

INSTITUTE  
OF ECONOMICS



Scuola Superiore  
Sant'Anna

LEM | Laboratory of Economics and Management

Institute of Economics  
Scuola Superiore Sant'Anna

Piazza Martiri della Libertà, 33 - 56127 Pisa, Italy  
ph. +39 050 88.33.43  
institute.economics@sssup.it

# LEM

## WORKING PAPER SERIES

### **Italian firms in times of troubles: Covid-19 pandemic as a test of structural solidity**

Stefano Costa <sup>a</sup>  
Federico Sallusti <sup>a</sup>  
Claudio Vicarelli <sup>a</sup>  
Davide Zurlo <sup>a</sup>

<sup>a</sup> Istat - Italian National Institute of Statistics, Rome, Italy.

**2021/47**

**December 2021**

**ISSN(ONLINE) 2284-0400**

# Italian firms in times of troubles: Covid-19 pandemic as a test of structural solidity

Stefano Costa, Federico Sallusti, Claudio Vicarelli, Davide Zurlo<sup>1</sup>

## Abstract

In this paper we study the structural robustness of Italian business system, using Covid-19 pandemic as an exogenous event to test it. To this aim, we use the ROC (Receiver Operating Characteristics) methodology, quite new for Economics, to classify Italian firms according to their economic solidity, obtaining a taxonomy based on a wide set of characteristics. Our results show that the number of “Solid” firms are less than one fifth of the universe of Italian enterprises but they represent the lion share in terms of employment and value added. “Fragile” and “Risky” firms, albeit much less relevant for the creation of value added, account for over one third of total employment, so that they are a worrisome issue for policy makers. The pandemic crisis has clearly both a size and sector-related dimension: Risky and Fragile conditions prevail among firms with smaller economic size (a broad definition of firm size) and among those operating in Construction and Other services. Finally, we find that factors such as firms’ performance, internal and external organization, although significant, play a less relevant role than economic size and digitalization/innovation in determining Italian firms’ solidity to shocks such as the Covid-19 one.

Keywords: Covid-19; ROC analysis; economic solidity to pandemic.

JEL Code: **F61, L25, L60, L80**

---

\* Istat – Italian National Institute of Statistics, Via C. Balbo, 16, 00184, Rome.

## 1. Introduction

Covid-19 pandemic spread rapidly affecting people and economies across the world, pushing countries into the worst recession since World War II. However, the economic effects have been far from uniform: the severity of the impacts has been different in timing and intensity across countries, industries, firms and people (OECD, 2021).

This heterogeneity of the pandemic's economic effects depends on several factors. As for industries and firms, administrative measures to limit the spread of contagion played a crucial role in hitting hardly some economic activities and much less some others, those that have been considered essential by Governments and have been allowed to operate. However, also structural characteristics of sectors and firm, such as their size, connection ability and digital upskills, contributed to determine the strength of the economic impact of pandemic.

More generally, the medium-long term recovery prospects of the business system also depends on the choices that firms had undertaken in the years preceding the spread of the pandemic: it could be very different depending on whether past investments in technology or in human and intangible capital have proved to be factors of resilience or not. For this reason, it is important to identify and decrypt the structural factors that can make economies more resilient to severe shocks like the one caused by Covid-19.

This latter is the main goal of this paper. We study the structural robustness of Italian production system, using Covid-19 pandemic as an exogenous event to test it. Starting from the operational risk signals reported by firms, a new taxonomy has been defined on the basis of firms characteristics of solidity/weakness before an exogenous shock such as that of Covid-19. In particular, we based the taxonomy on a wide set of both structural (economic dimension) and competitiveness conditions (relational characteristics, composition and quality of the workforce, degree of innovation and digitalization).

To build this taxonomy we use the ROC (Receiver Operating Characteristics) methodology. It has been widely adopted in medicine (Lusted 1960), and it is now a common standard of evaluation of medical and psychological tests (Pepe 2003). Furthermore, ROC methodology is used in machine learning (Majnik and [Bosnić](#), 2013) and natural science ([Warnock](#) and Peck 2010). Its application is quite new in Economics: to the best of our knowledge, so far it has been used to test the accuracy of business cycle classification made by the Business Cycle Dating Committee of the National Bureau of Economic Research (Berge and Jordà 2011) and in credit risk literature (Khandani et al. 2010). Furthermore, it has already been tested for the estimation of some components of the underground economy (Cavalli and Sallusti, 2019) and used to determine the minimum business and technological characteristics to access foreign markets (Costa et al 2019, 2021).

As far as we know, there are no other works trying to measure the structural robustness of a production system to the pandemic. However, a couple of strands of literature are close to the aim of our study: a) recent studies dealing with economic impact of Covid-19, in particular those trying to highlight the structural characteristics of sectors and firms as factors of resilience or weakness to exogenous shocks; b) papers studying economic consequences of "natural disasters" (earthquakes, terrorism or cyberattacks).

As for the first group of works, many recent papers try to measure the impact of Covid-19 on countries, industries, firms and workers, whose heterogeneous characteristics may amplify or mitigate the economic effects of the crisis and/or determine the resilience of economic systems with respect to exogenous events. At firm level, business dynamics, financial solidity, innovation and digital technology, among others, are factors that can help economies to be resilient to Covid-19 induced shock (OECD 2021). On the opposite, pre-

crisis structural weakness in these fields are factors that may have undermined firms' ability to resist to the economic effect of the crisis.

As for business dynamics (in terms of firm entry, growth and survival), the pre-crisis period has been characterized by increasing productivity gaps between leaders and laggards, declining entry rates and job reallocation and increasing industry concentration (Bajgar et al., 2019). These trends may be grounded in a lack of capabilities and incentives for younger and smaller firms to innovate and adopt new technologies (Calvino et al 2020). Furthermore, pre-crisis heterogeneity in firm size and age are also elements affecting the vulnerability to financial shock caused by the crisis. Small and young firms are often more financially constrained and are not usually equipped with financial cushions to allow them to survive a prolonged period of reduced activity or revenue (OECD, 2020; Bartik et al., 2020; WTO, 2021). This suggests that these firms, that under normal circumstances are an important source of innovation, employment and productivity growth (Calvino et al 2015), have been particularly sensitive to economic shock (Adelino et al., 2014).

As for financial solidity, high levels of corporate debt, particularly in the form of corporate bonds, had emerged in the pre-Covid-19 period (Çelik et al, 2019). This increase in debt amplified financial pressures during the Covid-19 outbreak (Aramonte and Avalos, 2020), with highly indebted firms predicted to see stronger impacts on leverage ratios and future investment (Demmou et al., 2021). High pre-crisis corporate debt could therefore be considered as an aggravating factor for the risk of debt overhang. Furthermore, micro, small and medium-sized enterprises have suffered more than larger firms from the effects of the pandemic, owing to their limited access to finance (WTO 2021).

Digital technologies have been a key element of economic resilience during the Covid-19 crisis. High-capacity communications infrastructure (like a high-speed broadband connection), digital skills and data security are all important factors enabling the use of such technologies. Countries, sectors and firms that were more involved in using these technologies before pandemic have had more chances to be resilient during the crisis. On the one hand, pre-existing divergences between firms in adoption of these digital technologies impacted on the resilience of firms. On the other hand, these divergences may have been exacerbated by the crisis: not all firms develop, adopt or use digital technologies in the same way, nor do they benefit equally from the digital transformation (Andrews et al., 2016; Gal et al., 2019). In particular, young, small, and less productive firms faced major difficulties in adopting and using digital technologies; this can be mainly due to the rising importance of complementary intangible assets (such as skills, internal and external organization) that entail economies of scale and network effects (Corrado et al., 2021).

As for the second group of works, Covid-19 pandemic could be considered a sort of a "natural disaster" episode, much more than 2007-08 financial crisis. This kind of literature has analyzed disruption of supply-chains as a consequence of these natural events. In this respect, the analogy between the effects of a natural event and those of Covid-19 is evident: the interruption of supply chains represents in fact a peculiar consequence of the pandemic episode. Trade-driven interdependence – especially the rise of global value chains – can increase firms exposure to sudden cut-offs in the supply or demand of inputs or outputs. It follows that even relatively small shocks to firms that are relevant in terms of linkages with other firms can temporarily block or disrupt highly interconnected networks, especially "just-in-time" production and distribution. In this vein, the 2011 Tōhoku earthquake in Japan is estimated to have reduced the growth rate of firms with disaster-hit suppliers by 3.6 percentage points, and the growth rate of firms with disaster-hit customers by 2.9 percentage points (Carvalho et al., 2021; Tokui et al, 2017). Furthermore, natural disasters trigger economic losses not only by destroying physical assets but also by causing bottlenecks in supply

chains. For example, in 2011, the Tōhoku earthquake triggered shortages along the global supply chains of multinationals relying on Japanese inputs (Boehm et al, 2019).

In the light of this literature, firm size, internationalization, productivity, digitalization, investments in advanced technology and human resources emerge as potentially relevant factors in determining the resilience and reaction capacity of the business system to an exogenous crisis such as the pandemic one. The taxonomy here proposed profiles firms according to these aspects, controlling for the main specific consequences of the pandemic, such as interruptions in supply chains, reduced demand and liquidity crisis.

The rest of the paper is organized as follows. Section 2 illustrates the main results of Covid-19 survey carried out by Istat in November 2020; Section 3 describes data we use. Section 4 shows the empirical strategy, with a brief illustration of ROC methodology from which we derive our taxonomy of economic solidity. Section 5 shows and comments the results; Section 6 concludes.

## **2. The Italian business system facing the Covid-19 crisis: results from an ad hoc survey**

The economic crisis resulting from the Covid-19 emergency had deep and heterogeneous effects on the activity of Italian firms and sectors. Lockdown measures, drastic reduction in demand, interruption or slowdown of value chains, the lack of liquidity have all put firms operativity at risk. In such circumstances, the effects of the crisis must be analyzed in a granular perspective, both to identify the structural factors of firms' resilience or vulnerability, and to study how firms react to the consequences of the shock.

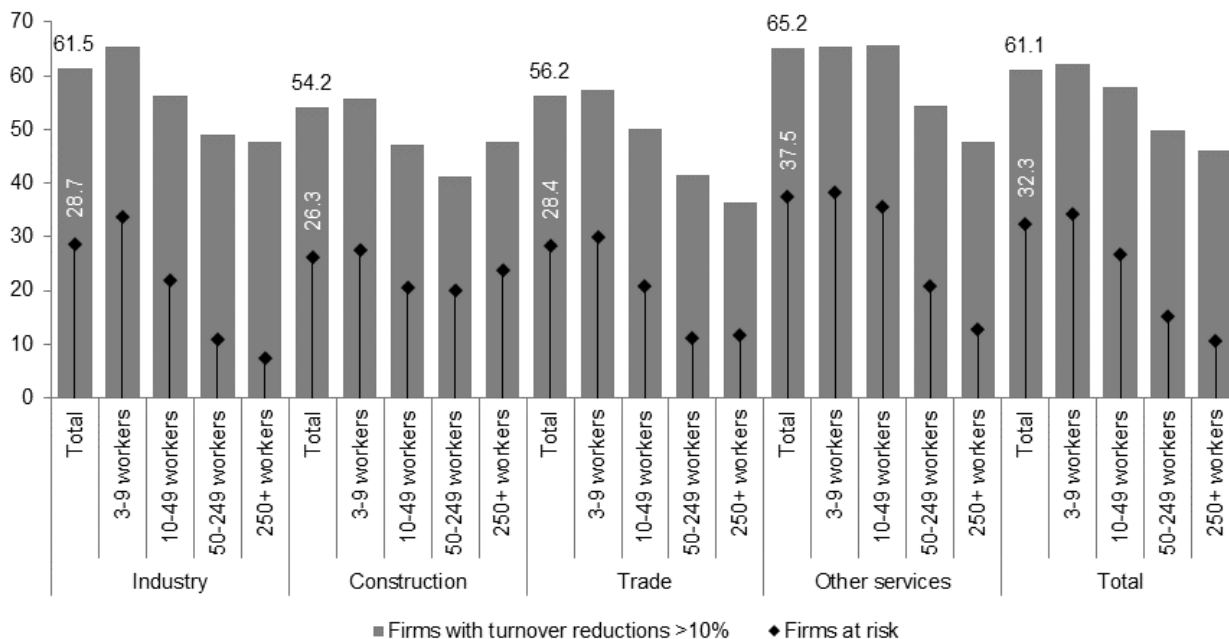
The crisis hit Italian firms in an extensive and severe way: according to the results of the survey on "Situation and prospects of companies in the Covid-19 emergency" carried out by Istat (2020), over two thirds of companies with at least 3 employees suffered a reduction in turnover with respect to the period June-October 2019. For almost 60% of firm the decrease in turnover was higher than 10%, and about 62% of firms expected revenues to decrease also in the first six months of 2021. Less than one out of five firms (about 18%) reported no consequences or even benefited from the crisis.

Such a widespread fall in activity hindered large sections of the Italian business system: in May 2020 about 38% of companies resulted at risk of closing down, in November 32.3% still reported the presence of economic and organizational factors capable of jeopardize their survival. Furthermore, at that time the expectations for 2021 were quite gloomy: less than one out of five firms expected to expand its activity or keep it up in the first half of 2021.

The fall in domestic demand and (to a much lesser extent) foreign demand, as well as the lack of liquidity, were reported as the main effects of the sudden recession: 38.3% of firms indicated the decrease in domestic demand among the major constraints on the possibility of recovery during the first half of 2021. A share of 15.8% of firms reported problems on foreign demand; 34.1% expected risks of illiquidity, to be coped with by a change in the structure of the sources of financing, mainly more bank credit.

Overall, the pandemic-related crisis had an evident size dimension (Figure 1): in all macro-sectors the share of firms with a sharp decline in turnover (over 10%), as well as that of firms at operational risk, tends to decrease as the firms size increases. On average, more than 34% of "micro-firms" (i.e. less than 10 workers) reported serious operational risks; this share is 26.8% in the case of small firms (10-49 workers) and drops between 10 and 15% for medium and large firms (50 workers and more), reaching a minimum for largest (250+ workers) industrial companies (less than 8%).

**Figure 1 – Firms with turnover reductions >10% and firms at risk, by macrosector and size class – November 2020 (%)**

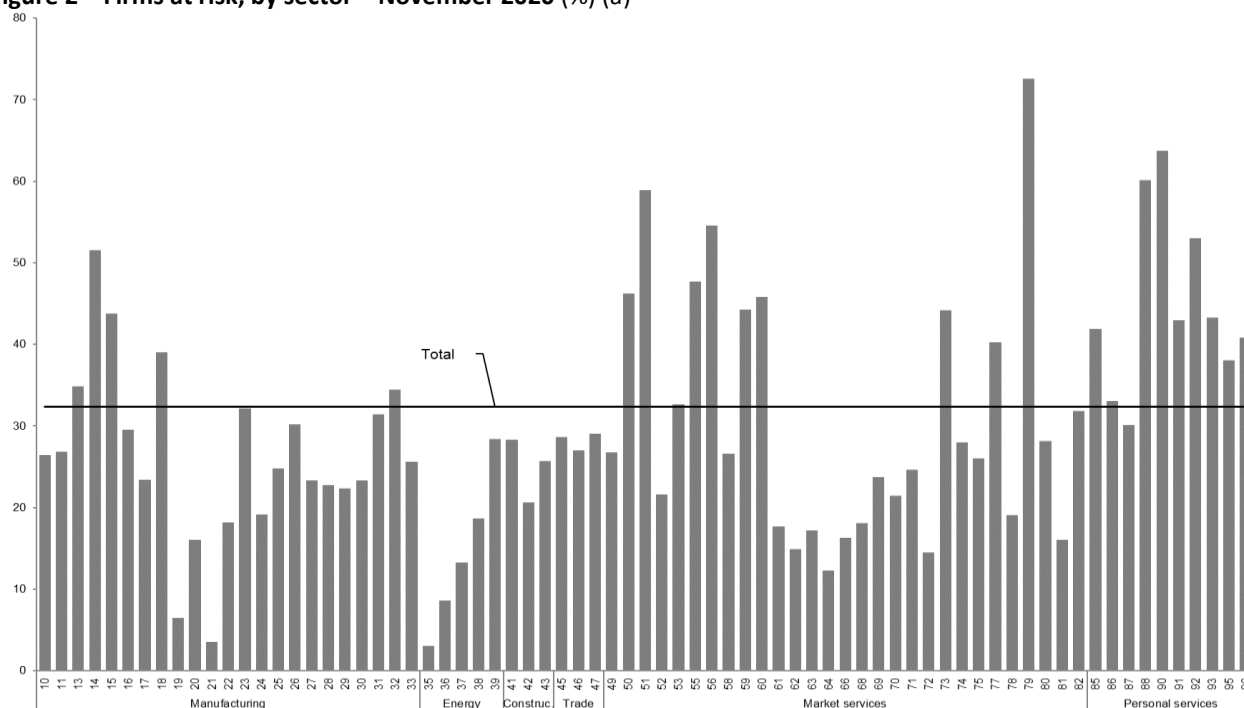


Source: Istat (2021)

Reductions in turnover of more than 10%, although widespread in all macro-sectors, characterized to a greater extent the units of industry and other services, but the impact was much deeper in the latter ones: in these activities the share of units at risk was the highest among all size class. The harsher conditions, as expected, prevailed in those sectors most affected by lockdown measures (Figure 2): the share of firms reporting risks of closure was notably high in travel agencies (over 73%), art and entertainment (over 60%), non-residential social assistance (about 60%), air transport (59%), restaurants (about 55%). Within the industrial sectors, however, the difficulties of the fashion supply chain stood out: clothing (over 50%), leather (about 44%), textile (about 35%).

In a context characterized by high heterogeneity, it is useful to identify the firm characteristics that may affect the survival of enterprises. In this way, it is possible to obtain an assessment of the resilience of the business system facing to an exogenous, violent and pervasive shock.

**Figure 2 – Firms at risk, by sector – November 2020 (%) (a)**



(a) 10= Food; 11= Beverage; 13=Textiles; 14= Wearing apparel; 15= Leather; 16= Wood; 17= Paper; 18= Print; 20= Chemicals; 21= Pharmaceuticals; 22= Rubber and plastic; 23= Non metallic products; 24= Basic metals; 25= Metal products; 26= Electronics; 27= Electrical equipment; 28= Machinery; 29= Motor vehicles; 30= Other transport equipment; 31= Furniture; 32= other manufacturing; 33= Repair; 45= Motor vehicles trade; 46= Wholesale trade; 47= Retail trade; 49= Land transport; 50= Water transport; 51= Air transport; 52= Warehousing; 53= Postal/courier services; 55= Accommodation; 56= Food and Beverage activities; 58= Publishing; 59= Video, TV, Sound and music; 60= Broadcasting; 61= Telecommunication; 62= Computer programs and consulting; 63= Information services; 68= Real estate; 69= Legal and accounting act.; 70= management consultancy; 71= Architect. And engineering act.; 72= R&D; 73= Advertising and market research; 74= Other professional act.; 75= Veterinary; 77= Rental and Leasing; 78= Employment activities; 79= Travel agency/tour operator; 80= Security and investigation; 81= Building and landscape activities; 82= Other business services; 85= Education; 86= Human health; 87= Residential care; 88= Social work without accommodation; 90= Creative, arts, entertainment; 91= Libraries, museums and other culture; 92= Gambling and betting; 93= Sport and recreation; 95= Computer repair; 96= Other personal services.

Source: Istat (2021)

### 3. The dataset

This work is based on a dataset integrating several sources, both of administrative and survey nature. The main statistical source is the aforementioned survey Covid-19, released by Istat in November 2020. This survey is census for firms over 20 workers, a sample for those between 3 and 19 workers. From this source we draw the information on risk perception and other Covid-related difficulties encountered by firms.

Structural information on Italian business system is drawn from “Frame-Sbs” register. Released annually by ISTAT since 2011, it provides information on the structure (e.g. number of employees, business sector, location, age) and the main economic variables (e.g. value of production, turnover, value added, labour cost) for the whole population of about 4.4 million of Italian firms. In this work, we use the 2018 release.

Furthermore, the following source are used:

- Racli Register, with information on employment composition (in terms of contract typology and education), wages and labor costs for the single employee job position and related firm of the non-agricultural private sector. From this archive, we draw information on employment composition and wages of the firms’ workforce (year 2018);

- Asia-groups register, which provides information on firms membership and positioning within domestic and multinational groups (year 2018);
- Multi-purpose survey linked to the first Istat permanent Business Census Plan (MPS survey). The sample includes approximately 280.000 firms employing 3 or more workers. From this source, data on the relational and strategic profiles of the production units are extracted, as well as those relating to investments on innovation and digitalization (year 2018).

Merging these different sources, we obtain a final dataset of over 40,000 firms depicted in Table 1, representative of the universe of over 1 million firms with 3 or more workers operating in Italy.

**Table 1 – The dataset: descriptive statistics**

	Firms	Turn-over		Value added		Workers	
	Units	Mln euros	Percentage	Mln euros	Percentage	Units	Percentage
Sample							
Industry	13740	489390	53.1	103085	47.7	1078744	38.4
Construction	3529	18860	2.0	5397	2.5	89131	3.2
Market services	19850	396897	43.1	100791	46.6	1522503	54.2
Personal services	3125	16162	1.8	6900	3.2	117623	4.2
<b>Total</b>	<b>40244</b>	<b>921309</b>	<b>100.0</b>	<b>216173</b>	<b>100.0</b>	<b>2808002</b>	<b>100.0</b>
Population							
Industry	192723	1204276	39.3	281654	38.2	3741755	29.9
Construction	109718	135376	4.4	43773	5.9	874339	7.0
Market services	621697	1638705	53.5	382889	51.9	7148718	57.2
Personal services	94087	85134	2.8	29606	4.0	742383	5.9
<b>Total</b>	<b>1018225</b>	<b>3063490</b>	<b>100.0</b>	<b>737921</b>	<b>100.0</b>	<b>12507194</b>	<b>100.0</b>

Source: Authors' calculation on Istat data

## 4. Empirical strategy

This section describes the methodology used to define the taxonomy of firms' robustness. In particular, Section 4.1 illustrates the ROC analysis as a classifying method; Section 4.2 presents the strategy that grounds the selection and aggregation of the relevant characteristics of Italian firms in determining their solidity. Starting from the definition of the different cut-offs obtained by applying the ROC analysis, Section 4.3 shows how the taxonomy is derived.

### 4.1 ROC analysis

The Receiver Operating Characteristics (hereinafter, ROC) analysis permits to identify a cut-off point along the value of an independent variable in a logit model, so as to efficiently cluster observations with respect to a binomial status. While this method is widely used in different disciplines – principally medicine, where it summarizes the ability of a marker (or diagnostic test) to discriminate between two groups of individuals (i.e. healthy and diseased) – the use of the ROC in economics is still very scarce (see Section 1).



The ROC analysis can be traced back to classification problems in which, according to Fawcett (2005), classifiers (the relevant characteristics chosen in order to explain a given status of observations) can give the four possible outcomes shown in the “confusion matrix” in Figure 3:

- True Positives (*TP*): positive observations are correctly classified as positive by the classifier;
- False Negatives (*FN*): positive observations are erroneously classified as negative by the classifier;
- False Positives (*FP*): negative observations are erroneously classified as positive by the classifier;
- True Negatives (*TN*): negative observations are correctly classified as negative by the classifier.

**Figure 3.** Confusion matrix

		Estimated classification	
		1	0
True classification	1	<i>TP</i>	<i>FN</i>
	0	<i>FP</i>	<i>TN</i>

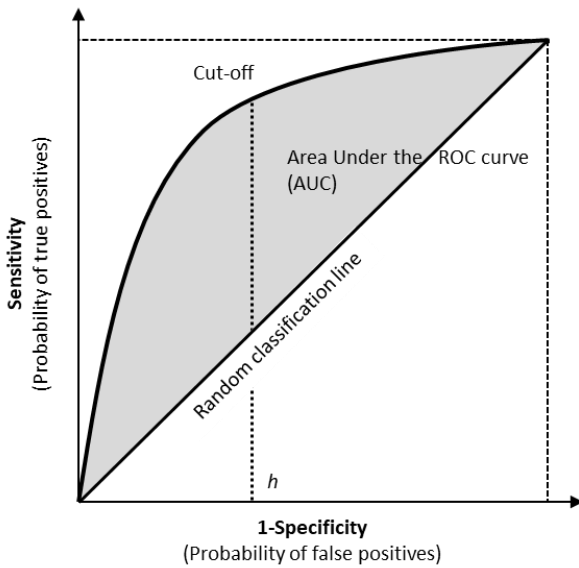
The efficiency of the classifier can be measured using two metrics: *Sensitivity* measures the ability of the classifier to detect true positives, i.e.  $TP/(TP + FN)$ ; *Specificity* measures the ability of the classifier to detect true negatives, i.e.  $TN/(TN + FP)$ , where it is usually considered in its reciprocal expression ( $1 - Specificity$ ), which measures the correct detection of false positives.

Considering a logit model that has a binomial dependent variable (reflecting a given status) and a classifier as a covariate, the distribution of probabilities resulting from the logit estimates can be displayed in the space of *Sensitivity* and  $1 - Specificity$  by the ROC curve in Figure 4.

In particular, the ROC curve represents the probabilities assigned by the model to each observation in the space of the trade-off between the probability of detecting true or false positives across all possible cut-off points along the values of the classifier (Kumar and Indrayan, 2011). The area under the ROC curve (AUC, the sum of the grey and white portions) provides a measure of the extent to which the classifier allows to define a more efficient classification than a pure random selection (the 45° line).<sup>2</sup>

<sup>2</sup> In this vein, the AUC criterion is largely used to measure the goodness of fit of logit models, and to define the relative relevance of a set of variables in determining the overall logistic distribution of probability.

**Figure 4.** The ROC curve



In order to single out, along the ROC curve, the observation that most efficiently discriminates between positives and negatives (*Cut*), the following equation needs to be maximized:

$$Cut = h * sensitivity - (1 - h) * (1 - specificity) \quad [1]$$

where  $h$  and  $(1 - h)$  represent the relative weights to manage the trade-off between true and false positives.

Setting-up a value of  $h$  identifies the cut-off observation and, consequently, the relative value of the classifier that discriminates between two estimated classes of observations ( “Manichean classification”, i.e. the positive and the negative status, according to whether the value of their classifier is over or under the threshold).

In this context, setting-up  $h < 0.5$  ( $h_-$ , hereinafter), i.e. finding true positives is less relevant than avoiding false positives, would correspond to a “conservative” selection, which assigns positive classifications only in presence of a strong evidence. Conversely, setting-up  $h > 0.5$  ( $h_+$ , hereinafter), i.e. finding true positives is more relevant than avoiding false positives, would correspond to a “liberal” selection, which assigns positive classification even in presence of a weak evidence. Finally, setting-up  $h = 0.5$  a “neutral” selection is obtained and the cut-off corresponds to Youden’s  $J$  index.<sup>3</sup>

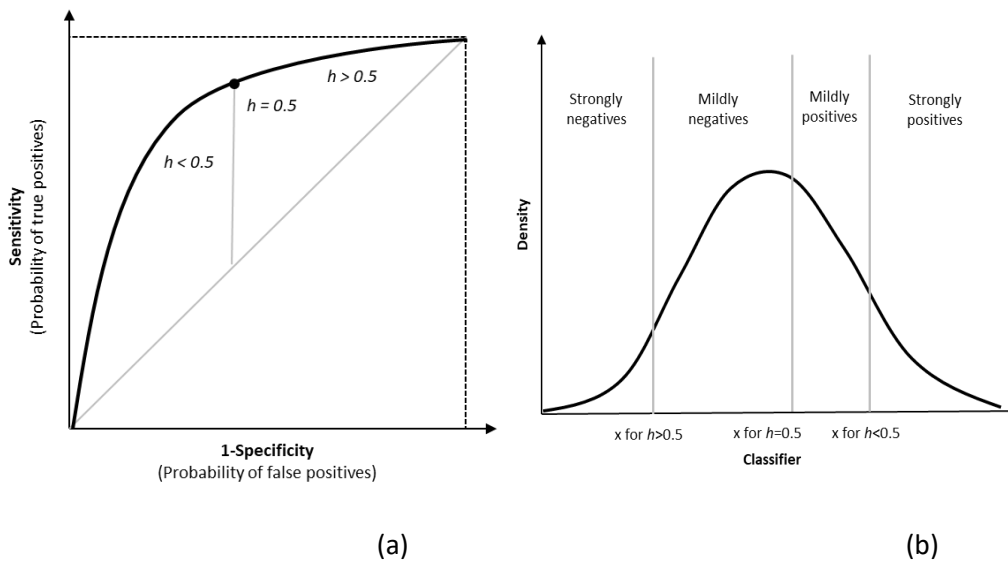
Shifting the value of  $h$  from 0 to 1, therefore, allows to define different cutoffs (and, thus, classifications). In particular, starting from a “neutral” selection ( $h = 0.5$ ), a move toward a “conservative” selection (i.e.  $h_-$ ) allows to define cut-offs in which the positive status is assigned only in case of strong evidence (i.e. higher values of the classifier). Symmetrically, moving toward “liberal” selection (i.e.  $h_+$ ) permits to define cut-offs in which the negative status is assigned only in case of strong evidence (i.e. lower values of the classifier).<sup>4</sup>

<sup>3</sup> For an extended treatment of the Youden’s  $J$  index see Costa et al., 2019.

<sup>4</sup> In building up Manichean taxonomies, the use of “neutral” strategy is somewhat “natural” when there is not a strong prior about the weight of errors. However, when this prior exists (this particularly holds in medicine, where the cost of

In this work, we exploit this symmetry to refine a Manichean classification. Indeed, a set of  $n$  cut-off may be used to generate  $(n + 1)$ -class taxonomy. Figure 5 shows a possible four-group classification derived from three cut-offs obtained by sliding the value of  $h$  in equation [1]. In particular, the (a) part of Figure 5 shows how three different cut-offs are identified along the ROC by using different value of  $h$ , while the (b) part illustrates how the different cut-offs can be projected along the density distribution of the classifier in order to obtain the taxonomy.

**Figure 5. Complex taxonomies using sliding  $h$**



In this context,  $h_+$  and  $h_-$  should be defined according to their capability of identifying homogeneous groups of observations. To do so, we choose them in correspondence of relevant jumps in the distribution of probability.

#### 4.2 The status of solidity and the composite indicator.

In our case, in terms of Section 4.1, the binomial status is the absence (presence) of an operational risk of Italian firms facing the Covid-19 pandemic crisis, as a proxy of solidity (fragility). In turn, the classifier is represented by a composite indicator covering five relevant “pillars” of firm economic solidity: economic size, performance, internal organization, external organization, digitalization and innovation. Recent literature (see Section 1) has highlighted the relevance of these factors in determining firm capability to cope with a crisis like Covid-19 pandemic.

The status about the operational risk of Italian firms is gathered from the Covid-19 Survey described in Section 2. In this context, productive units were asked to indicate whether they were at operational risk in the next six months. Even with considerable sectoral and dimensional heterogeneity, about 4 firms out of 10 considered themselves at operational risk.

---

badly classify healthy and diseased persons could be strongly different),  $h$  can be efficiently set-up to lower or higher values than 0.5.

The indicator representing our classifier is an aggregation of composite indicators accounting for the pillars of economic solidity. Table 2 reports for each composite indicator the elementary components taken into consideration (including the type of variable and the way in which they are calculated).

**Table 2. Pillars of economic solidity and their elementary components**

Composite indicators	Elementary components	Type	Notes
Economic size	Number of workers	Continuous	Positions
	Turn-over	Continuous	Level
	Age	Continuous	Months
	Capital intensity	Continuous	Depreciation of fixed asset per worker
Performance	Productivity	Continuous	Value added per worker
	Profitability	Continuous	Gross operating surplus / Value added
	Cost competitiveness	Continuous	Per worker value added / Average compensation of employees
Internal organization	Presence of external management	Binomial	Management other than the owner
	Belonging to groups	Binomial	Belonging to domestic or multinational groups
	Share of high skilled workers	Continuous	Workers with tertiary education / Total workers
	Share of workers with permanent position	Continuous	Workers with permanent position / Total workers
	Average compensation of employees	Continuous	Per capita compensation of employees
External organisation	Presence of investments in human resources	Binomial	Presence of investments in staff training
	Presence of non-arms length agreements with other firms	Binomial	Presence of collaboration agreements with other firms
	Number and typology of non arms-length agreements with other firms	Multinomial	Weighted measure of the number and complexity of relationships
	Capability of activation of the productive system	Continuous	Weighted average of the activation coefficient of the firm and characteristics of sectoral supply-chain
Digitalisation and innovation	Internationalisation	Binomial	Presence of exports and/or imports
	Presence of investments in innovation	Binomial	The firm has positive investments in innovation (product and/or process)
	Technology adoption	Continuous	Sum of expenses in licences and royalties, PC and software, R&D
	Presence of investments in digitalisation	Binomial	The firm has positive investments in digitalisation

Starting from the relative elementary components, each pillar has been build by firstly linearizing binomial and multinomial characteristics and, then, aggregating variables through a factor analysis, where each composite has been defined based on the first auto-rotated factor.

The final indicator (i.e. the classifier) is obtained by the following linear combination of the composites:

$$C_i = \alpha_1 ES_i + \alpha_2 P_i + \alpha_3 IO_i + \alpha_4 EO_i + \alpha_5 ID_i \quad [2]$$

where, for the  $i$ -th firm,  $ES$  is the economic size,  $P$  is the performance,  $IO$  is the internal organisation,  $EO$  is the external organisation,  $ID$  is the innovation and digitalisation.

Weights in Equation [2] are the coefficients of the following logit:

$$Prob(Solidity_i = 1 | ES_i, P_i, IO_i, EO_i, ID_i, nace_i, geo_i, liq_i, diff_i) = \Lambda(\alpha_1 ES_i + \alpha_2 P_i + \alpha_3 IO_i + \alpha_4 EO_i + \alpha_5 ID_i + \alpha_6 nace_i + \alpha_7 geo_i + \alpha_8 liq_i + \alpha_9 diff_i) \quad [3]$$

where  $nace_i, geo_i, liq_i, diff_i$ , in line with Section 1 contents, control for the industry (Nace rev.2 at 2 digit level), territory (NUTS2 level), presence of liquidity and demand or supply side issues related to Covid-19 pandemic, respectively. These latter two variables are built using information taken from Covid 2 survey (see Section 2). In particular,  $liq_i$  is a dummy variable assuming value 1 if the firm signalled severe liquidity

shortage as a consequence of the pandemic outburst, 0 otherwise.  $Diff_i$  is a categorical variable measuring the intensity of problems occurring on demand and/or supply side aspects.<sup>5</sup>

#### 4.3 Definition of cut-offs and taxonomy

Once the status (i.e. the economic solidity) and the classifier (i.e. the indicator obtained in Equation [2]) are defined, the ROC analysis can be carried out starting from the following logit:

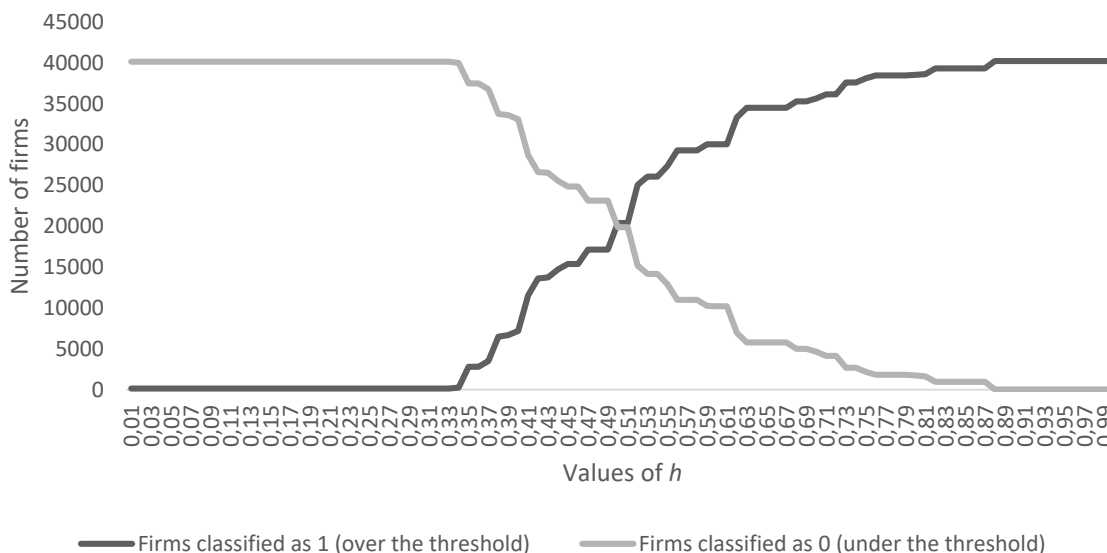
$$Prob(Solidity = 1|C)_i = \Lambda(\alpha C)_i \quad [4]$$

This allows for obtaining a ROC curve, from which we derive a four-class taxonomy following a three steps procedure.

The first step is to set-up  $h = 0.5$  in order to define the first “neutral” cut-off that classifies firms into “Solid” (i.e. classified as 1, value of the classifier over the threshold) and “Fragile” (i.e. classified as 0, value of the classifier under the threshold).

In the second step we run hundred ROC analyses (one for each 0.01 step in the value of  $h$ ) in order to determine which values of  $h$  (other than 0.5) should be set up to refine the Manichean taxonomy and distinguish between different degrees of solidity and fragility. Figure 6 shows the estimated number of Solids and Fragiles in correspondence of each value of  $h$ .

**Figure 6. Distribution of firms for sliding  $h$**



<sup>5</sup> In particular, demand side aspects include: reduction in attractiveness of goods and services, reduction in demand determined by anti-contagion measures (administrative restrictions, social distancing); reduction in domestic demand; reduction in foreign demand; increase in transport and logistic costs. Supply side aspects include: reduction or interruption of the supply of raw materials and/or intermediate inputs; price increase of raw materials and/or intermediate inputs; increase in transport and logistic costs. The variable takes value 1 if firm signal at least one of demand or supply side issue; it takes value 2 if firm signal difficulties on both demand and supply side aspects; it takes value 0 if no problems occur.

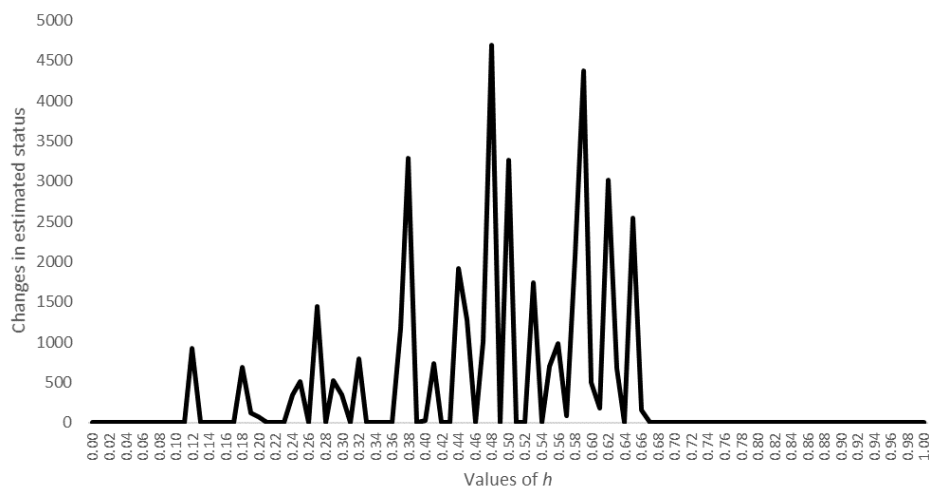
In the third step, as mentioned in Section 4.1, we move from a “neutral” selection ( $h = 0.5$ ), considering both a “conservative” ( $h < 0.5$ ) and a “liberal” selection ( $h > 0.5$ ). In particular, we identify the cut-offs- ( $h_-$  and  $h_+$ ) corresponding to the higher jumps in firms distributions along sliding  $h$ . To determine those values we consider the absolute changes in the distribution:

$$h_- = \max(n_h - n_{h-0.01}) \text{ for } \forall 0 \leq h \leq 0.5 \text{ [5a]}$$

$$h_+ = \max(n_h - n_{h+0.01}) \text{ for } \forall 0.5 \leq h \leq 1 \text{ [5b]}$$

where  $n_h$  represents the number of firms which are under ( $h_-$ ) or over ( $h_+$ ) the threshold for each value of  $h$ . The algorithm selected  $h_- = 0.48$  and  $h_+ = 0.60$  (see also Figure 7).

**Figure 7. Changes in estimated status for sliding  $h$**



In order to build up the taxonomy therefore, we chose three ROC estimates (for  $h_+$ ,  $h_-$  and  $h_+$ ).<sup>6</sup> Classes are defined by the intersection of the three statuses (i.e. over/under the threshold) as follows:

- **Solid** firms: those laying over the threshold estimated in correspondence of  $h=0.48$ ;
- **Resistant** firms: those laying over the threshold for  $h=0.5$  and under the threshold for  $h=0.48$ ;
- **Fragile** firms: those under the threshold for  $h=0.5$  and over the threshold for  $h=0.60$ ;
- **Risky** firms: those under the threshold for  $h=0.60$ .

## 5. The degree of solidity of Italian business system

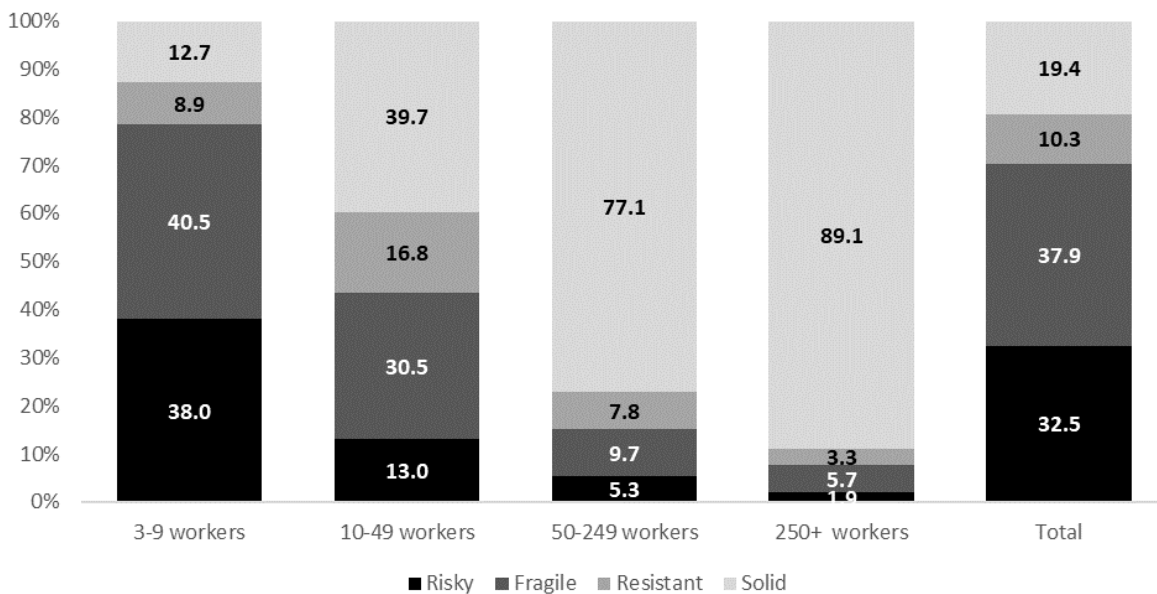
### 5.1. Solidity taxonomy: a description

This taxonomy helps to analyze the degree of solidity of the Italian business system against exogenous and violent shocks such as the pandemic episode of 2020-2021.

<sup>6</sup> We report fitting tests (accuracy and precision) of ROC estimates (for  $h_+$ ,  $h_-$  and  $h_+$ ) in Appendix A.

Firstly, our classification confirms that the pandemic crisis has clearly a size-related dimension. The distribution among size classes reported in Figure 8 shows that the impact has been much more severe for smallest firms. The micro enterprises (3-9 workers) have the largest incidence of units classified as Risky (38.0%) and Fragile (40.5%); among the small ones (10-49 workers) these percentages are 13.0 and 30.5% respectively. On the contrary, among medium-sized and large enterprises Solid firms largely prevail (77.1% and 89.1%, respectively).

**Figure 8 – A taxonomy of solidity: distribution of firms by size class and degree of solidity (%) (a)**



Source: Authors' calculation on Istat data

(a) The size classes refer to 2018; the degree of solidity refers to 2020.

The size issue is relevant, but as it is well known, the Covid-19 crisis also has a relevant sectoral dimension, primarily due to lockdown measures introduced to limit the virus spread, which selectively affected Italian business activities. In this respect, Table 3 reports the structural characteristics of each class by macro-sector.<sup>7</sup>

<sup>7</sup> More disaggregate results (Nace 2 digit level) are reported in the Appendix B.

**Table 3 – A taxonomy of solidity: structural characteristics, by sector and classes of solidity (a)**

Sector	Risky	Fragile	Resistant	Solid	Total
% of firms					
Industry	19.9	40.1	13.1	26.9	100.0
Construction	15.3	61.7	10.1	12.9	100.0
Market services	36.9	34.3	9.9	18.8	100.0
Other services	49.0	28.5	7.6	14.9	100.0
Total	32.5	37.9	10.3	19.4	100.0
% of workers					
Industry	5.3	17.0	9.1	68.6	100.0
Construction	8.0	46.9	13.0	32.2	100.0
Market services	18.5	21.4	8.0	52.1	100.0
Other services	29.2	22.5	8.9	39.4	100.0
Total	14.4	21.9	8.7	54.9	100.0
% of value added					
Industry	1.2	8.2	6.4	84.1	100.0
Construction	2.5	35.6	14.1	47.8	100.0
Market services	5.9	12.9	6.3	74.9	100.0
Other services	10.9	16.5	8.3	64.2	100.0
Total	4.1	12.6	6.9	76.4	100.0
Average size (no. of workers)					
Industry	5.2	8.2	13.5	49.5	19.4
Construction	4.1	6.1	10.2	19.9	8.0
Market services	5.8	7.2	9.3	31.9	11.5
Other services	4.7	6.3	9.2	20.9	7.9
Total	5.5	7.1	10.4	34.9	12.3

Source: Authors' calculation on Istat data

(a) Structural characteristics refer to 2018; the degree of solidity refers to 2020.

The group of Solids accounts for less than 20% of the universe of Italian businesses system, but represents by far the most significant share in terms of employment (54.9%) and even more so in terms of value added (76.4%). In other terms, at the end of 2020 the majority of Italian employment and three quarters of value added were still in “solid” conditions. The Risky units account for 32.5% of the total but they play a much less significant role in the economy (14.4% of employment and 4.1% of value added), due to their smaller size (5.5 workers on average, with respect to nearly 35 for the Solid). However, the relative majority of Italian firms (37.9%) are classifiable as Fragile; in these units, 21.9% of total workers are employed, generating 12.6% of total value added. Finally, only 10.3% of firms are “Resistant”, accounting for 8.7% of total employment and 6.9% of value added.

These results basically reflects the context of industrial sectors: among the macro-sectors considered in Table 3, Industry is the one whose contribute to the overall solidity – in terms of units, employment, value added – is higher. On the opposite, the condition of firms appears worrying especially in Construction and Other services activities, where 61.7% of firms are Fragile and nearly half (49%) are Risky respectively. In these two sectors over half of the employment results in Risky or Fragile firms. More in details, in all macro-sectors solid units have the highest shares in terms of value added, ranging from 47.8% in Construction to 84.1% in Industry. In terms of employment, however, Solids represent the largest class in Industry sector (59.3% of firms) and in Services (both Market and Other services, including personal services, 52.1% and 39.4% respectively), while in Construction and Other services more than half of workers are employed in Fragile or Risky firms.



## 5.2. The role of 5 pillars

To better investigate the role of the pre-pandemic firm's characteristics on the probability of being Risky, Fragile, Resistant or Solid, we report the values of the five pillars (aggregated by the composite indicators described in Section 4.2) across the macro-sectors and the classes of taxonomy in Table 4. In particular, for each pillar, the ratio between the class and the macro-sector average is reported. This latter shows how the value of each indicators (pillar) differs within the classes of solidity. For example, values above (below) 1 indicate that a given class value is over (under) the average: the higher the value, the more relevant the pillar is in characterizing that class.

Overall, for each indicator, the ratio increases moving towards higher solidity classes, implying that higher degree of solidity is positively associated to them.

A positive status (Resistant or Solid) is associated with above-average economic size, digitalization and innovation values. These elements confirm the peculiar characteristics of the crisis caused by the pandemic: the hardest effects have been suffered by small-sized enterprises (Istat, 2021) and by firms with an elementary level of digitalization (Marques-Santos et al., 2021). In fact, even high value (over 1) of the other three indicators (performance, internal and external organization) do not guarantee a status of solidity or resistance but it discriminates within smaller and less digitalized firms between a condition of fragility and risk. In addition to being large in size (1.6 times the average of the business system) and a high degree of digitalization (2.5 times the average), Solid companies are also characterized by a high degree of organizational complexity. Confirming the peculiarity of the current crisis, the firm performance indicator seems less able to discriminate the belonging of firms to different classes: having achieved good economic results in the pre-pandemic period did not represent – *per se* – a shelter from the current economic crisis.

**Table 4. Structural characteristics of firms according to their solidity: the role of the five pillars**

Indicator	Distance from the average by class (Class/Total average ratio)			
	Risky	Fragile	Resistant	Solid
<b>Industry</b>				
Economic size	0.852	0.891	0.934	1.303
Performance	0.977	0.997	1.005	1.020
Internal organisation	0.759	0.900	1.012	1.321
External organisation	0.654	0.962	1.066	1.279
Digitalisation and innovation	0.159	0.471	1.143	2.339
<b>Construction</b>				
Economic size	0.648	0.875	1.220	1.844
Performance	0.954	1.003	1.013	1.032
Internal organisation	0.822	0.964	1.074	1.324
External organisation	0.778	0.975	1.177	1.243
Digitalisation and innovation	0.335	0.652	2.058	2.626
<b>Market services</b>				
Economic size	0.597	0.781	0.922	2.233
Performance	0.968	0.999	1.017	1.056
Internal organisation	0.768	0.982	1.125	1.424
External organisation	0.638	0.985	1.228	1.617
Digitalisation and innovation	0.338	0.830	1.442	2.376
<b>Other services</b>				
Economic size	0.769	0.864	1.077	1.981
Performance	0.894	1.020	1.108	1.254
Internal organisation	0.838	1.015	1.155	1.424
External organisation	0.628	1.116	1.584	1.774
Digitalisation and innovation	0.375	0.886	2.100	2.711
<b>Total</b>				
Economic size	0.510	0.840	1.099	1.567
Performance	0.776	1.016	1.048	1.069
Internal organisation	0.640	1.068	1.128	1.403
External organisation	0.598	1.139	1.173	1.310
Digitalisation and innovation	0.303	0.694	1.480	2.512

Source: Authors' calculations on Istat data.

Average indicator values relating to the whole dataset, however, hide a high degree of sectoral heterogeneity. For example, in Construction and Other services, a condition of resistance implies above-average levels of digitalization and economic size; as regards Industry and Market services, however, the Resistant status is consistent with below-average economic size, while it still requires relatively high digitalization and innovation values. On the contrary, for the other two macro-sectors (Other services and Construction), it is necessary to reach higher than average levels in all 5 pillars to escape from a risky condition.

Consistently with total economy, in all macro-sectors the transition from a condition of resistance to one of solidity appears to be driven by a strong dimensional gap; as regards the level of digitalization, this difference is more pronounced in Industry and Market services. On the other hand, in all macro-sectors, the discriminants between Riskies and Fragiles, in addition to digitalization, are mainly related to the external organization; in Construction and Market services, on the other hand, the differences in the economic size values also contribute to avoiding a risk condition.

## 6. Conclusions

In this paper we study the robustness of Italian business system, using Covid-19 pandemic as an exogenous event to test it. To this aim, we use the ROC methodology, quite new for Economics, to classify Italian firms according to their degree of solidity.

In this respect our taxonomy shows that, a year after the beginning of the pandemic, the Italian business system appears fundamentally solid: even though the group of solid firms accounts for less than one fifth of the universe of Italian enterprises, it includes the most relevant ones in terms of employment and value added. However, even if the enterprises classified as “Fragile” and “Risky” are not so relevant for the creation of value added, they account for over one third of total employment, so that a possible disappearing of this business segment might cause severe problems for economy and society as a whole.

In line with the literature, the size-related effects of the crisis are confirmed by our taxonomy: among smallest firms, the percentage of units in risky condition is about seven (for 10-49 workers) and twenty (for 3-9 workers) times higher than among the largest size class (250+ workers); the share of “Fragiles” is about six and eight times higher respectively.

We find that there are several factors helping Italian economy to be resistant to shocks such as the Covid-19 induced one. In particular, firms’ performance, economic size, internal organization, external organization, digitalization and innovation are all relevant “pillars” to reach a higher solidity status.

However, there are some of these pillars that seems to be more relevant than others, confirming the peculiar characteristics of the crisis caused by the pandemic. Among them, firm economic size is crucial: above-average values strongly discriminate between positive (Resistant or Solid) and negative (Risky and Fragile) statuses. In industrial activities, Resistant or Solid status is associated with pre-pandemic above-average economic size values. In Construction and Services, on the contrary, an above average values of economic size is enough to be Solid but not to be Resistant.

At the same time, the hardest economic effects have been suffered by firms with an elementary level of digitalization and innovation. Risky and Fragile firms are by far less digitalized with respect to Resistant and Solid ones. This is consistent, on the one hand, with the gap of Italian firms in advanced digitalization and, on the other hand, with the strong technological polarization that seems to characterize the Italian business system.

As for the other three pillars (performance, internal and external organization), higher-than-average values do not guarantee a status of solidity or resistance. In particular, firm performance seems to be less able to discriminate between the belonging to positive and negative risk classes: having achieved good economic results in the pre-pandemic period does not represent – *per se* - a shelter from the economic consequences of the crisis.



The former measures the share of true positives over the total number of observations the model classifies as positives (i.e. percentage of firms correctly classified with positive status)<sup>8</sup>:

$$Precision = TP/(TP + FP) \quad [A1]$$

In turn, the latter measures the share of true positive and negative outcomes of the model (i.e. the proportion of firms correctly classified as exporters and non-exporters) over the total number of observations:

$$Accuracy = (TP + TN)/(Total\ observations) \quad [A2]$$

In this context, Table A1 displays the two indicators and the share of positives (true and false) and negatives (true and false) for the three ROCs defined by  $h=0.50$ ,  $h=0.48$  and  $h=0.60$  by industry (2-digits NACE rev.2). In particular, for each ROC, column 1 shows Accuracy, column 2 displays Precision, while columns 3 to 6 respectively contain the share of true positives, false positives, false negatives and true negatives on total observations.

---

<sup>8</sup> Note that for the different ROCs considering different value of  $h$ , the model gives dichotomous results, where positives are observations lying over the threshold defined by the given ROC while instead negatives are observations lying under the threshold of the given ROC.

## Appendix B. Distribution of firms by sector (2-digit NACE rev.2) and degree of solidity

This appendix reports the results of the taxonomy by industry (2-digit NACE rev.2). In particular, Table B1 displays, for each class of economic solidity, the distribution of the whole universe of Italian firms with no less than 3 workers (determined by using survey weights).

**Table B1. Distribution of firms by sector (2-digit NACE rev.2) and degree of solidity**

Sectors	Risky	Fragile	Resistant	Solid	Total
Mining and quarrying	16.6	30.6	41.5	11.3	100.0
Food	52.4	26.2	8.4	12.9	100.0
Beverage	16.2	27.3	14.5	42.0	100.0
Textile	20.6	44.8	11.4	23.2	100.0
Wearin apparels	35.7	38.8	8.4	17.1	100.0
Leather	24.6	40.2	11.0	24.2	100.0
Wood	19.5	61.1	8.8	10.5	100.0
Paper	8.2	44.9	13.6	33.3	100.0
Printing	13.6	49.9	14.8	21.7	100.0
Coke e refined petroleum products	2.8	19.8	14.9	62.6	100.0
Chemical	1.8	25.8	10.8	61.6	100.0
Pharmaceutics	0.0	1.4	6.8	91.9	100.0
Rubber and plastic	5.9	40.7	15.3	38.2	100.0
Non metallic minerals	15.5	50.4	9.6	24.6	100.0
Metals	4.5	28.6	13.8	53.1	100.0
Metal products	13.3	43.7	19.2	23.8	100.0
Electronics	4.8	36.2	10.9	48.1	100.0
Electric apparels	6.3	39.6	13.7	40.4	100.0
Machinery	2.3	28.6	17.9	51.1	100.0
Motor vehicle	6.8	28.5	21.7	43.0	100.0
Other trasport equipment	6.4	42.5	13.3	37.8	100.0
Furniture	15.1	58.8	10.8	15.3	100.0
Other manufacturing	19.7	51.3	11.7	17.4	100.0
Intallation and repair	10.0	48.4	14.1	27.5	100.0
Energy	3.2	5.8	7.7	83.3	100.0
Water	10.7	15.1	5.3	68.9	100.0
Sewerage	9.3	38.2	20.6	31.9	100.0
Waste	9.2	29.7	9.9	51.2	100.0
Remediation and other waste	13.9	35.9	14.4	35.7	100.0
Building construction	15.8	56.8	10.5	16.9	100.0
Civil engeneering	6.6	44.2	16.2	33.1	100.0
Specialised construction	15.5	64.3	9.7	10.5	100.0
Motor vehicle trade	29.9	53.6	6.5	10.0	100.0
Wholesale trade	13.1	42.1	13.6	31.2	100.0
Retail trade	37.4	40.6	8.4	13.7	100.0
Land transport	19.2	55.1	11.0	14.7	100.0
Water transport	10.6	18.0	9.9	61.5	100.0
Air transport	8.9	5.8	0.0	85.4	100.0
Wharehousing	12.2	27.5	15.6	44.8	100.0
Postal and courier activities	23.5	41.6	3.2	31.7	100.0
Accomodation	53.0	25.4	9.0	12.6	100.0
Food and beverage services	80.2	15.1	2.6	2.0	100.0
Publishing	4.1	28.1	18.2	49.6	100.0
Video and television	8.3	23.7	9.8	58.2	100.0
Programming and broadcasting	25.8	31.2	13.5	29.4	100.0
Telecommunications	6.7	27.8	8.3	57.3	100.0
Computer programming	1.7	17.0	13.7	67.6	100.0
Information services	8.6	56.1	15.6	19.7	100.0
Financial auxiliaries	7.4	46.6	19.6	26.4	100.0
Real estate	18.8	33.4	18.0	29.8	100.0
Legal and accounting	5.7	45.3	22.4	26.6	100.0
Management consultancy	5.9	16.8	8.3	69.0	100.0
Architecture and engeneering	4.0	29.0	22.1	44.9	100.0
Research and development	0.5	11.4	5.2	82.8	100.0
Advertising and market research	5.5	32.7	16.7	45.1	100.0
Other professional services	10.1	31.9	16.3	41.8	100.0
Rental and leasing	16.7	36.0	12.9	34.4	100.0
Employment activities	5.6	5.8	7.6	81.0	100.0
Travel agencies and tour operator	18.2	41.0	14.8	26.0	100.0
Security and investigation	27.9	33.8	16.7	21.5	100.0
Building and landscape services	62.9	27.8	4.2	5.1	100.0
Other business services	17.1	34.1	10.8	38.0	100.0
Education	29.5	29.2	10.1	31.2	100.0
Human healthcare	18.2	39.3	13.4	29.1	100.0
Residential care	41.3	29.9	8.5	20.4	100.0
Non-residential care	45.9	39.3	5.2	9.6	100.0
Creative activites, art and entertainment	19.0	49.3	13.6	18.0	100.0
Libraries and museums	32.4	45.0	7.5	15.2	100.0
Gambling and betting	31.7	44.9	8.8	14.5	100.0
Sport and amusement	64.0	21.6	4.5	9.9	100.0
Computer repair	31.6	51.0	6.3	11.1	100.0
Other personal services	73.5	18.3	3.9	4.2	100.0
<b>Total</b>	<b>32.5</b>	<b>37.9</b>	<b>10.3</b>	<b>19.4</b>	<b>100.0</b>

## References

- Adelino, M., S. Ma, Robinson D., 2014. Firm age, investment opportunities, and job creation. *NBER Working Papers*, No. 19845, National Bureau of Economic Research, Cambridge, MA. <https://doi.org/10.3386/w19845>.
- Andrews, D., Criscuolo C., Gal P., 2016. The best versus the rest: the global productivity slowdown, divergence across firms and the role of public policy. *OECD Productivity Working Papers*, No. 5, OECD Publishing, Paris. <https://doi.org/10.1787/63629cc9-en>.
- Aramonte, S., Avalos F. 2020. Corporate credit markets after the initial pandemic shock. *BIS Bulletin*, No. 26, Bank for International Settlements, Basel. <https://www.bis.org/publ/bisbull26.pdf>.
- Bajgar M., Berlingieri G., Calligaris S., Criscuolo E.L., Timmis J., 2019. Industry concentration in Europe and North America. *OECD Productivity Working Papers* 18, OECD Publishing. Paris. <https://doi.org/10.1787/2ff98246-en>.
- Bartik, A., Bertrand M., Cullen Z., Glaeser E.L., Luca M., Stanton C., 2020. The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, Vol. 117/30, pp. 17656-17666, <https://doi.org/10.1073/pnas.2006991117>.
- Berge, T. J., Jordà, Ò, 2011. Evaluating the classification of economic activity into recessions and expansions, *American Economic Journal: Macroeconomics*, 3, 246–277.
- Boehm C. E., Flaaen A., Pandalai-Nayar N., 2019. Input linkages and the transmission of shocks: firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics*, MIT Press, vol. 101(1), pages 60-75.
- Calvino, F., Criscuolo C., Menon C., 2015. Cross-country evidence on start-up dynamics. *OECD Science, Technology and Industry Working Papers*, No. 2015/6, OECD Publishing, Paris. <https://doi.org/10.1787/5jrxtkb9mxtb-en>
- Calvino, F., Criscuolo C., R. Verlhac, 2020. Declining business dynamism: Structural and policy determinants. *OECD Science, Technology and Industry Policy Papers*, No. 94, OECD Publishing, Paris. <https://doi.org/10.1787/77b92072-en>
- Carvalho V.M., Nirei M., Saito Y.U., Tahbaz-Saleh A., 2021. Supply chain disruptions: evidence from the great East Japan earthquake". *Quarterly Journal of Economics*, 1255–1321. doi:10.1093/qje/qjaa044.
- Cavalli L., Sallusti F., 2019. Detecting under-reporting of value added and the VAT fraud in national accounts. VII IMF Statistical forum, November, Washington D.C. <https://www.imf.org/en/News/Seminars/Conferences/2019/03/25/7th-statistical-forum>
- Çelik, S., G. Demirtaş, Isaksson M., 2019. Corporate bond markets in a time of unconventional monetary policy. *OECD Capital Market Series*, Paris. <https://www.oecd.org/corporate/Corporate-Bond-Markets-in-a-Time-of-Unconventional-Monetary-Policy.htm>.
- Corrado C., Criscuolo C., Haskel J., Himbert A., Jona-Lasinio C., 2021. New evidence on intangibles, diffusion and productivity. *OECD Science, Technology and Industry Working Papers* 2021/10, OECD Publishing.
- Costa, S., Sallusti, F., Vicarelli, C., Zurlo, D., 2019. Over the ROC methodology: productivity, economic size and firms' export thresholds. *Review of International Economics*, 27(3), 955-980.
- Costa, S., Sallusti, F., Vicarelli, C., Zurlo, D. 2021. Tech on the ROC: export threshold and technology adoption interacted", *Small Business Economics*, forthcoming. <https://doi.org/10.1007/s1187-021-00581-7>

- Demmou L., Calligaris S., Franco G., Dlugosch D., Adalet McGowan M., Sakha S., 2021. Insolvency and debt overhang following the COVID-19 outbreak: assessment of risks and policy responses. *OECD Economics Department Working Paper* No. 1651. OECD Publishing, Paris. <https://doi.org/10.1787/747a8226-en>.
- Fawcett, T. (2005). An introduction to ROC analysis. *Pattern Recognition Letters*, 27, 861-874.
- Gal P., Nicoletti G., Renault T., Sorbe S., Timiliotis C., 2019. Digitalisation and productivity: In search of the holy grail – Firm-level empirical evidence from EU countries. *OECD Economics Department Working Papers*, No. 1533, OECD Publishing, Paris. <https://doi.org/10.1787/5080f4b6-en>.
- Istat - Italian National Institute of Statistics (2020). Situazione e prospettive delle imprese nell'emergenza sanitaria Covid-19, *Statistiche Report*, 14th December. <https://www.istat.it/it/files//2020/12/REPORT-COVID-IMPRESE-DICEMBRE.pdf>
- Istat - Italian National Institute of Statistics (2021). *Rapporto sulla Competitività dei Settori Produttivi*, March, Rome, <https://www.istat.it/it/archivio/255558>.
- Khandani A. E., Adlar, J. K., Lo A., 2010. Consumer credit-risk models via machine-learning algorithms. *Journal of Banking and Finance*, 34(11), 2767–2787.
- Kumar R., Indrayan, A., 2011. Receiver operating characteristic (ROC) curve for medical researchers. *Indian Pediatrics*, 48(4), 277–287.
- Lusted L. B., 1960. Logical analysis in roentgen diagnosis: memorial fund lecture. *Radiology*, 74(2), 178-193.
- Majnik, M., Bosnić, Z., 2013. ROC analysis of classifiers in machine learning: a survey. *Intelligent Data Analysis*, 17, 531-558.
- Marques-Santos, A., Haegeman, K., Moncada-Paternò-Castello P., 2021. The impact of Covid-19 and of the earlier crisis on firms' innovation and growth: a comparative analysis. *JRC Working Papers on Territorial Modelling and Analysis* No. 03/2021, European Commission, Seville, JRC125490
- OECD 2020. Coronavirus (COVID-19): SME policy responses. *OECD Policy Responses to Coronavirus (COVID-19)*, OECD Publishing, Paris, <https://doi.org/10.1787/04440101-en>.
- OECD 2021. Strengthening Economic Resilience Following the Covid-19 Crisis: A Firm and Industry Perspective. OECD Publishing, Paris, <https://doi.org/10.1787/2a7081d8-en>.
- Pepe, M.S., 2003. *The Statistical Evaluation of Medical Tests for Classification and Prediction*". Oxford, UK. Oxford University Press.
- Tokui, J., Kawasaki, K., Miyagawa T., 2017. The economic impact of supply chain disruptions from the great East-Japan earthquake. *Japan and the World Economy* 41:59-70.
- Warnock, D.G., Peck C., 2010. A roadmap for biomarker qualification. *Nature Biotechnology*, 28, 444–445.
- WTO. 2021. Economic Resilience and Trade. *World Trade Report*. [https://www.wto.org/english/res\\_e/booksp\\_e/wtr21\\_e/00\\_wtr21\\_e.pdf](https://www.wto.org/english/res_e/booksp_e/wtr21_e/00_wtr21_e.pdf)