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ArticleTitle	Pandemic crisis and firm survival: evidence from the Italian manufacturing industry
Article Sub-Title	
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Journal Name	Journal of Industrial and Business Economics

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Schedule	Received	29 Dec 2023
	Revised	29 Mar 2024
	Accepted	1 Apr 2024

Abstract	The paper studies the characteristics that affected firms' ability to react to the economic crisis induced by the COVID-19 pandemic. We use firm-level data on Italian manufacturing companies to examine the role played by external relations and the characteristics of the local environment. In line with recent works, the study finds that micro-firms, highly indebted and less productive firms have a higher probability of exiting the market. Results also support the view that digital presence and financial soundness have favoured the survival of enterprises. Beyond firm-specific factors, we highlight that a firm's resilience capability is related to its external linkages, namely the participation in a group or to a network contact. As for local ecosystem factors, while firms in industrial districts have a higher default probability, our results suggest that an innovative local environment can mitigate the probability of permanently closing during the crisis.

Keywords (separated by '-')	Firm survival - IDs - Innovative environment - Digitalization - Small firms - COVID-19 - Italy
JEL Classification	D22 - L22 - L25 - O14 - O30 - G33
Footnote Information	The online version contains supplementary material available at https://doi.org/10.1007/s40812-024-00309-0.

Journal : SmallExtended 40812 | Article No : 309 | Pages : 33 | MS Code : 309 | Dispatch : 20-4-2024

Journal of Industrial and Business Economics
https://doi.org/10.1007/s40812-024-00309-0

Pandemic crisis and firm survival: evidence from the Italian manufacturing industry

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Received: 29 December 2023 / Revised: 29 March 2024 / Accepted: 1 April 2024

Abstract

The paper studies the characteristics that affected firms' ability to react to the economic crisis induced by the COVID-19 pandemic. We use firm-level data on Italian manufacturing companies to examine the role played by external relations and the characteristics of the local environment. In line with recent works, the study finds that micro-firms, highly indebted and less productive firms have a higher probability of exiting the market. Results also support the view that digital presence and financial soundness have favoured the survival of enterprises. Beyond firm-specific factors, we highlight that a firm's resilience capability is related to its external linkages, namely the participation in a group or to a network contact. As for local ecosystem factors, while firms in industrial districts have a higher default probability, our results suggest that an innovative local environment can mitigate the probability of permanently closing during the crisis.

Plain English Summary. Surviving the pandemic: Resilience through Unity? The paper investigates firm survival in Italy at the onset and during the COVID-19 pandemic. In addition to individual characteristics, we focus on the role played by external relations and the characteristics of the local environment. Building on previous research on a firm's resilience to shocks, the analysis considers traditional idiosyncratic determinants related to the internal organization (size, age, group membership, capitalization, profitability, productivity, debt maturity structure, …). and contextual, ecosystem factors. The study supports the view that specific individual factors (size, low debt and short-term exposure, productivity, presence of a website) have helped enterprises to waive the crisis. Besides, belonging to a group or a network contract is both associated with a lower probability of exiting the market in the period 2020–2022. Firms in traditional industries –fashion and furniture—have had a higher default probability than firms in other manufacturing industries. The location in industrial clusters increases the default probability with a moderating effect exerted by a specialization of the local labour system in the medium to high-tech industries and/or knowledge-intensive services. Finally, it is also worth noting that

A1 Extended author information available on the last page of the article

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the region-specific length of lockdown policies is not significantly associated with firm survival.

Keywords Firm survival · IDs · Innovative environment · Digitalization · Small firms · COVID-19 · Italy

JEL Classification D22 · L22 · L25 · O14 · O30 · G33

1 Introduction

The COVID-19 pandemic and the associated health crisis triggered the worst global economic downturn since the Great Depression with a dramatic increase in inequality and a huge rise in public and private debt (World Bank, 2022). Although social-distancing practices and lockdowns succeeded in mitigating the worst human losses, rising uncertainty and the disruption of supply chains may have contributed to amplifying the severe impact on business activity of a combined demand and supply shock, thus challenging their survival. In contrast to earlier crises, the outbreak of COVID-19 and its adverse impact on economic growth was met with unprecedented decisive and large economic policy responses by governments worldwide primarily aimed at helping firms manage the crisis (e.g., Didier et al., 2021; Garicano, 2020). Three years after the outbreak of the pandemic, the major advanced economies have recovered pre-shock levels, also thanks to significant public support measures. The deterioration was widespread, but Italy was among the hardest-hit countries worldwide with their small and medium enterprises (SMEs) recording the sharpest decline in Europe, in terms of turnover even compared to proximate similar EU countries such as Greece, Spain, and Slovakia (Bankowska et al., 2020). Italy was also among the first countries to implement strict containment measures such as lockdowns. Thanks to the successful vaccination campaign and policies to insulate incomes and profits of households and firms, the Italian economy achieved an impressive recovery from the pandemic shock, returning close to the pre-COVID level of output by late 2021 (IMF, 2022). These temporary measures inevitably caused a contraction of the Italian economy and radical changes in business operations and consumer behavior.

This study contributes to the limited but growing literature on the economic effects of COVID-19 on firm survival. The growing evidence of increased default risk during the COVID-19 pandemic (e.g., Fairlie & Fossen, 2022; Ho et al., 2023; Kaya, 2022; Miyakawa et al., 2021) might suggest that the severe economic crisis provides an opportunity for what Schumpeter calls creative destruction whereby firms have not been all hit by the crisis equally, instead less efficient firms have been more likely to exit or downsize their activities thereby 'cleansing' the market. In this vein, most of the extant literature investigates the role of firm-specific characteristics (internal factors), such as firms' financial conditions, innovation, and digital presence, beyond the usual firm-level control variables (e.g., size, age, productivity), and focused on SMEs, traditionally considered more exposed to adverse shocks. However, even if several studies acknowledge that firm exit varies substantially across industries and regions (e.g., Balduzzi et al., 2020; Ferragina & Iandolo, 2022; Miyakawa et al., 2021), less attention has been devoted to understanding the potential role played by the external environment where the firm operates. AQ5

In this study, using firm-level data from the AIDA-Bureau van Dijk database, we analyze whether and to what extent firm-specific factors and contextual factors are associated with the exit of Italian companies from the market following the pandemic shock. AQ6 In particular, firm's exit during the period 2020–2022 will be related not only to the internal economic and financial characteristics of firms (size, age, vertical integration, economic and financial performance) in the time window prior to the outbreak of the pandemic but also to external factors that capture the characteristics of the environment in which firms operate.

Our results suggest that restructuring processes are underway with both microfirms and less efficient firms affected more by the pandemic crisis. We find that firm survival is mostly explained by firm profitability, efficiency, company's financial health measured by a low share of short-term debt prior to the crisis (rollover), vertical integration, and group membership. Moreover, firms' size, productivity, digital presence, financial dependency, and network membership are significant predictors of the firm's ability to react to the crisis, but with lower marginal effects.

As for ecosystem variables, whereas location in an area classified by ISTAT (2015) as an industrial district increases the firms' default probability, a high incidence of medium- to high-tech industries and/or knowledge-intensive services in the LLS, provides a slight moderating effect for firms operating in these areas.

The inclusion of sector-specific fixed effects in the analysis allows us to uncover that firms operating in traditional Made in Italy value chains (i.e., textiles, clothing, leather, wood, and furniture) were negatively and more strongly affected than other industrial groupings while firms in construction-related sectors survived the pandemic more effectively than other industrial groupings. Finally, our result suggests that region-specific lockdown policies did not significantly affect the default probability of Italian manufacturing firms during the period 2000–2022.

The article is organized as follows. Section 2 presents an overview of previous contributions on the topic. Section 3 describes our empirical strategy and data. Section 4 presents and discuss the results while Sect. 5 offers some concluding remarks and avenues for future research.

2 Context of the analysis, motivation, and literature review

2.1 Financial distress, digital presence, and the hypothesis of a "cleansing" effect in the acute phase of the COVID-19 crisis: an internation outlook

This study contributes to the literature on firm survival during the economic crisis induced by the COVID-19 pandemic. Understanding why some firms survive while others fail is a central research question across applied economics and management studies. The literature on firms' survival is vast and it has gained momentum after the two major shocks that have hit the global economy in the first two decades of this century. There is a growing literature supporting an increased default risk during the COVID-19 pandemic. Kaya (2022) provides evidence that European SME insolvency risk increased by 21% during the COVID-19 pandemic. Ho et al. (2023), with an analysis of a wide sample of firms across several countries, confirm the higher default risk during a wide range of modern pandemic crises. While in Japan, exit rates increased by 10% relative to the year prior the pandemic (Miyakawa et al., 2021), in the United States, COVID-19 led to a massive shutdown of businesses in the second quarter of 2020, with estimates indicating that the number of active business owners dropped by 22% from February to April 2020 (Fairlie & Fossen, 2022). Despite effects were widespread in several countries, it has been underlined that firm exit varies substantially across industries and regions as in the cases of Japan (Miyakawa et al., 2021) and Italy (Balduzzi et al., 2020; Ferragina & Iandolo, 2022).

Most of the extant literature focused on the role of firms' financial conditions and the impact of credit constraints on firm behavior in times of crisis. Khan (2022) suggested that previous bank-lending credit constraints magnified the effects of the pandemic on small and medium-sized enterprises. More specifically, credit-rationed firms were more likely to experience greater liquidity and cash flow problems than unconstrained firms. Similarly, Bankowska et al. (2020) highlighted that the losses in turnover and profits and the adverse macroeconomic conditions raised concerns about access to finance, particularly among Spanish, Italian and Portuguese SMEs. Gourinchas et al (2022) warned about how a credit contraction may increase the default risk of business failures more than did the generous public policies enacted during the early phase of the COVID-19 crisis to support the private sector. Mirza et al. (2020) investigated the impact of COVID-19 on the solvency profiles of firms from 15 European countries. They documented a consistent increase in the probability of default and declining debt coverage ratios during the pandemic. Some early studies examined the early economic impacts of the COVID-19 pandemic with a focus on firm-level financial conditions such as liquidity (De Vito and Gomez, 2020; Qin et al., 2020), restructuring processes (Greenwood et al., 2020), cost of equity capital (Ke, 2021), and the speed of adjustments to target leverage (Vo et al., 2021). Further firm-level studies have already attempted to study the relationship between access to credit and firm survival in the context of the pandemic crisis, despite the scarcity of available data in several countries. Amin and Viganola (2023) found that access to finance helps to mitigate sales' decline in the early phase of the pandemic. The analysis of Acharya and Steffen (2020), based on data on firm-loan-level daily credit line drawdowns in the United States, reveals the significant impact of credit risk on corporate cash holdings in the observed firms' behavior. In the first phase of the crisis, which was characterized by extreme precaution and heightened aggregate risk, all firms drew down bank credit lines and raised cash levels. In the second phase, which followed the adoption of stabilization policies, only the highest-rated firms switched to capital markets to raise cash. Chundakkadan et al. (2022) further confirm that the coronavirus disease 2019 has severely affected the financially constrained SMEs. Their analysis focused on the impact of policies targeting SMEs and extend to 34 countries. Their results suggest that government support programmes supported mostly financially constrained firms. Moreover, financially constrained firms are more likely to lay off workers, and in the same category of firms, more

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male employees than female employees. In line with the view that financial conditions are important for firms to face economic crisis, Bozkurt et al., 2022 study the crucial firm-specific factors having an impact on financial distress and bankruptcy in the acute phase of the Covid-19 crisis. They found increased probability of both bankruptcy and financial distress for firms that had problems in accessing finance, younger firms, and more indebted firms. In addition, the size of the firm and the years of experience of its managers also have an impact on financial failure. In the work, Goel and Nelson (2022) focused on the role of female managers and female owners. Their results suggest that firms with female owners were less likely to exit the market while female managers were more likely to, even if for this second result a limited statistical support emerges. In addition, fertility and gender inequality made firms' exit more likely. Larger and older firms have a lower probability of permanently closing during the crisis. Finally, their study finds that firms located in urbanized nations and those located in nations with larger governments had a higher probability to exit, while the reverse was true in nations with better governance.

Several studies on the early impact of the pandemic crisis focused on SMEs, traditionally considered more exposed to shocks because of their higher difficulty in accessing credit and a higher fragility compared to large firms. Empirical evidence confirms that SMEs have been the category of firms most affected by the loss in sales during the onset of the COVID-19 crisis both in the Euro area (Bankowska et al., 2020) and in the United States (Bloom et al., 2021; Fairlie & Fossen, 2022). In the Euro area SMEs experienced a decline in turnover for the first time since the beginning of 2014, the deterioration was widespread but the sharpest decline in turnover was experienced by SMEs in Italy (Bankowska et al., 2020). In this respect, it is worth noting that while liquidity support programs in many European countries had provided breathing spaced during the lockdowns many firms might find themselves overindebted in the aftermath of the pandemic (e.g., Kaya, 2022). Moreover, the adoption of undifferentiated early policies might have altered the link between productivity and firm exit favoring the survival of unproductive firms (Muzi et al., 2022) and possibly postponing a vital reallocation of resources that is essential for business dynamics and growth-enhancing structural changes. Early evidence suggests that government support in Germany was important to avoid corporate bankruptcies of financially weak and small firms, thought it may also have altered the cleansing process (Dörr et al., 2022).

Similarly, Gourinchas et al. (2022) argued that the contraction of credit supply to the business sector in the aftermath of the emergency phase may prompt a significant rise in default risk to SMEs.

In this strand of the literature, it is commonly acknowledged that an important support mechanism for SMEs during crises is given by innovation and digitalization (e.g., Belitsky et al., 2022; Kaya, 2022; Muzi et al., 2022). Muzi et al. (2022) suggest that the economic crisis induced by the COVID-19 pandemic exhibits a Schumpeterian "cleansing" of less productive firms and small firms. They find that innovative firms have a lower probability of permanently closing during the crisis, suggesting that the process of cleansing out unproductive activities is occurring. In line with early evidence (Belitski et al., 2022; Wagner, 2021), they pinpointed the crucial role of digital presence to survive the pandemic. Kaya (2022) focussed on the role of innovation during the COVID-19 global economic downturn and highlighted that, while on the supply side, innovative firms are prone as noninnovative firms to the same obstacles on production costs and supply chain shocks, on the demand side, they can easily overcome the difficulties in reaching customers, most likely via digital solutions.[1] Additional support to the hypothesis of a "cleansing" effect of the COVID-19 induced economic crisis can be found in a recent study focused on the Egyptian industry (El-Haddad & Zaki, 2023).

Not only did they suggest that private, smaller, informal firms, have been more likely to close, but they also showed that firms not located in industrial zones had a higher exit probability pointing to a possible role of the local environment. Interestingly, the authors highlight counterintuitively sector-specific dynamics whereby the food sector and sectors identified as 'COVID sectors' showed lower vulnerability. They also suggest that pre-COVID behavioral characteristics mattered for firm dynamics during the pandemic, the latter were different by sector and firm size.

Overall, in the early evidence surveyed at the international scale, size, age, productivity, digital presence, and financial constraints are considered crucial determinants of firm exit during the COVID-19 crisis.

2.2 Firm survival in the Italian economy

Italy was the second country severely affected by the spread of the virus, with a highly concentrated and spatially persistent pattern of the early diffusion of the virus (Cutrini & Salvati, 2021), at least compared with neighbouring countries (Guibourg, 2020). Second, it was among the first countries to react with a first nationwide lockdown and a second round of lockdowns differentiated by NUTS2 regions. The fall in internal and external demand led to a sudden shortage of liquidity and seriously constrained the firms' capacity to finance their activities. Hence, it is not surprising that the government adopted extraordinary measures to support the liquidity of firms, bear the impact of financial distress and support business activity.[2] Credit demand, driven by the fall in interest rates and by the incentives to invest in the period 2018–2020, rose further in 2020 since the government intervened to guarantee credit and support the search for liquidity, the need for debt restructuring and refunding of previous debt (Istat, 2021). In fact, capitalization is central to understand firms' survival to the COVID-19 crisis in Italy and all the interventions

[1] In this respect, it is worth mentioning that recent empirical studies providing evidence on the positive impact of digital development on firms' survival are based on the World Bank's Enterprise Surveys where the online presence is proxied by having own company's website or social media page (i.e., Muzi et al., 2022; Wagner, 2021).

[2] First with the Cura Italia Legislative Decree (Decreto Legislativo Cura Italia) and then with the Liquidity Legislative Decree (Decreto Legislativo Liquidità), the intervention to support liquidity to firms was significantly strengthened in Italy by providing, among other things, eligibility without assessment of creditworthiness, the expansion of the group of beneficiaries, the increase in guarantee coverage (up to 100% for operations up to 30 thousand euros), the increase in the guaranteed amount per individual company and the expansion of the type of eligible operations. These measures exponentially increased the applications received by the Guarantee Fund for SMEs, preventing the flow of credit to businesses from drastically decreasing, as happened in previous economic crises.

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enacted by the Italian government between March and August 2020 to support firms damaged by the pandemic might have exerted a powerful mitigating effect on the economy (Orlando & Rodano, 2020).[3]

While the literature on firm survival in Italy during and in the aftermath of the COVID-19 pandemic is still limited, it is worth mentioning some recent studies that provide first evidence based on firm-level data during the early phase of the COVID-19 crisis. Costa et al., (2022) found that pre-crisis organizational structure is important, and the crisis should not be considered simply a cleansing, productivity-enhancing crisis, only affecting small unproductive zombie firms. In the medium run, it might turn out to be a strong reorganizational crisis affecting also the most productive and advanced segment, leading to a deep reconfiguration of the Italian industrial system, both in terms of sectoral composition and in terms of firms' organizational capabilities. Balduzzi et al. (2020), using data on expectations and plans of Italian firms prior and immediately after the outbreak of the pandemic, investigate the role played by credit constraints to explain the economic effects of the COVID-19 pandemic in Italy. They suggest that most firms revised downward their expectations for sales, orders, employment, and investment, and liquidity, while updated their expectations on inflation upward. Not surprisingly, the effects on demand and sales of the COVID-19 related shocks are relatively amplified for credit-constrained firms. Also, the authors highlight that the size of the effects is heterogeneous by sectors and regions.

Ferragina and Iandolo (2022) provides first evidence on how Italian firms responded to the shutdown of a significant share of economic activity. They measured each firm's exposure to the pandemic, the extent to which firms respond to the challenges of the pandemic, and the level of exposure to COVID-19 related demand and/or supply shocks. Time-series patterns of COVID exposure, risk and sentiment in 2020, show large differences between geographical regions, industries and across firms (e.g., the Tech sector versus the Transportation sector where there was an unprecedented collapse in demand). While they do not find a decrease in liquidity during the pandemic, they highlight the crucial role of several financial and structural conditions to shape firms' expectations. Their main results suggest that COVID-19 increased firm-level uncertainty, worsened the business outlook of most firms and impacted on credit behavior. They also report a variation in the debt exposure of Italian firms and in other asset status indicators (ROE and ROI) with greater exposure to the COVID-19 outbreak leading to an increase in the total debt of Italian firms. The perceived risk was also positively correlated with firms' total debts, but the increased uncertainty that firms have with respect to the future reduced their choice of incurring in short-term debt becoming more prone to long-term debt. The COVID risk measure is positively related to debt/equity and negatively correlated with short-term debt both towards suppliers and banks.

[3] In Italy, business crisis is substantially identified with firm undercapitalization (i.e., the firm displaying a level of equity below the legal limit). Orlando and Rodano (2020) suggest that undercapitalization often anticipates firm's exit: around 60 percent of involved firms go out of business within 3 years. According to their predictions, the number of firms that could be involved in early warning procedures may be almost twice as large as that foreseeable based on accounting data from 2018.

While the importance of the credit behavior of Italian firms during the pandemic was recognized by further contributions based on firms' surveys (e.g., ISTAT, 2021) there is also evidence of heterogenous responses to the COVID-crisis. A recent study conducted by the National Statistical Office (ISTAT) grouped Italian firms into three categories according to the path they have gone through the crisis. The first group was hit by immediate effects, adopting first defensive, then expansive strategies ("Reactive Suffering" group, 33% of the total sample). They first reorganized the supply chains and decreased employment, then reacted through innovations, activation of productive relationships, research of Industry 4.0 models, and staff training. The second group underwent moderate negative effects and no reaction strategy ("Static Resistance" group, 50%) and the third group was characterized by short-term negative effects and timely and effective reaction ("Successful resilience" group, 17%). The successful resilience of the third group has implied an acceleration of expansive strategies often already present in the pre-crisis period (adoption of 4.0 technologies, reorganization of processes, innovation, investment in human capital) (ISTAT, 2022a).

For the purpose of the present analysis, it is worth emphasizing that in Italy firms' investments in digitization accelerated during the first phase of the crisis but were more focused on internal communication than on e-commerce: "*Between May and November 2020, the share of companies that adopted technologies that facilitated internal communication or made it possible to meet social distancing requirements soared (video conferencing software, laptops and tablets, cloud); the spread of technologies related to electronic payment (cashless and online payments) and the marketing of goods and services (use of digital platforms, e-commerce) is more limited*" (*own translation*, p. 83, ISTAT, 2022a).

Previous empirical works on Italian manufacturing firms have studied firm's closure during the 2008 financial crisis and the 2012 European debt crisis. They provided additional insights into firm-specific and external factors that can help firms to survive economic downturns such as innovation (e.g., Antonioli & Montresor, 2021), intangibles (e.g., Landini et al., 2020), the mode of participation in global value chains and their governance structure (e.g., Brancati et al., 2017), business model changes and organizational structures (Cucculelli & Peruzzi, 2020), spatial agglomeration and the local economic environment (e. g., Basile et al., 2017; Cucculelli & Peruzzi, 2020; Ferragina & Mazzotta, 2014). As for the last determinant, when accounting for the role of agglomeration externalities, one should consider whether the local environment is characterized by an economic structure prone to innovation. In this respect, contamination between high value-added services and the manufacturing industry can favour the evolution of an industrial district toward what is called territorial servitization (e.g., Bellandi and De Propis, 2015; Bellandi et al., 2021; Lafuente et al., 2017) or place-based servitization (Sforzi & Boix, 2019). This kind of structural transformation at the local level can contribute to firms' internationalization strategy, innovation, and organizational upgrading (De Propis and Storai, 2019).

Finally, for two basic control variables, size, and age, it is important to control for non-linearities in the association between them and firm survival, as claimed by Landini et al., (2020). Previous results usually found a positive association even if an inverted-U relationship is observed in some cases, with the probability of survival increasing after entrance and decreasing in later years (Audretsch & Mahmood, 1994; Wagner, 1994).

We contribute to this strand of the literature and study the firm-specific determinants and external factors that may have affected the default risk at the onset and during of the pandemic. To this purpose, starting from the literature surveyed in Sects. 2.1 and 2.2, we have introduced in our estimation strategy most of the firm-specific control variables considered in previous studies to facilitate comparison with their results. The novelty of our article is that we focus on the role of external relationships of the firms (group, network contract) and territorial conditions, paying particular attention to the specialization of IDs in knowledge-intensive services and medium- to high-tech industries.

3 Methodology

3.1 Data sources and data quality

The AIDA database—the Italian section of Bureau Van Dijk—is based on official data retrieved from the Italian Registry of Companies and the Italian Chambers of Commerce. It contains disaggregated balance sheet and profit and loss statement information for approximately 540,000 Italian companies with up to ten years of history.

Several microdata can be drawn from the AIDA-Bureau van Dijk (AIDA-BvD): information on firm's characteristics, such as location, industry, age, legal form, the ownership and governance structure (e.g. the name of each shareholder and board member, the respective ownership share). In addition, it contains information on the present status of the firms (active vs. non-active vs. merged vs. acquired), which we use to distinguish between survivors and exiters, as explained below.

The procedure of data quality started by considering the 137,963 firm-level observations in the manufacturing industry with registered offices (headquarters) located in Italy and included in the AIDA-BvD database. We follow three steps of data quality:

(1) As a first step of data quality, we excluded all the observations for which the legal status resulted as "Ceased (merger)" or "Ceased (Split)", or the business name was not available. We then removed all the companies with an age of less than or equal to 4 years, considering them too young compared to the pandemic period under analysis. The hypothesis supporting the elimination of these observations is that companies born close to the pandemic constitute, by their very nature and proximity to the shock, a group of companies that is not consistent with the object of the analysis
(2) We then selected only limited liability companies, i.e., SPA, SRL, single shareholder SRL, simplified SRL. Based on the Italian legislation, these corporate

legal forms are those capable of guaranteeing reliable balance sheet data for most of the financial and accounting items.

(3) As a third step, before entering the analysis, the dataset was cleaned further by selecting all the companies with the most recent balance sheet available in one of the last 3 years.

After the three steps described above, the cleansed database is composed by a total of 112,879 companies with 104,250 active firms and the remaining 8629 resulting as "Default",[4] the “raw exit rate” stands at 7.64%.

The sample of 112,879 companies included in the analysis is composed by 101,359 firms with the latest balance sheet available as of 2021, 10,660 with the latest balance sheet as of 2020, and 860 firms with the latest balance sheet as of 2022.

Table 1 reports the default rates of Italian manufacturing firms by regions (panel A) and by size class (Panel B). Default rates are above the average in Tuscany (10%), Apulia (10.4%), Sicily (9.78%), Basilicata (9.31%), Liguria (9.41%), Lazio (9.13%), Campania (8.85%), among others. Default rates are instead below the average are found in Trentino Alto Adige (5.13%), Veneto (5.97%), Piemonte (6.35%), Lombardy (6.89%), Emilia Romagna (6.95%) and Abruzzo (7.5%) among others.

Interestingly, the breakdown of the sample by size-class allows us to uncover substantial variation of default rates. The default rate is particularly high for Micro-firms (11.89%) while they are significantly smaller for the other size classes: Small firms (1.91%), Medium-sized firms (1.06%) and Large firms (0.30%). This result does not appear flawed by an unbalanced coverage by size class of the initial sample relative to the reference population. In this respect, it is worth noting that limited liability companies with less than 10 employees are only slightly underrepresented AQ7 in the sample distribution by size class compared to the reference population while the weights of the other size classes are almost equal to the analogous shares in the reference population (Table 1, panel C).

Before proceeding with the econometric estimates, an essential step of data quality was required, and it was primarily related to the treatment of missing data. The functions used in the estimations do not accept observations with missing values or infinite values as input. The latter are the result of ratios with anomalous values in either the numerator or denominator. Excluding observations with such values from the dataset reduced the number of observations available for the analysis to 86,050, with an internal default rate of 3.07%. The decision to eliminate observations rather than artificially impute missing values was taken in order to avoid distortions in the estimates. Besides, particular attention was devoted to extreme values and the associated procedure of outlier detection. This phase entailed the use of a technique for classifying extreme values that would not lead to a high number of exclusions.[5] To

[4] We consider as “Default” firms whose legal status in the database AIDA-BvD is reported as “Ceased”, “Ceased– closure due to bankruptcy”, “Ceased in liquidation”, “In liquidation” or “Active enterprise in a state of insolvency”.

[5] In this case, the trade-off is between the loss of accuracy if one selects a procedure of outlier detection that remove “good” observations, and the bias of the estimates if the procedure keeps “bad” ones (anomalous observations).

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Table 1 Default rate of Italian manufacturing firms

Panel A: Default rate by region

	N. of firms	Exited	Default rate %
Abruzzo	2388	179	7.50
Basilicata	612	57	9.31
Calabria	1360	133	9.78
Campania	7420	657	8.85
Emilia Romagna	11,848	823	6.95
Friuli Venezia Giulia	2472	161	6.51
Lazio	5760	526	9.13
Liguria	1318	124	9.41
Lombardy	28,375	1956	6.89
Marche	4915	402	8.18
Molise	353	26	7.37
Piedmont	7938	504	6.35
Puglia	4873	509	10.45
Sardinia	1114	89	7.99
Sicily	3640	356	9.78
Trentino Alto Adige/Südtirol	1521	78	5.13
Tuscany	9862	990	10.04
Umbria	1749	140	8.00
Valle d'Aosta/Vallée d'Aoste	89	7	7.87
Veneto	15,272	912	5.97
Italy	112,879	8629	7.64

Panel A: Default rate by region

	N. of firms	Exited	Default rate %
Micro-firms	62,623	7448	11.89
Small firms	38,699	738	1.91
Medium-sized firms	7634	81	1.06
Large firms	1015	3	0.30
No size infos	2908	359	12.35
Total	112,879	8629	7.64

Panel C: Representativeness of the sample relative to the reference population of manufacturing firms

	N. of firms in the initial dataset	%	Total N. firms in the reference population*	%
Micro-firms	62,623	55.5	81,443	59.3
Small firms	38,699	34.3	45,752	33.3
Medium-sized firms	7634	6.8	8842	6.4
Large firms	1015	0.9	1318	1.0
Missing values	2908	2.6		
Total	112,879	100.0	137,355	100

*For the Total number of firms, we referred to the data from the National Statistical Office that was retrieved from iStat on 17 March 2024. We consider the total number of active limited liability companies (legal forms spa, sapa and srl) in the manufacturing sector -Section C, NACE Rev. 2—for the year 2019 to allow for comparability with the dataset used in the analysis.

Journal : SmallExtended 40812 | Article No : 309 | Pages : 33 | MS Code : 309 | Dispatch : 20-4-2024

this purpose, the procedure selected was to determine, for each explanatory variable, the 1st/99th percentiles and subtract/add 1.5 times the Interquartile Range (IQR)[6] to them. Hence the acceptance range for each explanatory variable is [$X_{0.01}$-IQR; $X_{0.99}$ + IQR] This technique helps to eliminate only extreme outliers below/above the calculated lower/upper limit and avoid discarding legitimate values.[7] After the treatment for extreme values, the sample of our analyses consists of 84,309 observations, with 2,302 that exited the market and the rest that are still alive by 2022, with an exit rate equal to 2.73%.[8]

Whether the company ceased to exist during the pandemic or is still active, the analysis carried out refers to the years 2020, 2021, 2022. The aim is to analyze how firms behave during the COVID-19 crisis. Specifically, the purpose is to study their ability to react to the shock by investigating the relationships between the firm-specific economic and financial characteristics in the pre-crisis period and their probability of exiting the market. We are particularly interested in studying the role of external factors as additional determinants of firm exit, such as industry, group, network contract, and the geographical context in which the firm is located. To this purpose, we match the AIDA-BvD database with Infocamere data based on a unique identification number that is present in both databases, i.e., the VAT registration number which is a assigned to every business for tax purposes. We also combine the resulting database with the classification of LLSs in industrial districts (ISTAT, 2015) and recent data on territorial characteristics at the level of local labour systems (LLS) ("Sistemi Locali del Lavoro") (ISTAT, 2022b). In particular, we have used the available data to construct a proxy that can capture the degree of specialization of the LLS in both medium to high-tech manufacturing industries and in the knowledge-intensive services (HTM-KIS

[6] The IQR is a measure of data dispersion that represents the range of values that extends from the first quartile (25th percentile) to the third quartile (75th percentile) of the data distribution.

[7] We recognize that using the Interquartile Range (IQR) is a rather crude technique for the determination of outliers that are defined as observations that appear to deviate markedly from the rest of the sample (Grubbs, 1969). Nevertheless, as highlighted by Barbato et al. (2011), the main appeals of this method are simplicity and low sensitivity to distortion due to outliers(robustness), since only the central part of the distribution is relied upon to compute IQR. Barbato et al. (2011) also distinguish between mild and extreme outliers and since the major weakness of the conventional IQR method is its tendency to discard legitimate values in large data sets, they suggest using modified IQR methods. The latter may allow for conserving the most attractive features and introducing some variations to allow for discarding only very extreme values. In the same vein, we followed a rather unconventional but more conservative sieve criterion. The upper and lower limits are based on the 1st/99th percentiles instead of the conventional 25th/75th percentiles. This range was aimed at avoiding removing too many observations and thus excluding from the analysis only the very extreme outliers, as suggested by Barbato et al. (2011). The use of similar techniques is also recommended for data that present asymmetric distributions (Hubert and Van der Veeken, 2008).

[8] The procedure of data quality led to a slightly different distribution of firms relative to the reference population with micro-firms under-represented and small firms over-represented in the cleansed sample relative to the initial database while the share of the other size classes remained unchanged (Table A1 in the Appendix).

Spec).[9] A detailed description of the explanatory and control variables used in the analysis and data sources is included in Table A2 in the Appendix.

3.2 Empirical strategy

The purpose of this analysis is to investigate the characteristics of firms and the characteristics of the local environment that most affected the probability of exiting the market during the economic crisis induced by the COVID-19 pandemic. We model the probability of firm exit as a function of two main types of pre-crisis initial conditions: variables related to internal characteristics and variables capturing external factors. On the one side, we consider firm-specific variables, such as age, size, financial independence, exposure to short-term debt, various indicators of profitability performance, productivity, digital presence. On the other hand, we consider ecosystem characteristics, such as basic sectoral characteristics of the region and the innovative environment or the local labour market in which the firm is located. As for sectoral dummy, we aggregated the 2-digit ATECO 2007 divisions of economic activity[10] into 5 more homogeneous industrial groupings, following Corsini and Pitingaro (2022). The definition of the manufacturing sector groupings is available in the Appendix A, Table A3.

Our empirical strategy is based on different specifications of a binary response model, where the response variable Y can assume only two possible outcomes (0,1), in the present case the unit value corresponds to the default of a firm. Formally, the baseline regression in this article assumes the following probit model:

$$\Pr(Exit_{ijr} = 1) = \Phi(\beta_0 + \beta_1' X_{ijr} + \beta_2' Z_r + \beta_3' D_j + \beta_4' D_r) \tag{1}$$

where the $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution. and subscript i denotes each firm, j the industry grouping, and r the location where the firm is located. Hence, the Probit model specification of Eq. (1) considers a binary dependent variable with default equals 1 and assume that the probability of a positive outcome is determined by the standard normal cumulative distribution function. Specifically, the dependent variable ($Exit_{ijr}$) measures the default probability that is the probability that a company which is 'active' at the end of 2019 ceased at the end of 2022. The parameters β are estimated by maximum likelihood.

[9] The indicator is defined, for each LLS, as the ratio between the number of employees of the local units active in medium-tech industries (21 and 26, Nace Rev. 2) and high-tech industries (Divisions 20, 27–30, Nace Rev. 2) and knowledge-intensive sectors (Divisions 50, 51, 58– 63, 64– 66, 69– 75, 78, 80, 84– 93 excluding Division 84) and the total number of employees of the local units (Istat, 2022b). The taxomomy refers to Eurostat (2020).

[10] ATECO 2007 is the classification of economic activities used by the Italian Institute of Statistics (ISTAT). It correspond to the "Nomenclature statistique des activités économiques dans la Communauté européenne" (NACE), the statistical classification adopted in the European Union. The latest classification is NACE Rev. 2, which was implemented from 2007.

As a robustness check we provide additional estimates based on the Logit model. The Logit model is an alternative binary response model with the same non-linear properties, and it is not obvious which one should be preferred in practice.

Formally, the Logit model takes the following form:

$$\Pr(Exit_{ijr} = 1) = \mathrm{F}(\beta_0 + \beta_1' X_{ijr} + \beta_2' Z_r + \beta_3' D_j + \beta_4' D_r) \tag{2}$$

$$= \frac{1}{1 + e^{-(\beta_0 + \beta_1' X_{ijr} + \beta_2' Z_r + \beta_3' D_j + \beta_4' D_r)}}$$

Compared to the Probit regression a different CDF is used, that is a standard logistic distribution. As an intermediate step we also report the coefficient estimates of the Linear Probability Model (LPM), even if the latter has a clear drawback in not being able to capture the nonlinear nature of the model and the predicted probabilities may lie outside the interval [0, 1].X_{ijr} in Eq. (1) is a vector of firm-specific explanatory variables while Z_r is a vector of ecosystem control variables that proxies for business environment. The other terms are as follows: D_j is a set of sectoral dummies (sector fixed effect) to account for the 5 industrial groupings defined by Corsini and Pitingaro (2022), D_r is a set of regional dummies (regional fixed effect) that allow to distinguish between the 20 regions at the NUTS2 level. Within the vector X_{ijr} we first consider basic economic and financial variables, such as size, age, financial dependence, rollover (i.e., incidence of short-term debt), firms' return on assets (ROA), return on investment (ROI), return on debt (ROD). We also include a dummy to capture digital development proxied by the presence of a firm's website. Two additional binary variables are added to consider whether the firm was part of a group or not, and whether the firm was part of a network contract[11] before the outbreak of the pandemic. Moreover, following Landini et al., (2020), we also include in the regressions the squared values of size and age to control for possible nonlinear relationships between them and the probability of exit.

Concerning the contextual variables (Z_r), we consider the role of a specialization in high-tech industry and knowledge-intensive services (KIS) (Eurostat, 2020; European Commission, 2012), measured as the incidence of the employment in high-tech manufacturing sectors and in KIS in the LLS,[12] and a dummy variable for the location of the firm in an industrial district. Concerning the second contextual variable, we rely on the most recent industrial districts' classification developed by ISTAT (2015). Only LLS with (i) high presence of small- and medium-sized firms and (ii) high degree of industry specialization are classified as Industrial Districts (ISTAT, 2015). Following this classification, we build the dummy variable District, which is equal to one if the firm belongs to an industrial district, and zero otherwise.

11FL01 11FL02 [11] Network contract is an industrial policy instrument introduced in the midst of the 2009 financial crisis by the Italian government within emergency legislation, Decree-Law No. 33/2009.

12FL01 12FL02 12FL03 12FL04 12FL05 [12] The high-technology industry is a set of economic sectors with the higher level of R&D intensity compared to the other categories, namely medium high-technology, medium low-technology, and low-technology industries (European Commission, 2012). Services are mainly aggregated into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS) based on the share of tertiary educated persons at NACE 2-digit level (Eurostat, 2020).

Following Cucculelli and Peruzzi (2020), the hypothesis is that firms in IDs has a higher adaptability to changing market conditions, due to the low information asymmetries and to the imitative and herding behaviors that characterizes IDs (Dei Ottati, 1995). To account for recent transformations in Italian industrial districts, we include an interaction term (Knowledge-intensive IDs) to capture the high-tech specialization and the local knowledge base of industrial clusters. This variable is aimed at capturing whether and to what extent a specialization of IDs in medium- to high-tech industries and knowledge-intensive services might have helped manufacturing firms to face the pandemic-related downturn, in line with the view that new knowledge accumulation is a crucial factor of adaptation and adaptability to shocks (Bellandi et al., 2018; Martin et al., 2016).

Finally, to evaluate the possible effects of lockdown policies, we include a variable capturing the length of the restrictions measured by the total number of lockdown days for each region where the firm is located. In Italy, in the first half of 2020, a nationwide lockdown (from March 9th to May 5th) was established. Afterwards, starting from the second half of 2020 until June 2021, lockdown policies were differentiated by NUTS2 regions. The rationale for the inclusion of this variable is to verify whether and to what extent the duration of quarantines, although inevitable to protect the collectivity from contagion, influenced the extent of financial distress experienced by firms, with prolonged periods of uncertainty that might have led to higher default rates. Buchheim et al., 2020 documented that firms' expectations on the length of the shutdown and on the further evolution of the COVID-19 pandemic affected the strength of the crisis response and mitigation strategies.[13]

We estimate cross-section models with all firm-level explanatory variables in Eq. (1) and (2) evaluated at the pre-crisis period. In particular, we consider most of the variables as averages over the years 2017– 2019; only when data are not available for the two preceding years, we include the value for 2019 (Table A2 provides definition and detailed information for each regressor included in the analysis). Hence, we use these variables to predict the probability that a firm exit the market during the pandemic (i.e., within the next 3 years), that is before 2023. Tables 3, 4, 5, 6 and 7 of Sect. 4.1 report the estimated coefficients and the marginal effects of the baseline regression (model with ROA) obtained with different binary response models (LPM, Probit, Logit), while Tables A4, A5, A6 and A7 provide additional results with different variables of firms' efficiency and profitability (ROI and ROD instead of ROA), respectively.

[13] Firms that expected the restrictions to last for more than four months were more likely to implement strong responses to reduce fixed costs such as dismissing employees or cancelling investment projects than firms that expected a quick return to normalcy.

Table 2 Mean for exiters and survivors, mean difference, and t test of significance

Variable	(1) Exited (1)	(2) Survivors (0)	(3) Difference (1) – (2)	(4) P-value	(5) Sign
Age	20.847	24.591	-3.744	0	***
Size	9.589	21.547	– 11.958	0	***
Micro-firm (D)	0.715	0.464	0.251	0	***
Small firm (D)	0.257	0.436	– 0.178	0	***
Medium-size firm (D)	0.027	0.089	– 0.062	0	***
Large firm (D)	0.001	0.012	– 0.011	0	***
Productivity (ln)	3.292	3.869	– 0.577	0	***
ROA	– 0.016	0.037	– 0.053	0	***
ROI	– 0.034	0.064	– 0.098	0	***
ROD	0.016	0.014	0.002	0	***
Rollover	0.859	0.831	0.028	0	***
Financial dep./Indebt	0.778	0.601	0.177	0	***
Website (D)	0.267	0.291	– 0.024	0.05	**
Vertical integration	0.4	0.373	0.027	0.00184	***
Group (D)	0.499	0.643	– 0.144	0	***
Network contract (D)	0.012	0.032	– 0.021	0	***
Industrial District (ISTAT, 2015)	0.364	0.411	– 0.047	0	***
High-Tech and KIS (HT-KIS) specialization of LLS	28.357	28.32	0.037	0.79994	
HTM-KIS specialization *District	9.257188	10.86934	– 1.612151	0	***
Lockdown days	91.28	91.09	– 0.185	0.6036	
Agri-food (D)	0.1	0.101	– 0.001	0.85558	
Construction (D)	0.049	0.051	– 0.002	0.60467	
Mechanics (D)	0.378	0.458	– 0.08	0	***
Fashion and furniture (D)	0.304	0.195	0.109	0	***

*, ** and *** indicate significance at the 10%, 5%, and 1%, respectively

4 Results

4.1 Basic results

Table 2 provides the summary statistics -mean values for each variable—for the survivors and the exited firms, separately. The third column reports the result the difference between the two sample averages, the last two columns report the results of the t-test on the difference between the mean values for alive and exited firms, the p-value and its significance level.

First, we highlight that exited firms are on average younger (Age), Micro-firm dummy), more exposed to short-term debt (Rollover, net working capital), more fragile in terms of undercapitalization (Financial dependence), and less productive (Value added per employee) than survivors. We also find significant differences between the two groups' mean in terms of pre-crisis return on debt (ROD) and profitability performance (ROI, ROA). Moreover, our results suggest that digital presence (Website) is more frequent in surviving firms than in the group of firms that exit the market and the difference is significant. Moreover, being part of a group (Group dummy) is more frequent in active firms (64%) than in the group that exited the market (50%). We find significant differences between the two groups in terms of both the contextual variables we have selected: the location in an industrial district as defined by ISTAT, and the specialization in high-tech or knowledge-intensives services. Finally, it is interesting to notice that the probability of exit from the market differs significantly also with the sector in which the firms operate. In some industrial groups – i.e., Fashion and Furniture and Mechanics- we find significant differences between the two groups.

As a starting point, we have preliminarily estimated a Linear Probability Model (Table 3). We first considered a specification based on hypotheses drawn from the theory and previous contributions in the literature. Variables are organized into two main blocks: firm-level factors and external factors. Among the former controls, we focus our attention on three variables capturing the organizational structure and the relationships with other firms, namely, Vertical integration, Group, and Network contract. As for the external factors, we further distinguish between three groups of variables related to industrial districts and the specialization in high-tech and medium-tech industries and knowledge-intensive services and an interaction term between the two, sectoral dynamics and a further control variable to evaluate a possible "lockdown effect".

Table 4 shows the results of the multivariate analysis based on a Probit model as explained in Sect. 3.2 and Table 5 provides the associated marginal effects on default probability.

As for the first group of explanatory variables, we find support for some of the traditional determinants of firm survival, such as productivity, ROA, and website presence. Moreover, our results suggest that financial fragility hinders the ability to overcome the crisis, that is firms more indebted show a higher sensitivity to the pandemic shock and its economic consequences. Similarly, a high exposure to short-term debt is associated with a higher default probability. Instead, survival probability increases with group's and network contract's membership. Firms located in industrial districts are more likely to exit the market than isolated firms, but in specialized HTM-KIS districts less than in the other IDs.

Overall, our results sound consistent with Muzi et al. (2022) and El-Haddad and Zaki (2023), which suggest that the economic crisis induced by the COVID-19 pandemic exhibits a Schumpeterian "cleansing" of less productive firms. Moreover, our results confirm previous evidence on the crucial role of digitalization in surviving the pandemic (Belitski et al., 2022; Muzi et al., 2022; Wagner, 2021).

Based on the models estimated in Table 4, we have estimated the average marginal effect of each variable on the probability that a firm permanently close during the period 2020– 2022 (Table 5).

As a first robustness check, we performed the same analysis using the Logit model. Table 6 provides the estimated coefficients while Table 7 provides the marginal effects. Overall, the results are essentially equivalent to the ones obtained

Table 3 Linear Probability Model results – baseline model

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Size	(–)	– 0.0242*** (0.00172)	– 0.0252*** (0.00173)	– 0.0252*** (0.00173)	– 0.0251*** (0.00173)	– 0.0251*** (0.00173)	– 0.0251*** (0.00173)
Size	(±)	0.00296*** (0.000254)	0.00332*** (0.000258)	0.00331*** (0.000258)	0.00330*** (0.000258)	0.00329*** (0.000258)	0.00330*** (0.000258)
Age	(–)	– 0.0156** (0.00786)	– 0.0183** (0.00785)	– 0.0183** (0.00785)	– 0.0179** (0.00785)	– 0.0179** (0.00785)	– 0.0179** (0.00785)
Age^2	(±)	0.00252* (0.00129)	0.00267** (0.00129)	0.00266** (0.00129)	0.00259** (0.00129)	0.00259** (0.00129)	0.00259** (0.00129)
Productivity	(–)	– 0.0146*** (0.00154)	– 0.0138*** (0.00154)	– 0.0138*** (0.00154)	– 0.0139*** (0.00154)	– 0.0138*** (0.00154)	– 0.0139*** (0.00154)
ROA	(–)	– 0.320*** (0.0166)	– 0.325*** (0.0166)	– 0.325*** (0.0166)	– 0.324*** (0.0165)	– 0.324*** (0.0165)	– 0.323*** (0.0165)
Rollover	(+)	0.0351*** (0.00364)	0.0356*** (0.00364)	0.0355*** (0.00364)	0.0351*** (0.00364)	0.0351*** (0.00364)	0.0349*** (0.00364)
Financial dependency (Indebt)	(+)	– 0.000580 (0.00366)	0.00123 (0.00365)	0.00124 (0.00365)	0.00127 (0.00365)	0.00127 (0.00365)	0.00128 (0.00365)
Website (D)	(–)	– 0.0153*** (0.00155)	– 0.0155*** (0.00155)	– 0.0156*** (0.00155)	– 0.0156*** (0.00155)	– 0.0156*** (0.00155)	– 0.0156*** (0.00155)
Vertical integration	(+)	0.0434*** (0.00514)	0.0443*** (0.00513)	0.0441*** (0.00513)	0.0441*** (0.00513)	0.0440*** (0.00513)	0.0441*** (0.00513)
Group (D)	(–)		– 0.0178*** (0.00126)	– 0.0179*** (0.00126)	– 0.0179*** (0.00126)	– 0.0179*** (0.00126)	– 0.0179*** (0.00126)
Network contract (D)	(–)		– 0.00397* (0.00234)	– 0.00397* (0.00234)	– 0.00394* (0.00234)	– 0.00394* (0.00234)	– 0.00401* (0.00234)
Industrial District (D)	(–)			– 0.00256** (0.00127)		– 0.00106 (0.00132)	0.0125** (0.00533)
HTM-KIS spec. of LLS	(–)				0.000356*** (9.11e– 05)	0.000331*** (9.43e– 05)	0.000509*** (0.000116)

Table 3 (continued)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
HTM-KIS *District	(–)						– 0.000485*** (0.000182)
Lockdown days	(–/+)	0.0173 (0.0233)	0.0190 (0.0233)	0.0194 (0.0233)	0.00783 (0.0235)	0.00880 (0.0235)	0.00507 (0.0235)
Agri-food (D)	(±)	0.00208 (0.00222)	0.00153 (0.00222)	0.00148 (0.00222)	0.00193 (0.00222)	0.00189 (0.00222)	0.00209 (0.00222)
Construction (D)	(±)	– 0.00890*** (0.00265)	– 0.00974*** (0.00265)	– 0.00984*** (0.00265)	– 0.00924*** (0.00265)	– 0.00932*** (0.00265)	– 0.00902*** (0.00265)
Mechanics (D)	(±)	– 0.00245* (0.00142)	– 0.00286** (0.00142)	– 0.00285** (0.00142)	– 0.00292** (0.00142)	– 0.00291** (0.00142)	– 0.00275* (0.00142)
Fashion and furniture (D)	(±)	0.00897*** (0.00194)	0.00855*** (0.00194)	0.00880*** (0.00194)	0.00921*** (0.00194)	0.00926*** (0.00194)	0.00903*** (0.00195)
Constant		0.0428 (0.109)	0.0489 (0.108)	0.0472 (0.108)	0.0890 (0.109)	0.0854 (0.109)	0.0973 (0.109)
R-squared		0.039	0.042	0.042	0.042	0.042	0.042
Observations		84,309	84,309	84,309	84,309	84,309	84,309

Dependent variable: firm exit: Dummy = 1 if the firm exits before 2023, 0 otherwise

Size, Age, Productivity, and Lockdown days are in logarithm. Regional fixed effects are included in all estimates.

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4 Probit results—baseline model

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Size	(–)	– 0.258*** (0.0255)	– 0.275*** (0.0256)	– 0.274*** (0.0256)	– 0.273*** (0.0256)	– 0.273*** (0.0256)	– 0.273*** (0.0256)
Size	(±)	0.0147** (0.00576)	0.0209*** (0.00579)	0.0207*** (0.00579)	0.0207*** (0.00578)	0.0207*** (0.00579)	0.0207*** (0.00578)
Age	(–)	– 0.199 (0.124)	– 0.225* (0.125)	– 0.226* (0.125)	– 0.217* (0.125)	– 0.218* (0.125)	– 0.217* (0.125)
Age^2	(±)	0.0372* (0.0214)	0.0363* (0.0217)	0.0365* (0.0216)	0.0349 (0.0217)	0.0350 (0.0217)	0.0348 (0.0217)
Productivity	(–)	– 0.262*** (0.0201)	– 0.262*** (0.0203)	– 0.262*** (0.0203)	– 0.264*** (0.0203)	– 0.263*** (0.0203)	– 0.266*** (0.0203)
ROA	(–)	– 4.406*** (0.171)	– 4.497*** (0.173)	– 4.494*** (0.173)	– 4.479*** (0.173)	– 4.479*** (0.173)	– 4.472*** (0.173)
Rollover	(+)	0.466*** (0.0559)	0.473*** (0.0563)	0.472*** (0.0563)	0.468*** (0.0564)	0.468*** (0.0564)	0.462*** (0.0564)
Financial dependency (Indebt)	(+)	0.0764 (0.0487)	0.124** (0.0493)	0.125** (0.0493)	0.126** (0.0493)	0.126** (0.0493)	0.126** (0.0493)
Website (D)	(–)	– 0.230*** (0.0218)	– 0.231*** (0.0220)	– 0.232*** (0.0220)	– 0.234*** (0.0220)	– 0.234*** (0.0220)	– 0.232*** (0.0220)
Vertical integration	(+)	0.627*** (0.0581)	0.654*** (0.0587)	0.650*** (0.0587)	0.650*** (0.0587)	0.649*** (0.0587)	0.651*** (0.0588)
Group (D)	(–)		– 0.309*** (0.0203)	– 0.309*** (0.0203)	– 0.311*** (0.0203)	– 0.311*** (0.0203)	– 0.311*** (0.0203)
Network contract (D)	(–)		– 0.162* (0.0900)	– 0.162* (0.0900)	– 0.161* (0.0900)	– 0.161* (0.0900)	– 0.164* (0.0902)
Industrial District (D)	(–)			– 0.0468** (0.0237)		– 0.0177 (0.0254)	0.261*** (0.0926)
HTM-KIS spec. of LLS	(–)				0.00636*** (0.00171)	0.00591*** (0.00182)	0.00945*** (0.00216)
HTM-KIS *District	(–)						– 0.0100*** (0.00322)
Lockdown days	(-/+)	0.164 (0.325)	0.206 (0.328)	0.215 (0.328)	0.00368 (0.333)	0.0214 (0.334)	– 0.0625 (0.335)

Table 4 (continued)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Agri-food (D)	(±)	0.0367 (0.0392)	0.0232 (0.0395)	0.0227 (0.0395)	0.0303 (0.0396)	0.0297 (0.0396)	0.0337 (0.0396)
Construction (D)	(±)	– 0.108** (0.0506)	– 0.128** (0.0511)	– 0.130** (0.0511)	– 0.119** (0.0511)	– 0.120** (0.0512)	– 0.115** (0.0512)
Mechanics (D)	(±)	– 0.0221 (0.0284)	– 0.0294 (0.0286)	– 0.0294 (0.0286)	– 0.0300 (0.0287)	– 0.0299 (0.0287)	– 0.0268 (0.0287)
Fashion and furniture (D)	(±)	0.152*** (0.0307)	0.147*** (0.0309)	0.151*** (0.0310)	0.158*** (0.0311)	0.159*** (0.0311)	0.155*** (0.0312)
Constant		– 1.483 (1.513)	– 1.447 (1.525)	– 1.480 (1.526)	– 0.722 (1.540)	– 0.786 (1.543)	– 0.504 (1.546)
Chi-squared		2999.8***	3234.7***	3238.6***	3248.7***	3249.2***	3258.9***
LogLikelihood		– 9059.227	– 8941.766	– 8939.815	– 8934.777	– 8934.534	– 8929.656
Pseudo-R-squared		0.142	0.153	0.153	0.154	0.154	0.154
Observations		84,309	84,309	84,309	84,309	84,309	84,309

Dependent variable: firm exit: Dummy = 1 if the firm exits before 2023, 0 otherwise

Size, Age, Productivity, and Lockdown days are in logarithm. Regional fixed effects are included in all estimates

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

After Model (6), we performed a significance test on the linear combination of the parameters relative to the dummy 'Industrial district' and the interaction term 'HTM-KIS*District'' with the Stata command testnl. Results are: chi2(1) = 7.83; Prob > chi2 = 0.0051

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Table 5 Marginal effects on default probability (Probit model)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Size	(–)	– 0.00984*** (0.00101)	– 0.00995*** (0.000965)	– 0.00989*** (0.000965)	– 0.00986*** (0.000962)	– 0.00984*** (0.000962)	– 0.00981*** (0.000960)
Size	(±)	0.000562** (0.000222)	0.000755*** (0.000213)	0.000746*** (0.000213)	0.000747*** (0.000212)	0.000745*** (0.000212)	0.000745*** (0.000211)
Age	(–)	– 0.00760 (0.00472)	– 0.00814* (0.00452)	– 0.00816* (0.00452)	– 0.00783* (0.00451)	– 0.00786* (0.00451)	– 0.00781* (0.00450)
Age^2	(±)	0.00142* (0.000817)	0.00131* (0.000783)	0.00132* (0.000782)	0.00126 (0.000781)	0.00126 (0.000781)	0.00125 (0.000779)
Productivity	(–)	– 0.00999*** (0.000769)	– 0.00949*** (0.000737)	– 0.00946*** (0.000737)	– 0.00951*** (0.000735)	– 0.00949*** (0.000736)	0.00955*** (0.000735)
ROA	(–)	– 0.168*** (0.00699)	– 0.163*** (0.00680)	– 0.162*** (0.00680)	– 0.161*** (0.00679)	– 0.161*** (0.00679)	– 0.161*** (0.00677)
Rollover	(+)	0.0178*** (0.00214)	0.0171*** (0.00205)	0.0171*** (0.00205)	0.0169*** (0.00205)	0.0169*** (0.00205)	0.0166*** (0.00204)
Financial dependency (Indebt)	(+)	0.00291 (0.00185)	0.00449** (0.00178)	0.00451** (0.00178)	0.00454** (0.00177)	0.00455** (0.00177)	0.00452** (0.00177)
Website (D)	(–)	– 0.00879*** (0.000838)	– 0.00837*** (0.000803)	– 0.00837*** (0.000802)	– 0.00842*** (0.000801)	– 0.00842*** (0.000801)	– 0.00836*** (0.000799)
Vertical integration	(+)	0.0239*** (0.00223)	0.0237*** (0.00214)	0.0235*** (0.00214)	0.0234*** (0.00213)	0.0234*** (0.00213)	0.0234*** (0.00213)
Group (D)	(–)		– 0.0112*** (0.000739)	– 0.0112*** (0.000739)	– 0.0112*** (0.000738)	– 0.0112*** (0.000738)	– 0.0112*** (0.000736)
Network contract (D)	(–)		– 0.00586* (0.00325)	– 0.00584* (0.00325)	– 0.00580* (0.00324)	– 0.00580* (0.00324)	– 0.00590* (0.00324)
Industrial District (D)	(–)			– 0.00169** (0.000857)		– 0.000638 (0.000916)	0.00936*** (0.00333)

Table 5 (continued)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
HTM-KIS spec. of LLS	(–)				0.000229*** (6.15e– 05)	0.000213*** (6.58e– 05)	0.000340*** (7.76e– 05)
HTM-KIS *District	(–)						– 0.000361*** (0.000116)
Lockdown days	(–/+)	0.00627 (0.0124)	0.00746 (0.0119)	0.00775 (0.0119)	0.000133 (0.0120)	0.000772 (0.0120)	– 0.00225 (0.0120)
Agri-food (D)	(±)	0.00140 (0.00149)	0.000837 (0.00143)	0.000821 (0.00143)	0.00109 (0.00143)	0.00107 (0.00143)	0.00121 (0.00142)
Construction (D)	(±)	– 0.00410** (0.00193)	– 0.00462** (0.00185)	– 0.00468** (0.00185)	– 0.00429** (0.00184)	– 0.00434** (0.00185)	– 0.00413** (0.00184)
Mechanics (D)	(±)	– 0.000841 (0.00108)	– 0.00106 (0.00104)	– 0.00106 (0.00104)	– 0.00108 (0.00103)	– 0.00108 (0.00103)	– 0.000964 (0.00103)
Fashion and furniture (D)	(±)	0.00578*** (0.00117)	0.00530*** (0.00112)	0.00547*** (0.00112)	0.00570*** (0.00112)	0.00574*** (0.00112)	0.00558*** (0.00112)

*, ** and *** indicate significance at the 10%, 5%, and 1%, respectively

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Table 6 Logit results – baseline model

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Size	(–)	– 0.478*** (0.0576)	– 0.522*** (0.0577)	– 0.520*** (0.0577)	– 0.521*** (0.0577)	– 0.520*** (0.0577)	– 0.519*** (0.0577)
Size	(±)	0.0121 (0.0139)	0.0265* (0.0139)	0.0261* (0.0139)	0.0267* (0.0139)	0.0265* (0.0139)	0.0265* (0.0139)
Age	(–)	– 0.281 (0.275)	– 0.368 (0.277)	– 0.369 (0.277)	– 0.355 (0.277)	– 0.356 (0.277)	– 0.358 (0.277)
Age^2	(±)	0.0570 (0.0479)	0.0600 (0.0483)	0.0603 (0.0483)	0.0573 (0.0483)	0.0575 (0.0483)	0.0577 (0.0483)
Productivity	(–)	– 0.552*** (0.0434)	– 0.558*** (0.0438)	– 0.556*** (0.0438)	– 0.560*** (0.0438)	– 0.560*** (0.0438)	– 0.564*** (0.0439)
ROA	(–)	– 9.704*** (0.357)	– 9.827*** (0.361)	– 9.817*** (0.361)	– 9.792*** (0.361)	– 9.791*** (0.361)	– 9.779*** (0.361)
Rollover	(+)	0.936*** (0.126)	0.964*** (0.127)	0.961*** (0.127)	0.951*** (0.127)	0.951*** (0.127)	0.941*** (0.127)
Financial dependency (Indebt)	(+)	0.179* (0.106)	0.278*** (0.107)	0.278*** (0.107)	0.280*** (0.107)	0.280*** (0.107)	0.279*** (0.107)
Website (D)	(–)	– 0.502*** (0.0487)	– 0.507*** (0.0488)	– 0.509*** (0.0488)	– 0.513*** (0.0488)	– 0.513*** (0.0488)	– 0.511*** (0.0488)
Vertical integration	(+)	1.309*** (0.125)	1.378*** (0.126)	1.369*** (0.126)	1.371*** (0.126)	1.368*** (0.126)	1.372*** (0.126)
Group (D)	(–)		– 0.711*** (0.0450)	– 0.712*** (0.0450)	– 0.714*** (0.0450)	– 0.714*** (0.0450)	– 0.715*** (0.0451)
Network contract (D)	(–)		– 0.387* (0.217)	– 0.387* (0.217)	– 0.387* (0.217)	– 0.387* (0.217)	– 0.392* (0.218)
Industrial District (D)	(–)			– 0.0984* (0.0528)		– 0.0345 (0.0565)	0.568*** (0.205)
HTM-KIS spec. of LLS	(–)				0.0139*** (0.00377)	0.0130*** (0.00403)	0.0206*** (0.00476)
HTM-KIS *District	(–)						– 0.0218*** (0.00716)
Lockdown days	(–/+)	0.231 (0.710)	0.348 (0.712)	0.362 (0.712)	– 0.102 (0.723)	– 0.0683 (0.726)	– 0.248 (0.728)
Agri-food (D)	(±)	0.0325 (0.0882)	0.00127 (0.0887)	– 0.000154 (0.0886)	0.0154 (0.0887)	0.0141 (0.0888)	0.0238 (0.0888)

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Table 6 (continued)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Construction (D)	(±)	– 0.230** (0.114)	– 0.264** (0.115)	– 0.267** (0.115)	– 0.247** (0.115)	– 0.249** (0.115)	– 0.237** (0.115)
Mechanics (D)	(±)	– 0.0471 (0.0643)	– 0.0599 (0.0645)	– 0.0595 (0.0645)	– 0.0603 (0.0645)	– 0.0601 (0.0645)	– 0.0525 (0.0646)
Fashion and furniture (D)	(±)	0.324*** (0.0681)	0.312*** (0.0683)	0.322*** (0.0686)	0.337*** (0.0687)	0.339*** (0.0687)	0.332*** (0.0689)
Constant		– 2.344 (3.300)	– 2.304 (3.312)	– 2.357 (3.312)	– 0.676 (3.344)	– 0.798 (3.350)	– 0.194 (3.356)
Chi-squared		2971.7***	3223.05***	3226.5***	3236.7***	3237.03***	3246.4***
LogLikelihood		– 9073.273	– 8947.591	– 8945.848	– 8940.786	– 8940.599	– 8935.942
Pseudo-R-squared		0.141	0.153	0.153	0.153	0.153	0.154
Observations		84,309	84,309	84,309	84,309	84,309	84,309

Dependent variable: firm exit: Dummy = 1 if the firm exits before 2023, 0 otherwise

Size, Age, Productivity, and Lockdown days are in logarithm. Regional fixed effects are included in all estimates.

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. After Model (6), we performed a significance test on the linear combination of the parameters relative to the dummy 'Industrial district' and the interaction term 'HTM-KIS*District'" with the Stata command *testnl*. Results are: chi2(1) = 7.60; Prob > chi2 = 0.0059

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Table 7 Marginal effects on default probability (Logit model)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
Size	(–)	– 0.00720*** (0.000904)	– 0.00740*** (0.000858)	– 0.00736*** (0.000857)	– 0.00736*** (0.000855)	– 0.00734*** (0.000855)	– 0.00731*** (0.000853)
Size	(±)	0.000182 (0.000210)	0.000375* (0.000200)	0.000369* (0.000200)	0.000377* (0.000199)	0.000375* (0.000199)	0.000374* (0.000199)
Age	(–)	– 0.00424 (0.00414)	– 0.00522 (0.00392)	– 0.00523 (0.00392)	– 0.00501 (0.00391)	– 0.00503 (0.00391)	– 0.00504 (0.00390)
Age^2	(±)	0.000858 (0.000722)	0.000851 (0.000685)	0.000853 (0.000684)	0.000809 (0.000683)	0.000813 (0.000683)	0.000812 (0.000681)
Productivity	(–)	– 0.00831*** (0.000660)	– 0.00790*** (0.000627)	– 0.00788*** (0.000627)	– 0.00791*** (0.000626)	– 0.00790*** (0.000626)	– 0.00794*** (0.000625)
ROA	(–)	– 0.146*** (0.00600)	– 0.139*** (0.00581)	– 0.139*** (0.00581)	– 0.138*** (0.00580)	– 0.138*** (0.00579)	– 0.138*** (0.00578)
Rollover	(+)	0.0141*** (0.00191)	0.0137*** (0.00181)	0.0136*** (0.00181)	0.0134*** (0.00181)	0.0134*** (0.00181)	0.0133*** (0.00180)
Financial dependency (Indebt)	(+)	0.00269* (0.00159)	0.00394*** (0.00151)	0.00394*** (0.00151)	0.00395*** (0.00151)	0.00395*** (0.00151)	0.00394*** (0.00150)
Website (D)	(–)	– 0.00756*** (0.000738)	– 0.00719*** (0.000699)	– 0.00720*** (0.000698)	– 0.00724*** (0.000697)	– 0.00724*** (0.000697)	– 0.00720*** (0.000695)
Vertical integration	(+)	0.0197*** (0.00190)	0.0195*** (0.00180)	0.0194*** (0.00180)	0.0194*** (0.00180)	0.0193*** (0.00180)	0.0193*** (0.00179)
Group (D)	(–)		– 0.0101*** (0.000644)	– 0.0101*** (0.000643)	– 0.0101*** (0.000642)	– 0.0101*** (0.000642)	– 0.0101*** (0.000641)
Network contract (D)	(–)		– 0.00549* (0.00308)	– 0.00547* (0.00307)	– 0.00546* (0.00307)	– 0.00546* (0.00307)	– 0.00552* (0.00306)
Industrial District (D)	(–)			– 0.00139* (0.000747)		– 0.000487 (0.000798)	0.00801*** (0.00289)
HTM-KIS spec. of LLS	(–)				0.000196*** (5.34e– 05)	0.000184*** (5.70e– 05)	0.000290*** (6.71e– 05)

Table 7 (continued)

	Expected sign	(1)	(2)	(3)	(4)	(5)	(6)
HTM-KIS *District	(–)						– 0.000308*** (0.000101)
Lockdown days	(–/+)	0.00348 (0.0107)	0.00493 (0.0101)	0.00513 (0.0101)	– 0.00144 (0.0102)	– 0.000964 (0.0102)	– 0.00349 (0.0103)
Agri-food (D)	(±)	0.000489 (0.00133)	1.80e– 05 (0.00126)	– 2.19e– 06 (0.00125)	0.000218 (0.00125)	0.000200 (0.00125)	0.000335 (0.00125)
Construction (D)	(±)	– 0.00346** (0.00172)	– 0.00374** (0.00162)	– 0.00378** (0.00162)	– 0.00348** (0.00162)	– 0.00351** (0.00162)	– 0.00334** (0.00162)
Mechanics (D)	(±)	– 0.000709 (0.000968)	– 0.000849 (0.000914)	– 0.000842 (0.000913)	– 0.000852 (0.000911)	– 0.000848 (0.000911)	– 0.000739 (0.000910)
Fashion and furniture (D)	(±)	0.00488*** (0.00103)	0.00442*** (0.000969)	0.00456*** (0.000971)	0.00476*** (0.000971)	0.00479*** (0.000972)	0.00467*** (0.000971)

*, ** and *** indicate significance at the 10%, 5%, and 1%, respectively

through the Probit estimates. Because our concern is especially related to the factors of the local economic environment that might favour innovation and resilience, we focus our attention on the binary variable "District" and its interaction with the variable "HTM-KIS spec. of LLS". We performed a test on the linear combination of the associated coefficients after the estimation of the Probit and the Logit Models. The results are reported at the bottom of Tables 4 and 6, respectively. The significant statistics of the joint test suggest that the estimated coefficients can be considered reliable confirming the hypothesis of a moderation effect of the variable HTM-KIS specialization that slightly offsets the negative effect of a location in an industrial district on the risk of bankruptcy.

Several variables show a significant relationship with the firm permanent exit and the expected sign. First, we found non-linearities in the association between size and age, and the probability of exit, in line with the U-shaped relationship highlighted in the literature (Audretsch & Mahmood, 1994; Landini et al., 2020, Wagner, 2021). among others). Among the idiosyncratic characteristics, ROA displays a higher marginal effect that is between – 0.16 in the Probit and – 0.14 in the Logit: thus a 1 unit increase in the ROA decreases the default probability of about 1.5 percentage points.

We found a negative association between digitalization and the probability of permanent exit, as expected. Still, the estimated marginal effect of about – 0.008 (0.007 in the Logit) suggests that firms with a website before the crisis are only 1 percentage less likely to exit the market than firms without a website, a marginal effect decisively lower than that found in previous cross-country analyses on microdata (Muzi et al., 2022; Wagner, 2021).[14]

As for the organization structure and external relationships, our results suggest that firms that belong to a group have a 1.1 percentage points (1 percentage point in the Logit) lower likelihood of permanently closing during the pandemic. Joining a network contract has lower importance: firms that are members of a network contract have a significantly lower probability to exit the market but with a marginal effect of – 0.006, that is, with a default probability of 0.6 percentage points lower than isolated firms.

Concerning the role of the external environment, we found that companies located in an industrial district have a higher probability of default than firms located outside an industrial district. This probability is mitigated to an extremely partial extent (the cumulative marginal effect would not deviate much from + 0.009 in the Probit and + 0.008 in the Logit) by a greater presence, in the district, of medium to high-technology sectors and or knowledge-intensive services.

Concerning the role of emergency policies, our estimates suggest that firms in regions with more prolonged lockdown policies do have not a significantly higher likelihood of permanently exiting the market during the pandemic. In Model 4 for the Probit specification (Table 4) and in Models (4), (5) and (6) for the Logit specification (Table 5) the sign of the associated coefficient turns from positive to negative suggesting that the longer the quarantine the lower the default probability. Overall,

14FL01 [14] Both Muzi et al., 2022 and Wagner et al., 2021 found marginal effects that they consider to be large on
14FL02 average: from – 0.046 to – 0.051 and from – 0.048 to – 0.028, respectively.

our results do not yield conclusive results on the role of the length of lockdown policy in Italy for firm survival.

Finally, the marginal effects reported in Tables 5 and 7 suggest that firms in different sectors may have been affected differently by the pandemic-related crisis. Firms belonging to a Made in Italy industry grouping—i.e., Fashion and furniture—have had a default probability of 0.4– 0.5 percentage points higher than firms operating in other industrial groupings.

As further robustness checks, we have performed the same analysis using different firm-level controls related to profitability and efficiency, namely ROI and ROD instead of ROA because an analysis with all of them might have raised some collinearity concerns, as it was evident from the preliminary assessment through correlation analysis among the regressors (Table A8 in the Appendix). The results presented in Tables A4-A5 and A6– A7 further confirm the role of financial costs and profitability of the firms in different areas. More importantly, our crucial results on the role of external relationships and ecosystem factors are robust to the inclusion of different firm-specific conditions related to profitability and financial soundness. With the additional sensitivity analyses, we still found evidence against a zero-interaction coefficient, and hence in favour of a significant moderating effect of the HTM-KIS specialization that slightly lowers the negative impact of an ID location on the default probability of firms during COVID-19. The joint significance test of the parameters relative to the 'Industrial district' and 'HTM-KIS*District' variables yields the following results: chi2(1) = 7.70; Prob > chi2 = 0.0055 for the Probit (Table A4), and chi2(1) = 7.31; Prob > chi2 = 0.0069 for the Logit (Table A6).

5 Concluding remarks and avenues for future research

This paper focuses on the behavior of firms in response to the huge COVID-19 related shock and analyzes the factors that most affected the probability of firms exiting the market during the pandemic. The empirical analysis was based on firm-level data drawn from the AIDA-Bureau van Dijk database and considered both idiosyncratic firm-specific characteristics, the organizational structure, the relationships with external firms, and the role of the local environment. In line with the related literature, we find substantial regional variation and sectoral heterogeneity of the firms' default rates. In general, we suggest that the incidence of supply-chain shocks might, at least in part, explain the sector-specific factors that have affected a firm's survival. For example, the higher default rate that we found for firms in traditional industries – fashion and furniture – can be because they were forced to adjust to widespread COVID-19-related supply chain disruptions more than firms active in other sectors.

We find a confirmation of some of the traditional firm-specific factors affecting firm exit. In this respect, our results are in line with previous studies in that we also find that micro-firms, highly indebted and less productive firms have a higher probability of exiting the market, thus supporting the view of a Schumpeterian cleansing effect being at work. In line with the literature, we also find that a low incidence of short-term debt has favored firm survival. Micro-firms have been the categories of enterprises that suffered the more from the COVID-19-related supply and demand shocks. Small, Medium-Sized and Large firms displayed significantly lower default rates -i.e., higher resilience capacity—in our sample of Italian manufacturing firms. However, it is worth noting that the effect of the firm's size on the default probability might be mitigated if the firm is part of a group or joined an inter-firm network contract before the onset of the COVID-19 pandemic. Interestingly, our results confirm previous works on the role of digital development (Belitski et al., 2022; Muzi et al., 2022; Wagner, 2021) in that we also find that having a digital presence is a relevant determinant of firm survival during the COVID-19 crisis. As for local ecosystem factors, being part of a district, in general, increases the risk of default, but in HTM-KIS districts less than in non-HTM-KIS ones. Finally, we find that the length of lockdown policies in the region where the firm is located is not significantly related to the risk of bankruptcy.

While we provide sensitivity analyses that support the robustness of our results, we also propose avenues for future research that can address the main limitations of the present study. First, extending the analysis by collecting more recent data is the first essential step to concluding the long-term impact of the COVID-19 crisis on firm survival and how and to what extent firm-level characteristics and ecosystem factors have played a role.

Second, including in the analysis control variables to account for government interventions would be important to verify whether public support has imposed some form of a moratorium on insolvencies slowing down a vital process of ''cleansing'' out of unproductive firms as suggested by the literature (e.g., Dörr et al., 2022; Kaya, 2022; Muzi et al., 2022). Moreover, a detailed assessment of the impact of policy measures enacted in Italy in the different phases of the crisis would be particularly relevant in terms of policy implications.

Finally, a deeper analysis of the joint positioning of firms in local clusters and global supply chains would certainly help to draw a clearer picture of the mechanisms through which the COVID-19-related supply and demand shocks may have affected different categories of manufacturing firms differently. AQ8

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40812-024-00309-0.

Acknowledgements The authors declare that funds and grants were received during the preparation of this manuscript.

Eleonora Cutrini acknowledges partial research support from the European Union—NextGenerationEU under the Italian Ministry of University and Research (MUR) National Innovation Ecosystem grant ECS00000041—VITALITY – CUP D83C22000710005. Federico Ninivaggi acknowledges financial support from the European Union—European Social Fund, under the program "Innovative Doctorate" – PhD Scholarships for the innovation of the regional system- 2020 edition, Marche Region (Italy). This article was presented at the XXI Annual Workshop of the Italian Society for Industrial Economics and Industrial Policy (SIEPI) in Naples (June 15-16, 2023) and the 64° Congress of the Italian Economic Association in L'Aquila (October 19-21, 2023). We are grateful to the participants for their comments and suggestions on an earlier draft.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Acharya, V. V., & Steffen, S. (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *The Review of Corporate Finance Studies, 9*(3), 430–471.

Adalet McGowan, M., Andrews, D., Millot, V., & Beck, T. (2018). The walking dead? Zombie firms and productivity performance in OECD countries. *Economic Policy, 33*(96), 685–736. AQ9

Amin, M., & Viganola, D. (2023). Does better access to finance help firms deal with the COVID-19 pandemic? Evidence from firm-level survey data. *Journal of International Development., 35*, 2578–2608.

Antonioli, D., & Montresor, S. (2021). Innovation persistence in times of crisis: An analysis of Italian firms. *Small Business Economics, 56*, 1739–1764.

Balduzzi, P., Brancati, E., Brianti, M., & Schiantarelli, F. (2020). The Economic Effects of COVID-19 and Credit Constraints: Evidence from Italian Firms' Expectations and Plans, IZA DP No. 13629, August 2020.

Bankowska, K., Ferrando, A., Garcia, J.A., 2020. The COVID-19 pandemic and access to finance for small and medium-sized enterprises: evidence from survey data. In: Economic Bulletin Issue 4/2020. ECB.

Barbato, G., Barini, E. M., Genta, G., & Levi, R. (2011). Features and performance of some outlier detection methods. *Journal of Applied Statistics, 38*(10), 2133–2149.

Basile, R., Pittiglio, R., & Reganati, F. (2017). Do agglomeration externalities affect firm survival?". *Regional Studies, 51*(4), 548–562.

Belitski, M., Guenther, C., Kritikos, A. S., & Thurik, R. (2022). Economic effects of the COVID-19 pandemic on entrepreneurship and small businesses. *Small Business Economics*, 1– 17.

Bellandi, M., & De Propris, L. (2015). "Three generations of industrial districts. *Investigaciones Regionales-Journal of Regional Research, 32*, 75–87.

Bellandi, M., Santini, E., & Vecciolini, C. (2018). Learning, unlearning and forgetting processes in industrial districts. *Cambridge Journal of Economics, 42*(6), 1671–1685.

Bloom, N., R. Fletcher, E. Yeh (2021), The Impact of COVID-19 on US Firms. *Working Paper 28314*

Bozkurt, İ., & Kaya, M. V. (2022). Foremost features affecting financial distress and Bankruptcy in the acute stage of COVID-19 crisis. *Applied Economics Letters*, 1– 12

Brancati, E., Brancati, R., & Maresca, A. (2017). Global Value chains, innovation and performance: Firm-level evidence from the great recession. *Journal of Economic Geography., 17*(1), 1039–1073.

Buchheim, L., Dovern, J., Krolage, C., & Link, S. (2020). Firm-level Expectations and Behavior in Response to the Covid-19 Crisis, IZA DP No. 13253, August 2020

Chundakkadan, R., Natarajan, R. R., & Sasidharan, S. (2022). Small firms amidst COVID-19: Financial constraints and role of government support. *Economic Notes, 51*(3), e12206.

Corsini, S., & Pitingaro, S. (2022). I contratti di rete: una lettura per macroarea geografica. In A. Cabigiosu (Ed.), *Osservatorio Nazionale sulle reti d'impresa 2022, Studi e ricerche sulle reti d'impresa* (pp. 7–24). Venice University Press Venezia Edizioni Ca' Foscari.

Costa S., De Santis, S., Dosi G., Monducci R, Sbardella A., Virgillito M.E. (2022) Firm responses to the COVID-19 crisis: sticky capabilities and widespread restructuring, Rivista di Statistica Ufficiale/ Review of Official Statistics N. 1/2022

Cucculelli, M., & Peruzzi, V. (2020). Post-crisis firm survival, business model changes, and learning: Evidence from the Italian manufacturing industry. *Small Business Economics, 54*, 459–474.

Cutrini, E., & Salvati, L. (2021). Unraveling spatial patterns of COVID-19 in Italy: Global forces and local economic drivers. *Regional Science Policy & Practice, 13*, 73–108.

De Propris, S., & Storai, D. (2019). Servitizing industrial regions. *Regional Studies, 53*(3), 388–397.

De Vito, A., & Gómez, J.-P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy, 39*(2), 106741. https://doi.org/10.1016/j.jaccpubpol.2020.106741

Dei Ottati, G. (1995). *Tra mercato e comunità: aspetti concettuali e ricerche empiriche*. Franco Angeli.

Didier, T., Huneeus, F., Larrain, M., & Schmukler, S. L. (2021). Financing firms in hibernation during the COVID-19 pandemic. Journal of Financial Stability, *53*.

Dörr, J. O., Licht, G., & Murmann, S. (2021). Small firms and the COVID-19 insolvency gap. *Small Business Economics*, 1– 31.

Dörr, J., Licht, G., & Murmann, S. (2022). Small firms and the COVID-19 insolvency gap. *Small Business Economics, 58*, 887–917.

Journal : SmallExtended 40812 | Article No : 309 | Pages : 33 | MS Code : 309 | Dispatch : 20-4-2024

El-Haddad, A., & Zaki, C. (2023). Storm survivors: Evidence from firms in times of pandemic. *The Journal of International Trade & Economic Development*, 1– 34.

European Commission. (2012). *Knowledge Intensive (Business) Services in Europe*. Berlin: European Commission.

Eurostat. (2020). High-tech industry and knowledge-intensive services (htech), Reference Metadata in Euro SDMX Metadata, Brussels. https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm. Accessed 20 Mar 2024

Fairlie, R., & Fossen, F. (2022). The Early Impacts of the COVID-19 Pandemic on Business Sales. *Small Business Economics, 58*, 1853–1864.

Ferragina A. M., Iandolo, S. (2022), Italian Firms Exposure, risk and sentiment to COVID-19: impact on credit behaviour and patrimonial status, in S. Capasso e G. Canitano (a cura di) Mediterranean Economies 2021– 2022, Bologna, Il Mulino, 2022 (ed. digit.: 2022, 10.978.8815/371034.

Ferragina, A. M., & Mazzotta, F. (2014). Local agglomeration economies: What impact on multinational and national Italian firms' survival? *Procedia-Social and Behavioral Sciences, 110*, 8–19.

Garicano, L., 2020. The COVID-19 bazooka for jobs in Europe. In: Baldwin, R., & diMauro, B.W. (Eds.), Mitigating the Covid Economic Crisis: Act Fast and Do Whatever It Takes. VoxEU.org Book.

Goel, R. K., & Nelson, M. A. (2022). Global coronavirus business closures: influences of executive gender, firm characteristics, and government involvement. *Applied Economics*, 1– 19.

Gourinchas, P. O., Kalemli-Ozcan, S., Penciakova, V., & Sander, N. (2022). COVID-19 and small- and medium-sized enterprises: A 2021 "time bomb"? *AEA Paper Proceedings, 111*, 282–286.

Greenwood, R.M., Iverson, B.C., & Thesmar, D., 2020. Sizing Up Corporate Restructuring in the COVID Crisis. *NBER Working Paper*, (w28104).

Grubbs, F. E. (1969). Procedures for detecting outlying observations in samples. *Technometrics, 11*(1), 1–21.

Ho, K.-C., Huang, H., Pan, Z., & Gu, Y. (2023). Modern pandemic crises and default risk: A worldwide evidence. *Journal of International Financial Management and Accounting, 34*, 211–242.

Hubert, M., & Van der Veeken, S. (2008). Outlier detection for skewed data. *Journal of Chemometrics: A Journal of the Chemometrics Society, 22*(3– 4), 235–246.

IMF. (2022). Italy: Staff Concluding Statement of the 2022 Article IV Mission, May 19, 2022, available at https://www.imf.org/en/News/Articles/2022/05/19/italy-staff-concluding-statement-of-the-2022-article-iv-mission

ISTAT. (2015). *I distretti industriali 2011*. ISTAT.

ISTAT. (2021). *Rapporto sulla competitività dei settori produttivi 2020*. ISTAT.

ISTAT. (2022a). *Rapporto sulla competitività dei settori produttivi 2021*. ISTAT.

ISTAT. (2022b). Indicatori del sistema integrato dei registri su imprese e territorio, Roma, *available at* https://www.istat.it/storage/IstatData/SIR/Indic_SIR_1_met_ITA.pdf

Kaya, O. (2022). Determinants and consequences of SME insolvency risk during the pandemic. *Economic Modelling, 115*, 105958.

Ke, Y. (2021). The impact of COVID-19 on firms' cost of equity capital: early evidence from U.S. public firms. *Finance Research Letters, 15*, 10. https://doi.org/10.1016/j.frl.2021.102242

Khan, S. U. (2022). Financing constraints and firm-level responses to the COVID-19 pandemic: International evidence. *Research in International Business and Finance, 59*, 101545.

Lafuente, E., Vaillant, Y., & Vendrell-Herrero, F. (2017). Territorial servitization: Exploring the virtuous circle connecting knowledge-intensive services and new manufacturing businesses. *International Journal of Production Economics, 192*, 19–28.

Landini, F., Arrighetti, A., & Lasagni, A. (2020). Economic crisis and firm exit: Do intangibles matter? *Industry and Innovation, 27*(5), 445–479.

Martin, R., Sunley, P., Gardiner, B., & Tyler, P. (2016). How regions react to recessions: Resilience and the role of economic structure. *Regional Studies, 50*(4), 561–585.

Mirza, N., Rahat, B., Naqvi, B., & Rizvi, S. A. (2020). Impact of covid-19 on corporate solvency and possible policy responses in the EU. *The Quarterly Review of Economics and Finance*. https://doi.org/10.1016/j.qref.2020.09.002. in Press.

Miyakawa, D., Oikawa, K., & Ueda, K. (2021). Firm exit during the COVID-19 pandemic: Evidence from Japan. *Journal of the Japanese and International Economies, 59*, 101118.

Muzi, S., Jolevski, F., Ueda, K., & Viganola, D. (2022). Productivity and firm exit during the COVID-19 crisis: Cross-country evidence. *Small Business Economics*, 1– 42.

Orlando, T., & Rodano, G. (2020). Firm undercapitalization in Italy: business crisis and survival before and after COVID-19. *Bank of Italy Occasional Paper*, (590).

Qin, X., Huang, G., Shen, H., & Fu, M. (2020). COVID-19 pandemic and firm-level cash holding—moderating effect of goodwill and goodwill impairment. *Emerging Markets Finance & Trade, 56*(10), 2243–2258.

Qing, B., & Shaonan, T. (2020). Innovate or die: Corporate innovation and bankruptcy forecasts. *Journal of Empirical Finance, 59*, 88–108.

Sforzi, F., & Boix, R. (2019). Territorial servitization in marshallian industrial districts: The industrial district as a place-based form of servitization. *Regional Studies, 53*(3), 398–409. AQ10

Vo, T. A., Mazur, M., & Thai, A. (2021). The impact of COVID-19 economic crisis on the speed of adjustment toward target leverage ratio: an international analysis. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2021.102157

Wagner, J. (2021). With a little help from my website Firm survival and web presence in times of COVID-19—evidence from 10 European countries. *Economics Bulletin, 41*(3), 1898–1906.

World Bank. (2022). *World Development Report 2022: Finance for an equitable recovery*.

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