Using machine learning to assess public policies: a real case study for supporting SMEs development in Italy

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***Abstract*—In recent years, several initiatives have been taken by governments to support investments in small and medium-sized enterprises. The aim is to foster their access to finance, and thus enhance their competitiveness. This paper investigates, through artificial intelligence, the socio-economic effects of these financial instruments on the performance and business continuity of the beneficiary companies. Moreover, this paper illustrates how artificial intelligence can support public decision-makers in creating and deploying regional policies. This study is a part of the collaboration among Arisk Srl and some policy-makers of the Regional Government of Piedmont (Italy).**

***Index Terms*—Small and medium-sized enterprises, bankruptcy prediction, machine-learning, policy-making**

I. INTRODUCTION

Small and Medium-sized Enterprises (SMEs) can be defined as the backbone of economies. Indeed, as [1] points out, SMEs are essential to the economies of European regions, both in terms of competitiveness, support in economic growth and innovation, and employment. In particular, SMEs make up over 99.8% of the total number of businesses in the EU in 2018. Moreover, according to the annual report [2], SMEs account for the majority of the increase in value-added (60%). On the one hand, SMEs support innovation and they gain from higher flexibility than the larger enterprises. On the other hand, they face different challenges such as limited resources and difficulties in attracting talented and high-skilled employees, as well as restricted access to finance [3]. In particular, as the authors in [4] point out, the fallout from the 2008 financial crisis has focused attention on access to financial capital for these companies.

Several initiatives arose to help SMEs in addressing these challenges and particularly, with respect to access to finance.

This paper aims at illustrating the effects on the performance and the state of health of companies receiving financial support under regional financial initiatives and public policies. More in detail, the funding scheme and the data used in this paper come directly from the analysis of the effects of the call POR FESR 2007/2013, *Tranched Cover*, conducted by Arisk Srl, spin-off Regtech/Fintech of the Politecnico di Torino (Turin, Italy), as a part of the collaboration with the Piedmont Region.

The main contributions of this paper are:

- We conduct a forward-looking predictive analysis according to Arisk's methodology to investigate the effects of the financial engineering instruments that rely on the Tranched Cover Fund in supporting the financial health of the beneficiary Italian companies in Piedmont. This is done through an *ex-ante* and *ex-post* evaluation of the socio-economic impact of regional policies, using artificial intelligence (AI).
- We illustrate as an artificial intelligence-based Decision Support System (DSS) could be a viable and powerful strategic tool. It helps decision-makers (e.g., local government, banks, and financial institutions) in assessing the financial health of companies that apply for economical help/fund and predicting well in advance the risk of bankruptcy in the future. It will contribute to favor an efficient allocation of financial resources and to evaluate the financial policies at regional and national levels.

The paper is organized as follows. Section II provides an overview of the initiatives to enhance the competitiveness of SMEs. Section III reviews the literature on prediction models for the risk of bankruptcy. Then, Section IV presents the methodology adopted to conduct our analysis, based on artificial intelligence. In Section V, we discuss the results. Finally, Section VI concludes the paper.

II. Enhancing the competitiveness of SMEs

As mentioned in the introduction, SMEs are essential for the economy of European regions (and therefore States), both from an employment and innovation point of view. Indeed, according to [5], SMEs are critical factors in driving economic development because of their impacts on wealth generation, innovation, skills and capabilities, the opening up of new markets, job creation, and job satisfaction [6], [7]. Thus, preserving and maintaining SMEs, while seeking to help their development become strategic. Public funds are useful in this sense. For example, as stated by [8], SMEs covered by support from European funds have a higher level of innovative investment implementation than other business entities. European SME policy launched different initiatives and programmes to SME development, e.g., the first *Community programme for SMEs* (1983), the *Integrated Programme in favour of SMEs and the Craft Sector* (1994 and 1996), and the *Competitiveness of Enterprises and Small and Medium-sized Enterprises* (COSME) programme 2014-2020 [3]. At the regional level, the Regional Government of Piedmont launched a call that set up a fund, named *Tranched Cover Piedmont* through the financial resources established by the regional programme “Programma Operativo Regionale 2007-2013 - Fondo Europeo di Sviluppo Regionale" (POR - FESR 2007-2013). With this call, different intermediaries that have signed a conventional agreement with Finpiemonte S.p.A., are identified to provide tranched cover operations. Their purpose is to support the competitiveness and employment in the region fostering innovation and productive transition, and access to finance for SMEs. In particular, the POR FESR 2007-2013 programme is introduced to counter the effects of the economic and financial crisis on the production system, creating the conditions to promote and give a new impulse to investment for innovation, the transition of sustainable growth. The measure aimed, in particular, at supporting the ability to access to credit for SMEs through the use of financial instruments able to overcome difficulties and high-risk reticence of the banking system. The programme includes the following types of actions as eligible for financing under the fund:

- investment in production and infrastructures;
- working capital requirements, liquidity stocks, and corporate capitalization;
- financial recovery (for the extinction of short and medium-term credit lines, and the adoption of debt re-entry plans).

These actions have different characteristics, but generally the funding ranges from 25K to 1 million euros. The remainder investigates the effects of these actions on the performance of the beneficiary companies.

III. Literature review

Different contributions in the literature propose models and quantitative approaches to efficiently assess the likelihood of company default. Traditional methods rely on statistical models. For example, the author in [9] proposed the *t*-test to obtain the significance of the default ratio for each company. The work by Altman (1968) [10] used multiple discriminant analysis (MDA). However, other researchers [11]–[14] have moved toward the development of conditional probability models (e.g., logistic regression) and discriminant analysis, to overcome the false statistical assumption underlying the MDA. In particular, the author in [11] proposed a logistic regression-based model to determine the default probability of a potential borrower. On the one hand, these models have the advantages of being able to derive an analysis of the certainty probability of the results and, to evaluate the effect of each feature individually. On the other hand, they are affected by the following limitations: (i) they have become inaccurate and thus, require enhancements in the modeling of bankruptcy risk [15]; (ii) to be accurate, they require the tuning of the parameters depending on the market in which they are applied; (iii) prediction is normally limited to the short-term horizon (i.e., 12 months) [16], [17]; (iv) they cannot be automatically incorporated into large time-series data and rely on the standard mean-value theory, while normally extreme-value theory might provide better results [18], [19]. These limitations led researchers to study and develop pattern recognition methods, demonstrating how machine learning models can outperform traditional classification methods. For example, the authors in [20]–[22] used artificial intelligence systems, such as neural networks and genetic algorithms. While, other studies [23], [24] demonstrated the power of ensemble models to deal with imbalanced data sets. Fagini et al. (2017) [25] investigated the difference between parametric and non-parametric methods to analyze the credit risk of SMEs, through multivariate outlier detection techniques. Moreover, the paper by Brédart (2014) [26] presented an application of neural networks using a limited number of features/ratios on Belgian SMEs, improving upon the performance of the previous works [27], [28]. Finally, the authors in [29] applied XGBoost to a data set audited by a Korean credit rating agency. The main advantage of these applications is the good accuracy that is, however, highly dependent on external factors (e.g., the presence of a regulation that obliges companies to undergo an external audit). Another problem is the difficult prediction capacity in the mid-term (i.e., 24 months).

To the best of our knowledge, at present, the best results have been obtained by Perboli and Arabnezhad [30], where the authors showed how, by using a two-phase dataset creation procedure and a proper feature section procedure, a Random Forest method can be derived with precision over 85% with a prevision horizon up to 60 months [30]. Thus, the derived Machine Learning predictor not only gives the best results in the classic 12 months time horizon considered in the literature, but it is reliable for a mid-term (3 years) and long-term (5 years) prediction. The method, incorporated in a DSS, was then used to analyze the effects on the economic environment in the long-term of the COVID-19 disease in Piedmont and to simulate the policies of the Italian Government.

IV. Methodology

In this section, we present the methodology adopted in our analysis, which is based on the work by Perboli and Arabnezhad [30].

We consider a sample of 329 companies in Piedmont that applied for and received secured funding from the Tranched Cover public fund in 2016. The value of the guaranteed amount by the public fund for the financial support received by these companies is equal to 54 million euros. According to [30] these companies have the following requirements:

- revenues between 1 to 40 millions euros;
- not less than 5 consecutive years of financial data.

In particular, we collect the last 5 years of financial data from companies' balance sheets and data concerning the structure of the governance. These data are extracted from the AIDA database, the largest financial and organizational database managed by Bureau van Dijk/Moody's [31].

Given that the secured funding has been granted in 2016 and the beneficiaries must use them and implement the planned interventions within 18 months, we analyze how the financial performance and the business interruption and bankruptcy risk vary over the five years [30], [32]. Moreover, we compared the financial performance before (i.e., in 2015) and after (i.e., in 2019) the funding. The aim is to derive lessons learned and insight about the adoption of financial engineering tools (e.g., tranched cover initiatives) in supporting SMEs. To support our analysis we also clusterized data according to the type of action (i.e., production and infrastructure investments; working capital requirements, liquidity, and capitalization; financial recovery), and the industry (i.e., commerce, manufacturing, agriculture, and services).

In doing so, we applied the AI-based DSS developed by Arisk Srl, for mid and long-term company crisis prediction. Indeed, by machine learning, we are able to accurately forecast and identify clues of crisis up to 60 months, compared to the 12 months of traditional prediction methods. The overall DSS structure is shown in Fig. 1. It is split into two different sections: a training and tuning module, and a prediction server. The training and tuning module collects public financial data from public databases, as well as other information from the proprietary interface by Arisk Srl, if available. Then, the data are cleaned, normalized and merged. Moreover, they are grouped in core and non-core sets. The former set contains data used by the machine learning pipeline for the feature selection procedure. The latter are secondary data, classified according to a SHELL-based taxonomy [33]. Non-core data are not directly incorporated in the predictor, but they are used for simulating perturbations on the machine learning features.

The prediction of a company's business interruption and bankruptcy risk is performed using a machine learning method based on supervised and certified decision trees, according to a Random Forest algorithm. It provides as output five predictions of the company's business interruption and bankruptcy risk (i.e., 12, 24, 36, 48, and 60 months) and a series of performance indexes created in compliance with the national and international regulations. The machine learning module has been tuned using the financial statement data of more than 160.000 Italian SMEs that are live and operational by the end of 2018, joint with about 3.000 bankrupted company's data covering the period 2001-2018. The reliability of our forecast is about 85% compared to 37% of the traditional techniques.

The interested reader may refer to [30] for more detailed information about the machine learning-based DSS.

V. Real policy-making evaluation: the POR FESR 2007/2013 Tranched Cover initiative case study

In this section, we conduct an experimental campaign to evaluate the socio-economic effects of the funding actions under regional development funding granted under the POR FESR 2007/2013 *Tranched Cover* initiative of the Piedmont region. In general, the aim is to assess through artificial intelligence the effects of policies and programs deployed by public decision-makers in supporting the competitiveness, the access to finance of SMEs, as well as the job creation, and providing useful practical insights.

With this in mind, we first analyze the risk of bankruptcy and financial performance of the beneficiary companies, in the following named as *beneficiaries*, before and after the public intervention. Then, we investigate their governance to identify any potential organizational constraints that hinder their enhancement.

A. Financial assessment and risk of bankruptcy

Starting from the financial statement data we first computed the prevision of bankruptcy expressed as the probability of a company crisis over the next 36 months. The severity of the probability is classified as low risk level of risk (i.e., the probability is under 30%), medium (i.e., between 30% and 50%), and high (i.e., greater than 50%). For each level of risk, we then measured the following indicators:

- percentage variation of the number of beneficiaries from 2015 to 2019 (Δ companies (%));
- percentage variation of the amount of the public guaranty fund from 2015 to 2019 invested in each level of risk (Δ guaranty fund (%)).

Table I gives the results of the prevision of bankruptcy for the overall sample of companies that received the financial support covered by the public guaranty fund. These results highlight an improvement in the resilience of the companies involved. Indeed, the number of beneficiaries that have a high level of risk to be affected by default in 2015 (i.e., before the funding) is reduced by about 34% in 2019. Indeed, on the contrary, the number of companies that after the public intervention improve their performances, and thus reduced their level of risk or nevertheless confirmed their good status, rises by 78%. In monetary terms, this corresponds to a reduction of the amount of the public guaranty fund that is invested in high-risk companies by 18.76% in 2019.

We also investigated to what extent the public policies and the access to finance supported the reduction of the riskiness and improved the performance of the companies that applied for financial help. In doing so, we extended the measurement of the Δ companies (%) in the same period, to all the other companies in the Piedmont region that have not benefited by

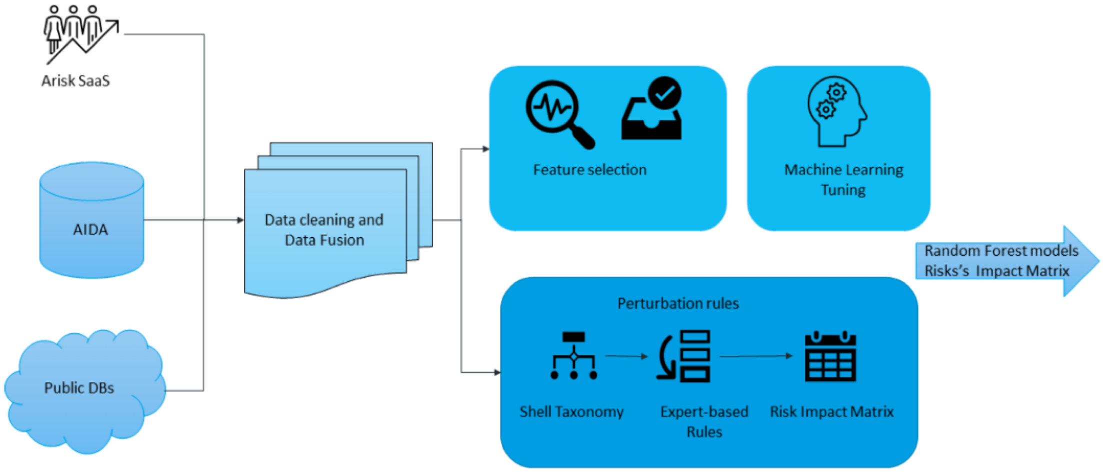

Fig. 1. Decision support system.

the Tranched cover, and for which financial statement data are available on the public database. This yields a sample of about 10.124 companies. Although these companies have reduced their level of risk, this improvement is about half comparing to beneficiaries. Indeed, the number of companies that have a high level of risk in 2015 is reduced by only 13% in 2019 than 34% of the beneficiary ones. Indeed, the number of companies that have reduced their level of risk or nevertheless confirmed their good status, rises by 30% than 78% of the beneficiary firms.

TABLE I
VARIATION (%) OF COMPANIES IN EACH LEVEL OF RISK FROM 2015 AND 2019.

	Beneficiary firms		*Other firms*
Level of risk	**∆ companies**	**∆ fund**	**∆ companies**
Low level of risk	+78%	+19.43%	+30%
Medium level of risk	+2%	+1.68%	-1%
High level of risk	-34%	-18.76%	-13%

As mentioned in Section IV, we clustered data to understand the contribution to the improvement of resilience of each type of action and industry. Table II provides the results of the cluster related to the type of action. The investment in production and infrastructures confirms the general trend discussed above, with a reduction by 33% of the companies with the high prediction of risk of default that moved to medium-low risk levels (+1% and +25%, respectively). The same trend can be highlighted for the working capital requirement action, while the 83% of companies that benefited from the financial recovery moved from the high to medium level of risks, without reaching the lowest risk. The investment in production and infrastructures emerges as the action that contributes the most to both the increasing of resilience and boosting employment. In fact, as shown in Fig. III, the companies that benefited from this action increases their number of workers by 20% from 2015 to 2019. In parallel, the investment in production and infrastructures contributes to the rise in the revenues of beneficiaries by 21%, which corresponds to about 215 million euros. More in general, the better level the resiliency reached in 2019 than 2015 is supported by an improvement of the financial performances. Indeed, Fig. 2 and Fig. 3 depicts how the average values of revenues and the earnings before interest, taxes, depreciation, and amortization (EBITDA), associated with each type of action, vary from 2015 to 2019. The figures highlight an average increase of the revenues of 22%, while EBITDA rises of 19%.

TABLE II
CLUSTER RELATED TO THE TYPE OF ACTION

Investment in production and infrastructures		
Level of risk	**∆ companies**	**∆ fund**
Low level of risk	+25%	-5.69%
Medium level of risk	+1%	+0.42%
High level of risk	-33%	-1.27%
Working capital requirement		
Level of risk	**∆ companies**	**∆ fund**
Low level of risk	+500%	-212,50%
Medium level of risk	-1%	-0.57%
High level of risk	-20%	-7.37%
Financial recovery		
Level of risk	**∆ companies**	**∆ fund**
Low level of risk	+0%	+0%
Medium level of risk	+83%	+100.78%
High level of risk	-83%	-78.20%

Focusing on the cluster related to the industry, beneficiaries belong mainly to the manufacturing and commerce, representing 85% of the overall sample. We report the results concerning all the industries in Table IV. However, for the sake of brevity, we discuss the results related to the two most significant sectors (manufacturing and commerce).

As shown in Table IV these industries have a significant improvement towards the low level of risk. In particular, 17% of manufacturing companies reduce the risk of being in bankruptcy in the next 3 years. Moreover, the amount of guaranty funds invested in low-risk activities increase by 88%.

TABLE III

EFFECTS ON EMPLOYMENT AND GROWTH OF REVENUES

Type of action	Δ n. of employees	Δ revenues
Investment in production and infrastructures	+20%	+21%
Working capital requirement	+7%	+16%
Financial recovery	-3%	-1%

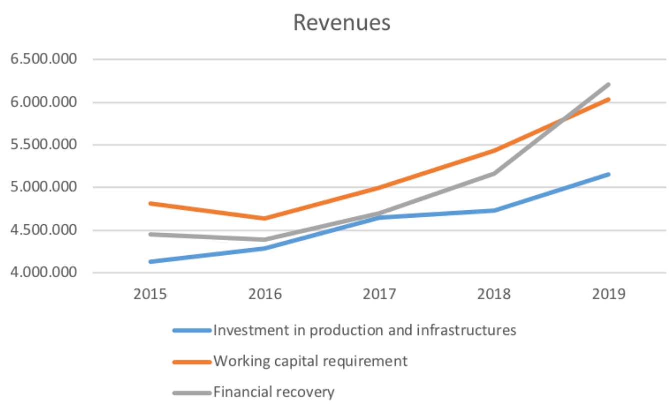

Fig. 2. Average revenues from 2015 to 2019.

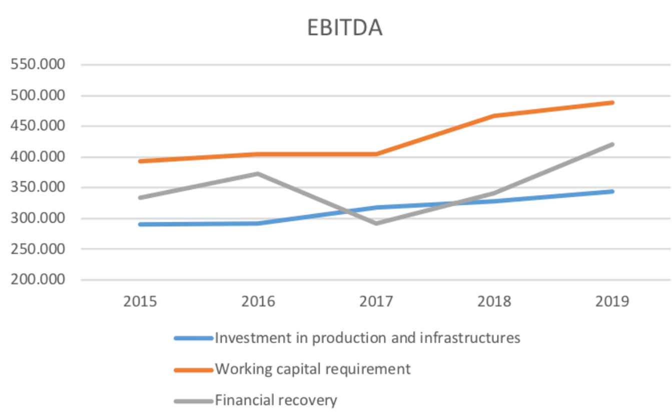

Fig. 3. Average EBITDA from 2015 to 2019.

B. Governance assessment

The DSS developed by Arisk Srl extends the current literature [29], [34] on the correlation between bankruptcy and non-financial variables. Indeed, it incorporates and analyzes the effects of both financial and non-financial data in the prediction model. In this case, we applied our prediction model to the organizational and governance data of the beneficiaries. These data are extracted from the AIDA database [31] and refer to the last year available at the date of the analysis (i.e., 2019). The prediction model analyzes the effects of organizational aspects, e.g., familiarity issues, number of shareholders and decision-makers, presence of an external audit, and seniority, on the financial performance. Thus, it provides a measure, named governance index, that represents the adequacy of the governance model and thus corporate bodies. The aim is to identify, for example, potential critical points or conflicts of interest that can lead to an increase in the risk of bankruptcy. The severity in terms of criticality, of the governance index is classified in low level (i.e., under 30%), medium (i.e., between 30% and 50%), and high (i.e., greater than 50%).

TABLE IV

CLUSTER RELATED TO THE INDUSTRY

Commerce		
Level of risk	**Δ companies**	**Δ fund**
Low level of risk	+67%	-6.02%
Medium level of risk	+3%	+10.46%
High level of risk	-36%	-54.27%
Manufacturing		
Level of risk	**Δ companies**	**Δ fund**
Low level of risk	+233%	+88.88%
Medium level of risk	-2%	-4.19%
High level of risk	-17%	+21.54%
Agriculture		
Level of risk	**Δ companies**	**Δ fund**
Low level of risk	-	-
Medium level of risk	+100%	+289.80%
High level of risk	-100%	-100%
Services		
Level of risk	**Δ companies**	**Δ fund**
Low level of risk	-67%	-80.95%
Medium level of risk	+16%	+14.05%
High level of risk	-80%	-57.98%

Table V highlights an overall critical situation in the level of governance adequacy for the companies benefiting from the fund. In fact, 64% of them have a high governance index, while none of the analyzed companies has a good organizational profile.

TABLE V

GOVERNANCE

Level of governance	% of companies
Low risk level of governance	+0%
Medium risk level of governance	36%
High risk level of governance	64%

VI. CONCLUSIONS

In this paper, we assessed the effects of public policies aimed at fostering the development and access to finance for SMEs, using artificial intelligence. In particular, we analyzed a sample of 329 SMEs that received financial support under the programme POR FESR 2007-2013 Tranched Cover launched by the Regional Government of Piedmont (Italy).

The outcomes highlighted that the companies that have benefited from the regional financial support increased their level of resilience compared to the other companies in the same area. In fact, for the latter, the increase of resilience was fewer than half those of beneficiaries.

This improvement can be mainly attributed to the action aimed to invest in production and infrastructures. In fact, it gave an employment boost of +20% in 2019 than 2015. While, for the other two actions (i.e., working capital requirements and financial recovery), the level of employment had marginal changes. In parallel with the job creation, the investment in production and infrastructures supported an increase in revenues by +22%.

Another important result concerns the adequacy of the organizational asset of the beneficiary companies. Generally, the critical governance structure might represent a threat and a constraint to the development of the SME, even after the financial support. For example, this is due to possible conflicts of interests, as well as high concentration on few shareholders and decision-makers or seniority. This result would suggest the need for an in-depth analysis of the organization, identifying proactive actions to increase resiliency.

To conclude, the DSS proposed in this paper can be a powerful tool to assess public policies in advance and scenarios of public intervention. This helps the decision-makers in defining the efficient allocation of financial resources and deploying the financial policies at regional and national levels.

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