase in indebtedness not balanced by company productivity (Zhang et al. 2020) and, moreover, generates phenomena defined as moral hazard (Döerr et al. 2021). For this reason, several authors expected, once government aid ended, a notable increase in the number of bankruptcies, especially among already weak and more vulnerable firms (less capitalized), due to a strong deterioration in the profitability-risk-growth parameter and due to further liquidity crisis phenomena linked to the excessive contraction of net worth compared to debt (Gourinchas et al., 2020). Smaller companies with a high share of bank debt are, in this sense, among the counterparties identified as riskier.

Given the importance of SMEs in Europe, both in terms of number and contribution to employment and general added value, much attention has been paid to studying the risk of insolvency of SME counterparties, from multiple fronts and with various perspectives and insights. Furthermore, SMEs have been particularly damaged by the pandemic condition and, consequently, most of the studies have focused on this type of company, including readjustments of forecasting models built on other firm targets.

The US line of studies, which empirically verified the effects on American businesses resulting from the first impacts of Covid crisis, was also numerically significant. Blom et al. (2021) record and explain these findings which describe very different implications in consideration of the actual activity carried out by the company and in reflection of the average size of the firm. The resulting econometric analyses, often performed through large surveys, are associated with a literature about the impacts of Covid even beyond American borders (Bartik et al.

2020; Papaniklaou & Schmidt, 2020; Buffington et al., 2020).

As for Italy, strongly affected by the pandemic crisis (Falavigna & Ippoliti, 2022) and by the economic effects of the long lockdown, Erdem (2020) describes the significance of government judgements to help firms overcome this extraordinary situation and Buchetti et al. (2022) delve into the specific effectiveness of national initiatives, especially on the profitability and growth of Italian companies. The academic attention towards Italy, confirmed by a long series of essays, derives from the fact that, Italian firms were probably the companies most in difficulty in 2020 (Ding et al., 2021), and the Italian Government was the first to move with a system of state subsidies and contributions to businesses, resulting in an artificial economic context tainted by multiple phenomena at the same time. In this regard, Affinito and Meucci analyze the historical period of companies through the statistics relating to the "returns to performing" of the counterparties already defined as UTP (*Unlikely to Pay*). In addition, there were several periodic reports and individual publications of the Bank of Italy to uphold the literature about this specific topic.

The latest literature on the topic is already inclusive of different aspects and insights offering a variety of perspectives. Academics have tried to find various approaches to estimate the risk of bankruptcy and the issues affecting firms (Fairlie & Fossen, 2021; Didier et al., 2021; Santos et al., 2021). In this regard Hu and Zhang (2020) analyzed the effects on the intrinsic value of companies in this specific crisis period. The negative repercussions on firms can be read by the estimates of the values of company assets, in the case of quantification of the enterprise value, and by the increase in the cost of equity capital, following the spiraling in the common uncertainty (Bankowska et al., 2020). The implications that involve the share prices of listed companies were evident in the sudden decline in the first months of 2020. These prices then regained after the earliest supplies of the vaccine (Neukirchen et al., 2021).

Still on the aspects about the share prices, empirical analyses (Shen et al., 2020) have shown the evident illiquidity of listed companies in the Covid period with peaks constrained to a short time (Ramelli & Wagner, 2020).

The aspects connected to uncertainties about the near future are also perceived in the volumes of productive investments preparatory to growth, on fewer corporate innovations (Chen & Ximing, 2020) and on the post-crisis entrepreneurial choices in internal organizational changes to mitigate the probability of insolvency (Cucculelli & Peruzzi, 2020).

Finally, the extensive literature on the causes and, above all, on the effects of the crisis triggered by the Covid pandemic supports the thesis that the historical period 2019-2022 is characterized by exceptional and new events. These properties are capable of significantly modifying the global economic dynamics. The firms, in this period, advance in a different context compared to the past and, presumably, to the near future and they are sharply conditioned. In a different macroeconomic scenario, with direct influences on businesses, it is logical to expect repercussions on corporate risk, especially in terms of new and different dynamics that lead to corporate default. As above-mentioned, in addition to the alterations in economic environ, in this period there are many explicit aspects that increase the bankruptcies.

Several authors point out an unbroken interest and concern for suggesting models to forecast the risk of bankruptcy. These bankruptcy expectation models purpose additional explanatory variables and statistical procedures and may supply expensive statistics concerning the financial performance of the firms and their consequences.

The copious literature on the subject suggests that financial ratio analysis is a useful method for predicting business bankruptcy. Nevertheless, the fact that the impact of indicators has changed from study to study has stimulated the use of a variety of methods for modeling business failures. The different techniques have contemplated both univariate and multivariate analysis methods. To best distinguish between failed and healthy firms, several authors demonstrated that a discriminant function could be more suitable as it counts connections among variables.

In addition, in this period it is crucial to adapt these models to the specificity of time. The primary difficulty of the bankruptcy prediction models is that these archetypes cannot be generalized because these were elaborated employing a specific sample of firms related to a specific time and region. The main literature about this topic is oriented towards defining the predictive power of a default prediction model strongly correlated with homogeneity of the sample used. The rating models can be really very different in consideration of territories, sector of activity, firms' ages, dimensions or time period.

The determination of this analysis is to forecast the bankruptcy of private companies by the techniques and variables that are conventionally used by banks to predict corporate's loans event (or to predict the specific default risk of counterparty). In this regard, therefore, the logistic regression technique was used to select the firms in consideration of the individual balance sheet indices in accordance with the standard approaches of the banks.

3. Description of the analysis

3.1 Objective

The focus of the analysis is centred on identifying the financial and economic paradigm capable of ordering companies by probability of insolvency after three years and, consequently, verifying whether a single mathematical model can be used to differentiate from a homogeneous sample (whole sample) the firms that will become insolvent over time (bad firms) from the firms that will remain healthy (good firms). In this way, the final purpose is to identify the differences between firms that defaulted in the pandemic period (2022), due to causes linked to sales shocks or the sudden increase in raw material and energy prices, and firms that have become insolvent in previous periods. More specifically, the comparison will focus on two periods of crisis expressed over a three-year period: 2007-2010 and 2019-2022.

The analysis is purely objective and was based exclusively on the analysis of the financial statements of the firms. Firms that have been reported by the Central Credit Register of the Bank of Italy as distressed and past-due, with an existence of credit overdue for more than three months, are defined as "bad firms" referring to a standardised definition formulated by the Basel Committee.

3.2 Data

The companies analyzed are small and medium sized enterprises (Note 1) with total revenues between 5 and 50 million euros, on the yearly statements under examination, operating in Central-Northern Italy for at least 5 years. Only the manufacturing firms are strictly included in the analysis). The firms with operational headquarters in Lazio and Abruzzo are excluded in order to give greater homogeneity to the samples used. The geographical characteristics of the two analysis samples are summarized in Table 1.

Table 1. Characteristics of the sample used in the research

Region of Italy	**Firms of 2007**				**Firms of 2019**			
	Whole sample		Bad firms		Whole sample		Bad firms	
Valle d'Aosta	5	0.18%	0	0.00%	2	0.07%	0	0.00%
Piemonte	277	9.81%	24	12.00%	245	8.68%	10	5.00%
Liguria	32	1.13%	6	3.00%	37	1.31%	3	1.50%
Lombardia	964	34.15%	56	28.00%	1122	39.74%	94	47.00%
Veneto	601	21.29%	35	17.50%	498	17.64%	18	9.00%
Trentino-Alto Adige	46	1.63%	0	0.00%	29	1.03%	3	1.50%
Friuli-Venezia Giulia	88	3.12%	6	3.00%	69	2.44%	4	2.00%
Emilia-Romagna	476	16.86%	39	19.50%	480	17.00%	30	15.00%
Toscana	247	8.75%	20	10.00%	260	9.21%	28	14.00%
Marche	37	1.31%	7	3.50%	41	1.45%	4	2.00%
Umbria	50	1.77%	7	3.50%	40	1.42%	6	3.00%
	2,823		**200**		**2,823**		**200**	
Geographic Area	**Firms of 2007**				**Firms of 2019**			
	Whole sample		Bad firms		Whole sample		Bad firms	
North West	1,278	45.27%	86	43.00%	1,406	49.81%	107	53.50%
North East	1,211	42.90%	80	40.00%	1,076	38.12%	55	27.50%
Center	334	11.83%	34	17.00%	341	12.08%	38	19.00%
	2,823		**200**		**2,823**		**200**	

The study extends the time frame period to three years following the analysis of the financial statements. Unlike the most common and regulatory statistical rating models (one-year rating model), this assessment is oriented towards being more forward looking by calculating the probability of default in three years. The consequence of this choice can be seen in lower accuracy of the results and, on the other hand, in greater utility (Note 2).

The financial statements analyzed are those relating to the year 2007 for the sample A, concerning to the period of the financial crisis, and year 2019 for the sample B, relating conversely to the current crisis that began with the Covid-19 pandemic. All firms that have not become insolvent until 2010 or 2022 are considered "good firms". On the other hand, firms that defaulted in 2010 or 2022 are defined as "bad firms". With this approach, the analysis horizon was set at exactly three consecutive years following the collection of the budget indicators and the financial ratios. The definition of "default" is narrower than the one largely applied in bank rating models, as these consider default to be the commencement of serious financial distress which borrowers cannot solve if unaided, and through which the credit and loans granted may be lost.

In addition to the companies that have had insolvencies within the following two years, off the analysis sample also are all those firms that have revealed significant shareholdings in other firms or counterparties that are supported by a parent company. We excluded public firms and firms with a portion of financial asset greater than 20% on total asset.

After the descriptive analysis of the means, firm-years for which the value of fixed assets, total assets, debt, firm's earnings or sales grew faster than normal or were in critical decline are removed. At the same time, firms with negative net worth and negative Ebitda in the starting year are eliminated. Furthermore, extreme values (outliers) that could produce instability in the means and in the distribution of the explanatory variables are removed. With regards to outliers, the observations which are situated outside the interval defined by the 2nd and the 98th percentile of distribution were deleted. Diagnostic test results no autocorrelation, residuals were normally distributed, no multicollinearity and there was no heteroscedasticity.

All the choices are based on underlying objective of having a sample homogeneous in terms of size, type and activity carried out, geography and market potential.

3.3 Descriptive Analysis

The financial ratios that form the explanatory variables of the model are determined by the annual financial statements of the 5,246 firms (Note 3) equally split into the two periods under investigation.

Table 2. Properties of distributions

Firms of 2007	Total Asset (€)	Net Worth (€)	Sales (€)	Ebitda (€)	Cash Flow (€)
Percentile 20	5.544.252	738.432	7.186.303	377.523	151.851
Percentile 40	8.023.413	1.437.951	9.429.849	643.521	313.902
Averages	**12.372.230**	**3.265.813**	**13.691.026**	**1.070.608**	**615.547**
Percentile 60	11.519.953	2.502.456	13.027.124	962.858	541.034
Percentile 80	17.508.533	4.441.769	19.583.587	1.584.184	963.753
Firms of 2019	**Total Asset (€)**	**Net Worth (€)**	**Sales (€)**	**Ebitda (€)**	**Cash Flow (€)**
Percentile 20	5.970.600	989.600	6.578.600	300.000	130.000
Percentile 40	9.243.400	1.857.000	9.874.600	535.000	336.800
Averages	**15.390.750**	**4.287.665**	**15.251.262**	**905.782**	**637.882**
Percentile 60	13.802.600	3.288.800	14.695.400	844.200	591.200
Percentile 80	21.991.800	6.129.600	21.758.800	1.415.200	1.047.000

In order to achieve sufficient functionality of the model (Note 4), therefore transferable in time and space, the feeding source essentially derives from clear, verifiable and accessible information (Gai, 2008) such as, in this case, the public mining of non-abbreviated financial statements.

After wiping the sample to consider the non-homogeneous counterparts, we proceeded to verify the specific distributions of each variable included in the analysis model. In groundwork for the descriptive analysis, the impacts of the outliers were verified by considering the frequencies and causes. As regards the treatment of the outliers, a "fairly broad" methodology was adopted with an introductory process, case by case, so as not to belittle the importance of the extreme values (Muscettola & Naccarato, 2013). In the case of distribution management, in order to eliminate non-ordinary cases, the methodology was implemented to truncate the ends of the distributions before the first percentile and/or after the ninety-ninth percentile, giving the anomalous value at the extreme of "normality" thus estimated (first or ninety-ninth percentile respectively). Indices with visibly skewed distributions, or with data ruined by significant discrepancies from the means, were not examined by the process in subsequent phases.

The distributions of the remaining single ratios, however, were found to be sufficiently symmetrical and with non-pronounced kurtoses. In addition, the outliers were numerically insignificant. As regards the "missing values" phenomenon, also due to the assumptions underlying the construction of the dataset, very few cases (twelve empty cells) of absence of data were recorded. In this case of missing data, not comparable with the value "0", the missing values were replaced using the "winsorization method". In this way the missing data, only if relevant, were replaced by boundary values (Note 5).

Below, the averages of the most well-known financial ratios (40 ratios of the 64 indicators used), which formed the explanatory variables of the models, are explained. *Table 3* shows the averages of healthy firms and *Table 4* lists the averages calculated on samples of insolvent firms after three years.

Table 3. Averages of ratios used. The financial ratios were determined by yearly statements of good firms

Ratio	Firms of 2007	Firms of 2019	***Ratio***	Firms of 2017	Firms of 2019
Total fixed assets / Total assets	26.34	30.85	Account receivable turnover	4.02	4.48
Cash and bank deposits/ Total assets	5.30	5.83	Inventory turnover	12.58	10.55
Inventory/ Total assets	21.77	23.64	Investment turnover	1.31	2.94
Trade receivables/ Total assets	41.39	33.66	Trade payables turnover	2.91	3.83
Intangible fixed assets/ Total assets	2.39	3.86	Current liabilities / Sales	50.77	52.90
Long term liabilities/ Total assets	10.41	14.17	Fixed assets turnover	25.94	8.34
Borrowings/ Total assets	29.58	35.30	Operating cash flow / Current liabilities	11.03	8.81
Total shareholders' equity / Short term debt	51.39	57.03	Operating cash flow coverage	9.75	87.86
Total shareholders' equity/ Total assets	23.09	24.79	Ebit / Total liabilities	9.19	4.86
Quick ratio	92.19	90.85	Operating cash flow / Sales	4.30	3.89
Total shareholders' equity/ Total fixed assets	154.67	142.47	Operating profit / Sales	4.36	6.47
Current ratio	134.31	133.61	Gross profit / Sales	23.05	24.75
Consolidated liabilities and equity / Total fixed assets	249.10	239.30	Ebitda / Interest expense	12.97	14.09
Net working capital / Total investment	15.44	60.82	Ebitda / Net Financial Position	-0.01	0.21
Interest expense / Total debt	2.42	1.38	Ebitda / Total investment	10.52	17.23
Gearing	0.46	0.51	Depreciation and amortization on sales	3.37	3.64
Total debt / Sales	61.56	68.74	Roi	6.34	7.54
Current liabilities / Total debt	85.16	79.58	Roa	5.52	3.12
Interest expense / Financial debt	6.91	3.32	Net working capital / Sales	11.65	28.84
Interest expense / Sales	1.57	1.00	Total shareholders' equity / Sales	21.67	27.34

For the descriptive analysis and to understand which indicators change over time between healthy or insolvent companies, we clustered the 64 ratios by type. The groups are seven: Asset composition, Capital structure, Liquidity, Financial ratios, Turnover ratios, Profitability and Efficiency. The key highlight on financial ratio analysis is to see how firms are classified in risk cluster. Each group of ratios provides information that is needed to analyze the financial evidence.

Furthermore, in order to better understand the differences between the arithmetic means of the ratios, a parallel study was conducted by standardizing (or normalizing) the individual means of the samples using the standard deviance of the ratio. This conversion method is called "standardizing of average" and this "standard score" (Note 6) is the number of standard deviations a datum is above the average.

In this way we understand more intuitively how the greatest differences can be circumscribed in the turnover ratios, where the basis of the relationship is just the size of gross sales, and the indices deriving from the operating cash flow or from the specific variations for flows, which can be seen in the cash flow statement. The asset composition and capital structure indices remained aligned, while there were lower averages of cost of debt over time, following the reduction in market interest rates (Note 7). In this regard we can see that, after an initial period of adjustment, companies have returned to prefer bank debt (financial debts on total liabilities start from 29.6% in 2007 to 35.3% in 2019), especially medium-long term debt.

We can say that the starting point is different and firms in 2019 are changed compared to the average firms in 2007, in several areas and aspects. Very significant are the differences about the group of ratios related to free cash flow. In this way we also note the expanded revenues in this sample with all that derives on the improved turnover indices.

Table 4. Averages of ratios used. The financial ratios were determined by yearly statements of bad firms

Ratio	Firms of 2007	Firms of 2019	***Ratio***	Firms of 2017	Firms of 2019
Total fixed assets / Total assets	33.02	29.73	Account receivable turnover	8.17	3.98
Cash and bank deposits/ Total assets	2.34	3.68	Inventory turnover	9.45	8.79
Inventory/ Total assets	25.43	27.29	Investment turnover	1.05	2.60
Trade receivables/ Total assets	32.67	31.89	Trade payables turnover	4.56	3.50
Intangible fixed assets/ Total assets	4.65	5.62	Current liabilities / Sales	71.61	74.14
Long term liabilities/ Total assets	13.00	15.75	Fixed assets turnover	42.78	8.45
Borrowings/ Total assets	42.53	42.73	Operating cash flow / Current liabilities	6.40	1.45
Total shareholders' equity / Short term debt	39.77	30.82	Operating cash flow coverage	20.87	58.78
Total shareholders' equity/ Total assets	18.44	15.83	Ebit / Total liabilities	4.70	-1.86
Quick ratio	71.02	71.12	Operating cash flow / Sales	3.11	1.81
Total shareholders' equity/ Total fixed assets	98.24	104.51	Operating profit / Sales	7.32	1.99
Current ratio	118.40	114.92	Gross profit / Sales	22.97	22.32
Consolidated liabilities and equity / Total fixed assets	149.73	210.47	Ebitda / Interest expense	2.77	2.49
Net working capital / Total investment	3.67	64.79	Ebitda / Net Financial Position	-1.70	0.03
Interest expense / Total debt	4.20	2.30	Ebitda / Total investment	6.81	9.84
Gearing	0.69	0.66	Depreciation and amortization on sales	4.08	4.73
Total debt / Sales	89.35	97.75	Roi	3.21	1.39
Current liabilities / Total debt	82.67	80.70	Roa	2.89	-1.38
Interest expense / Financial debt	8.20	5.01	Net working capital / Sales	4.32	33.12
Interest expense / Sales	3.68	2.28	Total shareholders' equity / Sales	26.80	21.14

The firms of the current crisis show also greater fixed asset, fewer trade receivables and greater financial debt, especially long-term debt, as mentioned above, in relation to total assets. These differences we can see between good firm in 2007 compared to firms of 2019 but they aren't statistically significant if we break down the analysis on bad firms or consider the specific variation between bad firms and good firms.

Some explanations for these dynamics can be found in recent Italian economic history. In the last decade, especially at the end of the 2008-2012 crisis, the mean structure of the Italian company has changed (Muscettola, 2015 B), also accepting the positive and general strengthening of the banking system and a combined reduction in corporate insolvencies. Regardless of the crises overcome, therefore, the two periods of analysis can be considered different also due to the differences in their respective starting macroeconomic scenarios (pre-crisis). Even before the Covid-19 pandemic, consequently, the typical structural and accounting organization of the company can be considered to have changed compared to the previous decade.

If we compare only the insolvent companies of 2010 with the insolvent ones of 2022, we realize that those who fall into the latest crisis, unlike in the past, are the firms that, at the same time, had a stressed financial structure, as already seen, but with a slow turnover of assets and low profitability. We can see it better with the mentioned standardized averages method.

The analysis of the variations between the bad firms and good firms of the respective year is very complex. In this case we observe indices that move differently and a cash conversion cycle with non-linear dynamics. In these sub-samples, we can see lower interest expenses, but the economic indices (Note 8) and capital structure ratios are highly controversial. Several variables remain very similar to the previous period, and they don't show a clear temporal dynamic of the balance sheet ratios if we move from one period of crisis to another.

The relative differences between the indices associated with bad firms and the average values associated with good firms, concerning the same period, include the relevance of fixed assets and of commercial working capital. The relative share of fixed asset on total asset, for bad firms in 2007, increases compared to the good firms, the opposite is plain for firms of 2019. Inverse case for the incidence of commercial working capital which decreases for the 2017 bad firms while increasing for the same category in 2019.

However, the above, using two large samples, representative of Italian industrial firms (SMEs), we achieve that the effects of the pandemic and the raw material price crisis, still ongoing in this period, have changed the vulnerabilities of firms, as well as having led to a different economic and financial scenario compared to previous economic downturn and, obviously, also compared to non-crisis periods. The capital structure of companies in 2007 it was already clearly distorted with a large portion of short-term debt. In fact, from the descriptive analysis of the bad firms of 2007, the firms have approximately 7% more short-term debt on total liabilities compared to the bad firms of 2019.

Furthermore, on the other hand, some variables, especially the economic ratios, have more marked differences. “Operating cash flow / Current liabilities”, “Operating cash flow / Sales”, “Ebit / Total liabilities”, “Operating profit / Sales”, “Roi” and “Roa” assigned to the bad firms in 2019 have relative worsening compared to the respective good firms, decidedly more relevant than the companies of 2007.

Finally, very sticky is the links and the consequences of the cash conversion cycle about the differences between the bad firms and good firms in 2019. It is very difficult to interpreter the descriptive analysis when it is noted a reverse movement between the rotation of trade credits and debts to suppliers. Specifically, the good firms of 2007 had 90 days of account receivable (Note 9), as average, which drop approximately to 45 days for the bad firms while, as regards 2019, the average duration of trade credits change from 81 days for the good firms to 92 days for insolvent companies. This last detail overlaps with the data for healthy firms in 2007. On the contrary, for the average duration of commercial debts, there is a reduction for bad firms in 2007 compared to healthy firms in contrast to the trend of the counterparts in 2019 where the companies that will become insolvent after three years record an average of days account payable (Note 10) (extension granted by suppliers) of 104 days (95 days for healthy firms).

In this context, it is noticeable that the forecasts of greater expected risk have not yet been revealed with the impacts predicted in 2019/2020. The financial resilience of Italian SMEs has had significant evidence for the economy as a causal phenomenon effect which implied an unexpected virtuous circle. Government support weighs heavily in support of this explanation: the Italian Government has introduced various measures to support businesses through new financing with public guarantees. It has influenced considerably to the survival of firms.

On the other hand, over the last two years, we can see some undercurrents like a tightening in the rotation of credits and debts, and some particular phenomena linked to sales volumes and to the average duration of bank debts. This is distinctly observed in company balance sheets highlighting that the divergent cases have different colors in some sectors both in terms of intensity and times and durations but, despite it all, directly or indirectly affecting all the Italian firms.

3.4 Expected loss

The two samples of firms compared were also analyzed at portfolio level, verifying the overall expected loss of the two combinations. This is an exercise to estimate the effects of model’s errors. The effects of these misclassifications are computable in the calculation of the expected loss that was determined in an unsophisticated way per portfolio. The expected loss was calculated as the product:

$$EL = EAD \times PD \times LGD$$

We consider the exposure in the event of default (EAD) as the total financial exposure equal to the total indebtedness expiring within one year net of the liquidity of the individual counterparty; the probability of default (PD) estimated by the logistics regression deriving from the function of the respective model and relative period; the loss in case of default (LGD) estimated as an assumption using three ratio (Note 11) trying to summarize the potential of the insolvent firms to cope its obligations after the bankruptcy, liquidating rigid assets or company shares. From this assumption is possible to simulate a calculation of expected portfolio loss, starting by the sample and the model. Like a bank that must set provisions in proportion to its risk.

The expected loss of the two portfolios was calibrated with a "k factor" to reproduce also the different historical and economic moments, the different country risk, and internal factors of the credit institutions which in 2019 denoted both a greater efficiency of the Italian banks and a better state of strength compared to 2007. On the other hand, the types and impacts of risk mitigation are not considered, referring above all to government guarantees widely used by Italian firms especially in the emergency period.

Table 5. Expected Loss

Expected Loss	EAD	PD	Ind 1	Ind 2	Ind 3	Fact K	LGD media	Total €
Expected Loss Sample 2007	*Ead i*	*Pd 2007 i*	*i1*	*i2*	*i3*	*0,59*	$\left[\frac{i1+i2+i3+k}{4}\right]$	**1.109.516.726**
Expected Loss Sample 2019	*Ead i*	*Pd 2019 i*	*i1*	*i2*	*i3*	*0,33*	$\left[\frac{i1+i2+i3+k}{4}\right]$	**1.110.354.043**
Expected Loss Ptf 2007 with PD logit 2019-2022	*Ead i*	*Pd 2019 i*	*i1*	*i2*	*i3*	*0,59*	$\left[\frac{i1+i2+i3+k}{4}\right]$	**1.939.351.182**
Expected Loss Ptf 2019 with PD logit 2007-2010	*Ead i*	*Pd 2007 i*	*i1*	*i2*	*i3*	*0,33*	$\left[\frac{i1+i2+i3+k}{4}\right]$	**834.973.495**

The overall expected portfolio loss is very similar in the two samples analyzed with the respective predictive models (equal to 1,110 million euros) just due to the initial intention of evaluating two homogeneous samples also in terms of starting risk. By exchanging the methodology, although the EADs and LGDs remain unchanged, the expected loss would increase significantly for the 2007 sample (+75%) emphasizing the effect of the greater PDs from the 2019-2022 model while the 2019 sample, analyzed with the 2007-2010 model, would generate a lower overall expected loss than the original version. In other words, the evidence describes a very strongly growing expected loss if we use a model built on last crisis. If we changed the model the expected loss grows up to 70% but, on the other side, if we use the model of financial crisis on sample of firms of 2019 the expected loss would be quantified with an underestimation of 25%.

These differences are statistically significant and highlight the different effects for banks. By contextualizing the banks' provisions, it is clear that these model differences are considerable and produce significant effects also in the banks' accounting and financial reserves. In this case, for example, if a bank had used the old forecasting model (2007-2010) to quantify the riskiness of its portfolio in 2019, it would have underestimated the losses. In the opposite case, the bank would have been highly prudent by setting aside larger reserves.

Several empirical studies (Hu and Perraudin 2002, Altman et al. 2005) confirm the occurrence of a negative correlation between default rates and recovery rates. The prevailing literature, therefore, asserts that PD and LGD are not stochastic independent variables. Frye (2020), with his evidence and his model, in parallel with the empirical details published by Moody's, also certifies that in periods of crisis the inverse links between PD and RR (recovery rate, equal to the inverse of the LGD) become more perceptible, due to the "chain" or sectoral effects that reduce the value of company assets and, therefore, the potential coverage debt. Altman et al. (2001), through a simulation exercise, demonstrate that, by dropping the LGD parameters uncorrelated with the PD and set them on a deterministic basis, the expected loss is underestimated. In periods of crisis this underestimation exceeds significant proportions (30%). For this reason, it is essential to keep the rating models and the main risk parameters as updated as possible, especially in periods in which adverse economic-financial conditions are expected.

4. Empirical Analysis

After the descriptive analysis, the study continues with the empirical analysis. In this study, the logistic regression technique was used to create a discrimination function between firms to forecast the default event after three years.

When operating bankruptcy data, it is ordinary to identify one of the categories as healthy (good firms) or default (bad firms) and to appoint them the values 0 and 1 correspondingly. In this way the dataset consists of a binary response variable "Y" and a set of explanatory variables "x" undertaken by financial ratios. In other words, the event insolvency is the dependent variable (binary discrete variable - dichotomous) and the functional procedure selected for this research was, therefore, the logistic regression model. The explanatory variables are the indices of financial statements shaped as averages of three years before the evaluation of the dependent variable.

The logistic model option acts consistently to the specific characteristics of the analysis sample (Note 12) and it is developed with a process of progressive reduction of variables known as "forward stepwise" (Note 13). In this process, each variable is forced, one at a time, starting from the most predictive indicator, until no new index makes a significant contribution to the model. Through this approach, the model allows a massive use of all 64 independent variables and we form a ladder of discrete values that are able to sort the manufacturing firms for probability of default.

It is conceivable to write the function of the logit model, in which the odds are a linear function of the explanatory variables and the exemplary factors (*β1- β64*) are estimated via the maximum likelihood approximation, in the following manner:

$$p_i = f(k + \beta_1 x_1^i + \beta_2 x_2^i + \ldots\ldots + \beta_{64} x_{64}^i) = \frac{1}{1 + e^{-(\alpha + \beta_1 x_1^i + \beta_2 x_2^i + \ldots\ldots + \beta_{64} x_{64}^i)}}$$

The results of the logistic regression, developed with the forward stepwise procedure, are descripted in the following Table 6, for the sample of firms of 2007, and in the Table 7, for the firms of 2019. The tables of the results, which considers in the first step all the 64 designed financial ratios, show the coefficients (*β)* of the factors with a significant level between 1% and 5%, the standard errors (S.E.) of the evaluated coefficients, the "wald" chi-square test and exponentiation of the *β* coefficient, which is an odds ratio (identifies the change in the probabilities of default for a one unit change in the predictor).

Table 6. Stepwise logistic regression - Event: default in 2010 - Sample: firms of 2007

	β	*S.E.*	*Wald*	*Exp(β)*
Cash and bank deposit / Total assets	-0.090	0.026	11.783	0.914
Trade receivables / Total assets	-0.043	0.009	23.563	0.958
Intangible fixed assets / Total assets	0.056	0.016	12.701	1.058
Total shareholders' equity / Total assets	-0.064	0.017	13.913	0.938
Quick ratio	0.018	0.005	14.943	1.019
Total shareholders' equity / Fixed assets	0.012	0.002	28.163	1.012
Consolidated liabilities and equity / Total fixed assets	-0.011	0.002	29.874	0.989
Interest expense / Total debt	0.271	0.101	7.257	1.311
Current liabilities / Total debt	0.035	0.009	15.363	1.036
Interest expense / Sales	0.733	0.123	35.305	2.081
Investment turnover	0.554	0.242	5.253	1.741
Trade payables turnover	0.036	0.016	5.315	1.036
Return on sales (ROS)	0.067	0.029	5.269	1.069
Ebitda / Total investment	-0.099	0.031	10.462	0.906
Total shareholders' equity / Sales	0.016	0.008	3.649	1.016
Constant	-6.536	1.001	42.621	

The other indicators (financial ratios excluded) available in the list will assist as control variables in order to prove the correlation of distributions with the event insolvency.

Table 7. Stepwise logistic regression - Event: default in 2022 - Sample: firms of 2019

	β	*S.E.*	*Wald*	*Exp(β)*
Intangible fixed assets / Total assets	0.029	0.011	6.390	1.029
Shareholder debt / Total assets	-0.036	0.019	3.730	0.964
Interest expense / Total debt	0.608	0.130	21.815	1.837
Interest expense / Sales	0.287	0.133	4.663	1.332
Total debt / Total assets	0.061	0.008	56.532	1.063
Current liabilities / Sales	0.019	0.005	15.045	1.019
Operating profit / Sales	-0.063	0.018	12.606	0.939
Ebitda / Cost for employees	-0.005	0.002	3.757	0.995
Net working capital / Sales	0.014	0.004	13.046	1.014
Constant	-9.660	0.710	185.308	

The last step concerns the justification of the results looking for, if it's possible, a logical interpretation of the same outputs. In this regard it should be noted that the coefficients of the two functions show a particular unexpected correlation trend for firms of 2007 while, on the other hand, they highlight more logical signs in the regression function built on the 2019 sample. So, in this case we observe that the composition of asset, liability composition and the liquidity ratios are less important than the corporate leverage, the economic and turnover indices with regards to the last period of crisis.

We use the two regression functions to construct two ranking scales by dividing each sample into ten clusters. The cut-off between the classes are identified with the median technique and the ten classes are uniformly numerous.

5. Results

In order to measure the effectiveness of model selection, the error matrix is used. It provides the accuracy and the type of error most committed by the model. In this way, an error matrix includes information about actual and predicted classifications obtained through a classification procedure. The performance of a rating model is generally estimated using the data in the error matrix. The following Table 8 shows the confusion matrix for a two-class classifier.

Table 8 therefore describes the quantity (percentage) of firms correctly classified. Accuracy is also used as a statistical measure of a binary classification test's ability to correctly detect or reject a condition. Accuracy, in this case, is defined by the percentage of true results (both true positives and true negatives) in the sample.

To maximize the accuracy of the model but, at the same time, to avoid the problem of overfitting, it is necessary to increase the sensitivity against a minimum level of specificity or, in other words, minimize false positives (proportions of events predicted as non-events error type I) for an acceptable maximum false negative rate (proportion of non-events predicted as events type II error).

In consideration of the different cost of the error (Note 14), the cut-off of the four distributions was set at the seventy-seventh percentile. It is acceptable considering the average level of false negatives of the four clusters.

Table 8: Error matrix

Firms: year 2007 Function: Logit 2007-2010	Error Type I	21	10.50%
	Error Type II	471	17.96%
	HIT (true default)	179	89.50%
	TRUE (true positive)	2,152	82.04%
	ACCURACY	**82.57%**	
Firms: year 2007 Function: Logit 2019-2022	Error Type I	55	27.50%
	Error Type II	505	19.25%
	HIT (true default)	145	72.50%
	TRUE (true positive)	2,118	80.75%
	ACCURACY	**80.16%**	
Firms: year 2019 Function: Logit 2007-2010	Error Type I	78	39.00%
	Error Type II	528	20.13%
	HIT (true default)	122	61.00%
	TRUE (true positive)	2,095	79.87%
	ACCURACY	**78.53%**	
Firms: year 2019 Function: Logit 2019-2022	Error Type I	48	24.00%
	Error Type II	498	18.99%
	HIT (true default)	152	76.00%
	TRUE (true positive)	2,125	81.01%
	ACCURACY	**80.66%**	

The separation function between the healthy sample and the companies that will become insolvent allows us to test the efficacy of the model and answer the question: is it possible to use a single forecasting model over the two periods?

If in the period 2007-2010 the logistic regression model achieved excellent accuracy scores, the results of the other function, for the period 2019-2022, are less correct. Synthesizing the performances of the two models it is quite clear, as expected, that the model built over one specific period is less successful in a different time. Even if the overall data seems aligned, they are related and fueled by different type of error. In fact, a greater number of "false defaults" stands out in the distribution of firms of 2019 classified by the model built on the 2007-2010 sample (*Error Type I* equal to 39%).

Specifically, it is highlighted that the regression built on the 2007-2010 sample shows 21 cases of *Type I error*, false positives, equal to 10.5%, with an accuracy of 82% while the regression built on the 2019-2022 sample brings 48 false positives and 80.6% accuracy. It reveals that in the latest crisis the group of insolvent companies is more various. In other words, it seems that the bad firms of 2022 have a greater number of peculiar cases three years earlier and a greater volatility of the ratios such making them less easily intercepted.

In order to explain the results of the research, a rating scale is constructed in connection with the sample used and the model used. In that way it is possible to verify the effectiveness of the predictive model using four ranking scales in consideration of the two logistic functions remarked in previous section. In other words, the analyzed sample is divided into ten (Note 15) equally numerous classes and, therefore, each observation will have 10% probability of falling into one of the ten ordinal classes based on the risk of default.

Table 9 and subsequent figures describe the distributions of default cases in relation to the logistic function and sample used.

Unlike the *error matrix*, calibrated with a *cut-off* at the seventy-seventh percentile of the distribution, a "true positive" is defined as the *bad firm* located within the three worst classes of rating. *Table 9* highlights the greater predictive power of the model built on firms of 2007 to search for insolvencies during the 2010. In this way we can see that the regression built on financial crisis intercepts 185 defaults among firms of 2007 and only 134 defaults among companies of 2019. On the other hand, the regression built on last crisis, has a lower performance in the reference sample with 155 true defaults on 200. The worst performance is attributable to the logistic function built on 2007 companies, but to search for bad firms of 2022 (33% of insolvent firms are in the first seven rating classes).

Table 9. Defaults into the worst classes of rating

Bad firms - situated into the worst three classes of rating	No.	%
Firms: year 2007 - Function: Logit 2007-2010	**185**	**92.50%**
Firms: year 2007 - Function: Logit 2019-2022	155	77.50%
Firms: year 2019 - Function: Logit 2007-2010	**134**	**67.00%**
Firms: year 2019 - Function: Logit 2019-2022	171	85.50%

The same properties are expressed by the following graphs which show the specific distributions of firms that have registered insolvency, reflecting the model used.

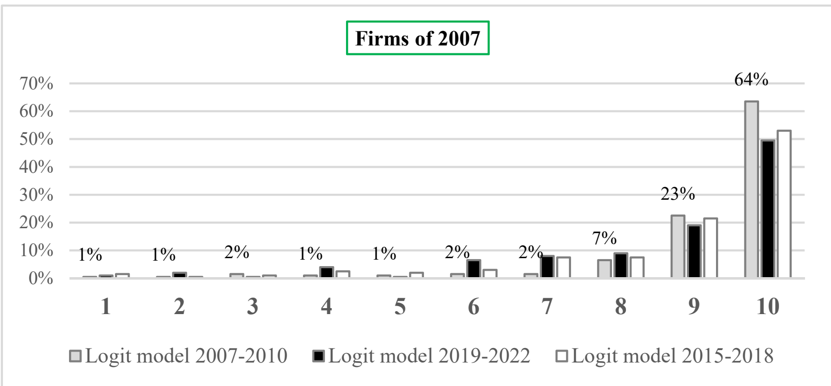

Figure 1. Distribution of defaults for firms of 2007

The predictive capacity of the models built just on the analyzed sample is more evident. On the other hand we can see highest histograms of the central classes regarding the default distributions of the samples not aligned with the year of the logistic function. In particular, the growth in the last classes of firms in default in 2010 (sample of firms of 2007) can be noted through the rating scale constructed with the 2007-2010 logit model. In this distribution, the last class achieve 64% of the total cases. This evidence is not re-performed by the 2019-2022 logit model on the firms of 2019, confirming the hypothesis that in the last crisis the companies that became insolvent were more heterogeneous.

To point out the differences between the models, in terms of predictive capacity, is included also another rating scale constructed using another logistic function to forecast the insolvencies of firms during a non-crisis time. More specifically, the third forecast model is built on firms of 2015 in consideration of the insolvencies that occurred in 2018, after three years with the same methodology. For the 2007 sample of firms (Figure 1) we can see that the 2015-2018 model has fewer errors compared to the logit 2019-2022, at least as regards the extreme classes.

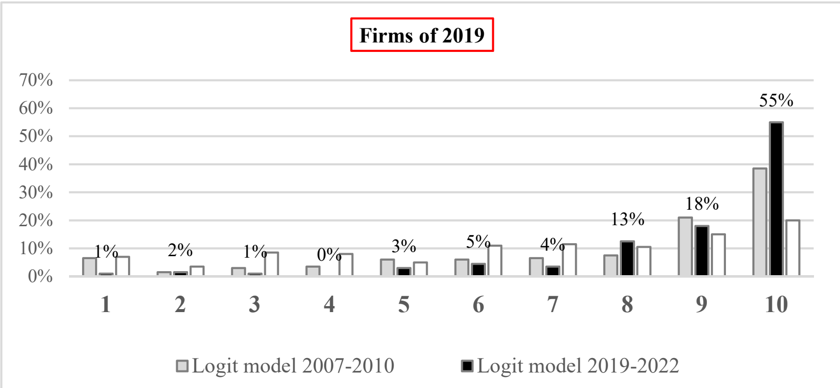

Figure 2. Distribution of defaults for firms of 2019

Models based on a different crisis period compared to the time in which they were built are undoubtedly less successful. A lower predictive capacity is attributable to the logistics model built on sample of 2007 aimed at finding the defaults of 2022. As already mentioned, the results support the hypothesis that the latest crisis has affected different economic-financial dynamics compared to the past and the companies were influenced by an unprecedented macroeconomic scenario. The graph (Figure 2) also highlights an even worse predictive capacity than the model built in the non-crisis period. Both for the distribution of defaults in the ten classes of risk and in the accuracy statistics, the 2015-2018 model is the worst in the classification of insolvencies of sample of firms of 2019.

All this underlines the attention of this study in warning banks to use a single model for all periods, even in times of crisis.

Furthermore, it is noted that the firms with a "divergent" classification are quantified as 197 cases in the sample of 2019 and 63 in the sample of 2007. The "divergent" classification is defined by an assignment within the first three classes for one model contrasted with a classification within the three worst classes in the other model or vice versa.

Table 10. Divergent classification

Sample	Divergent classification type	No.	Defaults
Sample 2007	Best firms by model 2007-10 and worst firms by model 2019-22	42	1
	Worst firms by model 2007-10 and best firms by model 2019-22	21	4
		63	**5**
Sample 2019	Best firms by model 2007-10 and worst firms by model 2019-22	100	1
	Worst firms by model 2007-10 and best firms by model 2019-22	97	18
		197	**19**

The key discrepancies are also joint with the default statistics, underlining that, if in the sample of 2007 only one firm was correctly identified as a "bad firm" by the 2019-2022 model, 18 cases were incorrectly identified as solvent by the 2019-2022 model using the sample of reference period (18 firms which became insolvent in 2022). Table 10, therefore, adds further statistical justifications in defining the latest economic and financial crisis as more unpredictable. This aspect also affects the quality of the logistic regression built on the reference period and the consequential predictive capacity of the 2019-2022 model.

This Table shows a presence of more cases of discrepancy evaluations in the 2019 sample, demonstrating that the last crisis period was filled with greater pressures and problems on multiple fronts at the same time. The effect of this difference can also be read from the fact that in these divergent classifications there are also companies that have become insolvent, and these cases weigh on the last period.

The last note concerns a particular aspect of the empirical investigation: searching for any peculiarities of the firms, included in the high-risk cluster, which (nevertheless) did not lead to default in the following three years for the counterparty. Therefore, we study 442 firms that have a score deriving from the logistic function such as to place them in the two worst rating classes (class 9 and class 10) and survived the crisis period without becoming insolvent. The selection of these good firms of 2019 is determined by the 2007-2010 logistics model and, consequently, the major differentials of the averages are compared with the bad firms of the same year.

The comparison highlights how high-risk good firms have a higher capitalization compared to short-term debt, lower inventories but also higher fixed assets (Note 16) (including intangible ones). Financial debt on total liabilities is lower, partly counterbalanced by debts to suppliers. Relevant is also the difference between the ratio formed by interest expenses and revenues from sales (1.55% versus 2.29% of bad firms in 2019). Other aspects that distinguish the two sub-samples are noted in the greater turnover of trade credits, for the good firms, and the negative operating income, for the bad firms.

All the aspects listed above demonstrate that, even in a period of strong turbulence, it is possible to distinguish the firms that have greater potential to recover, also in the group of high-risk counterparties (Muscettola, 2019).

6. Conclusion

Using two large samples, representative of Italian industrial firms (SMEs), we achieve that the effects of the pandemic and the raw material price crisis, still ongoing in this period, have changed the vulnerabilities of companies, as well as having led to a different economic and financial scenario compared to previous economic downturns and, obviously, also compared to non-crisis periods.

The specific model built on the period of the beginning of the financial crisis (2007), which can be defined as the largest global financial crisis, has been recalibrated on a typical firm structure that starts in a different way in 2019. The capital structure of companies in 2007, in fact, was already clearly distorted with a large portion of short-term debt. In fact, from the descriptive analysis of the bad firms of 2007, the firms have approximately 7% more short-term debt on total liabilities compared to the bad firms of 2019. This dynamic mainly depends on the most qualified offer of banks, after 2012, more than the effects of the financial crisis. In this regard, the better selection of financial institutions was evident, which increased the intensity of bank loans only on more solid client firms.

The differences between the insolvent firms of the two periods are statistically significant, with an expression of the greater errors found in the different predictive models. In this sense, a rating model built in the reference economic period is certainly more accurate in predicting insolvencies than a generic model that has been in undertaking for several years. Furthermore, the last period is affected by different economic and financial conditions compared to the past and that have implications on the typical structure of the Italian firm and influence its developments and solvency. From this we can say that the logistics built to discriminate insolvent firms appear to have a higher number of misclassifications compared to other periods. Consequently, a significant lack of homogeneity is assumed in the sub-samples and in the characteristics of the companies that will become insolvent during the last period of crisis.

According to the prevalent econometric literature, the worsening of the rating status due to economic effects, rather than financial causes, is less dangerous than the opposite (Muscettola, 2016). From this point starts the discussion about the slowdown in GDP, the strong general decline in sales and the problems with returns, much more evident than in previous crises, will be overcome more quickly than the problems connected to the leverage (ratio between financial debts and net worth) or to the general unstable capital structure. Companies that will overcome this period of "loss of earnings" will return stronger than before. On the other hand it is clear that there are now the basilary conditions for this: corporate indebtedness is still at tolerable levels considering the still "not too high" (at least until 2022) interest rates and, above all, the current firms have begun just several years ago a critical capital strengthening.

The empirical analysis highlights that the samples of firms, over the two different time periods, have dissimilar characteristics due to the performance of healthy companies, which show a capital structure and asset organization that has changed over time, and due to the different turnover and financial ratios of insolvent firms. Predicting insolvencies in the last years is more complex than in the past and the forecast model has a lower level of accuracy than in the past if built on the period 2019- 2022. In other words, the companies that became "default firm" in 2022 had, three years earlier, a greater volatility of the averages of ratios such as to induce greater misclassifications in a hypothetical forecasting model.

This means, therefore, that firms that became insolvent during the pandemic period, or due to economic disruptions linked to the energy (and price) crisis, were "less identifiable" and fell due to possible "anomalies" that were different and more disparate than in the past.

The analysis reveals that:

- The most predictive indicators of corporate insolvency have changed in the last period: the characteristics of insolvent companies have changed.
- Forecasting models need updating, especially in times of crisis: it is not possible to use just a single estimation model to identify insolvencies over the time.
- Not updating the forecast models may lead to incorrect quantifications of expected portfolio losses with an impact on banks' provisions and on the related regulatory capital.

The development of a rating model calibrated on a specific historical period, and on a longer timeframe (three years), offers significant points for debate both to economic and financial players and to supervisory authorities in order to design a rating system capable of appropriately capturing the market specificities induced by the changing macroeconomic scenarios, in which banks and firms work. In conclusion, the research conducted underlines the critical value of maintaining and updating the forecasting models which, especially in periods of crisis or significant economic changes, can quickly become obsolete or, at least, ineffective.

The limitation of this essay is the complexity of evaluating firms through the analysis of financial ratio without basing on their behavioral, sectoral and qualitative analysis. It was complicated to get their behavioral statistics relating to their year's supplied financial statements. It would also be beneficial to) we use statistics on bank overdrafts and about the applications of granted loans. In order to judge their real solvency, it is important to also include the bank trend analysis and the quality of the guarantees provided. More so as a threshold of this study, we can find the attention only on manufacturing sector that was taken account into this production. On the other hand, the greater homogeneity of the sample treated allowed us an excellent level of temporal comparison among firms to be achieved.

Nonetheless, the result explained remains adequate as a whole. For the potential next study, other methods or statistical approaches can be used in addition to the multidimensional analysis to prove very distinctly which of financial ratios and firms are closed to each other.

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Notes

Note 1. Mutual companies, consortia and non-capital partnership are excluded.

Note 2. In consideration of the approvals of the financial statements, which very often arrive several months after the end of the accounting year, having a forecasting model restricted to one year could signal difficulties when it is too late or when the problems are already visible through other areas of investigation (overdue, financial difficulties, delays).

Note 3. The yearly statements are provided by FourFinance Rating, which assembled, cleaned, regulated and reclassified financial statements collected from multiple databases. As for the construction of the statistical form, the preliminary procedures on the data, the choice of the outliers and the formation of financial ratios, the reader ought to refer exclusively to the authors.

Note 4. For the same reason, it was preferred to limit the peculiarities of the firms in a specific geographic and size cluster. In addition, the number of elements and the number of the independent variables are restricted.

Note 5. The absent records are replaced by the averages relating to the reference percentile of the specific ratio, taken from a predetermined table.

Note 6. A “standard score” that is precisely on the mean of whole population corresponds to a z of 0. Positive scores are over the average while negative scores are under the average. Scientifically it is the ratio between the difference from the whole sample mean and the whole sample standard deviation.

Note 7. The interest rate applied by banks also significantly decreases due to the general trend period, reducing the interest expense of firms.

Note 8. As regards the economic indices, in forecasting insolvencies, it is necessary to specify that the profitability ratios obtain greater significance only near the time of insolvency (Muscettola and Pietrovito, 2012) and, therefore, remain less significant in the specific approach used: mathematical forecast of defaults after three years.

Note 9. No. of days accounts receivable: Account receivable/Sales x 365. In accountancy, days sales outstanding is a calculation used by a firm to estimate their average collection period and it measures the number of days on average that customers take to pay invoices. It is an index of the relationship between trade receivables and net sales achieved over one year.

Note 10. No. of days account payable: Accounts payables/Purchases x 365. Days payable outstanding measures the average number of days a firm takes to pay its suppliers and it provides one measure of how long a business holds onto its cash.

Note 11. The three financial ratios used as the basis for the calculation for the LGD are: "i1" = ratio between the net between tangible and financial fixed asset and debts expiring beyond one year and net debt; “i2” = ratio between net equity and net debt; “i3” = ratio between total debts and total assets. They are, therefore, the coverage of fixed asset, the coverage of debt through equity and the ratio formed by total debt and total asset.

Note 12. This empirical method is typically used for low levels of computational complexity, like this essay.

Note 13. That is a statistical technique to reduce the number and the redundancy of the independent variables (Muscettola & Naccarato, 2013). The process will reveal as a first step the formation of a function with the assistance of each explanatory variable. Afterwards it goes on through a progression repeated until the record of a new variable in the function does not affect an advancement in the performance of method.

Note 14. There is a non-symmetric cost structure such that one type of misclassification is more costly than the other. For this reason, the cut-off value should be selected to minimize the cost of errors rather than the number of cases.

Note 15. With the score of logistic regression, the distribution is included in 10 classes equally distributed from class 1, which identifies a low probability of insolvency after three years, to class 10 of maximum risk.

Note 16. “During a crisis period, the fixed capital investment does not properly mean a major source to develop better technologies for the industry, but even a cause of vulnerability for firms due to the greater production costs and increased inflexibility of corporate assets.” (Muscettola, 2014).