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Financial constraints prediction to lead socio-economic development: An application of neural networks to the Italian market

G.G. Calabrese [a,b], G. Falavigna [a], R. Ippoliti [c,*]

[a] Research Institute on Sustainable Economic Growth (IRCrES), National Research Council of Italy (CNR), Torino (TO), Italy
[b] Center for Automotive and Mobility Innovation (CAMI), Ca' Foscari University, Venice, Italy
[c] Department of Law and Political, Economic and Social Sciences (DIGSPES), University of Eastern Piedmont (UPO), Alessandria, Italy

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ABSTRACT

This study applies a neural network framework to optimize the classification of firms and to predict their difficulties in collecting external financial resources in the short term. In detail, we adopt replicated bootstrapped algorithms optimized on sensitivity and specificity as error measures and we propose a comparative analysis to identify the best-performing one. According to our results, the Conjugate gradient backpropagation with Fletcher-Reeves updates (i.e., CGF) is the best-performing algorithm, with sensitivity equal to 74.41 % and specificity equal to 70.11 %. Then, we use this algorithm and its weights to provide a classification of the Italian manufacturing industry in 2019, identifying the geographical areas in which firms under financial constraints are located, as well as the most critical industrial sectors. Based on this evidence, and considering the implementation of a cohesion policy, we highlight interventions by policy makers to support firms' access to the capital market, fostering their investments and the consequent socio-economic development.

1. Introduction

Financial constraints represent the difficulties encountered by firms in collecting external financial resources on the capital market. Thus, firms under financial constraints have restricted access to the capital market to fund their business and/or innovative projects, which causes them to rely on alternative resources, including, for instance, trade credits [1,2], tax avoidance (e.g. Refs. [3,4], and their own savings [5]. According to the literature, difficulties in gathering external financial resources are mainly due to the internal characteristics of firms, which might amplify asymmetric information between them and their investors, such as, for example, their size and their seniority [6,7]. Another driver of financial constraints is represented by the decision to be innovative and make investments in R&D and/or new technologies [8, 9]. Hence, asymmetric information, uncertainty and the related risks of insolvency are the main problems that might prevent access to external resources, which are fundamental to support both growth and innovation in firms—a relevant topic for all stakeholders. Managers need to correctly shape their corporate strategies to survive on the market, while policy makers need to support businesses by means of appropriate industrial and fiscal policies to increase their access to external financial resources [10]. Therefore, it is extremely important to develop specific algorithms and classification rules to predict whether firms' applications for resources to the capital market will be rejected, since this knowledge can guide appropriate interventions, fostering socio-economic development and welfare growth.

The relation between financial development and economic growth is well known and uniquely robust [11]. Among the different features that might affect the development of a financial market, the present work focuses on access to its resources. This is a crucial aspect to support the investments, innovation, and growth of firms, as well as to facilitate trading and exchange of goods and services [12]. Precluding access to the capital market can prevent all these key business dynamics, limiting the economic development of specific territories and/or industrial sectors, with adverse impacts on society. The literature suggests that financial constraints cause investment loss in tangible assets [13,14] and in R&D activities [15], forcing firms to avoid all "sub-optimal" strategies [16]. Therefore, the condition of being under financial constraints can have a significantly negative effect on firms' efficiency and productivity (e.g. Refs. [17,18], as well as on employment during a credit crisis [19]. Furthermore, focusing on environmental policies, this condition can have a significantly negative effect on firms' decisions to pursue social targets such as, for instance, reducing pollution and gas emissions [20]. Indeed, even though environmental responsibility might have a positive

* Corresponding author.
E-mail address: roberto.ippoliti@uniupo.it (R. Ippoliti).

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influence on corporate financial performance [21,22], firms with no access to external financial resources to fund green strategies and their related costs cannot survive on the market [23].

Although the current literature on financial constraints is widespread and researchers generally agree on their main drivers behind such a condition, there is no common consensus on the most appropriate classification rule to predict whether firms will have difficulties in collecting financial resources on the market [24]. In other words, consensus has not been reached on how we can understand whether firms might see their applications rejected by financial institutions. Some works use specific cashflow-based indicators as proxies for application failures, extracting key information on access to the capital market from the behavior of firms (e.g., Refs. [25,26]. Other studies integrate different types of information to predict rejections, proposing complex indexes like the Hadlock and Pierce index, the Kaplan and Zingales index and the Whited and Wu index [27]. The most common technique adopted in these contributions is a logistic regression model, introducing explanatory and control variables to predict the odds of being under financial constraints. Then, according to these coefficients, researchers classify their observations by replicating their techniques and applying them to other samples of firms (e.g., Ref. [28].

The contribution of this work is twofold. First, we can study the condition of being under financial constraints, proposing a new neural network framework to optimize the classification of firms and predict their difficulties in gathering external financial resources in the short term. Second, we adopt this framework to provide a classification of the Italian manufacturing industry in 2019, identifying which industrial sectors and geographical areas have the highest percentage of firms under financial constraints, leading the policy maker in the implementation of a cohesion policy. To the best of our knowledge, there are no applications of neural networks to financial constraints and our study might contribute to filling the gap, drawing the attention of experts to this under-investigated research topic. Indeed, the focus of current research has largely been on the financial distress of firms (e.g., Refs. [29,30]. On the other hand, the evidence collected may help policy makers to promote innovation, supporting investments and socio-economic development within a framework of ad-hoc interventions that are in line with the European Union cohesion policy program for 2021–2027.[1]

Our study is based on the Italian industry. As a first step, in order to assess the ability of neural networks in determining whether innovative firms are under financial constraints, thereby preventing their investments, we adopt a specific sample of firms, i.e., the Italian automotive supply chain between 2017 and 2020.[2] As a second step, after selecting the best-performing algorithm, we classify the firms of the Italian manufacturing industry in 2019, identifying the observations under financial constraints and then mapping their distribution on the territory and across industrial sectors.

According to the results of our investigation, the Conjugate gradient backpropagation with Fletcher-Reeves updates (i.e., CGF) is the best-performing algorithm. Moreover, considering specificity and sensitivity, we show that the proposed framework better balances researchers' expectations than a simple logistic regression model, modulating the admissible type I and type II errors. Finally, among the determinants of being under financial constraints, the most relevant proxies are net profit to added value, spread and percentage increase of sales. Indeed, these three proxies account for almost 40 % of cases of being under financial constraints. More precisely, when these values increase, we expect a decrease in the odds of having difficulties in gathering external financial resources. Next, considering the classification of manufacturing firms in 2019, we estimate that 22.56 % of the observations are under financial constraints. Looking at the most significant sectors, the share of firms under financial constraints ranges between 19 and 20 % (i.e., NACE codes 25, 28, 22 and 33) and 29 % (i.e., code 10). In addition, we observe strong heterogeneity among geographical areas (North vs. South of Italy) and within regions (i.e., at the level of provinces).

The remainder of this paper is organized as follows. The second section presents current literature, highlighting the main approaches to predict whether firms are under financial constraints. The third section introduces the methodology and an overview of current algorithms, as well as the dataset and related variables. The fourth section shows the collected results, while the fifth section describes the policy implications of our study. Finally, the sixth section presents our conclusions and some practical implications.

2. Literature review: how to predict financial constraints

Firms are under financial constraints when they have difficulties in collecting external financial resources on the capital market. To understand whether firms are in such a condition, we need them to disclose key information. In particular, firms need to disclose whether they submit an application to collect external financial resources, and whether this application is rejected by banks or financial institutions (e.g., Refs. [19,31]. Only surveys can collect this key information, providing primary data to estimate whether firms have difficulties in funding their business strategies [32]. According to this information, researchers can identify the main determinants of being under financial constraints, and then to classify firms and to predict whether they have difficulties in collecting external financial resources (e.g., Refs. [33,14]. The most popular indexes created in this vein are Kaplan and Zingales, Whited and Wu, and Hadlock and Pierce [27], which are calibrated on US public companies and financial information extracted from their balance sheets, limiting their use to a specific population of firms [34]. With no direct information on this disclosure, researchers must adopt proxies that could denote this condition, focusing on firms' behavior (e.g., payment of dividends) or firms' financial condition (e.g., expected solvency). In the former case, we expect that firms able to pay dividends to their shareholders are not under financial constraints [35]; while, in the latter case, we expect that credit rating scores may affect firms' access to the capital market and its resources [36,37]. Alternatively, researchers adopt cash flow-based indicators to predict whether firms are under financial constraints (e.g., Refs. [38,39].

Another key point in the analysis of financial distress or financial constraints is represented by the problem of imbalanced sample. Indeed, the population of firms in default and/or with difficulties in collecting external financial resources is smaller than the healthy one. Hence, even if the sample under investigation is relevant, the distribution of observations could be imbalanced, with very few observations financially distressed and/or under constraints. If this is good news from the economic point of view, there is concern from the technical point of view since it is necessary to understand how to balance the sample, especially when machine learning algorithms are adopted. Indeed, these techniques might suffer of overfitting and/or overspecialization, i.e., if we adopt an unbalanced sample of observations, it is possible that the

[1] The European Union cohesion policy program 2021–2027 contributes to reducing disparities between the levels of development of the various regions within the Union, and to reducing the backwardness of the least favored regions through participation in the structural adjustment of regions whose development is lagging and in the conversion of declining industrial regions, including by promoting sustainable development and addressing environmental challenges. Among its various objectives, the program aims to generate a more competitive and smarter Europe by promoting investments and leading to innovative and smart economic transformation, as well as regional ICT connectivity [126].

[2] This is an interesting sample on which to develop the neural network framework and identify the best-performing algorithm. Indeed, this supply chain must invest in R&D to develop sustainable solutions and achieve the expected targets set by green policies to curb global warming (Krupniket al., 2022). However, innovation and R&D investments are key drivers of financial constraints, precluding firms' access to external financial resources [127].

learner will be able to recognize those observations that are very similar to those more frequent in the database, and the risk of incorrect classification could be quite high. A possibility to address this problem is to evaluate the accuracy of the model testing different database specifications (sampling-based method, as suggested by Ref. [40] or, alternatively, the adoption of statistical methods to balance the sample, obtaining more robust results. In addition, data might also present anomalous observations (i.e., outliers), and authors need to adopt techniques for achieving together the two goals (i.e., balancing the sample and detecting the outliers). For instance, starting from the ROSE algorithm [41]; and [40,42] propose the robROSE algorithm, which improves the ability to detect the outliers in the sample under investigation, considering the covariance structure of a sample artificially generated. These authors show that the algorithm can be applied with success in many fields such as, for instance, credit scoring, churn prediction, and fraud detection. Other algorithms are proposed in literature such as, for instance, the SMOTE [43], which combines an over-sampling of the class under-represented, and an under-sampling of the over-represented class. Performance is measured considering the ROC curves and the ROC convex hull, and results suggest that the combined proposed strategy of re-sampling the minority and the majority performs better than under-sampling the over-represented. It is worth nothing that the sampling strategy is not the unique solution proposed by the literature (see for instance: [44–46]). In the present paper, we have adopted a sampling-based method, testing the accuracy of the learner on different sample. Moreover, to improve the robustness of results and to weaken the problem of outliers, we introduce a sampling methodology (i.e., the bootstrapping) that allows to mitigate both the problem of unbalanced sample and outliers. Considering the case studies that focus on finance, which are characterized by unbalanced sample (e.g., default probabilities, fraud detection, financial constraints, and so on), the combination of machine learning techniques and statistical methods for balancing sample is a field worthy of study, as suggest by recent literature [47], with opportunities to contribute the current knowledge. Indeed, we can observe an increasing number of studies that focus on finance and machine learning in the last years (Henrique et al., 2019; Rundo et al., 2019; Sagu et al., 2023), with a significant effort in defining algorithms able to overcome the so-called problem of black-box (e.g., the eXtreme Gradient Boosting algorithm as suggested by Ref. [48]. Until few years ago, this was the big problem of deep learning methods, but research shows that the combination of different techniques can improve the performance of models, and it can support the understanding of their functioning.

Our contribution concerns the opportunity to study the condition of being under financial constraints, adopting firms' disclosure on their difficulties in collecting external financial resources, and proposing a new neural network framework to optimize the classification of firms. To the best of our knowledge, there are no applications of neural networks to financial constraints and our study might contribute to filling the gap. Moreover, our study considers both private and public firms, proposing a more generalized approach to predicting difficulties in gathering external financial resources in the short term by firms. Finally, even if this study is methodologically very similar to investigations on credit rating scores and the estimation of default probabilities through neural networks (e.g., Ref. [49]; and [50], we use unique survey data, significantly increasing the contribution of this paper [32].

3. Method and data

Neural networks have been adopted in many fields to support the decision making of stakeholders, forecasting events and/or conditions in sectors like health [51,52] and finance [30,53], as well as to investigate social interventions [54] and development [55,56]. This section presents new algorithms applied to a feed-forward neural network able to optimize the stratification of firms with difficulties in collecting external financial resources on the capital market, i.e., their probability of being under financial constraints. The framework is then adopted to highlight the implementation of policies that could foster investments by firms, thereby promoting socio-economic development.

The first sub-section features the basic artificial neural network topology, as well as a brief overview of the current literature and its applications in finance. The second sub-section describes the combination of the *threshold search algorithm* and the *sensitivity–specificity search algorithm*, while the third sub-section shows the *replicated bootstrapped procedure*. Next, the fourth sub-section illustrates the different training algorithms tested in our case study and the fifth sub-section focuses on the Garson index. Finally, the sixth sub-section examines the dataset and related variables, which are used to predict financial constraints.

3.1. Feed-forward neural network (FFNN): an overview and related works

Artificial Neural Networks (ANNs) are the fundamental unit of deep learning methodologies and they have been widely applied to many different fields [57]. ANNs are formed by simple units with memory, called neurons, and interconnected together by synapses, which, in mathematical terms, represent weights. Different topologies of ANNs are suggested in the literature, ranging from the number of layers to the functioning of each neuron and the activation functions among layers [58]. The neurons, also defined as nodes, are the mathematical representation of the biological neurons in the brain. The first scholar who had the intuition to formalize the neuron as the basic brain cell was the psychologist McCulloch and, together with the mathematician Pitts, he proposed the so-called McCulloch-Pitts Neuron (i.e., MP neuron) in the late 1940s. Figure A1 in Appendix A provides a graphical representation of an MP neuron, where the summing function collects information from the inputs through the synapses. The result is translated into the output of the neuron through an activation function that, in the case of the MP neuron, is a *hardlim function* (i.e., only two possible outcomes exit: 0 or 1)[3] and, in general, a non-linear function.

In the following years, thanks to improved computational performance, researchers developed even more complex connections between layers of neurons, adopting activation functions suited to the specific types of problems under investigation. In particular, scholars focused on the learning ability of the neurons elaborating supervised and unsupervised learning algorithms, allowing the ANNs to recognize relations or rules among inputs and to apply them to unknown items. This is the significant advantage of the bottom-up approach of deep learning methods, that is to say, the ability to collect information from data and generalize/predict outputs.

The model adopted in this paper is based on a neural network with two layers and feed-forward connections. In detail, the topology proposed here is shown in Fig. 1, where the connections go from left to right without the possibility of coming back, the inputs are $x_1, \ldots, x_n$, W_{ih} and W_{ho} are weight matrixes and two activation functions are provided: one from the input layer to the hidden layer (f_1) and another from the hidden layer to the output one (f_2). The backpropagation algorithm allows estimating and correcting the weights of the network, considering the comparison between the output of the network (i.e., output) and the real value (i.e., target). There are different algorithms for updating the weights and we consider several of them to compare and assess the performance of the FFNN.

As for the number of hidden layers and related nodes, the debate is still open. In general, the literature suggests identifying the optimal topology (i.e., number of layers and nodes) on the basis of trial-and-error procedures, or following some heuristics/algorithms [59]. In this paper, starting from the universal approximation theorem proposed by Ref. [60]; we have chosen to adopt only one hidden layer and to set the number of neurons in the hidden layer (represented by h in Fig. 1)

[3] $y = hardlim(u) : y = 1 \text{ if } u \geq 0; y = 0 \text{ otherwise}.$

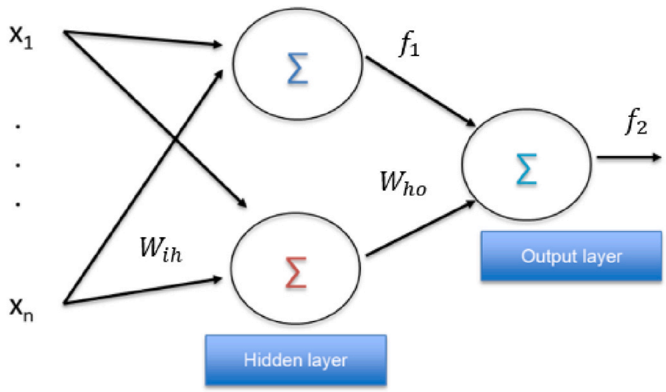

Fig. 1. Feed-forward neural network (FFNN).

according to the following rule of thumb:

$$\text{Number of hidden nodes} = \frac{\text{Number of inputs} + \text{Number of outputs}}{2} \tag{1}$$

This type of architecture has been widely used in the economic and financial literature because it has been proved that an ANN with only one hidden layer (also called Shallow Neural Network) is able to approximate any functional form, so that generalization and prediction of the proposed model perform well.

Two activation/transfer functions have been adopted between the input layer and the hidden one, as well as between the hidden layer and the output one. A hyperbolic tangent sigmoid transfer function has been set from the input to the hidden layer and a log-sigmoid transfer function from the hidden to the output layer. As suggested by Ref. [61]; these are the activation functions used in most applications.

The hyperbolic tangent sigmoid transfer function ranges between −1 and +1. It is equal to:

$$y = tansig(u_i) = \frac{2}{\left(1 + e^{-2u_i}\right)^{-1}} \tag{2}$$

The log-sigmoid transfer function varies between 0 and +1. It is calculated as:

$$y = logsig(u_o) = \frac{1}{1 + e^{-u_o}} \tag{3}$$

where

$$u_i = \sum_{i=1,h=d}^{n,d} w_{hi} \cdot x_i \tag{4}$$

and

$$u_o = \sum_{h=d}^{d} w_{ho} \cdot o \tag{5}$$

In detail, the ANN starts analyzing a training set of data, from which rules and relationships among the inputs and the output are extracted to estimate the synapses and evaluate which neuron is the most representative of the problem analyzed. Once a performance goal is reached, the weights (i.e., synapses) and the ANN architecture are applied to out-of-sample data (i.e., validation set), with the aim to assess the performance of the model. To do so, many parameters have been set, e.g., the activation functions between the input, hidden and output layer, the number of neurons in the hidden layer, the training function, the performance function, or the epochs of the ANN. While nothing new has been presented so far, what we propose in this paper is the definition of a replicated bootstrapped procedure applied to the ANN.

Due to their flexibility and ability in generalizing, ANNs can be employed in several fields. Although we are aware that the following brief overview is not exhaustive, we try to summarize their main applications, focusing on three relevant categories: function approximation; clustering; classification and prediction.

First, ANNs are successfully used for function approximation, which is the basis for real-world applications [62], i.e., when outputs, real values, and inputs are linked through an underlying function that needs to be determined from noisy training data. Regarding this topic, many investigations on the optimal topology have been conducted like, for instance, the study by Ref. [63]; where the performance of radial basis functions (RBFs), backpropagation neural networks (BBNNs) and generalized regression neural networks (GRNNs) are compared. Second, ANNs have also been applied to clustering problems, often combined or compared with other techniques, such as support vector machine (SVM) or fuzzy logic [64,65]. In comparison to the classical clustering methodology, as well as the k-means approach, through unsupervised learning algorithms, ANNs (traditionally the Self-Organizing Maps, SOMs) can distinguish elements from each other with high accuracy [66, 67].

Third, classification and prediction is the most popular approach in the literature, thanks to the ability of ANNs to classify elements. Indeed, one of the strengths of neural networks is their ability to determine, from a set of inputs, which class a given object falls in. The inputs are variables describing the object and the target output represents the associated class, which, in general, is a dichotomous vector. If the network can learn well, the object will be assigned to the correct class. This might well be the most significant advantage of such supervised learning models because the majority of applications start from a classification problem where, thanks to convolutional neural networks, key advancements have been reached [68,69]. At the same time, an ANN can be trained, usually by means of supervised learning algorithms, to predict outputs from a given input. Although the prediction problem is common to many fields of study, we focus on the main applications in finance, where ANN approaches provide interesting evidence. In financial markets, deep learning methodologies are widely used for forecasting the volatility of stocks, as seen in the study by Ref. [70]; where a combined model ANN-ARMA process is defined and tested on a Chinese data sample. The authors show that the ANN-ARMA methodology outperforms alternative models across all statistical metrics and over different forecasting horizons. Recent applications consider the Long-Short Term Memory (LSTM) neural networks as optimal solution for forecasting, like in the work by Ref. [71]; where LSTMs with machine learning methods are successfully combined for forecasting bitcoin prices. A very interesting survey on the applications and performance of ANN, support vector machine (SVM) and LSTM methodologies to stock market predictions is presented by Ref. [72]; where the authors review the strengths of the three models analyzed. Concerning corporate finance, default probability/financial distress prediction is the main issue addressed by researchers. Most studies apply the feed-forward neural network (FFNN) with backpropagation algorithm, the same used in the present paper, but this framework is known to suffer from overfitting. To prevent this problem and achieve optimal performance, scholars have introduced new regularization algorithms, like in Ref. [73]; or recurrent networks instead of feed-forward ones, as seen in Ref. [29]; where an adaptive Elman neural network design is chosen to minimize the classification error. The authors show that the Elman neural network outperforms the feed-forward neural network but, comparing the Elman framework with logistic regression, the goodness of the performance depends on the error type considered.

Considering the above overview and coherently with the most popular network topology used in finance [74,75], our paper aims to provide an innovative optimization algorithm, which applies a simple multilayer feed-forward neural network to control for the overfitting problem and to minimize the type of error according to the user's objectives. The next sub-section describes the suggested threshold algorithm.

3.2. The threshold search algorithm combined with the sensitivity–specificity search algorithm

An initial version of this threshold algorithm was presented in Ref. [76] and successfully applied in studies on corporate finance [77,78]. The main goal of this algorithm is to find the threshold between 0 and 1 able to minimize the errors of the network when the targets are dichotomous, e.g., when the aim of the network is to forecast whether a firm is in default (1) or financially healthy (0). Obviously, although the target of the ANN is 0 or 1 for each observation under investigation, the output generated by the ANN computation can be continuous. The threshold algorithm iteratively considers possible values between 0 and 1 to approximate the continuous output to 0 or 1. In its native definition, the algorithm selects the threshold to minimize the number of errors.

The threshold search algorithm works by starting from a vector of thresholds, where $th \in [0,1]$ with a step T,[4] o_n is a vector of network's outputs and t_n a vector of targets. It is possible to define vector o_n^* as:

$$o_n^* = \begin{cases} 0 \ \ if \ (th - o_n) > 0 \\ 1 \ \ if \ (th - o_n) < 0 \end{cases} \tag{6}$$

for each value of th. Now, for each value of th, the number of errors is calculated applying the difference between o_n^* and o_n. In this manner, the minimum error selects the optimal threshold.

The performance measure of the network is a crucial topic and, in most contributions, it is measured in terms of Mean Squared normalized Error (i.e., MSE)[5] if the output is continuous, or in terms of minimum number of errors if the output is dichotomous. In the present paper, we adopt both performance measures. In the first case, the output of the network comes from a logistic function, so it is continuous, and we calculate the MSE. In the second case, the threshold search algorithm allows transforming the continuous outputs into dichotomous ones, minimizing the incorrect classification. This approach relies on the target under investigation (i.e., the real output), which is dichotomous (see Section 2.6 below), and analyzes the network performance considering the minimum errors. In detail, we adopt both the MSE and the percentage of total errors, as well as different accuracy measures, such as sensitivity, specificity and Area Under the Curve (i.e., AUC).

It is worth nothing that, in general, researchers use the Receiver Operating Characteristics curve (ROC) and the Area Under the Curve (AUC) to compare alternative classifiers and to evaluate their performance. Nevertheless, this approach might not be robust when the number of true positive is particularly relevant and, at the same time, the sub-sample of the true positive is quite small such as, for instance, in case of studies on default firms [79]. Indeed, financially distressed firms are usually fewer than the healthy ones and, according to the author, a combined methodology could sound more robust, adopting together ROC and Cumulative Accuracy Profile (CAP) to identify optimal threshold. In our case, the problem is very similar since the aim of our algorithm is to identify firms that can be under financial constraint in the short time, which represent a quite small sub-sample of our dataset. Moreover, the threshold algorithm proposed in this work combines the maximization of sensitivity and specificity, with a particular attention both to true positive and to the false negative, searching the optimal threshold able to maximize the sensitivity, without going below a certain level of specificity. The proposed approach is not very different from the one proposed by Ref. [79]; even if we can observe alternative objective functions. On the one hand [79], proposes a true rate as a measure of accuracy while, on the other hand, we propose an optimal performance measure represented by the combination of sensitivity and specificity rates. Taking the specific case study into consideration, we can support our strategy arguing that the policy maker is clearly interested in maximizing the number of true positives (i.e., correct classification of firms under financial constrained) and in minimizing the false negatives (i.e., firms under financial constraints, but incorrectly classified by the model as healthy observations). Indeed, the combination of these two key elements can guarantee an appropriate intervention through an ad-hoc cohesion policy. So, with the ambition of creating a successful tool for detecting firms under financial constraints, we propose a specific algorithm able to identify firms with (real) financial difficulties in collecting external financial resources on the capital market, leading the policy maker in his interventions.

The threshold search algorithm and the sensitivity-specificity search algorithm work together to obtain a specific value of sensitivity and/or specificity established a priori. Hence, the threshold search algorithm allows building a matrix where the number of rows is equal to the number of tested thresholds, while the columns correspond to the total number of errors, the true positive, the false negative, the false positive and the true negative. The confusion matrix (Table 1) makes it possible to understand the meaning of different error types and to build the sensitivity and specificity indexes [80,81].

Specifically, the *sensitivity* is defined as:

$$\frac{TP}{TP + FN} \tag{7}$$

and a high value means that a positive element in reality is not classified as negative by the model, while the *specificity* is defined as:

$$\frac{TN}{FP + TN} \tag{8}$$

and a high value means that a negative element in reality is not classified as positive by the model. Lastly, the sum of false positive (FP) and false negative (FP) results corresponds to the total error.

The AUC represents the probability of correct prediction based on probabilities estimated by the model, and the curve is the Receiver Operating Characteristic curve (i.e., ROC curve). When the AUC is equal to 0.50, the model has no discriminatory capacity, the higher the value, the better the model's discriminatory power. For this reason, the object function of the threshold search and sensitivity-specificity search algorithms is not to find the minimum number of classification errors, but to find the number of errors that make it possible to obtain specific values of sensitivity and specificity.

Table 1
Confusion matrix (adapted from [82].

Model (output)	Reality (target)	
	P	N
+	*True Positive (TP)* A positive element in reality that is classified as positive by the model	*False Positive (FP)* A negative element in reality that is classified as positive by the model (Type I error)
-	*False Negative (FN)* A positive element in reality that is classified as negative by the model (Type II error)	*True Negative (TN)* A negative element in reality that is classified as negative by the model

[4] The algorithm allows setting different step levels of the threshold. In this case, the program considers 10,000 values of threshold.

[5] The standard performance measure is proposed and the Mean Square Error is calculated as follows:

$$mse = \frac{1}{N}\sum_{n=1}^{N}(t_n - o_n)^2$$

The main idea is to modify the threshold search algorithm with a new function aiming not only to select the threshold able to minimize errors but also to reach pre-defined values of sensitivity or specificity. The result selected as optimal might not actually be the one that minimizes the number of errors, but the one that minimizes the number of FP and FN results, so as to obtain sensitivity and specificity values close to those identified a priori by researchers.

Accordingly, the algorithm allows us to set a priori the level of sensitivity (*sens**) and specificity (*spec**) that we expect to reach (first approach) or, alternatively, it allows us to decide whether to maximize either sensitivity or specificity (second approach). In the latter approach, the maximum sensitivity is 1 and the specificity is 0.7, while the values are inverted if the algorithm maximizes specificity. The algorithm works as follows.

Considering the threshold values, the following matrixes are defined:

$$diff\_sens = \begin{bmatrix} th=0 & abs(sens_{th=0} - sens*) \\ \vdots & \vdots \\ th=1 & abs(sens_{th=1} - sens*) \end{bmatrix} \tag{9}$$

$$diff\_spec = \begin{bmatrix} th=0 & abs(spec_{th=0} - spec*) \\ \vdots & \vdots \\ th=1 & abs(spec_{th=1} - spec*) \end{bmatrix} \tag{10}$$

In detail, the matrixes *diff_sens* and *diff_spec* represent the difference between the sensitivity and specificity values and the theorical ones established a priori for each threshold value.

The goal of the algorithm is to select the optimal threshold (th*) where:

$$min\_diff = min([diff\_sens + diff\_spec]) \tag{11}$$

This means that the optimal threshold is the one able to minimize the sum of the differences.

A similar algorithm was applied in Ref. [83]; where it was defined for the purpose of supporting medical decisions.

3.3. Replicated bootstrapped feed-forward neural network (RBFFNN)

There are two main reasons for applying the bootstrap to training data:

- the first reason is due to the fact that the training sample may not be representative, and repeated random sampling with re-entry increases the robustness of the results (i.e., the probability of encountering the overfitting problem diminishes);
- the second reason concerns the fact that, each time the network runs, the weight matrixes are randomly initialized [84]; therefore, it is worthwhile for it to be run several times to find the weights with the best performance.

After splitting the whole sample into training (T) and validation (V), the bootstrap procedure is applied to the training sample and the FFNN is replicated a number of times equal to the replications (*rep_boot*) set for the bootstrap. By doing this, each time the FFNN runs, the weight matrixes and performance indexes are calculated and stored in *rep_boot* arrays. At the end of the replications, the algorithm selects the array with the weight matrixes and network parameters associated with the best performance (a^*). In this step (i.e., *bootstrap step*), the network is replicated *rep_boot* times, so that the probability of obtaining best results increases (see Figure A2 in Appendix A).

To improve performance, we propose an algorithm replicating the whole bootstrap step *rep_net* times. In this manner, the *rep_boot*rep_net* FFNN will run and the selection of the best array of parameters can be made after numerous replications of the network (i.e., *replication step*).

Fig. 2 shows the replication step. The result is the set of the best arrays found in the bootstrap step. Just like in the previous case, considering the fixed performance goals, the algorithm proceeds to select the best array (a^{**}).

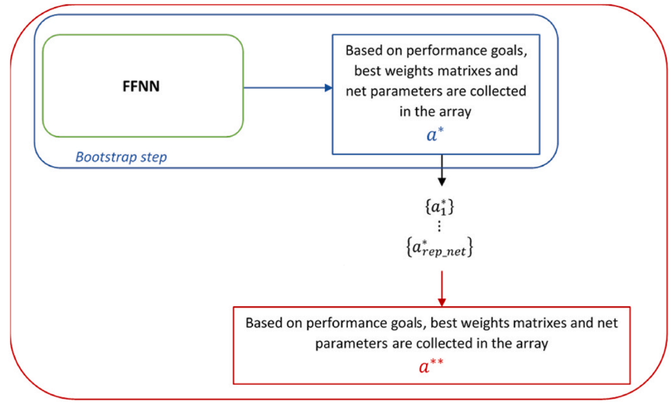

Fig. 2. Replication step.

3.4. Different backpropagation training algorithms

As previously mentioned, in this paper different backpropagation algorithms are compared in terms of performance. The learning process represents how the neural network updates the free parameters with the aim to capture the correct pattern from the presented sample. The basic idea is common to all applied algorithms, which differ from each other in how the weight modifications are made. The most popular algorithm adopted is the gradient descent algorithm, which adjusts synaptic weights in the opposite direction of the gradient vector [75].

In general, gradient descent algorithms allow finding parameter values (i.e., weights) that minimize the errors, evaluated through the loss function (the MSE in the present work), with the goal to best approximate and represent the data.

Using the gradient descent algorithm [85], weight updates are calculated as follows:

$$dW_t = \alpha \cdot \delta_t \tag{12}$$

where dW_t represents the updates of weights (and biases) at time t, α is the learning rate (or step size), indicating the size of the steps that are taken to reach the minimum, while δ_t is the gradient, calculated as the derivatives of the performance function with respect to the weight and bias variables (i.e., $\frac{dmse}{dW}$).

A simple modification of the gradient descent algorithm is to adjust the formula with the momentum. In this case, the weight updates are calculated as follows [85]:

$$dW_t = m \cdot dW_{t-1} + (1-m) \cdot \alpha \cdot \delta_t \tag{13}$$

where dW_t and dW_{t-1} represent the updates of weights and biases at time *t* and *t-1*, *m* is the momentum constant, α is the learning rate (or step size), indicating the size of the steps that are taken to reach the minimum, while δ_t is the gradient at time *t*.

However, these are time-consuming approaches, and a high number of computations are required. Therefore, in this research, we apply the *gradient descent with adaptive learning rate backpropagation (GDA)* and the *gradient descent with momentum and adaptive learning rate backpropagation (GDX)*, which are faster than the previous algorithms.

The first one (i.e., *GDA*) is very similar to the gradient descent and weight updates are computed as follows [85]:

$$dW_t = \eta \cdot \delta_t \tag{14}$$

where η is the learning rate and it is set to 0.1. It increases by a factor equal to 1.05 when the performance decreases toward the goal. If the performance exceeds a maximum threshold (set to 1.04), the learning rate is adjusted by a factor equal to 0.7.

The *gradient descent with momentum and adaptive learning rate backpropagation* (i.e., *GDX*) corrects the previous formula with the momentum:

$$dW_t = m \cdot dW_{t-1} + (1 - m) \cdot \eta \cdot \delta_t \tag{15}$$

The algorithm is the same as the previous one, except for the momentum constant, which is an additional parameter in the training phase and is set to 0.1.

The conjugate gradient algorithm is similar to the gradient descent method but faster to converge. It is used for solving linear systems whose matrixes are symmetrical and positively defined [86,87]. In comparison to gradient descent, conjugate gradient algorithms exploit the linear direction and they reach the goal faster. Here, we compare different conjugate gradient algorithms, in particular: the *Scaled Conjugate Gradient* (i.e., *SCG*; [88], the *Conjugate Gradient with Powell/Beale Restarts* (i.e., *CGB*; [89], the *Fletcher-Powell Conjugate Gradient* (i.e., *CGF* [90,91]; and, finally, the *Polak-Ribiére Conjugate Gradient* (i.e., *CGP*; [85]. In general, the main difference between SCG and the other specification algorithms is that the search direction in SCG is not determined at each iteration, while the other methods adapt the search direction iteratively.

Lastly, we compare the performance of RBFFNN also considering the *Levenberg-Marquardt backpropagation* (i.e., *LM*; [85,92–95], the *Resilient Backpropagation* (i.e., *RB*; [96], the *Broyden-Fletcher-Goldfarb-Shanno Quasi-Newton* (i.e., *BFG* [97,98], and the *One Step Secant* (i.e., *OSS*, [99].

The script with the code for all the algorithms and simulations is written in Matlab R2022b.

3.5. Garson index

Finally, we apply the Garson methodology with the aim to investigate the contribution of our variables to financial constraints. The literature suggests several approaches (see Ref. [100] but, among these, the Garson index is one of the most widely adopted (e.g., Refs. [76,101,102,103]. The index works as follows.

Let n be the input variables (where $n = 1, \ldots, \mathrm{N}$), j the hidden nodes (where $j = 1, \ldots, \mathrm{J}$) and o the output neurons (where $o = 1, \ldots, \mathrm{O}$). The matrixes are indicated by capital letters and their elements by lowercase letters. The Garson index is a vector made by:

$$G_{no} = \frac{W^*_{no}}{Z_o} \cdot 100 \tag{16}$$

where

$$W^*_{no} = \frac{|W_{nj}|}{S_j} \cdot |W_{jo}| \tag{17}$$

$$S_j = \sum_{n=1}^{N} |w_{nj}| \tag{18}$$

$$Z_o = \sum_{n=1}^{N} w^*_{no} \tag{19}$$

See Appendix B for a detailed explanation of Garson index and its computation, with an illustrative example to enhance understanding of this methodology.

Note that, an alternative method to evaluate contribution of inputs in predicting the output is provided by Shapley [104]. Shapley values derive from game theory where they represent the average marginal contribution of a player in a cooperative game. In the context of artificial intelligence and machine/deep learning, they are applied to calculate the contribution of each feature to the classification or prediction [105,106]. These values are calculated for each observation of the sample under investigation, considering each input introduced in the model, estimating their average to interpret the observed features [107,48]. However, this methodology is very expensive in terms of computational resources [108] and, even more relevant, Shapley values have lower stability when the sample is imbalanced [109]. Accordingly, this work adopts the Garson indexes to interpret the contribution of inputs in predicting whether firms are under financial constraints. Note that, we also estimate the Shapley values for 2 firms under constraints and 2 firms with no difficulties in collecting external financial resources, emphasizing the potential contribution of this approach (See Figure A4 in the Appendix). Indeed, the Shapley values can evaluate the contribution of each feature in single observation, leading the policy maker in adopting specific individual interventions to support their access to the capital market according to the peculiarity characteristics of these firms.

3.6. Input-output variables

The aim of this paper is to assess whether a firm is under financial constraints in the short term (1 year). Accordingly, the output of our prediction model is represented by the reported firms' difficulties in collecting financial resources on the capital market while, on the other hand, the inputs of our model are financial and economic information extracted from their balance sheets. These inputs are potential determinants of financial constraints and can be adopted to stratify other sample of firms and to predict whether firms will be under financial constraints.

Considering the output, we adopt a unique dataset based on the Italian automotive supply chain between 2017 and 2020, which contains key information about firm difficulties in gathering external financial resources. The information is extracted from a survey carried out by the "Observatory on the Italian Automotive Supply Chain"[6] between 2018 and 2021, and merged with additional economic and administrative data from AIDA (a Bureau van Dijk dataset). Note that these surveys are submitted by firms at time *t* (e.g., at time 2021) referring to their condition at time *t-1* (i.e., at time 2020). In detail, considering the main survey question about the existence of financial constraints, the target variable (t) is set as a dichotomous item. The question on financial constraints requires a choice among five levels of difficulties in collecting external financial resources on the capital market to fund innovative projects and/or R&D proposals, i.e., from 1 to 5. Higher values correspond to an increasing level of constraints. According to our approach, the target variable takes on value 0 when a firm reported a level equal to 1, while it takes on value 1 if a firm indicated a level equal to 4 or 5. Hence, a target value equal to 0 represents a situation with no financial constraints, while a target value equal to 1 denotes a firm under financial constraints. Note that, we lose observations limiting the analysis to the extreme values reported in the survey (i.e., observations with values equal to 1, 4 and 5). We adopt this approach to obtain a more accurate estimation of our prediction model, removing all observations that cannot clearly suggest whether firms have difficulties in collecting financial resources on the market (i.e., observations with values equal to 2 and 3). In detail, the initial total sample consists of 1123 observations and, excluding classes 2 and 3, we have reduced the sample of 472 observations (i.e., 42.03 %). Considering the remaining observations (i.e., 651), the sub-sample of firms under constraints is equal to 244 observations (i.e., 37.48 %), while the sub-sample of firms not under constraints is quale to 407 observations (i.e., 62.52 %). Taking the difference in terms of size between the two subsamples into account, we have adopted a sampling-based method as empirical strategy to verify the appropriateness of our approach [40],

[6] This observatory and its national survey are a joint initiative by the Chamber of Commerce of Turin, the Italian National Association of the Automotive Supply Chain (ANFIA) and the Center for Automotive and Mobility Innovation (CAMI) of the Ca' Foscari University of Venice. See www.to.camcom.it/osservatorio-sulla-componentistica-automotive-italiana.

comparing the performance of our models in adopting alternative combination of classes. Even if literature suggests that using extreme observations might be more performing (i.e., classes 5 versus 1),[7] the adopted approach has been revealed as the most appropriate (i.e., combination of observations in classes 4 and 5 versus observations in class 1). Moreover, we have verified the sample selection considering the approach One-Versus-All (OVA) as suggested by Ref. [110]. According to results, we can confirm that the selected approach is still the most performing one (see Figure A5 in Appendix A, which shows the obtained ROC curves).

Considering the inputs, predictive variables are introduced into the model according to data availability and considering previous studies on credit rating (e.g., Refs. [76,111]) and financial constraints (e.g., Refs. [27,112])[8]:

1. Fixed assets to equity (i.e., FA_E), which is an index that represents the ability of firms to settle their long-term debts and relative financial debt exposure;
2. Percentage increase of sales (i.e., Sales%), which is a variable that indicates the ability of firms to sell, thereby generating liquidity, as well as a proxy used to represent their size;
3. Leverage (i.e., Lev), which is a very popular indicator representing the weight of financial debts on shareholders' capital (it is calculated as total financial debts to equity);
4. Spread (i.e., Spread), which represents the reward for the shareholders and it is calculated as the difference between the return on investments and the interest rate, with the former being equal to EBIT on total assets and the latter being equal to financial interests on financial debts[9];
5. Seniority (i.e., Sen), which indicates the age of each firm and represents both its experience and a proxy for available information on the market;
6. Return on assets (i.e., ROA), which is a profitability index referring to the managerial ability to generate profit from total assets (calculated as Net Income on Total Assets);
7. Total debts to total assets (i.e., TD_TA), which denotes an additional leverage index, representing the weight of total debts (operating and financial) in relation to the invested capital and indicating the extent to which the investments of firms are financed by external investors;
8. Net profit to added value (i.e., NP_AV), which is a ratio that compares the net profit with the added value; it can be regarded as the net profit correction for non-monetary costs, suggesting how significant the operating activity of firms actually is[10];
9. Return on sales (i.e., ROS), which is another profitability index successfully used for comparing the profitability of firms having different sizes; it represents the ability of firms to convert sales into operating profit (calculated as EBIT on sales);
10. Payment of dividends (i.e., Div_Pay), which is a dummy variable equal to 1 if the firms decided to pay dividends, 0 otherwise.[11]

Table 2
Descriptive statistics of the sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
Financial constraints	391	0.332	0.472	0.000	1.000
FA_E	391	1.262	2.349	0.008	40.932
Sales%	391	−0.029	0.265	−1.000	2.762
Lev	391	3.147	7.171	0.129	91.330
Spread	391	−14.081	203.427	−3667.083	0.342
Sen	391	29.179	16.325	1.000	82.000
ROA	391	0.078	0.068	−0.047	0.348
TD_TA	391	0.550	0.189	0.097	0.971
NP_AV	391	0.715	11.225	−0.373	222.084
ROS	391	0.073	0.078	−0.157	0.780
Div_Pay	391	0.588	0.493	0.000	1.000

Note: All the variables are introduced into the model at time t-1.

Table 2 presents some descriptive statistics concerning the variables introduced in our model. Note that the total number of observations is 1716 but, considering data availability, the sample size is reduced to 391. The FFNN is trained on 261 observations (2/3) and validated on 130 items (1/3).

Lastly, Figure A3 in Appendix A illustrates the net framework used, with parameters set based on the sample under investigation. The input layer is formed by 10 neurons (the number of predictive variables), the output layer contains 1 node, and the hidden layer contains 6 nodes (10 input + 1 output/2).

Taking current knowledge into consideration, we can formulize some hypothesis on these inputs. On the one hand, according to literature [113,114], we expect a negative sign by seniority (i.e., Sen) and size (i.e., Sales%). Indeed, we expect that small and young firms are under financial constraints due to the problem of asymmetric information on the market, which can be amplified by their size and seniority. Then, considering the signaling hypothesis [115,116], we expect a negative sign by firms' capacity to create profit (i.e., ROS and ROA), as well as by the proxies introduced to account the remuneration of shareholders (i.e., Div_Pay and Spread). Indeed, these could represent positive messages transmitted by the firms to support their access to external financial resources (e.g., attracting new investors) and, in this way, to reduce the possibilities of being under financial constraints. On the other hand, considering current literature [117,118], we expect a positive sign by total debts to total assets (i.e., TD_TA) and leverage (i.e., Lev), assuming a higher probability of being under financial constraints for firms that have a significant financial disequilibrium. Finally, considering the net profit to added value (i.e., NP_AV) and fixed assets to equity (i.e., FA_E), we expect a negative sign, imagining that the collateral and the entity of the operating activity can support access to the capital market and its financial resources. The successive discussion of the collected results will shed new light on these variables, confirming or rejecting these expectations.

4. Results

According to results, the algorithm with the best performance is the Conjugate gradient backpropagation with Fletcher-Reeves updates (i.e., CGF). Table A1 in Appendix A presents the results of the FFNN considering all backpropagation algorithms, showing the measures of performance discussed in the previous section.

Focusing on the most performing algorithm, Fig. 6 reports graphically the collected results. In detail, the blue stars (*) identify the

[7] According to literature, we might obtain more performant results considering the extreme values since the accuracy of the models increases when they are trained on a sample where observations are very different. In other words, the ANN learns well to distinguish between black and white, but its performance decreases if it must distinguish between two similar gray shades (see for instance Ref. [128].

[8] See Ref. [129] for an overview of the determinants of being under financial constraints.

[9] The spread is strictly linked to the financial leverage [130,131]. Indeed, positive values indicate good profitability of firm investments, which is why this term is a key determinant of shareholders' gains.

[10] In sum, while the net profit represents the final result of the income statement, the added value considers only the operating activity of a firm, excluding financial or extraordinary operations (i.e., financial interests or capital gains/losses due to the sale of fixed assets).

[11] Clearly, this is a crucial piece of information for shareholders and investors, representing a positive signal as to the reliability of firms on the market.

Table 3
Comparison between logistic model and FFNN.

Performance measures	Logistic	FFNN
Total Errors	38	37
Correct classification (%)	70.77 %	71.54 %
AUC	0.6731	0.7227
Sensitivity	20.93 %	74.41 %
Specificity	95.40 %	70.11 %

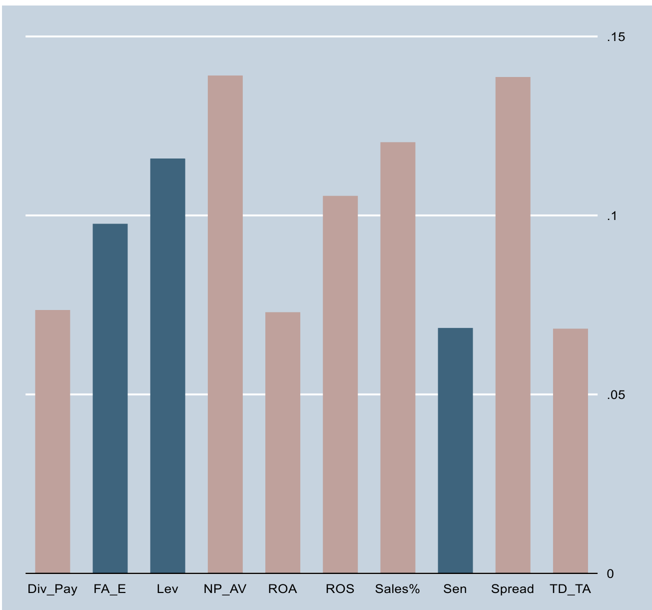

Fig. 3. Bar plot of Garson Indexes.

Table 4
Garson Indexes and contribution.

Variables	Garson	Sign
Sen	6.85 %	+
Lev	11.58 %	+
TD_TA	6.83 %	–
FA_E	9.76 %	+
NP_AV	13.90 %	–
Sales%	12.04 %	–
ROS	10.54 %	–
ROA	7.29 %	–
Spread	13.86 %	–
Div_Pay	7.35 %	–

empirical outputs (i.e., outputs) of the network, while the red plus symbols (+) represent the theoretical outputs (i.e., targets), the vertical red lines indicate the distance between the target and the output, while the horizontal green line shows the optimal threshold (i.e., 0.5033). The outputs (blue stars) exceeding the threshold are errors and the threshold search algorithm works iteratively to find the threshold value that minimizes the number of errors. The sum of the squared red lines divided by the number of observations represents the MSE, which is the standard performance measure adopted in deep learning studies. The total number of errors is equal to 37, corresponding to 28.46 % of the validation set. However, the innovation of the sensitivity-specificity search algorithm allows us to find the algorithm able to minimize the number of false negatives, which is a key determinant for the sensitivity measure. Indeed, it is crucial that the algorithm does not mislead us into identifying a firm as not being under financial constraints while, in reality, it is. Considering 100 replications for the bootstrap, 100 replications of the model, the threshold algorithm and the sensitivity-specificity algorithm, we can find the weight matrixes able to maximize the sensitivity without any loss in terms of specificity.[12]

Next, to highlight the power of our results, we run a logistic model on the training set and then a prediction on the validation set. Note that the logistic regression is a traditional classification model [119] and, for this reason, a good candidate to compare our results. Table 3 displays the collected results.

The results in terms of AUC and correct classification are slightly better in the case of the FFNN. Indeed, the AUC is equal to 0.6731 and the correct classification is equal to 70.77 % if we adopt the logistic regression model, whereas the AUC is equal to 0.7227 and the correct classification is equal to 71.54 % if we adopt the FFNN. Nevertheless, for what concerns the sensitivity and specificity, the performance gap between the two approaches is rather substantial. On the one hand, the specificity of the logistic model is equal to 95.40 %, and its sensitivity is equal to 20.93 %. This means that the probability of incorrect classification of firms under financial constraints by the logistic model is very high, i.e., about 79.07 %. On the other hand, the specificity of the FFNN is equal to 70.11 % and its sensitivity is equal to 74.41 %. Afterwards, Fig. 3 and Table 4 offer graphical and descriptive representations of the main determinants adopted to predict difficulties in collecting external financial resources by firms. The blue bars in Fig. 3 indicate variables whose increase corresponds to an increase in financial constraints, while the pink bars refer to a decrease in the variables' weight on financial constraints. Table 4 reports the Garson percentages for each variable, which represent the expected contribution in explaining the prediction of the target under investigation. Note that the signs reported in Table 4 are computed following [103]; and this information provides the main contribution in terms of practical managerial implications.

Next sub-section proposes a discussion of the collected results, highlighting which might be the interpretation of Garson Indexes in explaining whether firms are under financial constraints.

4.1. Discussion

Garson indexes suggest the contribution of each input (expressed in terms of percentage) to identify firms under financial constraints, as well as their impact (expressed in terms of sign). According to the sample under investigation and the adopted model definition, we can imagine several patterns of being under financial constraints.

First, the results suggest that firms with higher seniority (i.e., Sen) are those observations with higher probability of being under financial constraints (i.e., plus sign). An interpretation of these counter-intuitive results could concern the interventions adopted by the policy maker in those years to support young firms and their innovation, such as an ad-hoc policy to support investments in Industry 4.0 (i.e., *Calenda 4.0*). Nevertheless, looking at the contribution of this input (expressed in terms of percentage), we can observe that it is one of the least relevant in explaining the condition of being under financial constraints (i.e., 6.85 %).

Second, looking at firms' leverage inputs, we can observe a plus sign for the leverage (i.e., Lev) and a minus sign for the total debts to total assets (i.e., TD_TA). Accordingly, in the former case we expect to observe a higher probability of being under financial constraints for firms that have a disequilibrium between financial debts and shareholder capital, i.e. the weight of external financial resources with respect the internal capital supplied by shareholders is too high, which negatively affects access to additional financial resources on the capital market, since it further increases this disequilibrium. On the other hand, in the latter case we expect to observe a lower probability of being under financial constraints for firms that have a higher debt exposure with respect to total assets. It is worth noting that, in this case we are considering both

[12] The weight matrixes and vectors are reported in Appendix C. Note that the network considers one bias in the input layer and one bias in the hidden one.

financial and operating debts, and the evidence collected is consistent with the theory of information asymmetry and complementary effect between financial debts and trade credits. In other words, with incomplete information, financial institutes use available data extracted from the balance sheet (e.g., operating debts), to decide whether firms can have access to additional external resources, expecting supplier behavior to be based on more accurate information extracted from the market. Lastly, looking at the contribution of these two inputs (expressed in terms of percentage), we can observe that it is much more relevant for leverage (i.e., 11.58 %) than for total debts to total assets (i.e., 6.83 %). It is worth noting that the proposed interpretation of leverage (i.e., Lev) is consistent with the results on fixed assets to equity (i.e., FA_E), while the interpretation of total debts to total assets (i.e., TD_TA) is consistent with the results on net profit to added value (i.e., NP_AV). On the one hand, according to the results on fixed assets to equity, we can observe a plus sign, which implies that firms with a higher ratio (e.g., higher fixed assets on a given amount of equity) are those with a higher probability of being under financial constraints. An interpretation of this result could concern an already too high debt exposure that could negatively affect access to additional financial resources on the capital market. On the other hand, we have the results on net profit to added value (i.e., NP_AV), which is a proxy of firms' internal operating activity and their efficiency, as well as representative of firms' exposure to financial costs. According to these results, we can observe a minus sign, implying that – all other things being equal – if we decrease the financial debt exposure, we expect to observe a lower probability of being under financial constraints.

Third, we can observe a minus sign for the percentage increase of sales (i.e., Sales%), which is a variable that indicates firms' ability to sell, thereby generating liquidity, as well as a proxy used to represent their size. Accordingly, we expect to observe a lower probability of being under financial constraints for firms that have higher growth, and they become bigger and bigger. This interpretation is in line with the problem of asymmetric information on the market, which can be mitigated by the size of companies, supporting their access to external financial resources. At the same time, we cannot reject the hypothesis that firms' ability to generate liquidity can positively affect their access to the capital market. Looking at the contribution of this input, we can observe it is one of the most relevant in explaining the condition of being under financial constraints (i.e., 12.04 %).

Afterwards, considering firms' capacity to create profit (i.e., ROS and ROA) and to remunerate shareholders (i.e., payment of dividends), the results denote a negative contribution to the probability of being under financial constraints (i.e., minus sign). An interpretation of these results could concern the signaling hypothesis, i.e., the impact of positive messages transmitted by the firms to support their access to external financial resources (e.g., attracting new investors), reducing the probability of being under financial constraints. Focusing on dividends, these results are extremely interesting since the literature also suggests another counter-expectation. On the one hand, the possibility of paying dividends may indicate that firms are not under financial constraints since they have access to external resources to make such a decision. On the other hand, if firms are facing financial constraints, they might pretend to be in a good financial position by paying dividends and, through these positive messages, they might try to attract new investors and/or lenders, stemming a moral hazard problem in the market. According to the results, we cannot exclude the signaling hypothesis, although further studies would be necessary to identify the precise dynamics behind our observations.

Finally, we must acknowledge that the signaling hypothesis is also consistent with the spread (i.e., Spread), which represents the reward for the shareholders and is calculated as the difference between the return on investments and the interest rate. According to the results, we can observe a minus sign, which implies that firms with a higher reward are those firms with a lower probability of being under financial constraints. As well as that which was suggested with the aforementioned profitability indexes and the dividend payout policy, we can interpret this result in terms of positive messages to financial institutions, highlighting opportunities for investment. It is worth noting that, looking at the contribution of this input (expressed in terms of percentage), it is one of the most relevant (i.e., 13.86 %).

These results highlight what the managerial implications of our study might be, i.e., managers should pay particular attention to the opportunities represented by the signaling hypothesis, as well as the equilibrium between internal and external financial resources. Accordingly, focusing on these key aspects, managers can shape their business and corporate strategies to decrease the probability of encountering difficulties in collecting external financial resources on the capital market to fund their investments.

Appendix C presents the matrixes of optimal weights, so that readers can use them in the FFNN illustrated above, replicating the classification of being under financial constraints and applying it to other samples of firms.

The next section adopts the proposed methodology to classify the Italian manufacturing industry. Then, we describe how policy makers can implement targeted interventions to decrease difficulties in gathering external financial resources on the capital market, fostering investments and socio-economic development within the framework of a cohesion policy.

5. Policy implications

This work proposes several policy implications, considering the European Union cohesion policy program for 2021–2027 and keeping in mind an innovation policy (i.e., *Calenda 4.0)*, which was introduced by the Italian government with the budget law of 2017 (i.e., *Legge 11 dicembre 2016, n. 232*), within a strategic plan for the next four years (i.e., 2017–2020). The main target of this policy was to foster the fourth industrial revolution, creating incentives to drive Italian firms toward implementing new technologies in their production and operational processes, such as Big Data Analytics (BDA), Artificial Intelligence (AI), Information and Communication Technologies (ICT) and Internet of Things (IoT). Among the incentives, the policy maker adopted a higher contribution to cover financial interests paid by firms for investments in industry 4.0 (+30 %) and granting of public guarantees on external financial resources collected on the capital market (up to 80 % of bank loans) through the Central Guarantee Fund (i.e., *Fondo Centrale di Garanzia*). All Italian SMEs had access to these incentives, creating an "indiscriminate all-round distribution" of available resources, as well as highlighted by Ref. [120]. The alternative approach could be the selection of key targets, such as firms located in under-developed geographical areas and/or the most critical industrial sectors, fostering interventions that are coherent with the European Union cohesion policy program for 2021–2027. Considering the current public budget constraints and the limited financial resources, the adoption of the former or the latter approach could have significant consequences for the policy maker, preventing the adoption of alternative industrial policies and/or social interventions. This work does not investigate the appropriateness of such innovation policy and/or adequacy, but, according to our results, it investigates what these potential targets might be (i.e., geographical areas and industrial sectors), showing an alternative to this "indiscriminate all-round distribution".

5.1. Simulation of cohesion policy's targets

Considering the active firms in the Italian manufacturing industry in 2019, we extract administrative, financial and economic data from AIDA (BvD dataset). Then, we use the estimated weights to classify these firms and, accordingly, to identify which industrial sectors (i) and geographical macro areas (ii) need interventions by policy makers, who are interested in implementing a cohesion policy. In details, we classify more than 60,000 observations to detect the industrial sectors (NACE codes – 2 digit) with the greatest difficulties in gathering external financial resources on the capital market to fund innovation, as well as the most critical geographical areas. Based on the collected results, we suggest which interventions the policy makers might adopt to fill the gap among industrial sectors and/or geographical areas through the identification of consistent targets.

Table 5 shows the results of this classification, indicating the number of firms under financial constraints according to their NACE codes, both at the national level and across Italy's five geographical macro areas (i.e., North West, North East, Center, South and Islands).

The first result regards the heterogeneity found among geographical macro areas. Indeed, moving from the North to the South of Italy, difficulties in gathering external financial resources tend to increase. In detail, the North East is the macro area with the lowest percentage of firms under financial constraints (i.e., 19.77 %), while the Islands have the highest level (i.e., 28.09 %). The second result concerns the differences existing among industrial sectors. Looking at the most significant sectors in terms of observations at the national level (i.e., codes 25, 28, 10, 22 and 33, which together make up more than 50 % of the firms), the share of firms under financial constraints ranges between 19 and 20 % (i.e., codes 25, 28, 22 and 33) and 29 % (i.e., code 10).

Fig. 4 presents the number of firms under financial constraints according to their credit rating score (i.e., KR). Specifically, we examine the area with the lowest difficulties in collecting external financial resources (i.e., the North East, represented by an orange line) and the area with the greatest difficulties (i.e., the Islands, represented by a blue line). We can observe that, if the expected solvency in the short term (i.e., 1 year) increases, the difficulties in gathering external financial resources decrease in both areas, although they remain greater in the Islands. Hence, the previous evidence on geographical heterogeneity is confirmed and a firm's expected solvency emerges as a key determinant of being under financial constraints.

These results can guide policy makers in adopting key interventions to foster investments, growth and socio-economic development [77]. First, considering the evidence in Table 5, it is possible to identify the most critical industrial sectors, i.e., those with greater difficulties in collecting external resources on the market. For instance, NACE code 10 is one of the biggest sectors and, on average, it features a higher percentage of firms under financial constraints, making it a good candidate

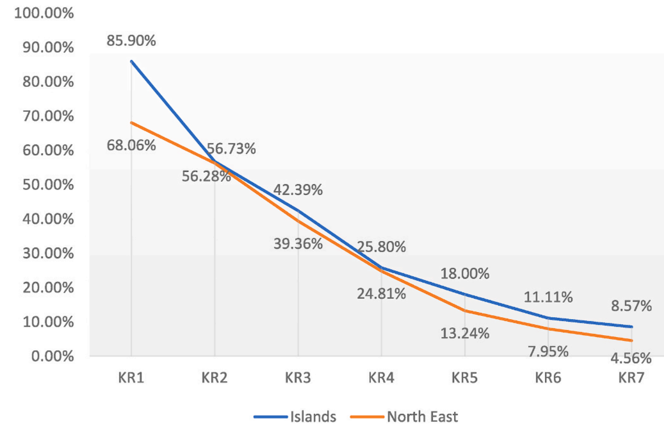

Fig. 4. Conditional probability of being under financial constraints according to credit score (KR).
Note: KR7 represents the highest level of expected solvency in the short term (i.e., 1 year), while KR1 represents the lowest level. Source: AIDA - BvD dataset.

to implement a national policy aimed at supporting firm access to the capital market. Second, the evidence in Fig. 4 points the appropriateness of the intervention adopted by the aforementioned innovation policy to support access to the capital market (i.e., *Calenda 4.0*), i.e., public guarantees on loan applications.

Accordingly, we expect the solvency of these firms to increase, supporting their access to the capital market. Lastly, focusing on the map reported in Fig. 5, we can provide some final insights for the local governments. Indeed, we can observe significant heterogeneity within Italy's regions, with specific areas characterized by a high percentage of firms under financial constraints. Therefore, regional governments might consider implementing additional targeted interventions to decrease the internal heterogeneity within their territories. Note that, recalling the aforementioned evidence proposed in Table 5, the same interventions could be adopted by the central government to foster cohesion among territories, supporting the geographical macro areas where difficulties in collecting external resources on the capital market are greater (e.g., Campania, Sicily and Abruzzi in the South of Italy).

Table 5
Classification of firms under financial constraints Italian manufacturing industry in 2019.

NACE code	Italy		North East		North West		Center		South		Islands	
	Obs.	Constrained	Obs.	Constrained	Obs.	Constrained	Obs.	Constrained	Obs.	Constrained	Obs.	Constrained
10	5693	29.19 %	1387	26.32 %	1302	29.57 %	915	30.93 %	1506	30.21 %	583	29.85 %
11	870	32.87 %	246	29.67 %	193	27.46 %	120	30.83 %	216	40.74 %	95	36.84 %
12	8	50.00 %	4	50.00 %	–	–	3	33.33 %	1	100.00 %	–	–
13	2032	22.15 %	334	24.25 %	972	22.33 %	537	21.23 %	175	20.57 %	14	14.29 %
14	2502	26.90 %	613	23.33 %	578	28.37 %	605	25.45 %	672	29.76 %	34	35.29 %
15	2087	24.58 %	504	21.43 %	211	32.23 %	927	24.27 %	436	25.00 %	9	33.33 %
16	1960	23.01 %	671	20.86 %	517	23.21 %	338	22.78 %	314	26.11 %	120	26.67 %
17	1158	20.29 %	297	15.82 %	376	21.81 %	264	20.45 %	176	22.16 %	45	28.89 %
18	1756	25.97 %	459	24.40 %	628	24.20 %	348	27.87 %	249	27.71 %	72	36.11 %
19	142	33.10 %	13	30.77 %	40	25.00 %	33	36.36 %	43	34.88 %	13	46.15 %
20	1822	19.92 %	433	18.01 %	867	20.76 %	267	23.22 %	187	17.11 %	68	16.18 %
21	276	21.01 %	45	13.33 %	120	19.17 %	71	30.99 %	33	21.21 %	7	0.00 %
22	3315	20.00 %	934	14.67 %	1464	22.95 %	480	15.83 %	341	25.51 %	96	28.13 %
23	2896	25.97 %	833	23.65 %	626	24.28 %	603	25.37 %	575	28.35 %	259	33.59 %
24	1150	20.96 %	274	20.80 %	635	19.53 %	128	23.44 %	90	26.67 %	23	26.09 %
25	13,374	20.06 %	4260	17.04 %	5454	21.34 %	1821	20.04 %	1482	22.27 %	357	27.45 %
26	1734	21.34 %	475	18.74 %	757	23.12 %	336	20.54 %	129	24.03 %	37	16.22 %
27	2208	22.55 %	733	21.28 %	971	23.69 %	280	22.86 %	182	22.53 %	42	16.67 %
28	7067	19.61 %	2741	17.69 %	2992	21.12 %	757	18.89 %	478	21.34 %	99	24.24 %
29	803	25.16 %	238	24.37 %	342	23.98 %	101	26.73 %	101	25.74 %	21	42.86 %
30	745	28.72 %	164	24.39 %	243	32.10 %	149	29.53 %	139	28.78 %	50	24.00 %
31	2256	24.20 %	902	21.95 %	548	26.09 %	486	24.28 %	274	25.55 %	46	36.96 %
32	1980	20.56 %	583	18.18 %	628	21.66 %	494	19.43 %	215	26.05 %	60	21.67 %
33	3118	18.89 %	855	17.54 %	1017	19.47 %	563	19.01 %	479	19.42 %	203	20.20 %
Total	60,952	22.56 %	17,998	19.77 %	21,481	22.83 %	10,626	22.87 %	8493	25.86 %	2353	28.09 %

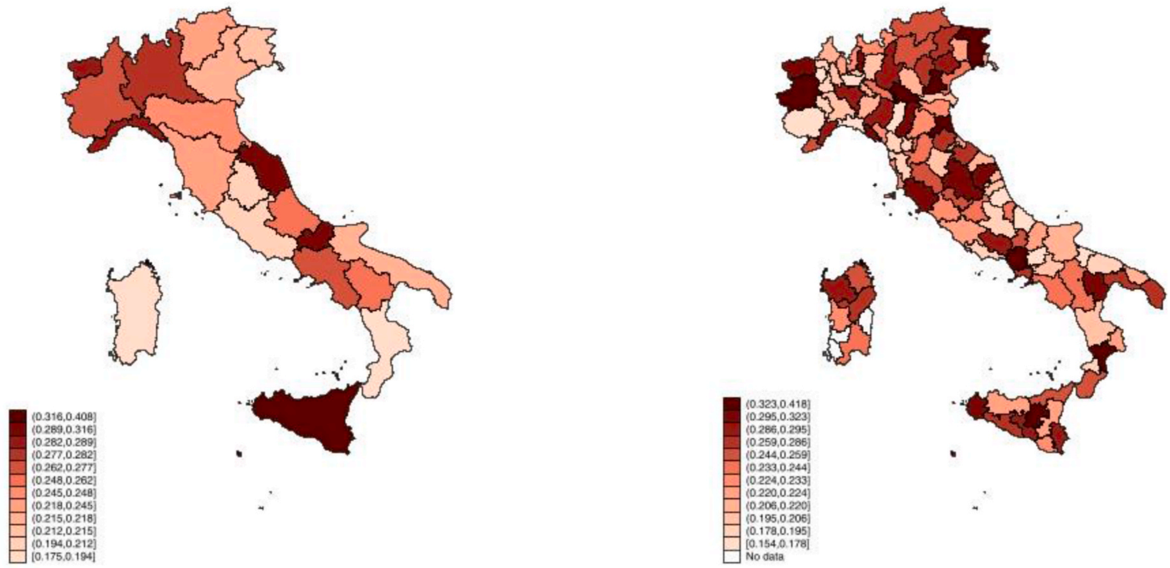

Fig. 5. Percentage of firms under financial constraints at the regional and provincial level.
Note: The map on the left considers the regions as administrative units, while the map on the right considers the provinces as administrative units.

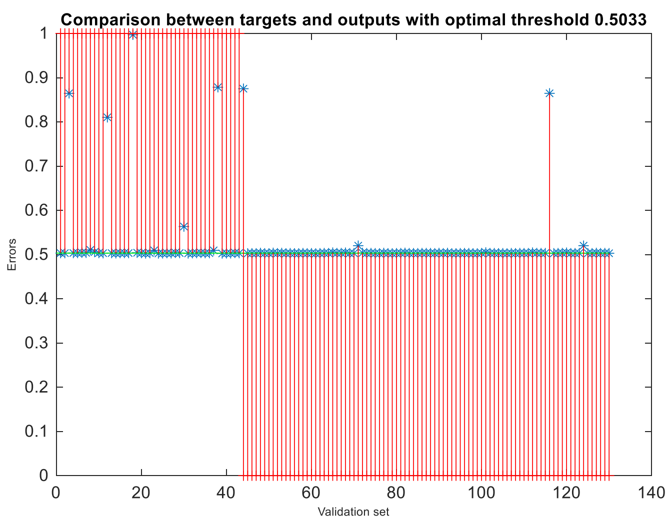

Fig. 6. FFNN results with CGF algorithm.

5.2. Limits

Even if these results are interesting and they might lead to relevant policy implications, we have to acknowledge their limits. The authors had the opportunity to collect key qualitative data from a survey submitted to firms in the automotive supply chain, understanding whether these companies were under financial constraints or not. This information is essential in calculating an algorithm able to identify such firms and then, accordingly, to map this condition across the manufacturing industry. Although the authors adopt the bootstrap estimate to minimize potential sample bias, we must acknowledge that the number of available observations included in the proposed deep learning method is quite low (i.e., almost 400 firms), and the results collected should be interpreted with caution. Indeed, there might be an overfitting problem in using a small sample of observations, which is only reduced by the bootstrap approach and its resampling technique.

Another limitation concerns the adoption of observations collected during the pandemic year, which might affect our prediction models. Indeed, data availability forced the authors to make a trade-off between the accuracy of our results, which is clearly limited by the pandemic year, and the necessity to have an appropriate sample of firms, including all available observations. We accepted the latter option and due caution should be taken in results interpretation.

Afterwards, considering the interpretation of the Garson index and the determinants of being under financial constraints, we must acknowledge the existence of an alternative explanation. For instance, considering the dividend payout policy, we might explain the collected results in terms of corporate financing strategies. Firms with high growth prospects usually tend to avoid the payment of dividends, so that they can internally retain the liquidity to support such a strategy (e.g., fostering investments); whereas firms with low or no growth prospects usually distribute dividends to shareholders. Hence, we might explain the evidence collected in terms of investment strategies and the pecking order theory, instead of the proposed signaling hypothesis. Based on these results, future studies will focus on the determinants of being under financial constraints, testing alternative hypotheses and adding more robust evidence on these dynamics.

Finally, we cannot properly investigate which might be the determinants of being under financial constraints. Indeed, the Garson indexes can only highlight the relevance of inputs in explaining whether firms are under financial constraints, but they cannot explain their impact. Future studies might focus on the investigation of such relation, identifying the determinants of being under constraints.

6. Conclusions

Access to external financial resources is fundamental to support the productivity of firms [37,121], especially in times of external shocks [122,123], which might affect their survival [124,125]. Being able to accurately predict the condition of being under financial constraints is crucial to lead successful interventions by all stakeholders (i.e., managers and policy makers). In this regard, the present work offers a contribution to the current knowledge.

In detail, this study applies a neural network framework to optimize the classification of firms, predicting their difficulties in collecting external financial resources in the short term. According to our results, the Conjugate gradient backpropagation with Fletcher-Reeves updates (i.e., CGF) is the best-performing algorithm. Moreover, considering specificity and sensitivity, the proposed framework can balance the researchers' expectations more effectively than a simple logistic regression model, modulating the admissible type I and type II errors.

The practical implications of our results concern both the policy makers and the managers of manufacturing firms. On the one hand, the policy makers can adopt the proposed framework and, through the weights reported in Appendix C, they can investigate access to external financial resources across industrial sectors and geographical areas, leading the implementation of ad-hoc interventions that are coherent with the European Union cohesion policy program for 2021–2027. Indeed, these weights give the opportunity to replicate our study, mapping whether heterogeneity among industrial sectors and/or territories might exist, thereby shaping appropriate industrial policies to support access to external financial resources to fund innovation and foster socio-economic development. On the other hand, the managers of firms can adopt the same weights to predict whether their applications to the capital market to fund innovative projects might be rejected, while also reflecting on the collected Garson indexes to shape their business and corporate strategies, facilitating future loan applications.

Obviously, the proposed investigation is not without limits, which we must highlight. The sample of firms used to calculate the weights is quite small (<400) and, if opportunities to gather other data present themselves, we expect to validate our insights on a bigger sample of firms. In addition, the target of our analysis is extracted from a survey, and it might suffer from all the problems related to this kind of investigation. Surveys are undoubtedly a time-consuming activity, and we cannot control who is responsible for the answers, which might cause a selection bias in the sample of firms. Regardless of its limits, we believe that the study illustrated here represents an interesting contribution to the current literature, able to foster new investigations on financial constraints adopting neural networks.

CRediT authorship contribution statement

G.G. Calabrese: Writing – review & editing, Data curation. **G. Falavigna:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **R. Ippoliti:** Writing – original draft, Investigation, Formal analysis, Conceptualization.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2024.101973.where $n = 1, \ldots, N$ and represents the number of firms, t_n identifies the real output (i.e., the target) and o_n indicates the empirical output (i.e., the output of the network).

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Giulio Giuseppe Calabrese is director of research at CNR-IRCrES, editor in chief of the *International Journal of Automotive Technology and Management* and member of the International Steering Committee of GERPISA. His main research areas include the automotive supply chain and its technological innovation.

Greta Falavigna is senior researcher at CNR-IRCrES, associate editor of the *Journal of Public Affair* and lecturer in Political Economy at the Polytecnic of Turin. Her main research areas include complex systems and evaluation of firms' performance.

Roberto Ippoliti is senior assistant research in applied economics at University of Eastern Piedmont, and associate editor of the *Journal of Public Affair*. His main research areas include institutional efficiency and firms' behavior under financial constraints.