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Research article

COVID-19 and firms' financial health in Brescia: a simulation with Logistic regression and neural networks

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Abstract: COVID-19 has generated an unprecedented shock to the global economy causing both the decrease in demand and supply. The purpose of this paper is to simulate the effect of COVID-19 on firms' financial statements in Brescia. The shocked information is then fed into two bankruptcy models with the aim of providing an up-to-date picture of firms' economic health in one of the most prosperous industrial areas in Italy and Europe.

Keywords: COVID-19; financial statements; logistic regression; neural networks; Brescia

JEL Codes: G33, C45, C52, R11, L23

1. Introduction

The recent pandemic crisis has generated an unprecedented shock to the global economy. It was severe and unexpected so to be considered even worse than the 1929 crisis, which saw, after the October 29th stock market crash, a contraction in GDP and a rise in unemployment. COVID-19 has generated a real challenge to the national health systems worldwide and its consequences have put the world economy at risk, causing a sharp decline both in demand and supply.

In order to counteract the virus transmission, most governments have decided to adopt measures unimaginable since the day before. The Italian reaction was particularly severe compared to other countries. In a matter of weeks (from February 21 to March 22, 2020), Italy went from the discovery of the first official COVID-19 case to a government decree that essentially prohibited all movements of people within the whole territory, and the closure of all non-essential business activities. The pandemic has disrupted factories, supply chains and demand for goods and the consequences to industrial production and sales has been heavy.

Given the uncertainty related to the economic repercussions of the virus starting from the second quarter of 2020 and the still unclear developments of COVID-19, it becomes very difficult to understand the state of the economy of the recent past, the present, but also to predict the short term future.

The last picture we have regarding the manufacturing sector health is related to the economic activity of 2019. However, the information on that year is available to the public for all firms with a delay of several months. We thus won't have the financial statement information on year 2020 for all firms until the middle/end of 2021.

The aim of this article is to simulate the consequences of the COVID-19 shock to the industrial structure of a very wealthy and industrialized area of the Lombardy region in Italy, Brescia. Brescia is the fourth city in Italy in terms of value added in the industrial sector, and the fifth in terms of exported goods in 2019. The representative sectors of this industrial excellence are Mechanics and Metallurgy which are both renowned all over the world. The city has been also severely hit by COVID-19.

In order to measure the effects of COVID-19 we proceed in three steps: 1) we construct a bankruptcy model for the Manufacturing sector in Brescia, choosing between logistic regression and artificial neural network; 2) we shock the 2019 financial statements to have an estimate of firms' financial conditions in 2020; 3) with the shocked information and the parameters of the chosen model we predict firms' financial health in Brescia providing some insights on the characteristics of the firms that turned out to more vulnerable from the simulation exercise.

Our results show that in the PRE-COVID period (2019) the Manufacturing sector in Brescia is strong and sound with 88.9% of the firms belonging to the most healthy classes (A and B). After the outburst of COVID-19 the economic situation of the firms worsened compared to the PRE-COVID period. The percentage of firms in the most healthy classes (A and B) reduces from 88.9% to 78.6% and the percentage of firms in the worst off classes (C and D) increases from 11.1% to 21.4%. Small enterprises and the Mechanics and Textiles sectors turn out to be the hardest hit by the crisis.

The rest of the paper is structured as follows: Section 2 reports the literature review and our contribution, Section 3 describes the dataset, Section 4 outlines the bankruptcy prediction models, their evaluation and provides some results on the best forecasting performance model, Section 5 delineates the simulation exercise with the aim of estimating the input variables in 2020, Section 6 shows our results and Section 7 concludes.

2. Literature review and our contribution

2.1. The economic effect of COVID-19

The literature on the economic effects of COVID-19 is in a rapid state of expansion. Recent articles have focused on the impact of the COVID-19 pandemic on various economic aspects: labor (Dingel and Neiman, 2020; Coibion et al., 2020); consumption (Cox et al., 2020; Chetty et al., 2020); credit allocation (Core and De Marco, 2020) and also firm bankruptcy. Our paper is closely related to the literature interested in showing the effects of COVID-19 on this last topic. The key issue in this literature is the lack of timely and granular data on financial positions of firms especially SMEs. Some studies have analyzed one single country—the US (Bartik et al., 2020), France (Guerini et al., 2020), Italy (Schivardi and Romano, 2020; Carletti et al., 2020)—others have instead focused on multiple countries (Gourinchas et al., 2020; Bosio et al., 2020; Demmou et al., 2021).

The main contribution of the above mentioned articles is to give an estimate of firms' economic conditions after COVID-19. Some studies have focused on estimating the liquidity shortage (Gourinchas et al., 2020; Carletti et al., 2020; Guerini et al., 2020; Demmou et al., 2021), others have also based their analysis on equity shortfall and insolvency (Carletti et al., 2020). Bartik et al. (2020) have focused on the effect of COVID-19 basing their analysis on survey data from 5,800 US small businesses. Bosio et al. (2020) estimate the survival time of nearly 7,000 firms in a dozen high-income and middle-income countries using the World Bank's Enterprises Surveys.

Schivardi and Romano (2020), Carletti et al. (2020), Demmou et al. (2021) focus on the demand drop caused by the pandemic, whereas Gourinchas et al. (2020) and Guerini et al. (2020) develop a model-based estimate of firms liquidity looking also at the supply shock deriving from the labor supply contraction due to confinement. The first approach is based on the idea that, as a consequence of the reduction in demand, companies reduce their operating revenues and also their demand for factors, but the rigidities in the factors market imply that there is a less than proportional reduction with respect to the fall in sales. These rigidities lead to an inequality between the reduction in revenues from output sales and the reduction in input related expenditures. Such inequality potentially leads to negative profits. The second approach, which is model-based, explains the company's choice of factor consumption in an environment very strongly disturbed by three negative shocks: a negative demand shock; rationing of the labor factor supply due to confinement; a reduction in productivity following telework. Our work is closely related to Carletti et al. (2020). We also focus on the consequences of the demand shock, but differently from the literature, we develop a multivariate bankruptcy model, fitted on Brescia historical data, and we use the available information on the expected Total Sales drop for 2020 to shock 4 firms' financial ratios which represent the input variables of our bankruptcy model. The latter has the aim of providing a financial health score to each single firm and to provide a comparison of the scores before and after COVID-19 outburst. Differently from the literature we focus on the Manufacturing sector and we do not consider other sectors such as Services. The reaction of these two sectors to COVID-19 has been very diverse. The latter faced a more intense crisis and a longer lockdown period. Focusing only on the Manufacturing sector has the advantage of making the analysis more homogeneous. In the next section we provide a literature review on bankruptcy prediction models.

2.2. *Bankruptcy prediction models*

The first methodology used for bankruptcy prediction purpose was ratio analysis (Beaver, 1966). The aim of these first studies on the topic was to compare two sets of firms (Bankrupt and Non Bankrupt) with respect to a selection of financial ratios, focusing on the years prior to failure. These analysis were at first univariate and defined a potential list of ratios as predictors of bankruptcy. In general ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators. Given the shortcomings related to univariate analysis, which often reports ambiguous results, the literature has moved towards combining several measures into a meaningful predictive model, moving from univariate to multivariate techniques. An early and widely used approach was to summarize the individual ratios into a score. The famous Z score model developed by Altman (1968) uses MDA (Multivariate Discriminant Analysis) to separate sound and distressed.

After this important contribution, MDA (Altman et al., 1977; Deakin, 1972; Blum, 1974) and Logistic Regression (Ohlson, 1980) were the most widely used methods in the field in its early stage. More recently the literature has started to depart from the more traditional statistical methodologies

(MDA and Logistic Regression) towards machine learning techniques* starting with Artificial Neural Networks (Altman et al., 1994; Zhang et al., 1999), but also decision trees and genetic algorithms (Back et al., 1996; Gordini, 2014; Zelenkov et al., 2017), support vector machine (Danenas and Garsva, 2015), and other sophisticated ensemble methods such as multiple classifiers (Tsai and Wu, 2008), Random Forests (Kruppa et al., 2013), bagging or boosting procedures, such as FS (Feature Selection) Boosting (Wang et al., 2014) and XGBoost (Son et al., 2019).

Barboza et al. (2017) and Zhao et al. (2017), among others, have compared statistical models (logistic regression) with state of the art machine learning techniques, whereas Son et al. (2019) have focused on an optimization process to select input variables in intelligent techniques.

In this paper we decide to use two different models: a more traditional statistical methodology, i.e. logistic regression (LR) and an artificial algorithm, i.e. the artificial neural network (ANN). The purpose of our paper is not so much to select the best model in terms of bankruptcy prediction, nor to make an optimal selection of the input variables. Our aim is to provide an accurate forecast of firms' financial health in Brescia after COVID-19. We thus consider two simple and recognized models and a set of well established input variables (i.e the 4 financial ratios that compose Altman Z score).

3. Data

In order to develop our forecasting models we extract financial statement information on Manufacturing firms in Brescia using AIDA Bureau van Dijk in the period 2010–2018. At first we create a response variable which takes the value of 0 if the AIDA status of the firm is "bankruptcy" and 1 otherwise. This dummy variable enables us to distinguish two groups of firms: NB (Not Bankrupt) and B (Bankrupt). We consider B firms one year before they become bankrupt (B firms are taken over the entire period 2010–2018) and we consider all the NB firms in 2018. After having cleaned the dataset to exclude missing observations, inconsistencies and extreme values we remain with 362 B firms and 2,902 NB firms (12.47% of imbalance between B and NB).

Secondly we construct our input variables selecting those considered by Altman (1968) to construct the Altman's Z score and later also used by Carletti et al. (2020) to estimate the COVID-19 impact at the national level. Table 1 reports the list of input variables.†

Table 1. List of Input variables.

X1	Working capital/Total assets
X2	Earnings before interest and taxes/Total assets
X3	Net Worth/Total Liabilities
X4	Sales/Total assets

Notes: Altman (1968) selected input variables.

* Kumar and Ravi (2007) have published a comprehensive review of the work done, during the period 1968–2005, in the application of statistical and intelligent techniques to solve the bankruptcy prediction problem faced by banks and firms.

† From the Altman 1968 ratios we exclude Retained Earnings/Total Assets because, from a preliminary logistic regression on the whole dataset of manufacturing firms in Brescia, the variable turns out to be not significant.

Table 2. Summary statistics for B and NB.

	B (362 firms)			
	X1	X2	X3	X4
1q	–0.726	–0.403	–0.414	0.334
median	–0.210	–0.074	–0.085	0.687
mean	–0.737	–0.317	–0.148	0.859
3q	–0.006	0.019	0.046	1.138
min	–50.889	–5.190	–0.981	0.000
max	0.948	1.591	4.727	8.389
	NB (2,902 firms)			
	X1	X2	X3	X4
1q	0.048	0.024	0.162	0.842
median	0.204	0.050	0.388	1.117
mean	0.218	0.073	0.813	1.196
3q	0.382	0.107	0.917	1.453
min	–1.059	–0.854	–0.482	0.024
max	0.959	0.810	27.674	13.173

Notes: The ratios for B firms are taken 1 year prior Bankruptcy over the period 2010–2018. The ratios for NB firms are taken in 2018.

4. Bankruptcy prediction models

4.1. Logistic regression (LR)

The Logistic Regression model (LR) is used in this context for classification purposes rather than regression. As it is well known, through LR we set $Y = 0$ if bankruptcy occurs, 1 otherwise and we estimate the bankruptcy probability $\pi_i = P(Y_i = 1|X_i = x_i)$ supposing that:

$$\pi_i = \frac{exp(x_i \cdot \beta)}{[1 + exp(x_i \cdot \beta)]} \tag{1}$$

in which $x_i = (x_{i1}, \ldots, x_{ip})$ is the vector of explanatory variables observed for the i-th firm, $x_i \cdot \beta = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_p x_{ip}$, and $\beta_0, \ldots, \beta_p$ are $p + 1$ parameters to be estimated.

It is now worth noting that the log-likelihood function used to estimate the parameters is a sum of n terms, each one corresponding to a firm, and consequently it can be split into two parts as follows:

$$L = \sum_{i=1,\ldots,n} [y_i \cdot log(\pi_i) + (1 - y_i) \cdot log(1 - \pi_i)] = \sum_{y_i=1} log(\pi_i) + \sum_{y_i=0} log(1 - \pi_i) = L_1 + L_0 \tag{2}$$

If the number of observed $y_i = 0$ are rare (i.e. if the number of B is small compared to NB) the estimated probabilities π_i tend to be too small and biased, together with the related standard errors which depend on $\pi_i \cdot (1 - \pi_i)$. To account for this bias we follow the method proposed by King and Zeng (2001) and estimate a WLR (Weighted Logistic Regression) in which the parameters are estimated maximizing the modified log-likelihood function $L_w = w_1 \cdot L_1 + w_0 \cdot L_0$, where $w_1 = w_B = n/2n_B = 4.51$ and $w_0 = w_{NB} = n/2n_{NB} = 0.56$, where n=3,264 is the total number of B and NB firms, n_{NB}=2,902 is the number of NB firms and n_B=362 is the number of B firms.

4.2. *Artificial Neural Network (ANN)*

Artificial Neural Networks (ANN) are one of the most widespread artificial intelligence methods, widely used for regression, patter recognition and data analysis. The observed Altman variables are fed as inputs in the Neural network and elaborated through a sequence of steps ("layers") formed by many "neurons". Each neuron in a layer firstly computes the weighted sum of the inputs provided by all the neurons in the preceding layer, and then produces its own output through an "activating function". Such outputs are in turn fed as inputs for the neurons in the following layer, and so on. The Weights in the weighted sums are the parameters to be trained. In this work, we use a feed-forward neural network which contains five layers. The first layer is the input layer with 5 neurons since the dataset contains 5 input variables (attributes). The last layer has a single neuron that generates the response value, which in our case is the probability for the i-th firm to be classified as bankrupt. In the middle between the input layer and the output layer we have three hidden layers, each containing 200 neurons. We use the back propagation algorithm to train the network. This means that the weights are altered by feeding back the differences between output signals and desired output values. The activation function for the hidden units is ReLU whereas the activation function for the output unit is the logistic function. Weights are estimated minimizing a given loss function, which in this case is cross-entropy. The optimization method we use is the stochastic gradient decent.

4.3. *Monte carlo evaluation*

In order to measure the predictive performance of the techniques used, we conduct a Monte Carlo evaluation exercise in which we randomly split the universe (made of 2,902 NB and 362 B) into 500 splits (training 75% and test 25%), both characterized by the 12.47% universe imbalance ratio.[‡]

For the training sets we consider both a balanced training (same number of B and NB) to construct LR and ANN and an unbalanced training (where B and NB are different) to construct a weighted LR (WLR). The test set is always unbalanced. For each iteration in the Monte Carlo evaluation we estimate the different models (LR, ANN and WLR) on the training set and use the models parameters to calculate the predictive performance on the test set. To compare the predictive performance of the models we have used, we report T1 and T2 errors and F1 metrics. In particular given the confusion matrix reported below we calculate the following quantities: T_1 error=FP/(FP+TN) and T_2 error=FN/(FN+TP), whereas F1 is the harmonic mean between Precision (TP/(TP+FP)) and Recall (TP/(FN+TP)). We then end up with 500 T1 and T2 errors and F1.

4.4. *Models' forecasting performance*

We show the results on forecasting performance comparing LR and ANN. Table 4 reports the summary statistics of the 500 T1 and T2 errors and the average F1 metrics both in the training sample and in the testing sample.

[‡] We have also constructed a different Monte Carlo evaluation exercise in which we first divide the universe in training (75%) and test (25%) and separately for each of the two sets we extract 500 repeated random samples using only 85% of the data. Results are very similar.

Table 3. Confusion matrix.

		Predicted	
		Not Bankrupt	**Bankrupt**
Actual	**Not Bankrupt**	TP	FN
	Bankrupt	FP	TN

Notes: TP= True Positives; TN=True Negatives; FP=False Positives; FN=False Negatives.

If we compare training and testing samples the forecasting performance, as expected, is better in the training sample especially for ANN. Moreover, the inter quartile range of the T1 and T2 errors distributions is lower in the training sample for both models.

If we consider the testing sample results, LR and ANN are similar in terms of forecasting performance. Both models are very good in predicting NB firms correctly making a median T1 error around 11% and also good in predicting B firms correctly making a median T2 error around 15%.[§] LR has a lower T1 median and a higher T2 median, compared to ANN. However, the variance and the inter quartile range of the distribution of T1 and T2 errors is higher for ANN compared to LR. This makes ANN similar, but somewhat less reliable than LR.

This result is also emphasized by Figure 1a which compares the histograms of T1 and T2 for ANN and LR. The LR distributions have a lower variance compared to ANN. Figure 1b compares LR on a balanced training set as the one reported above, with WLR estimated on an unbalanced training set in which the number of NB is not equal to the number of B firms. Given that in this case we are using an unbalanced dataset in which the number of B firms is very small compared to NB, we estimate the modified logistic regression, called Weighted Logistic Regression (WLR), explained in Section 4.1.

Figure 1b shows that WLR (estimated on an unbalanced training set) produces better performing results than LR (estimated on a balanced training set), given that for WLR the variance of the distributions is lower especially if we consider T2. For this reason we build our simulation exercise on WLR. Table 5 reports the estimated coefficients over the whole dataset of 3,264 firms.

4.5. The score

Given the model (WLR), its parameters (Table 5) and the input variables (Table 1) we are now able to provide a score, i.e. a number from 0 to 1, which summarizes the financial health of each firm. In order to better describe our results we divide the different scores into 4 classes as reported in Table 6. If the input variables are related to 2019, we can compute the PRE COVID score, otherwise if they are related to the estimated values in 2020 we can compute the POST COVID score. In the next Section we explain how the estimated values are calculated.

5. COVID-19 shock to firms' input variables

Financial statements coming from AIDA Bureau van Dijk have the limitation of not being updated frequently. The 2020 data will be available only in Autumn 2021 and the latest available financial statements are the ones referred to 2019, which relates to the pre COVID period. In order to be able to

[§] These results are comparable and actually better than the ones published by Barboza et al. (2017) on US firms.

Table 4. Forecasting performance logistic regression and artificial neural network (training and testing sets).

training set

	T1 (B)					
	1q	**median**	**mean**	**3q**	**var**	**IR**
Logistic Regression	13.36%	14.22%	14.35%	15.52%	0.0003	0.0216
Artificial Neural Network	10.78%	13.36%	13.21%	15.95%	0.0012	0.0517
	T2 (NB)					
	1q	**median**	**mean**	**3q**	**var**	**IR**
Logistic Regression	10.34%	11.64%	11.81%	12.93%	0.0003	0.0259
Artificial Neural Network	6.03%	9.48%	9.66%	12.50%	0.0019	0.0647
	average F1					
Logistic Regression	64.15					
Artificial Neural Network	64.86					

test set

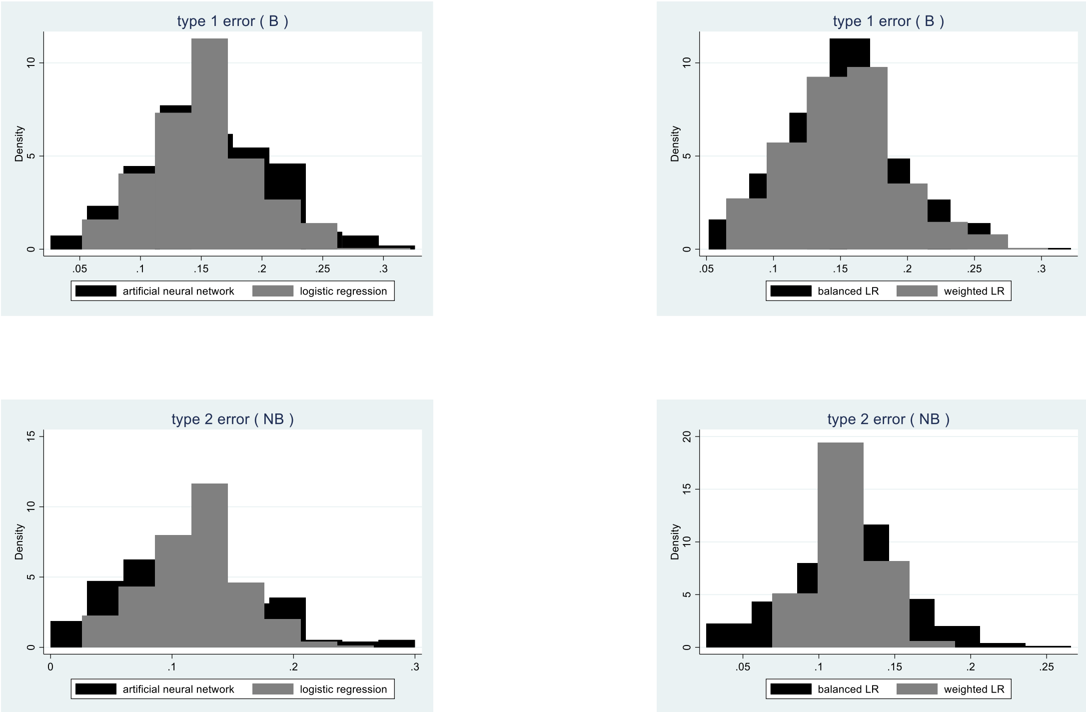
	T1 (B)					
	1q	**median**	**mean**	**3q**	**var**	**IR**
Logistic Regression	11.69%	14.29%	15.12%	18.18%	0.0018	0.0649
Artificial Neural Network	11.69%	15.58%	15.47%	19.48%	0.0029	0.0779
	T2 (NB)					
	1q	**median**	**mean**	**3q**	**var**	**IR**
Logistic Regression	9.09%	11.69%	11.80%	14.29%	0.0015	0.0519
Artificial Neural Network	6.49%	10.39%	11.07%	14.29%	0.0034	0.0779
	average F1					
Logistic Regression	64.19					
Artificial Neural Network	64.79					

Notes: var=variance; IR= inter-quartile range. F1 is the harmonic mean between precision and recall.

Table 5. WLR Coefficients.

		Coefficient	**SE**
	Intercept	−1.306***	(0.109)
X1	Working capital/Total assets	2.041***	(0.270)
X2	EBIT/ Total assets	6.254***	(0.641)
X3	Net Worth/Total Liabilities	3.189***	(0.262)
X4	Sales/Total assets	0.736***	(0.086)
Pseudo R^2		0.595	

Notes: Standard Errors in parenthesis. Significance levels: $*$: 10% $**$: 5% $***$: 1%.



(a) LR versus ANN

(b) LR versus WLR

Figure 1. T1 and T2 errors distributions (Monte Carlo results on 500 replications).

Table 6. Scores.

class	score range	health status
A	0.75–1	high
B	0.50–0.75	medium-high
C	0.25–0.50	medium-low
D	0–0.25	low

calculate the impact of COVID-19 on firms' bankruptcy we need to first make some estimates of the evolution of the financial statement ratios in 2020. In this section we propose a way to shock the input variables of the models presented in the previous sections. The literature has already started to estimate the liquidity needs of firms (see for example Schivardi and Romano (2020) and Carletti et al. (2020)).

The first information we consider in order to make some assumptions on the shocks is to use the first estimates related to the evolution of Total Sales in 2020 for the various components of the manufacturing sector in Brescia. Table 7 reports this number showing a YoY decrease of 11% for the whole manufacturing sector with peaks of 17% YoY decrease for the Wood sector and 13% YoY decrease for the Metallurgy sector. These estimates of sales variations in 2020 (with respect to 2019) are the outcome of a specific question asked to a sample of 100 manufacturing firms, members of Confindustria. Firms were asked the following: "With reference to the period January–December 2020, what is the percentage variation of Total Sales compared to the same period in 2019?". The question is part of a survey conducted quarterly by Confindustria Brescia, with the aim of reporting the short-term economic conditions of the manufacturing sector in Brescia. The sample was constructed in a stratified way to reflect the population characteristics in terms of sectors and size.

This is the only piece of information we have, thus we need to make an estimate of the other financial statement items we are using in our models. The aim of our simulation is to make some assumptions on how Total Sales variations impact on other variables in both the Profit and Loss Account and also in the Balance Sheet.

At first, we need to make an estimate on how Total Costs react to a change in Total Sales. It is probable that firms may reduce their variable costs (costs of raw materials and services) as a consequence of a reduction in sales, but not their fixed costs (personnel, depreciation and other costs).

As in Schivardi and Romano (2020) we regress the percentage annual change (the log difference) in the respective voices of costs (raw materials, services, other costs and charges and labor costs) on the percentage change in sales, controlling for year and firm fixed effects. For this panel regression we use the 2,902 manufacturing firms of our sample over the period 2009–2019. In order to account for the fact that we want to calculate the elasticities of costs to sales when sales drop rather than when sales increase, we repeat the regressions using only observations for which the change in sales is below −0.1. Table 7 reports these elasticities which we calculate for each sector, their statistical significance and standard errors. As expected, while the elasticities of raw materials are highly elastic (1.25 for Total manufacturing and 1.82 for the Metallurgy sector), Services and Other costs and charges are more difficult to cut in the short run and thus their elasticities tend to be much lower or sometimes not significant. Labor elasticities are around 0.4 for most sectors. If we take the elasticities calculated on Total Manufacturing our results are in line with the ones calculated by Schivardi and Romano (2020) on the Italian national data.

We develop two different scenarios. In a first scenario we report a reduction in Total Sales without adjusting for a possible reduction in variable costs (we call it "zero elasticity"). This first not so realistic scenario represents a worst case scenario. In a second scenario (we call it "panel elasticity") we use the elasticities reported in Table 7. The reduction in sales and the estimated cost rigidities to sales' variation have an impact on some of the variables that we use to feed our bankruptcy forecasting model. Table 8 summarizes the impact of the shock on the single balance sheet items which compose our input variables. The first two variables affected by the simulation are Sales/Total assets and EBIT/Total assets. A change in EBIT though will eventually impact the Profit or Losses of the firm that will ultimately affect firm's Net Worth. A change in Net Worth implies also a change in Total Assets that we decide to counteract with a change in Total Liabilities. So Total Assets remain unchanged, but the variable Net worth/Total Liabilities will be also affected by the simulation both for a movement in the numerator and in the denominator.[¶]

[¶] The remaining indicator (X1) is not influenced by the simulation since it is very hard to predict how Working Capital would change after COVID-19.

Table 7. Elasticities.

	Expected YoY Total Sales 2020	Share of Total Sales	Cost Elasticities to a 1 % change in Sales				Variable costs/ Total Sales
			Raw Materials	Services	Other	Labour	
Food	−3.0%	9.4%	1.01***	0.50***	0.62	0.45**	86.0%
			(0.17)	(0.14)	(0.70)	(0.18)	
Chemicals	−4.4%	7.6%	1.19***	0.48***	0.49***	0.58***	74.4%
			(0.11)	(0.04)	(0.10)	(0.16)	
Wood	−17.5%	3.0%	1.58***	0.71***	0.42**	0.35***	74.0%
			(0.20)	(0.07)	(0.18)	(0.05)	
Mechanics	−12.2%	48.7%	1.05***	0.61***	0.16**	0.39***	73.0%
			(0.03)	(0.03)	(0.07)	(0.03)	
Metallurgy	−13.1%	25.7%	1.82***	0.28***	0.51**	0.40***	84.8%
			(0.10)	(0.04)	(0.25)	(0.06)	
Textiles	−12.9%	3.0%	1.39***	0.11***	0.05	0.06***	78.0%
			(0.09)	(0.02)	(0.05)	(0.02)	
Other	−9.5%	2.6%	2.07***	0.58***	0.03	1.17***	71.3%
			(0.20)	(0.12)	(0.26)	(0.10)	
Total	−11.0%	100.0%	1.25***	0.37***	0.18***	0.27***	77.6%
			(0.03)	(0.02)	(0.04)	(0.02)	

Notes. Cost elasticities are calculated from a panel regression over the period 2009–2019 of almost 3,000 manufacturing firms in Brescia; variable costs= raw materials+services. The percentages of Variable Costs/Total Sales by sector is in line with the national number (Mediobanca). Standard Errors in parenthesis. Significance levels: $*: 10\%$ $**: 5\%$ $***: 1\%$. We consider the costs for which the elasticities are not significant as inelastic.

Table 8. Shock to balance sheet items.

Balance sheet items	**Definition**	**Shock impact**
Sales	Amount coming from sales of goods and services	Confindustria Survey estimates a reduction in sales for 2020. We assume that this reduction (through the estimated elasticities)translates in a contraction in variable costs.
Working Capital	(Current Assets - Current Liabilities)	We assume it remains unchanged in 2020.
EBIT	(Sales – Operating Costs)	This item changes as a consequence of sales and costs changes.This in turn impacts on the profit/loss for the year.
Net Worth	(Assets – Liabilities) or (Share Capital + Retained Earnings+ Profit/Loss)	The item reflects changes in profit/loss.
Total Assets	(Total Liabilities + Net Worth)	We assume it remains unchanged in 2020.
Total Liabilities	(Total Assets - Net Worth)	The item moves in the opposite direction to net worth to ensure a balance between assets and liabilities.

6. Results: financial health in different scenarios

Figure 2 compares the different scenarios and predicts that the COVID-19 crisis will reduce in 2020 the percentage of firms characterized by high financial health (with A and B scores) and increment the percentages of firms characterized by low financial health (with C and D scores). The PRE COVID scenario reports around 88.9% of firms in the high and medium-high class and the remaining 11.1% in the low and medium-low class, underlining the strength and soundness of the manufacturing sector in Brescia before the pandemic. The worst case scenario predicts a reduction from 65.7% to 32.6% of firms in the A class and an increase from 1.3% to 29.1% in the D class as a consequence of the COVID-19 crisis. The more realistic scenario, which considers the elasticities of costs to sales contractions in the 2009–2019 period, shows a less pessimistic scenario in which the percentage of firms in the A class reduces from 65.7% (1,908) to 57.4% (1,665) and the percentage of firms in D increases from 1.3% (38 firms) to 5.1% (149 firms).

Table 9 reports the results of the simulation across sectors. The first part of the Table shows that the manufacturing sector in Brescia is dominated by the Mechanics sector. In terms of Sales it produces 49% of total Manufacturing Sales and incorporates 64% of the firms. The importance of this sector is also reflected on the impact of COVID-19 crisis on the firms' scores. The Mechanics sector together with Textiles and Apparel report the highest reduction of firms in the high and medium-high class and the highest increase in the low and medium-low class.

Table 10 reports the same information as the previous Table but dividing firms according to their size. The upper part of the Table shows the prevalence of micro and small firms in the Brescia territory. Results on the COVID-19 effect on financial health shows that the most hit by the crisis are the SMEs especially micro and small firms who see a contraction in the A and B classes and an increase in the C and D classes. The vulnerability of small firms in the context of COVID-19, implied by our results, is not a surprise in the firm size literature (see for example Amatori et al., 2013), which highlights both the greater ability of larger firms to face new competitive challenges through innovation and internationalization and also the better capacity of the same firms to attract financial resources and high skilled workers. Consequently, through all these channels, larger firms were probably more prepared compared to smaller firms to face the negative shock implied by COVID-19. In the Appendix we report the transition matrices divided by sector and firm size.

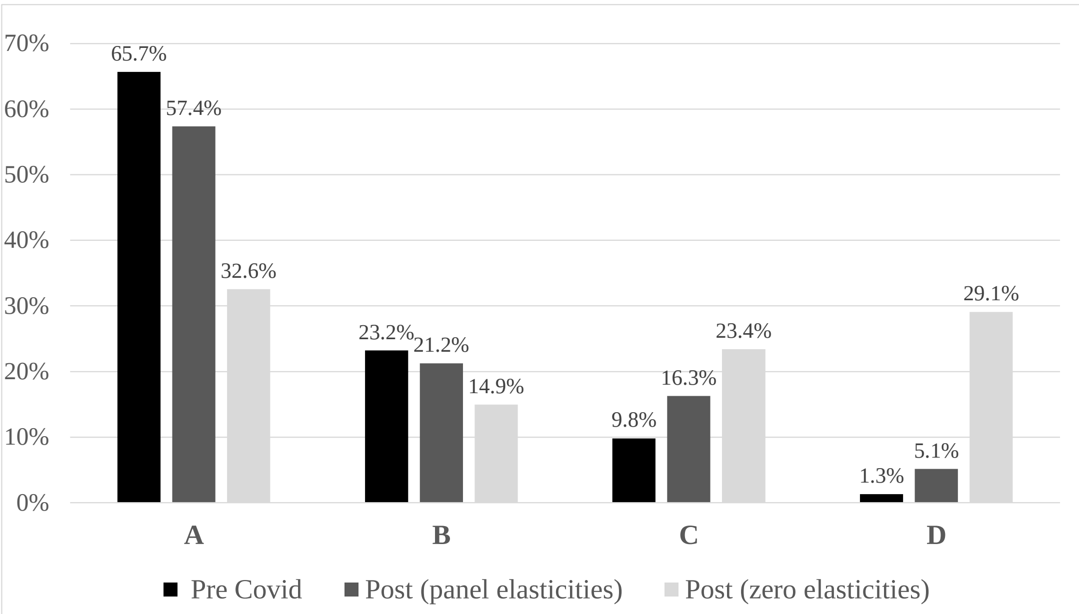


Figure 2. Score comparison PRE-POST COVID-19.

7. Concluding remarks

COVID-19 has generated a real challenge to national systems worldwide and its consequences have put the world economy at risk causing a sharp decline both in demand and supply. Given the uncertainty related to the economic repercussions of the virus starting from March 2020 and the still unclear developments of COVID-19 it becomes very difficult to understand the state of the economy

Table 9. Firms' characteristics by sector and the score distribution PRE and POST COVID.

	Food Beverages	Chemicals, Rubber Plastic	Wood non metallic mineral	Mechanics	Metallurgy	Textiles Apparel	Other Manuf.	Total
firms	140	252	193	1,855	202	139	121	2,902
share (firms)	4.8%	8.7%	6.6%	63.9%	7.0%	4.8%	4.2%	100.0%
share (sales)	9.4%	7.6%	3.0%	48.7%	25.7%	3.0%	2.6%	100.0%
Expected Sales*	−3.0%	−4.4%	−17.5%	−12.2%	−13.1%	−12.9%	−9.5%	−11.0%
				PRE COVID percentage of firms				
A	62.9%	72.2%	60.1%	65.2%	69.8%	71.9%	57.9%	65.7%
B	27.1%	16.3%	29.0%	23.8%	17.8%	20.1%	26.4%	23.2%
C	7.9%	9.9%	10.9%	9.7%	10.9%	4.3%	15.7%	9.8%
D	2.1%	1.6%	0.0%	1.2%	1.5%	3.6%	0.0%	1.3%
				POST COVID percentage of firms				
A	62.1%	67.9%	59.1%	53.2%	74.3%	51.8%	69.4%	57.4%
B	25.0%	20.2%	24.9%	21.8%	10.4%	22.3%	21.5%	21.2%
C	10.0%	9.1%	13.5%	19.2%	11.4%	14.4%	7.4%	16.3%
D	2.9%	2.8%	2.6%	5.8%	4.0%	11.5%	1.7%	5.1%
				POST COVID reduction/increase				
A	−0.7%	−4.4%	−1.0%	−12.0%	4.5%	−20.1%	11.6%	−8.3%
B	−2.1%	4.0%	−4.1%	−2.1%	−7.4%	2.2%	−5.0%	−2.0%
C	2.1%	−0.8%	2.6%	9.5%	0.5%	10.1%	−8.3%	6.5%
D	0.7%	1.2%	2.6%	4.5%	2.5%	7.9%	1.7%	3.8%

Notes: Post COVID estimations based on panel elasticities.* Expected Total Sales are YoY growth rates 2020 over 2019, estimated by Confindustria Brescia.

Table 10. Firms' characteristics by size and the score distribution PRE and POST COVID.

	micro	small	medium	large	Total
firms	830	1,405	524	143	2,902
share (firms)	28.6%	48.4%	18.1%	4.9%	100.0%
share (sales)	3.3%	17.9%	31.8%	47.0%	100.0%
			PRE COVID percentage of firms		
A	58.4%	64.6%	75.2%	84.0%	65.7%
B	24.9%	24.9%	19.3%	11.1%	23.2%
C	14.8%	9.5%	4.6%	2.8%	9.8%
D	1.9%	1.0%	1.0%	2.1%	1.3%
			POST COVID percentage of firms		
A	49.0%	55.3%	68.9%	83.9%	57.4%
B	20.8%	22.6%	21.4%	9.8%	21.2%
C	22.4%	17.1%	7.6%	4.2%	16.3%
D	7.7%	5.1%	2.1%	2.1%	5.1%
			POST COVID reduction/increase		
A	−4.5%	−2.5%	−2.1%	1.1%	−3.5%
B	−2.2%	−0.7%	0.8%	−1.1%	−1.0%
C	4.5%	3.1%	1.1%	0.0%	3.0%
D	2.2%	0.0%	0.2%	0.0%	1.4%

Notes. Post COVID estimations based on panel elasticities.

today. The purpose of this article is to simulate the effect of COVID-19 on firms' financial statements in Brescia and then feed the shocked information into a bankruptcy model in order to provide an up to date picture of firms' financial health before and after COVID-19. Results have shown that in the PRE-COVID period (2019) the Manufacturing sector in Brescia has proven to be strong and sound with 88.9% of the firms belonging to the most healthy classes. After the outburst of COVID-19 the economic situation of the firms worsened compared to the PRE-COVID period. The percentage of firms in the A class reduce from 65.7% to 57.4% and the percentage of firms in the D class increase from 1.3% to 5.1%. Small enterprises and the Mechanics and Textiles sectors turn out to be the hardest hit by the crisis. In general, however, results show that the Manufacturing sector in Brescia holds up, despite the difficulties faced. If it is true that the "Made in Brescia" has somehow managed to overcome the pandemic crisis, drawing conclusions on sectors such as Services and Construction is a different matter as these latter faced a more intense crisis and a longer period of lockdown. Further research could expand the analysis including other sectors and/or other geographical areas in Italy.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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