Received: 13 May 2022 | Revised: 6 December 2022 | Accepted: 9 February 2023

DOI: 10.1111/manc.12433

ORIGINAL ARTICLE

The Manchester School WILEY

Access to bank financing and start-up resilience: A survival analysis across business sectors in a time of crisis

Angelo Castaldo[1] | Rosanna Pittiglio[2] | Filippo Reganati[1] | Domenico Sarno[2]

[1]Department of Juridical and Economic Studies (DSGE), Sapienza University of Rome, Rome, Italy

[2]Department of Political Science "Jean Monnet", University of Campania "Luigi Vanvitelli", Caserta, Italy

Correspondence
Rosanna Pittiglio.
Email: rosanna.pittiglio@unicampania.it

Abstract

The presence of exogenous global shocks due to the 2007/2008 economic and financial crisis and the current global pandemic crisis are deeply hampering economic operators' overall ability to access credit. Small and medium-sized enterprises and start-ups are most severely affected by credit rationing. This paper investigates whether access to bank loans in the early stage of a start-up's lifecycle is a predictor of a firm's default in a time of economic crisis. We ground our analysis on a firm-level longitudinal data set of Italian new capital companies born from 2004 to 2006. Implementing a discrete-time proportional hazard model we study their likelihood of default up to 2014 after controlling for a consistent number of other firms, industry and innovation related characteristics. The main findings confirm that access to bank loans significantly enhances the resilience of Italian start-ups. By taking into consideration the sectoral degree of innovation where firms operate, we also find that bank financing still exerts a positive influence on firm survival in both less and more innovative industries. However, there is evidence of a stronger positive influence on of long-term debt on the survival of firms operating in low- and medium-low innovative industries.

KEYWORDS
access to external financing, bank loans, discrete-time proportional hazards, Italy, start-up business survival

1 | INTRODUCTION

Firms' access to bank credit has always played a crucial role in understanding the environmental factors that can influence the consolidation and growth of the productive structure of modern economies. For instance, the European Commission reports that European SMEs depend on banks for 70% of their external financing, compared to approximately 40% in the US (European Commission, 2017). In Italy, the share of SMEs that were reliant on banks for external financing was 86.6% in 2007 (ISTAT, 2011). It is therefore evident how bank financing becomes particularly relevant when considering firms in the early stages of their business cycle: start-ups are, in fact, a particularly risky customer for the bank to deal with, as they have no established credit history to show when applying for a loan.

Furthermore, another element that characterises both SME and start-up access to credit markets in several European countries is the lack of a well-developed risk capital market. In 2008, for example, Italy's venture capital investment as of percentage GDP (0.007) placed it seventh to last among European countries (only Hungary, Poland, Czechia, Romania, Greece and Bulgaria present a lower value).

It must be stressed that the strong dependence of SMEs on bank credit makes them more vulnerable during crises. In Italy, the precrisis level of bank financing, which was approximately 180 billion euros per quarter in 2008, halved in 2014, and remained roughly constant until 2018 (Castaldo, 2020). In fact, in times of financial turmoil, banks become more reluctant to lend (i.e., the credit crunch), while on the one hand, they will have less capacity to lend; on the other hand, the rising rate of business failure makes it increasingly difficult for banks to distinguish between creditworthy and noncreditworthy potential borrowers (Bernanke, 1983). In 2009, SMEs were the first to suffer from the global economic crisis because of depressed demand and financing constraints. Several authors (Deloof & Vanacker, 2018; Ma & Lin, 2010; Stelletto et al., 2017) have shown that in the presence of credit rationing, it is SMEs and start-ups that are more adversely affected due to their greater financial fragility than larger firms.

However, despite the great attention given to the survival of start-ups, there are only a limited number of studies on the relationship between access to bank financing and their survival. To date, the empirical literature has mainly focussed on the effects of total debt on the probability of survival of the firm (among many, Astebro & Bernhardt, 2003; Cole & Sokolyk, 2018; Musso & Schiavo, 2008; Wamba et al., 2017) and, to a lesser extent, on the effects of the duration of bank debt (Castaldo et al., 2020; Collett et al., 2014). In both cases, the results have been mixed with regard to the adopted empirical strategy and the country environment in which the analysis has been conducted. In addition, from a policy perspective, the importance of access to credit for investments and/or liquidity has induced national governments worldwide to implement a set of loan measures, such as direct lending, co-funding, interest rate subsidies, and public credit guarantee (PCG) schemes (Arping et al., 2010; Castaldo, 2020; Minelli & Modica, 2009).[1]

An issue that has not yet been adequately analysed in the previous empirical literature is to what extent the effect of bank credit on start-up survival depends on some specific sectoral characteristics.

[1]In Italy from 2010, for instance, the Central Guarantee Fund for facilitating the access to credit of SMEs has come into operation.

The presence of heterogeneity between and within sectors implies a continuous adaptation of firms to changing environmental conditions, which, on the one hand, increases the survival rate of those companies that are able to innovate and change rapidly and, on the other hand, increases the failure rate for companies lacking these capabilities. An interesting stream of literature on firm survival (Audretsch, 1995; Christensen, et al., 1998; Jensen et al., 2008) argues that the technological regime and market structure play an important role in explaining the variation in firm survival. In a similar vein, Suarez and Utterback (1995) found that survival is substantially affected by technological evolution. In addition, Christensen et al. (1998) argue that the combination of market and technological strategies is one of the major predictors for firm survival in the United States.

From our perspective, this implies that when considering access to bank credit, overall credit availability is strictly related to the potential and effective sectoral growth rate, thus resulting in heterogeneity across economic activities (Giannetti, 2019; Robson et al., 2013). Furthermore, as innovation is an effective driver of SME survival (Rosenbusch et al., 2011), the heterogeneity of innovation intensity between and within sectors, from a dynamic efficiency perspective, may explain the probability of start-up survival differently. That is, from our theoretical and empirical perspective, the effect exerted by the type of bank credit (short- and long-term) could be heterogeneous once exploring macro-sectoral innovation intensity.

Combining both strands of literature, the main aim of this study is to investigate whether access to bank loans in the early stage of a start-up's lifecycle is an effective predictor of a firm's default over time. In particular, the following research questions are addressed: what is the relationship between bank loan financing and start-ups' survival rates? Are there some differences, in terms of survival, between short- and long-term bank loan financing? Does the impact of bank financing differ between macro sectors of the Italian economy? To what extent does the impact of bank financing differ between sectors according to their degree of innovativeness?

To deal with these issues, firm-level data for three different cohorts of start-ups[2] established in 2004, 2005 and 2006 of more than 50,000 firms was used. The data span from 2007 to 2014 and cover all two-digit industries. The empirical analysis has been carried out using a discrete-time-dependent proportional hazard model where several firm- and industry-specific covariates were controlled for. In specifying the model, the total sample was first divided into the manufacturing and service sectors and the hypotheses for the two macro-sectors were tested separately. In addition, to address possible heterogeneity both within and between macro sectors in the effect of bank loan on start-ups' survival, the data were further broken down according to the degree of innovation intensity of the sector in which the start-ups were involved.

The study contributes to the literature as follows. First, unlike previous work, the relationship between bank debt and survival were tested by considering the impact of specific environmental factors. In particular, the differences in the resilience of start-ups were analysed due not only to the industrial heterogeneity of belonging to the manufacturing or service sector, but also to the different innovation intensity of the sectors in which start-ups operate. Second, this paper enriches previous studies (Deloof & Vanacker, 2018) of new firm survival in depressed and stagnant environments. Since the years observed range from 2007 to 2014, this analysis allows for observing the extent to which the exogenous shocks of the financial crisis and the sovereign debt crisis affected the relationship between bank financing and start-up survival. Third, the analysis focuses on the Italian context, which, for the research question raised, is a compelling case. In fact, Italy represents an important country study for

[2]In our analysis the start-ups are defined as new born companies over the years 2004–2006, identified among a population that excludes firms that are 100% owned subsidiaries of existing businesses, inherited from someone or purchased from existing businesses. Several restrictions were then imposed on the data.

at least four main reasons: (i) small and medium-sized firms represent the backbone of the economic system; and (ii) the specialisation model of Italian industry is notoriously oriented towards sectors defined as traditional and medium-low technology. This is an eccentric model compared to more advanced countries; nevertheless, this characteristic of the Italian system has not prevented it from growing thanks to the boost provided by incremental innovations on processes and product quality. (iii) The venture capital market is very immature, and, therefore, external funding is almost entirely provided by banks. From this, it follows that the frictions encountered by start-ups in accessing bank credit can significantly hamper their potential to operate and survive (static efficiency), on the one hand, and to innovate and scale up in the transition from new ventures to mature enterprises, on the other. (iv) The credit crunch originated by the global financial crisis (2007/2008) and the sovereign debt crisis (2011–2012), comparatively to other similar national economic systems in Europe (i.e., France and Germany), has hit the Italian economy more extensively and deeply.

The remainder of the paper is organised as follows. In Section 2, the related literature is reviewed and some hypotheses are proposed. Section 3 discusses the characteristics of the sample of firms and provides some descriptive statistics. Sections 4 and 5 outline the econometric model and the main empirical results. Section 6 provides some robustness analyses, and finally, Section 7 ends with some concluding remarks.

2 | LITERATURE REVIEW AND HYPOTHESES

The role that access to bank credit plays in determining firms' survival is well known in the academic literature (Ang, 1992; de Bettignies and Brander, 2007; Robb & Robinson, 2014). Since the pioneering work of Stiglitz and Weiss (1981), the literature agrees in identifying bank credit rationing as one of the crucial nodes limiting SME development and start-ups, in particular. Large companies are subject to disclosure requirements and balance sheet controls that facilitate the bank assessment of their capital strength and related loan riskiness. In contrast, SMEs tend to have less complete accounts, which makes the information asymmetry between potential borrowers and lenders more severe, resulting in less reliance on bank debt (Aristei & Angori, 2022; Deloof et al., 2019; Myers, 1984; Myers & Majluf, 1984).[3]

Moreover, starting with the seminal paper of Cressy (1996), a relevant part of the literature has empirically investigated the role of bank credit relative to both SMEs and start-ups' survival (Astebro & Bernhardt, 2003; Carter & Van Auken, 2006; Castaldo et al., 2020; Cole & Sokolyk, 2018; Cosh et al., 2009; Crepon & Duguet, 2003; Deloof & Vanacker, 2018; Wamba et al., 2017). However, as pointed out by Briozzo et al. (2016), the main findings are still, to some extent, puzzling.

On the one hand, several studies have empirically assessed an irrelevant role of access to bank credit on start-ups' resilience. Crepon and Duguet (2003), using a quasi-experimental design approach, evaluated the impact of bank loans and subsidies on the survival of 13,504 French start-ups. The main findings provide evidence that bank loans alone do not exert any significant effect on the survival rate of start-up companies. Cosh et al., 2009 implemented a multivariate Tobit and probit estimation on a sample of 2520 start-ups in the United Kingdom. Their results show that start-ups are always able to secure the desired level of external financing among different types of investors (banks, venture capital funds, leasing firms, and other sources) and that this element does not displace effects on their survival.

[3]SMEs and start-ups are exposed to higher information costs arising from these asymmetries.

On the other hand, other empirical studies found a positive correlation between total bank credit and start-up survival (Astebro & Bernhardt, 2003; Castaldo et al., 2020; Cole & Sokolyk, 2018; Wamba et al., 2017). Using a probit regression model for a sample of 738 United States start-ups over the period 1987–1991, Astebro and Bernhardt (2003) found that, although the correlation between having a bank loan and business survival is negative, having a bank loan is a ceteris paribus positive predictor of the survival of start-ups. Based on a sample of 7350 Cameroonian start-ups born between 1990 and 2008, Wamba et al. (2017) showed that both access to bank loans during the creation phase and the level of these loans have a positive impact on the probability of survival in the early years, but this effect fades over time. Using data from a survey (Kauffman Firm Surveys) of approximately 5000 start-ups founded in 2004 and interviewed annually from the start-up year (2004) to eight subsequent years (2005–2012), Cole and Sokolyk (2018) found that start-ups with higher bank debt in the early stages of business are significantly more likely to survive and achieve higher levels of revenue three years after the incorporation of the start-up. A more recent work, Castaldo et al. (2020), using a 2SLS regression method on 49,111 Italian start-ups born in 2003, 2004, and 2005, showed that, after controlling for firm characteristics and performance, the initial recourse to bank debt negatively influences their probability of default. Moreover, the authors found that the intensity of the effect exerted on survival is heterogeneous across the different levels of overall bank credit contracted by the firm.

The above discussion leads to the first hypothesis:

Hypothesis 1. The weight of overall bank credit available to start-ups significantly increases (or decreases) the likelihood of survival of the new entrepreneurial activity.

In addition, the type of bank credit (short-term vs. long-term) that start-ups have access to may also influence the probability of survival. However, the results of the theoretical and empirical literature do not seem to be unambiguous. On the one hand, since long-term bank loans allow for investments (tangible or intangible) with longer amortisation periods that can create an increase in the expected future cash flows, it is likely to assume that they exert a stronger positive influence on the survival of companies than short-term bank credit (Castaldo et al., 2020; Collett, et al., 2014); in addition, long-term bank relationships are also more cost-efficient given that interest rates are lower (Bodenhorn, 2003). For instance, applying a logit regression model to 228 Finnish SMEs, Collet et al. (2014), in studying the determinants of turnaround strategies, found that start-ups with low access to long-term credit financing are less able to strategically react to financial shortages, showing a higher probability of default. Additionally, in the aforementioned Castaldo et al. (2020), the recourse to long-term bank credit displaces a stronger effect over the start-ups survival probability with respect to the short-term bank credit.

On the other hand, short-term bank credit lines are more effective in securing the external liquidity essential to ensure the operational capacity of start-ups, thus enabling the company to be resilient over time (Mach & Wolken, 2011). In the presence of a credit crunch and economic-financial turbulence, the basic need to access ordinary liquidity bank credit loans becomes even more relevant for firms' resilience. In particular, Mach and Wolken (2011), implementing a logistic regression and a proportional hazard model approach on approximately 4000 United States small firms, found that credit-constrained firms were significantly more likely to go out of business than unconstrained firms. Given these considerations, the following further hypothesis is proposed:

Hypothesis 2. By considering the time horizon of bank financing, short-term bank credit weights show a greater (or lower) effect on the probability of start-ups' survival compared to the long term.

In the literature, several authors have focussed on the role of environmental conditions in influencing the risk of firm failure. For example, Mata and Portugal (1994) showed how the probability of default decreases with the increase in the firm's industry growth rate and market dynamics. An important source of heterogeneity in firm survival is the degree of sectoral innovation.

The analysis of the relationship between the degree of sectoral innovation and the survival probability of firms active in that sector can lead to ambiguous findings (Audretsch, 1995). On the one hand, in highly innovative sectors, firms are able to grow, discovering new products and exploiting new markets. There is consistent evidence that product and process innovations are important for both firms' growth and survival; even incumbent firms must continuously innovate to mitigate the disruptive threat of new technologies (Christensen, 1997). In particular, Cefis and Marsili (2006) found that sectors with a high intensity of technology, that is, science-based and specialised suppliers, are the most favourable environments for the survival of firms. However, on the other hand, it has been argued that the risk of exit may be higher for firms in high-tech sectors because of the uncertainty associated with innovation patterns (Ericson & Pakes, 1995).

Linking this discussion to our analysis, the effect exerted by access to bank credit could be heterogeneous once exploring macro-sectoral innovation intensity. The existence of information asymmetry might cause uncertainties in the market and cause firms that operate in high innovative sectors to suffer more from financial constraints with respect to firms operating in low innovative intensity sectors.

Moreover, even when considering the different combinations between short-term and long-term bank credit available to start-ups, the effect generated on survival could be heterogeneous with respect to the macro-sectoral innovation intensity. Indeed, by reversely exploiting previous arguments, start-ups operating in low innovation-intensive sectors, compared to firms operating in high-intensity sectors, more heavily need to rely on long-term investments to acquire tangible assets that are crucial for granting operational capacity and resilience. That is, when accounting for sectoral differences, long-run financial constraints are inversely related to the level of innovation intensity.
This leads to the following final hypotheses:

Hypothesis 3. In the high innovative sectors, the higher the incidence of bank credit availability, the higher the start-up survival, compared to the effect exerted in the low innovative sectors.

Hypothesis 4. In the low innovative sectors, the higher the incidence of long-term bank credit availability, the higher the start-up survival, compared to the high innovative sectors.

3 | DATA AND DESCRIPTIVE ANALYSIS

The empirical analysis included in this paper has been conducted using firm-level data from the AIDA database (Analisi Informatizzata Delle Aziende) provided by Bureau Van Dijk. AIDA collects annual balance sheets from Italian corporate companies and contains information on a wide set of economic and financial variables, such as sales, costs, employees, value added, start-up year, sector of activity at the five-digit ATECO 2007, as well as legal and ownership status. The 'legal status' variable indicates whether a firm is either active or inactive (i.e., in liquidation, dissolved or in receivership). However, since the inactive status could conceal an acquisition or a merger, or even a change in the firm's location in the middle of the period covered by the analysis, we supplemented this information with that of the Italian Business Register (ASIA) on the timing of the 'real' legal default of the firm's activity. In the ASIA register, all active firms that are inactive in both year $t + 1$ and year $t + 2$ are considered to have exited in year t (National Institute of Statistics—ISTAT, 2012). The comparison with the popu-

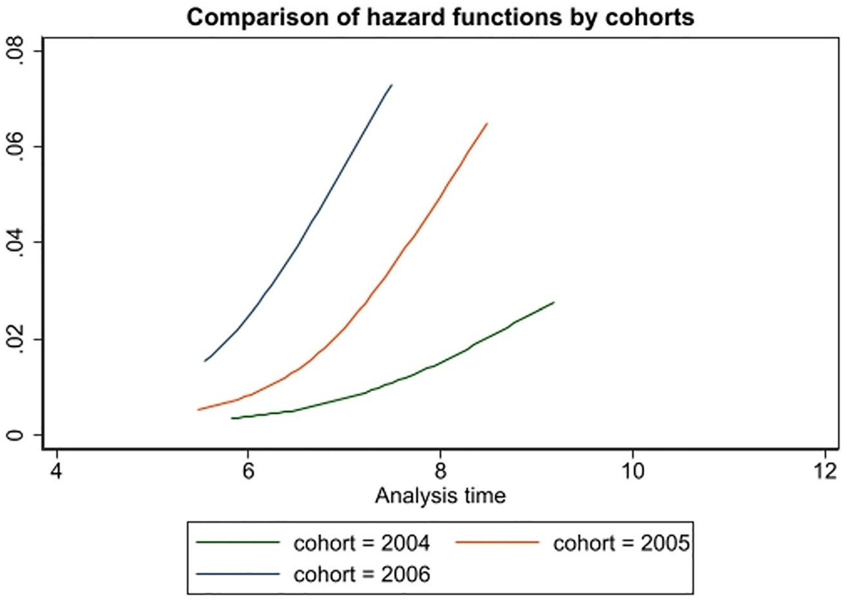

FIGURE 1 Hazard functions over the period 2007–2014 (2004–2005 and 2006 cohorts).

lation of active firms in the following 2 years is useful to exclude firms that could be reactivated. This paper uses three different cohorts of firms established between 1 January 2004 and 31 December 2006 and examines their likelihood of surviving for up to three years after birth (i.e., 2007 for 2004 cohort; 2008 for 2005 cohort and 2009 for 2006 cohort) to 31 December 2014. By considering the dynamics of start-ups from their third year of life, the focus of our analysis was only on those firms that have reached at least the early-stage phase.

By omitting all observations for which the necessary data are incomplete, an unbalanced panel of approximately 50,000 new firms was obtained for a total of approximately 120,000 observations, covering the years 2004–2014.[4] The selected cohorts span all two-digit Italian Standard Industrial Classification (ATECO 2007) industry classifications.

Before testing the relationship between bank loan and start-up survival, some descriptive statistics are provided. Figure 1 displays exit rates for our three cohorts. All cohorts show an increase in the failure rate from the fifth year. This is easily explained as it is from 2009 onwards that the Italian economy is most affected by the economic crisis. Furthermore, it can be observed that the firms born in 2004 show greater resilience. One possible explanation for this evidence may be linked to the fact that the latter completed the transition phase to break even before the onset of the effects of the 2007/2008 economic crisis. That is, at the stage when start-ups are most fragile, the 2004 cohort suffered relatively less than the other two from the enhancement of restrictions to access to bank credit.

Figure 2 shows hazard rates by macro-sector of economic activity. In line with ISTAT (2016), we found that the failure rates of start-ups are considerably higher in services than in manufacturing. This

[4]Our dataset is representative of the entire population of Italian firms. Regarding the 2004 cohort, for instance, approximately 64% of start-up firms survived up to 2009 compared with 50.5% reported by ISTAT. This difference is because ISTAT considers all Italian firms (including individual firms), whereas AIDA collects information mainly on those types of Italian firms which typically have a higher survival probability, namely, public limited companies (Società per azioni, S.p.a.), private limited companies (Società a responsabilità limitata, S.r.l.), and partnerships limited by shares (Società in accomandita per azioni, S.a.p.a.).

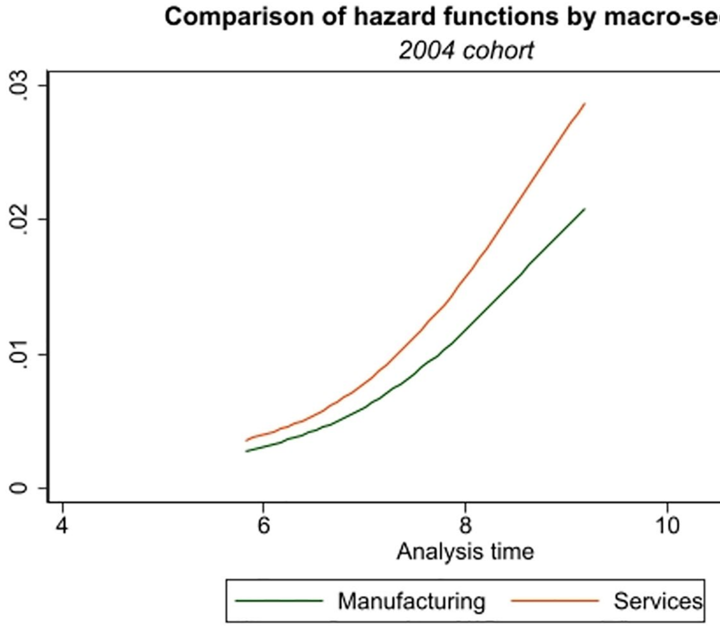

FIGURE 2 Hazard functions over the period 2007–2014 (2004 cohort).

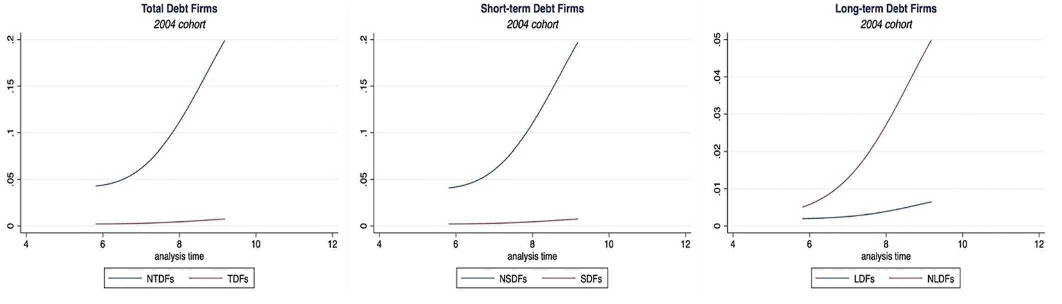

FIGURE 3 Comparison of hazard functions by debt duration (2004 cohort).

higher vulnerability of service start-ups is much more evident after the sixth year of their existence, whereas the likelihood of default is about the same for both during the first years. A similar picture is confirmed for the other two cohorts.

In Figure 3, we compare the survival pattern between leveraged (i.e., those with bank debt) and unleveraged start-ups. In particular, the left panel plots the hazard rates of start-ups with bank loans (TDFs) and those without (NTDFs), the central panel displays the failure rate of start-ups that have short-term debts with banks (SDFs) or those with no bank debt (NSDFs), and the right panel shows the hazard rates of start-ups with (LDFs) and without long-term leverage with banks (NLDFs).

An inspection of the hazard rates of Figure 3 provides several interesting points. First, it makes it clear that the chances of failure are always remarkably higher for those firms without bank loans. Second, whereas the likelihood of firm survival in the beginning years is about the same for both leveraged and unleveraged firms, after 6 years the likelihood of going out of business is relatively higher for the unleveraged firms.

4 | THE ECONOMETRIC METHODOLOGY

4.1 | The model

This empirical work was carried out by using survival methods and, in particular, a multivariate analysis based on the semiparametric Cox Proportional Hazards Model (CPHM, Cox, 1972).[5] Developed in the medical field, these techniques have been widely used in finance and economics with reference to the survival patterns of start-ups (Audretsch & Mahmood, 1995; Boyer & Blazy, 2014; Cole & Sokolyk, 2018; Santarelli, 2000). They allow for the consideration of both the occurrence of an event (i.e., whether a firm exits) and the timing of the event (that is, when the exit takes place) by properly controlling for a few firm- and industry-related characteristics that may be associated with the survival probabilities.

Although firm survival occurs in a continuous time, our data come in a discrete form, that is, on a yearly basis. Thus, a firm's spell length is observed only in intervals of 1 year of length, that is, from its birth year to the end of the jth year, at which the firm's spell is either complete (the firm turns out to exit) or right censored (the firm exits the sample without experiencing the event).

Given the discrete nature of the duration variable, a discrete time representation of an underlying continuous time CPHM is required (Jenkins, 2005). Following Prentice and Gloeckler (1978) and Allison (1982), we estimated a discrete time duration model with time-varying covariates. We choose to follow this econometric strategy rather than the more common CPHM or probit model because these modes do not easily incorporate time-varying covariates and unobserved heterogeneity.

The discrete-time hazard function of each firm (i.e., the probability of exit in the jth interval for a firm that has survived up to interval $j - 1$) is given by:

$$h(j, X) = 1 - \exp\left[-\exp\left(b'X + \gamma_j\right)\right] \tag{1}$$

where γ_{j} is the baseline hazard rate for the jth interval; X represents a vector of firm and industrial covariates that affect firm survival; and b denotes the vector of parameters to be estimated.

The complementary log–log transformation of this function (cloglog model) is:

$$\log(-\log(1 - h(j, X))) = b'X + \gamma_j \tag{2}$$

The cloglog model has several advantages over more conventional event duration models. First, the parameter γ_j depends on j but not on X and it gives information about the duration dependence in the interval hazard that is assumed to be common to all firms. Moreover, this model specification utilises a panel data structure that can easily accommodate both time-varying and time-constant variables.

Although the discrete cloglog specification imposes no prior restrictions on the function form of the baseline hazard function, to proceed with the estimation, γ_j must be specified. Here, the baseline hazard is specified using a set of γ_j time dummies. Our complementary log-log model was estimated using the cloglog command developed in Stata.

[5]As pointed out in Section 2, empirical works that have addressed the issue of the effects of bank credit on the survival of start-ups are few and have used different econometric techniques. In particular, Wamba et al. (2017) used a logistic regression model, while Castaldo et al. (2020) adopted a 2SLS regression approach. To the best of our knowledge, only one study (Cole & Sokolyk, 2018) has addressed a similar issue using a Cox proportional hazards model. However, different from our approach, the analysis did not exploit the difference between short- and long- term bank debt. Moreover, Cole and Sokolyk (2018) unfold their analysis on a very limited sample of start-ups (4928 firms, with data retrieved by the Kauffman Firms Survey), while our method is applied on the entire population of start-ups born in 2004, 2005 and 2006.

To interpret the estimates, a statistically significant hazard ratio lower (higher) than one implies that the hazard rate decreases (increases) and the corresponding probability of survival increases (decreases), other things being equal.

4.2 | The variables

To test the hypotheses outlined in Section 2 above, the following set of variables was used.

4.2.1 | Key strategic variables

In our empirical analysis, three indicators were used that reflect bank debt financing: (i) the firms' total bank debt on total debt (Debt_TOT), (ii) the firms' ratio of short-term bank debt on total short-term debt (Debt_ST), and (iii) the firms' ratio of long-term bank debt on total long-term debt (Debt_LT). All variables are expressed in natural logarithm. We are conscious that there may be other outside financing channels other than bank credit (i.e., venture capital funds, trade customers and suppliers, and private individuals); however, as mentioned earlier, Italy is a strongly bank-centric country, and bank credit is the almost exclusive type of external financing for companies. Moreover, with regard to external financing sources, Aida only provides information on bank debt without distinguishing either the nature (private/public) or the type of banks (commercial or cooperative).

4.2.2 | Firm-specific control variables

With regard to firm-specific determinants that might affect start-ups' survival, first firm size (SIZE) was considered. Several studies provide evidence that firm size is negatively correlated with the hazard rate of firm exit (Audretsch & Mahmood, 1994; Esteve Pérez & Mañez Castillejo, 2008; Mata & Portugal, 1994; Segarra & Callejon, 2002). Some arguments may explain this result: (i) the output levels of smaller start-ups are further away from the minimum efficient scale required to operate efficiently in the market; (ii) smaller start-ups face a higher risk of insolvency and illiquidity due to more difficult access to capital markets; and (iii) smaller start-ups are less capable of recruiting qualified workers. Size (L_SIZE) is measured by the natural logarithm of each firm's employment. Moreover, to allow for nonlinearities, the square of firm size (L_SIZE_SQ) was also introduced in the model.

Furthermore, empirical analysis found that legal status at birth matters for firm survival. For example, Harhoff et al. (1998) found that limited liability as a legal form is positively correlated with firm exit, while Mata and Portugal (1994) and Esteve Pérez and Mañez Castillejo (2008) argued that firms adopting unlimited liability experience more bankruptcies. In our analysis, firms' legal status at birth is controlled for by a set of dummy variables, namely, (i) public limited companies (Società per azioni, S.p.a.), (ii) private limited companies (Società a responsabilità limitata, S.r.l.), (iii) partnerships limited by shares (Società in accomandita per azioni, S.a.p.a.), and (iv) other legal status (i.e., Consortia and Cooperatives).

Finally, a set of duration dummies have been included in the empirical model to measure the age after the firm's birth. Several empirical studies (Ericson & Pakes, 1995; Jovanovic, 1982) found that older firms have lower hazard rates than their younger counterparts since older firms could benefit from experience, reputation and built business relationships. On the other hand, younger firms are more likely to survive as they are more flexible, less bureaucratic and more entrepreneurial in seeking market opportunities (Barron et al., 1994). Here, young firms were expected to have a higher risk of failure than older ones because of their opacity, particularly within the financial and labour markets, which makes it difficult for them to adequately procure financing and capabilities. Moreover, Esteve Pérez and Mañez Castillejo (2008) found that the relationship between age and firm exit follows a “U” shape—initially high, but lower afterwards, before becoming high again. This can be explained by the fact that the firms' stock of knowledge increases with time but at a decreasing rate, and the relationship between age and survival might not be monotonic.

4.2.3 | Industry-specific control variables

The degree of market competition (CONC) is measured by the logarithm of the Herfindahl index. The expectation of the effect of market concentration on survival is not clear-cut. On the one hand, firms in highly concentrated markets may be subject to fierce aggressive behaviour by rivals with monopolistic power, which may reduce the chances of new venture survival (Mata & Portugal, 1994; Strotmann, 2007). On the other hand, higher market concentration may lead to higher price-cost margins, which increase a plant's probability of survival (Audretsch, 1995; Segarra & Callejon, 2002). Moreover, as pointed out by Audretsch (1995), the probability of survival for young companies is highly heterogeneous across business sectors. The hypothesis is that the provision of bank credit is related to the potential and effective sectoral growth rate and is thus heterogeneous across economic activities (Giannetti, 2019; Robson et al., 2013). Therefore, we include dummy variables at the two-digit NACE sectoral level to control for unobserved heterogeneity in the economic activity sectors.

Finally, the model includes a set of regional dummies (REG) at the NUTS-2 level to control for unobserved heterogeneity at the geographical level and some dummy variables for the three cohorts to control for the influence of the business cycle.

The summary statistics of the covariates are reported in Table A1 in the Appendix.

5 | ECONOMETRIC RESULTS

Our empirical strategy follows three steps. First, a baseline model is presented where we analyse the impact of banking financing considering debt duration (short- vs. long-term debt). Second, separate regressions were run for manufacturing and services industries to determine whether firms respond in different ways according to the macro-sectors where they operate. Finally, whether the propensity for firm survival varies systematically across industries according to their degree of innovation intensity was examined.

5.1 | Baseline model

As a starting point for the analysis, a discrete time complementary log–log model, without controlling for unobserved heterogeneity, was estimated. Table 1 reports the hazard ratios and the associated robust standard errors, which are adjusted for clustering at the firm level. The Wald test provides satisfactory support for model specifications. The first column presents estimates where the total bank debt of the start-up was considered, and the second and third columns report the hazard ratios of start-ups that have access to either short- or long-term bank financing, respectively.

Looking at Column 1, it can be see that the hazard ratio for total bank debt is lower than 1 and statistically significant at the 1% level. This means that Italian start-ups with an increasing weight of bank

TABLE 1 Estimation results: Discrete Cox proportional hazard regression model.

Variables	(1) Total debt	(2) Short-term debt	(3) Long-term debt
Debt_TOT	0.793***		
	(0.00301)		
Debt_ST		0.781***	
		(0.00303)	
Debt_LT			0.876***
			(0.00373)
LSIZE	0.215***	0.213***	0.0829***
	(0.0137)	(0.0135)	(0.00470)
LSIZE_sq	1.225***	1.228***	1.316***
	(0.0173)	(0.0172)	(0.0184)
LHI_4	0.999	0.997	1.017
	(0.0324)	(0.0320)	(0.0324)
D1	0.0118***	0.0118***	0.00723***
	(0.00179)	(0.00178)	(0.00103)
D2	0.00664***	0.00661***	0.00546***
	(0.00116)	(0.00115)	(0.000893)
D3	0.00218***	0.00217***	0.00293***
	(0.000474)	(0.000473)	(0.000598)
D4	0.000979***	0.000968***	0.00159***
	(0.000239)	(0.000237)	(0.000379)
D5	0.0374***	0.0372***	0.0655***
	(0.00306)	(0.00304)	(0.00471)
D6	0.129***	0.129***	0.179***
	(0.00926)	(0.00919)	(0.0119)
D7	0.507***	0.506***	0.601***
	(0.0328)	(0.0325)	(0.0378)
Constant	3.943***	3.929***	3.445***
	(0.889)	(0.881)	(0.740)
Legal status dummies	YES	YES	YES
Sector dummies	YES	YES	YES
Cohorts dummies	YES	YES	YES
Regions dummies	YES	YES	YES
Observations	118,473	118,465	118,390
Log likelihood	−7632.83	−7655.84	−9809.20
Wald test	8758	8775	7093

Note: Robust standard errors in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

loans have an approximately 20% decreased risk of failure. Our finding does fully confirm Hypothesis 1 and is in line with previous studies (Castaldo et al., 2020; Cole & Sokolyk, 2018; Wamba et al., 2017).

By splitting bank credit according to its duration, we found that a higher level of both short-term and long-term debt reduces the risk of exit. Moreover, our estimates show that the impact of short debts is greater than that of long debts. In fact, a 1% increase in the weight of the short-term bank debt reduces the exit rate by 22%, while the share of the long-term bank debt reduces by approximately 12%.

This finding is not surprising considering the empirical evidence of the effect of financial constraints on Italian SMEs (Butzbach & Sarno, 2019; Donati & Sarno, 2014; Sarno, 2005, 2008). That is, financial constraints are more relevant for carrying out operational activities than for investments. This is especially true for start-ups, for which the business plan makes investment financing less difficult than financing needs arising from ordinary operating activities.[6] Moreover, in the period under observation—characterised by the 2007–2008 economic and financial crisis—this effect was exacerbated, making the need for young companies to acquire working capital and liquidity to finance their current activities even more serious.

Obtaining insights into the extent of the effect of access to credit banks on the probability of exit might differ between macro-sectors. For this reason, the model has been estimated for both manufacturing and services separately. In particular, Columns (1–2) of Table 2 show our estimates on Italian start-ups' survival for manufacturing sectors (MAN) corresponding to ATECO-2007 10–39, while Columns (3–4) show those for service sectors (SERV) corresponding to ATECO-2007 40–74.

Looking at our strategic variables (Debt_ST and Debt_LT), we found that access to bank financing exerts a positive effect on firm survival, both in manufacturing and in services. In particular, a robust and expected finding across the four different samples was that the higher the level of debt, the lower the risk of market exit. The hazard ratios for bank debts were always less than one and statistically significant at the 1% level across all specifications. Thus, Hypothesis 1 is still confirmed regardless of the macro-sectors in which the companies operate. Reliance on credit regardless of duration has a greater impact on survival in manufacturing. This reaffirms that, generally, the financing needs for manufacturing start-ups are larger because the operating scale is greater and consequently the financing demand is higher, especially for banking loans. Furthermore, short-term bank credit lowers the probability of exit more than long-term credit, and once again, Hypothesis 2 is confirmed. The econometric findings show that this result has a stronger magnitude for firms operating in the manufacturing industry: a 1% increase in the incidence of short (long) term debt reduces the risk of exit from the market in the manufacturing sector by 23% (15%), while a 1% increase in the incidence of short (long) term debt reduces the risk of exit from the market in the service sector by 21% (12%). With respect to previous works, in which the effects of bank credit between macro-sectors were not explicitly analysed, our estimates show that even when investigating macro-sectoral heterogeneity, the results obtained in the baseline seem to be generalisable.

Turning to firm- and industry-specific control variables, firm size has a significant nonlinear effect on survival. A hump-shaped relation emerges between survival and firm size, confirming the results of previous studies (Esteve Pérez & Mañez Castillejo, 2008; Strotmann, 2007). Up to a certain threshold, an increase in start-up size increases the chances of survival, in line with the liability of smallness hypothesis (Audretsch & Mahmood, 1995; Esteve Pérez & Mañez Castillejo, 2008; Mata & Portugal, 1994). Above that threshold, however, the advantages of having a larger start-up size

[6]It must also be considered that generally, in all industrialised countries, start-ups rely on laws and tools that make investment financing less difficult, whereas assistance for operational activities is less frequent and, where appropriate, limited to the first years of the business.

TABLE 2 Estimation results by macro-sectors: discrete Cox proportional hazard regression model.

Variables	(1) Short-term debt MAN	(2) Long-term debt MAN	(3) Short term debt SERV	(4) Long-term debt SERV
Debt_ST	0.775***		0.793***	
	(0.00739)		(0.00333)	
Debt_LT		0.854***		0.881***
		(0.00896)		(0.00411)
LSIZE	0.190***	0.0649***	0.216***	0.0852***
	(0.0308)	(0.00712)	(0.0151)	(0.00536)
LSIZE_sq	1.271***	1.404***	1.225***	1.310***
	(0.0529)	(0.0351)	(0.0181)	(0.0191)
LHI_4	0.897**	0.887**	1.065	1.098**
	(0.0480)	(0.0484)	(0.0420)	(0.0416)
D1	0.0283***	0.0147***	0.00888***	0.00568***
	(0.00860)	(0.00425)	(0.00157)	(0.000941)
D2	0.00962***	0.00821***	0.00575***	0.00476***
	(0.00388)	(0.00306)	(0.00112)	(0.000869)
D3	0.00282***	0.00348***	0.00197***	0.00271***
	(0.00148)	(0.00175)	(0.000473)	(0.000608)
D4	0.00177***	0.00286***	0.000791***	0.00131***
	(0.000868)	(0.00136)	(0.000224)	(0.000364)
D5	0.0578***	0.0954***	0.0324***	0.0579***
	(0.0106)	(0.0152)	(0.00298)	(0.00472)
D6	0.181***	0.222***	0.116***	0.167***
	(0.0286)	(0.0332)	(0.00933)	(0.0124)
D7	0.613***	0.698**	0.480***	0.577***
	(0.0879)	(0.101)	(0.0345)	(0.0402)
Constant	5.180***	5.941***	2.347***	1.348
	(1.837)	(2.074)	(0.537)	(0.300)
Legal status dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Region dummies	YES	YES	YES	YES
Observations	32,251	32,229	86,183	86,130
Log likelihood	−1548.24	−1946.00	−6076.25	−7827.72
Wald test	2547	1926	6508	5391

Note: Robust standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

decrease. The size of this effect is greater for firms with a higher incidence of long-term bank debt regardless of the sector in which they operate. In manufacturing, the degree of industry concentration has a significant and positive effect on survival. In contrast, Audretsch and Mahmood (1995) found that new firms in highly concentrated manufacturing sectors are subject to stronger competition by incumbents and, therefore, are more likely to exit the market. However, our findings reveal that start-ups might have an increase in survival due to their higher capabilities (with respect to incumbents) in adapting to future market dynamics. The coefficients of the duration dummies are significant and suggest that the likelihood of exit increases over time but then starts to decrease after the 6-year period. This finding supports the liability of adolescence hypothesis (vis-à-vis the 'pure' liability of newness hypothesis), as in Strotmann (2007).

5.2 | Industrial degree of innovation

In the baseline estimations, we found that bank credit, both as a whole and in its time differentiation, positively impacts the survival of start-ups regardless of the macro-sector in which the companies operate. However, as mentioned earlier, an issue that has not yet been adequately analysed in the empirical literature is the extent to which the effect of bank credit on the survival of start-ups depends on specific sectoral characteristics and, in particular, on the varying degree of innovativeness of sectors.

Our model was then re-estimated by disaggregating the manufacturing and service sectors according to their degree of sectoral innovation. Specifically, manufacturing and service sectors were aggregated into (i) high-innovative industries and (ii) low-innovative industries. To classify sectors, sectoral-level data provided by ISTAT concerning the share of innovative enterprises in the total number of a specific industry was used. A sector is classified as innovative (noninnovative) if the share of innovative enterprises in the total is higher (lower) than the average of the reference macro-sector (manufacturing or services). For a detailed list of these industries along with their ATECO 2007 codes, see Table A2 in the Appendix.

The estimates in Tables 3 and 4 reveal that, when controlling for innovation intensity, start-ups' access to bank credit reduces the risk of exit.

However, our findings show that bank financing incidence relative to start-ups belonging to higher innovative industries, ceteris paribus, impacts their survival probability more strongly with respect to low-innovative industries start-ups. That is, for firms that compete in highly dynamic contestable markets, access to external financing more effectively expands their ability to face global market outlets. This evidence provides a sounding confirmation of Hypothesis 3.

Moreover, some interesting results emerge when the effects of bank credit according to its duration was considered. In this respect, for firms operating in the most innovative sectors, it is confirmed that the impact of the incidence of short-term debt on survival is greater than that of long-term debt. This is especially the case for manufacturing start-ups, where a 1% increase in the share of debt financing lowers the probability of exit by 24% in manufacturing and by 14% in services. On the other hand, regarding the less innovative sectors, our results indicate that it is long-term debt that has a greater impact on firm survival regardless of the macro sector in which they operate. These findings provide confirmation to Hypothesis 4, implying that when accounting for industrial innovativeness differences, long-run financial constraints are more significant in the increase of firms' innovation intensity.

By considering other firm- and industry-specific controls, we found that the results are generally in accordance with expectations and are similar to those obtained in the more aggregate analysis.

TABLE 3 Estimation results by manufacturing: discrete Cox proportional hazard regression model.

Variables	(1) Short-term debt MAN-HI	(2) Long-term debt MAN-HI	(3) Short-term debt MAN-LI	(4) Long-term debt MAN-LI
Debt_ST	0.763***	0.779***		
	(0.0137)	(0.00882)		
Debt_LT			0.863***	0.849***
			(0.0158)	(0.0109)
LSIZE	0.248***	0.174***	0.0588***	0.0677***
	(0.0877)	(0.0321)	(0.0116)	(0.00922)
LSIZE_sq	1.191*	1.300***	1.419***	1.397***
	(0.118)	(0.0592)	(0.0645)	(0.0440)
LHI_4	0.945	0.871**	0.864	0.891*
	(0.0919)	(0.0611)	(0.0836)	(0.0594)
D1	0.0224***	0.0316***	0.00976***	0.0174***
	(0.0126)	(0.0114)	(0.00536)	(0.00594)
D2	0.00425***	0.0133***	0.00396***	0.0106***
	(0.00352)	(0.00625)	(0.00311)	(0.00457)
D3	0.00223***	0.00317***	0.00292***	0.00363***
	(0.00189)	(0.00213)	(0.00238)	(0.00233)
D4	0.00210***	0.00132***	0.00359***	0.00202***
	(0.00145)	(0.000980)	(0.00235)	(0.00147)
D5	0.0390***	0.0695***	0.0719***	0.107***
	(0.0123)	(0.0157)	(0.0199)	(0.0211)
D6	0.151***	0.199***	0.186***	0.236***
	(0.0395)	(0.0398)	(0.0472)	(0.0446)
D7	0.618**	0.613***	0.693	0.698*
	(0.145)	(0.112)	(0.162)	(0.130)
Constant	2.992*	5.495***	5.838***	5.182***
	(1.862)	(2.202)	(3.567)	(2.103)
Legal status dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Region dummies	YES	YES	YES	YES
Observations	12,020	20,224	12,019	20,203
Log pseudo-likelihood	−535.21	−1022.62	−679.82	−1257.41
Wald test	890	1744	686	1278

Note: Robust standard errors in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 4 Estimation results by services: discrete Cox proportional hazard regression model.

Variables	(1) Short-term debt SERV-HI	(2) Long-term debt SERV-HI	(3) Short-term debt SERV-LI	(4) Long-term debt SERV-LI
Debt_ST	0.793***	0.790***		
	(0.00461)	(0.00499)		
Debt_LT			0.904***	0.851***
			(0.00520)	(0.00690)
LSIZE	0.212***	0.184***	0.0761***	0.0756***
	(0.0235)	(0.0177)	(0.00668)	(0.00637)
LSIZE_sq	1.293***	1.230***	1.431***	1.306***
	(0.0325)	(0.0239)	(0.0265)	(0.0214)
LHI_4	1.122**	0.991	1.185***	0.993
	(0.0534)	(0.0697)	(0.0520)	(0.0677)
D1	0.00445***	0.0191***	0.00336***	0.00992***
	(0.00115)	(0.00451)	(0.000800)	(0.00226)
D2	0.00327***	0.0105***	0.00323***	0.00717***
	(0.000895)	(0.00292)	(0.000814)	(0.00192)
D3	0.00112***	0.00350***	0.00177***	0.00420***
	(0.000386)	(0.00118)	(0.000563)	(0.00134)
D4	0.000586***	0.000981***	0.00107***	0.00148***
	(0.000214)	(0.000454)	(0.000379)	(0.000676)
D5	0.0186***	0.0557***	0.0368***	0.0902***
	(0.00260)	(0.00681)	(0.00456)	(0.00973)
D6	0.0810***	0.171***	0.124***	0.228***
	(0.00971)	(0.0184)	(0.0136)	(0.0230)
D7	0.394***	0.585***	0.500***	0.668***
	(0.0419)	(0.0570)	(0.0491)	(0.0665)
Constant	2.663***	2.865***	1.142	1.923*
	(0.786)	(0.995)	(0.293)	(0.663)
Legal status dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Region dummies	YES	YES	YES	YES
Observations	45,101	41,082	45,077	41,053
Log pseudo-likelihood	−3198.37	−2820.72	−4180.86	−3575.27
Wald test	3085	3618	2775	2649

Note: Robust standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6 | ROBUSTNESS

In this section, some additional robustness checks on the results shown in Table 2 were performed.

6.1 | Unobserved heterogeneity

A potential source of bias in discrete-time hazard models is the presence of individual unobserved heterogeneity (or frailty), arising when idiosyncratic risk factors influence the duration. The failure to control for unobserved individual heterogeneity can produce severe biases in the estimates of the parameters associated with both duration dependence and explanatory variables (Heckman & Singer, 1984). Unobserved heterogeneity was accommodated with the inclusion of a multiplicative error term (v) in the hazard function:

$$h(j, X, v) = 1 - \exp\left[-\exp\left(b' X + \gamma_j\right) v\right] \tag{3}$$

where $v > 0$ is a normally distributed ($v \sim N(m, \sigma 2)$) individual random effect that scales the non-frailty component.

Thus, the cloglog transformation of Equation (3) is given by:

$$\log(-\log(1 - h\,(j, X, v)) = b' X + \gamma_j + u \tag{4}$$

where

$$u = \log(v) \tag{5}$$

As a final consideration, it must be pointed out that although the random effects cloglog Model (4) allows one to control for unobserved heterogeneity, it still presents some limitations due to the assumption of orthogonality between unobserved heterogeneity and the explanatory variables, which is typical of any random effects model. Therefore, the econometric results based on this assumption must be interpreted with caution because they cannot be fully understood as causal relations. The model is estimated using the xtclolog command of Stata.

In the random effects cloglog models, the relative importance of unobserved individual heterogeneity is indicated by the parameter ρ, which measures the share of individual variation in the hazard rate due to unobserved factors. In the estimates of Table 5, unobserved heterogeneity ("frailty") is unimportant only for the specification in Column (1) since the likelihood ratio test cannot reject the null hypothesis of $\rho = 0$.

Substantially, the results (see Table 5) from the recloglog model are similar to those presented above, lending support to both Hypotheses 1 and 2.

6.2 | Reverse causation

Another possible concern when using time-varying variables is that the results might suffer from reverse causation bias. That is, the duration process influences the values of a variable that in turn drives the duration. As a solution to address this problem, we estimate our baseline model by dropping the time varying portion from our time-varying covariates. In other words, for all time-varying covariates, we used their initial value, thus ignoring their variations over time.

TABLE 5 Estimation results: random effects version of the cloglog model.

Variables	(1) Short-term debt MAN	(2) Long-term debt MAN	(3) Short term debt SERV	(4) Long-term debt SERV
Debt_ST	0.775***		0.786***	
	(0.00918)		(0.00362)	
Debt_LT		0.853***		0.869***
		(0.00948)		(0.00483)
LSIZE	0.190***	0.0622***	0.197***	0.0553***
	(0.0436)	(0.00903)	(0.0145)	(0.00531)
LSIZE_sq	1.271***	1.413***	1.243***	1.400***
	(0.0624)	(0.0441)	(0.0203)	(0.0273)
LHI_4	0.897**	0.886**	1.067	1.114**
	(0.0476)	(0.0513)	(0.0433)	(0.0476)
D1	0.0283***	0.0140***	0.00756***	0.00337***
	(0.0118)	(0.00439)	(0.00129)	(0.000626)
D2	0.00962***	0.00783***	0.00477***	0.00285***
	(0.00517)	(0.00311)	(0.000875)	(0.000559)
D3	0.00282***	0.00331***	0.00158***	0.00155***
	(0.00186)	(0.00173)	(0.000351)	(0.000360)
D4	0.00177***	0.00270***	0.000629***	0.000732***
	(0.00111)	(0.00134)	(0.000182)	(0.000219)
D5	0.0578***	0.0910***	0.0271***	0.0362***
	(0.0203)	(0.0165)	(0.00297)	(0.00439)
D6	0.181***	0.216***	0.105***	0.128***
	(0.0444)	(0.0350)	(0.00944)	(0.0120)
D7	0.613***	0.692**	0.464***	0.519***
	(0.0972)	(0.103)	(0.0334)	(0.0374)
Constant	5.179***	6.403***	2.610***	1.674**
	(2.438)	(2.578)	(0.625)	(0.428)
Legal status dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Region dummies	YES	YES	YES	YES
Observations	32,251	32,229	86,183	86,130
Log pseudo-likelihood	−1548.24	−1949.86	−6067.35	−7798.40
Wald test	1359	949	4591	2521

Note: Robust standard errors in parentheses.

$***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

TABLE 6 Estimation results: discrete Cox proportional hazard regression model with time-invariant covariates.

Variables	(1) Short-term debt MAN	(2) Long-term debt MAN	(3) Short term debt SERV	(4) Long-term debt SERV
Debt_ST	0.882***		0.951***	
	(0.0158)		(0.00899)	
Debt_LT		0.984**		1.000
		(0.00615)		(0.00309)
LSIZE	0.543***	0.538***	0.530***	0.505***
	(0.0746)	(0.0762)	(0.0307)	(0.0290)
LSIZE_sq	1.078**	1.059*	1.085***	1.086***
	(0.0325)	(0.0331)	(0.0130)	(0.0131)
LHI_4	0.944	0.951	0.975	0.980
	(0.0566)	(0.0570)	(0.0383)	(0.0382)
D1	0.0123***	0.0128***	0.00631***	0.00635***
	(0.00346)	(0.00362)	(0.000979)	(0.000986)
D2	0.00691***	0.00713***	0.00508***	0.00510***
	(0.00251)	(0.00260)	(0.000889)	(0.000893)
D3	0.00346***	0.00357***	0.00312***	0.00302***
	(0.00170)	(0.00176)	(0.000680)	(0.000668)
D4	0.00346***	0.00357***	0.00162***	0.00163***
	(0.00161)	(0.00166)	(0.000445)	(0.000447)
D5	0.143***	0.145***	0.0792***	0.0790***
	(0.0212)	(0.0214)	(0.00573)	(0.00572)
D6	0.274***	0.276***	0.196***	0.196***
	(0.0407)	(0.0410)	(0.0136)	(0.0136)
D7	0.826	0.825	0.617***	0.617***
	(0.123)	(0.123)	(0.0421)	(0.0422)
Constant	1.144	0.278***	0.374***	0.211***
	(0.476)	(0.0981)	(0.0973)	(0.0503)
Legal status dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Region dummies	YES	YES	YES	YES
Observations	32,254	32,220	86,170	86,086
Log pseudo-likelihood	−2893.45	−2912.31	−10202.99	−10188.98
Wald test	1269	1215	4909	4833

Note: Robust standard errors in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The reverse causation analysis (see Table 6) provides further robustness to the results of the baseline models. Hypotheses 1 and 2 are confirmed, with the only exception of long-term bank credit that in the service sector, although not statistically significant, holds a neutral effect on the probability of survival. When accounting for the risk of reverse causation, in contrast to manufacturing start-ups, the results seem to suggest that the long-run investments for start-ups belonging to the service sector that are promoted thanks to access to long-term bank loans are not decisive factors in determining the resilience capacity of the new entrepreneurial activity.

6.3 | Differences by firm size

Access to bank credit may be easier for large start-ups than for small ones. If small firms are less likely to have access to bank financing than large firms, they might be especially vulnerable to drops in demand. Therefore, it is expected that as bank credit increases, the impact on survival for small companies will be greater than that on large companies.

To see whether this is the case, our model was re-estimated by dividing the sample into two groups according to the number of employees at birth: small start-ups (firms with fewer than 20 employees) and medium-large start-ups (firms with more than 20 employees).[7] The results in Tables 7 and 8 (full set of results are presented in Appendix Table A3) indicate that there do not appear to be any substantial differences from the estimates in the baseline model: both hypotheses (1 and 2) on the effects of

TABLE 7 Estimation results: discrete Cox proportional hazard regression model. Small-sized firms.

Variables	(1) MAN_short	(2) SERV_short	(3) MAN_long	(4) SERV_long
Debt_ST	0.774***	0.794***		
	(0.00771)	(0.00337)		
Debt_LT			0.848***	0.880***
			(0.00949)	(0.00418)
Constant	4.262***	2.298***	5.669***	1.442
	(1.597)	(0.560)	(2.046)	(0.339)
Firm level controls	YES	YES	YES	YES
Duration dummies	YES	YES	YES	YES
Legal status dummies	YES	YES	YES	YES
Sector/Industrial dummies	YES	YES	YES	YES
Cohorts dummies	YES	YES	YES	YES
Regions dummies	YES	YES	YES	YES
Observations	27,360	81,078	27,344	81,025
Log pseudolikelihood	−1445.61	−5959.78	−1822.40	−7638.88
Wald	2275	6237	1801	5564

Note: Robust standard errors in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

[7]We have also estimated this model by changing the classification of start-up size (small 0–49, medium-large >50). The estimation results hold and are available upon request.

TABLE 8 Estimation results: discrete Cox proportional hazard regression model. Medium-large-sized firms.

Variables	(5) MAN_short	(6) SERV_short	(7) MAN_long	(8) SERV term
Debt_ST	0.793***	0.751***		
	(0.0384)	(0.0272)		
Debt_LT			0.914**	0.917***
			(0.0356)	(0.0255)
Constant	0.0155	0.000139	0.00144	0.000273
	(0.122)	(0.00181)	(0.0127)	(0.00248)
Firm level controls	YES	YES	YES	YES
Duration dummies	YES	YES	YES	YES
Legal status dummies	YES	YES	YES	YES
Sector/Industrial dummies	YES	YES	YES	YES
Cohorts dummies	YES	YES	YES	YES
Regions dummies	YES	YES	YES	YES
Observations	2302	3615	2301	3615
Log pseudolikelihood	−77.66	−134.53	−88.88	−162.22
Wald	247	300	186	273

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

bank debt are indeed confirmed, albeit with some differences in the magnitude of the effects. Furthermore, as expected, bank financing exerts a positive impact on survival that is greater for small firms than for large ones, especially in the manufacturing sector.

A possible justification for this result can be found in the composition of our sample regarding firm size: being newly established enterprises, 94% of them have fewer than 10 employees.

7 | CONCLUSIONS

Small and medium-sized enterprises (SMEs) and start-ups play an important role in the economy, especially in Europe. In Europe, SMEs heavily depend on bank financing, with an incidence of approximately 70% of their external financing, while in the US, this value shrinks to approximately 40% (European Commission, 2017). Therefore, the conditions of their access to external finance are of crucial importance, and policies to remove obstacles that sometimes make such access difficult are central to the European Commission's policy agenda. It is therefore evident how the issue of bank financing, in the absence of a highly developed venture capital market, becomes more relevant when considering firms in the early stages of the start-up business cycle.

Using a discrete-time proportional hazard model, this paper presents an empirical analysis of the impact of access to banking credit on the survival of start-up firms in Italy between 2004 and 2014, a period covering both the global financial crisis (2007–2009) and the sovereign debt crisis (2011–2012).

Our study contributes to the literature as follows. First, unlike previous work, the relationship between bank debt and survival was tested by considering the impact of specific environmental factors. In particular, the differences in the resilience of start-ups due not only to the industrial heterogeneity of belonging to the manufacturing or service sector, but also to the different innovation intensity of the sectors in which start-ups operate was analysed.

Our baseline results largely confirm that, whatever the macro sector of activity, access to bank financing exerts positive effects on the survival of Italian start-up firms, although these results must be interpreted with some caution because of the multifaceted start-up level unobserved heterogeneity in terms of debt duration (short- and long-term) and specific environmental factors (type of macro-sector and industrial innovation intensity).

In summary, controlling for these further factors, our findings are as follows: (i) Italian start-ups with an increasing weight of bank loans have a decreased risk of failure both in manufacturing and in the services. This result confirms Hypothesis 1 and is in line with previous studies (Castaldo et al., 2020; Cole & Sokolyk, 2018; Wamba et al., 2017); (ii) once we split the bank credit according to its duration, we found that a higher level of both short-term and long-term debt reduces the risk of exit. In particular, our estimates show that the impact of short debts will be greater than that in the long term; thus, Hypothesis 2 is confirmed. The econometric findings show that this result has a stronger magnitude for firms operating in the manufacturing industry. (iii) By disaggregating the manufacturing and service sectors according to their degree of sectoral innovation, our findings show that bank financing incidence relative to start-ups belonging to higher innovative industries, ceteris paribus, impacts more strongly on their survival probability with respect to low-innovative industries start-ups. This evidence provides a sounding confirmation of Hypothesis 3; (iv) when we consider the effects of the incidence of bank credit according to its duration, in the less innovative sectors, our results indicate that it is the incidence of long-term debt that has a greater impact on firm survival regardless of the macro-sector in which they operate. These findings provide confirmation to Hypothesis 4.

Finally, from a policy perspective, this result is potentially important, particularly in a country such as Italy, where the bank channel is by far the main source of external finance. Our results here suggest that access to short- and long-term banking credit can be considered a predictor of the probability of start-up survival, given the sectorial or innovation conditions. Therefore, policies facilitating access to credit by SMEs and start-ups are a crucial driver for the growth and resilience of new businesses.

ACKNOWLEDGMENTS

The authors thank two anonymous referees which reviewed our paper. Any error or omission remains responsibility of the authors.

Open Access Funding provided by Universita degli Studi della Campania Luigi Vanvitelli within the CRUI-CARE Agreement.

ORCID

Angelo Castaldo https://orcid.org/0000-0002-7586-5100
Rosanna Pittiglio https://orcid.org/0000-0002-1717-2453
Filippo Reganati https://orcid.org/0000-0002-5028-0421

REFERENCES

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. *Sociological Methodology*, *13*, 61–98. https://doi.org/10.2307/270718

Ang, J. (1992). On the theory of finance for privately held firms. *Journal of Small Business Finance*, *1*(3), 185–203. https://doi.org/10.57229/2373-1761.1121

Aristei, D., & Angori, G. (2022). Heterogeneity and state dependence in firms' access to bank credit. *Small Business Economics, Springer*, *59*(1), 47–78. https://doi.org/10.1007/s11187-021-00545-x

Arping, S., Lóránth, G., & Morrison, A. D. (2010). Public initiatives to support entrepreneurs: Credit guarantees versus co-funding. *Journal of Financial Stability*, *6*(1), 26–35. https://doi.org/10.1016/j.jfs.2009.05.009

Astebro, T., & Bernhardt, I. (2003). Start-up financing, owner characteristics, and survival. *Journal of Economics and Business*, *55*(4), 303–319. https://doi.org/10.1016/s0148-6195(03)00029-8

Audretsch, D. B. (1995). *Innovation and industry evolution*. MIT Press.

Audretsch, D. B., & Mahmood, T. (1994). The rate of hazard confronting new firms and plants in U.S. manufacturing. Review of Industrial Organization, *9*(1), 41–56. https://doi.org/10.1007/bf01024218

Audretsch, D. B., & Mahmood, T. (1995). New-firm survival: New results using a hazard function. *The Review of Economics and Statistics*, *77*(1), 97–103. https://doi.org/10.2307/2109995

Barron, D. N., West, E., & Hannan, M. T. (1994). A time to growth and a time to die: Growth and mortality of credit unions in New York, 1914–1990. *American Journal of Sociology*, *100*(2), 381–421. https://doi.org/10.1086/230541

Bernanke, B. S. (1983). Non-monetary effects of the financial crisis in the propagation of the great depression. *The American Economic Review*, *73*(3), 257–276.

Bodenhorn, H. (2003). Short-term loans and long-term relationships: Relationship lending in Early America. *Journal of Money, Credit, and Banking*, *35*(4), 485–505. https://doi.org/10.1353/mcb.2003.0025

Boyer, T., & Blazy, R. (2014). Born to be alive? The survival of innovative and non-innovative French micro-start-ups. *Small Business Economics*, *42*(4), 669–683. https://doi.org/10.1007/s11187-013-9522-8

Briozzo, A., Vigier, H., & Martinez, L. B. (2016). Firm-level determinants of the financing decisions of small and medium enterprises: Evidence from Argentina. *Latin American Business Review*, *17*(3), 245–268. https://doi.org/10.1080/10978526.2016.1209081

Butzbach, O., & Sarno, D. (2019). To what extent do regional effects influence firms' capital structure? The case of Southern Italian SMEs. *International Journal of Financial Studies*, *7*, 1–20. https://doi.org/10.3390/ijfs7010003

Carter, R., & Van Auken, H. (2006). Small firm bankruptcy. *Journal of Small Business Management*, *44*(4), 493–512. https://doi.org/10.1111/j.1540-627x.2006.00187.x

Castaldo, A. (2020). Strumenti pubblici per l'accesso alle PMI. In a cura di F. Amatori & M. D'Alberti (Eds.), *L'impresa Italiana* (Vol. II, pp. 171–184).

Castaldo, A., De Luca, G., & Barile, B. (2020). Does initial access to bank loans predict start-ups' future default probability? Evidence from Italy. *Contemporary Economic Policy*, *39*(1), 83–106. https://doi.org/10.1111/coep.12480

Cefis, E., & Marsili, O. (2006). Survivor: The role of innovation in firms' survival. *Research Policy*, *35*(5), 626–641. https://doi.org/10.1016/j.respol.2006.02.006

Christensen, C. M. (1997). Patterns in the evolution of product competition. *European Management Journal*, *15*(2), 117–127. https://doi.org/10.1016/s0263-2373(96)00081-3

Christensen, C. M., Suárez, F. F., & Utterback, J. M. (1998). Strategies for survival in fast-changing industries. *Management Science*, *44*(12-part-2), 207–220. https://doi.org/10.1287/mnsc.44.12.s207

Cole, R. A., & Sokolyk, T. (2018). Debt financing, survival, and growth of start-up firms. *Journal of Corporate Finance*, *50*(C), 609–625. https://doi.org/10.1016/j.jcorpfin.2017.10.013

Collett, N., Pandit, N. R., & Saarikko, J. (2014). Success and failure in turnaround attempts. An analysis of SMEs within the Finnish Restructuring of Enterprises Act. *Entrepreneurship & Regional Development*, *26*(1–2), 123–141. https://doi.org/10.1080/08985626.2013.870236

Cosh, A., Cumming, D., & Hughes, A. (2009). Outside entrepreneurial capital. *The Economic Journal*, *119*(540), 1494–1533. https://doi.org/10.1111/j.1468-0297.2009.02270.x

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B: Methodological*, *34*(2), 187–220. https://doi.org/10.1111/j.2517-6161.1972.tb00899.x

Crepon, B., & Duguet, E. (2003). Bank Loans, start-up subsidies and the survival of the new firms: An econometric analysis at the entrepreneur level. University of Paris I Working Paper No. 2003.77.

Cressy, R. (1996). Commitment lending under asymmetric information: Theory and tests on U.K. start-up data. *Small Business Economics*, *8*(5), 397–408. https://doi.org/10.1007/bf00389557

de Bettignies, J. E., & Brander, J. A. (2007). Financing entrepreneurship: Bank finance versus venture capital. *Journal of Business Venturing*, *22*(6), 808–832. https://doi.org/10.1016/j.jbusvent.2006.07.005

Deloof, M., La Rocca, M., & Vanacker, T. (2019). Local banking development and the use of debt financing by new firms. *Entrepreneurship: Theory and Practice*, *43*(6), 1250–1276. https://doi.org/10.1177/1042258718783486

Deloof, M., & Vanacker, T. (2018). The recent financial crisis, start-up financing and survival. *Journal of Business Finance & Accounting*, *45*(7–8), 928–951. https://doi.org/10.1111/jbfa.12319

Donati, C., & Sarno, D. (2014). Are firms in 'backward' areas of developed regions more financially constrained? *The Case of Italian SMEs*, *6*, 1353–1375.

Ericson, R., & Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *The Review of Economic Studies*, *62*(1), 53–82. https://doi.org/10.2307/2297841

Esteve Pérez, S., & Mañez Castillejo, J. (2008). The resource-based theory of the firm and firm survival. *Small Business Economics*, *30*(3), 231–249. https://doi.org/10.1007/s11187-006-9011-4

European Commission. (2017). *Small and medium-sized enterprises' access to finance*. European Semester Thematic Factsheet.

Giannetti, C. (2019). Debt Specialization and performance of European firms. *Journal of Empirical Finance*, *53*(C), 257–271. https://doi.org/10.1016/j.jempfin.2019.07.008

Harhoff, D., Stahl, K., & Woywode, M. (1998). Legal form, growth and exit of west German firms – Empirical results for manufacturing, construction, trade and service industries. *The Journal of Industrial Economics*, *46*(4), 453–488.

Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica*, *52*(2), 271–320. https://doi.org/10.2307/1911491

ISTAT. (2012). *La Demografia d'impresa, Statistiche in breve*. ISTAT.

Istituto Nazionale di Statistica (ISTAT). (2011). *L'accesso al credito delle piccole e medie imprese Report*. ISTAT.

Istituto Nazionale di Statistica (ISTAT). (2016). *La demografia d'impresa statistiche*. Report. ISTAT.

Jenkins, S. P. (2005). *Survival analysis*. Mimeo. Department of Economics, University of Essex.

Jensen, P., Webster, E., & Buddelmeyer, H. (2008). Innovation, technological conditions and new firm survival. *The Economic Record*, *84*(267), 434–448. https://doi.org/10.1111/j.1475-4932.2008.00509.x

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica*, *50*(3), 649–670. https://doi.org/10.2307/1912606

Ma, Y., & Lin, S. (2010). 'Credit crunch' and small- and medium-sized enterprises: Aspects affecting survival. *Journal of Financial Services Marketing*, *14*(4), 290–300. https://doi.org/10.1057/fsm.2009.26

Mach, T. L., & Wolken, J. D. (2011). Examining the impact of credit access on small firm survivability. In G. Calcagnini & I. Favaretto (Eds.), *Small businesses in the aftermath of the crisis international analyses and policies* (pp. 189–210). Physica Heidelberg.

Mata, J., & Portugal, P. (1994). Life duration of new firms. *The Journal of Industrial Economics*, *42*(3), 227–246. https://doi.org/10.2307/2950567

Minelli, E., & Modica, S. (2009). Credit market failures and policy. *Journal of Public Economic Theory, Association for Public Economic Theory*, *11*(3), 363–382. https://doi.org/10.1111/j.1467-9779.2009.01414.x

Musso, P., & Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics*, *18*(2), 135–149. https://doi.org/10.1007/s00191-007-0087-z

Myers, S. C. (1984). The capital structure puzzle. *The Journal of Finance*, *39*(3), 575–592. https://doi.org/10.2307/2327916

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*, 187–221.

Prentice, R. L., & Gloeckler, L. A. (1978). Regression analysis of grouped survival data with application to breast cancer data. *Biometrics*, *34*(1), 57–67. https://doi.org/10.2307/2529588

Robb, A. M., & Robinson, D. (2014). The capital structure decisions of new firms. *Review of Financial Studies*, *27*(1), 153–179. https://doi.org/10.1093/rfs/hhs072

Robson, P., Akuetteh, C., Stone, I., Westhead, P., & Wright, M. (2013). Credit-rationing and entrepreneurial experience: Evidence from a resource deficit context. *Entrepreneurship & Regional Development*, *25*(5–6), 349–370. https://doi.org/10.1080/08985626.2012.729091

Rosenbusch, N., Brinckmann, J., & Bausch, A. (2011). Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs. *Journal of Business Venturing*, *26*(4), 441–457. https://doi.org/10.1016/j.jbusvent.2009.12.002

Santarelli, E. (2000). The duration of new firms in banking: An application of Cox regression analysis. *Empirical Economics*, *25*(2), 315–325. https://doi.org/10.1007/s001810000019

Sarno, D. (2005). Liquidity constraint on the production of the firms in Southern Italy. *Small Business Economics*, *25*(2), 133–146. https://doi.org/10.1007/s11187-003-6452-x

Sarno, D. (2008). Capital structure and growth of the firms in the backward regions of the South Italy. *Applied Financial Economics*, *18*(10), 821–833. https://doi.org/10.1080/09603100701222309

Segarra, A., & Callejon, M. (2002). New firms' survival and market turbulence: New evidence from Spain. *Review of Industrial Organization*, *20*, 1–14. https://doi.org/10.1023/a:1013309928700

Stelletto, E., Scellato, G., & Cowling, M. (2017). Cost of capital and public loan guarantees to small firms. *Small Business Economics*, *49*(2), 319–337. https://doi.org/10.1007/s11187-017-9845-y

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, *71*(3), 393–410.

Strotmann, H. (2007). Entrepreneurial survival. *Small Business Economics*, *28*(1), 87–104. https://doi.org/10.1007/s11187-005-8859-z

Suarez, F. F., & Utterback, J. M. (1995). Dominant designs and the survival of firms. *Strategic Management Journal*, *16*(6), 415–430. https://doi.org/10.1002/smj.4250160602

Wamba, L. D., Hikkerova, L., Sahut, J. M., & Braune, E. (2017). Indebtedness for young companies: Effects on survival. *Entrepreneurship & Regional Development*, *29*(1–2), 174–196. https://doi.org/10.1080/08985626.2016.1255435

How to cite this article: Castaldo, A., Pittiglio, R., Reganati, F., & Sarno, D. (2023). Access to bank financing and start-up resilience: A survival analysis across business sectors in a time of crisis. *The Manchester School*, 1–30. https://doi.org/10.1111/manc.12433

APPENDIX

TABLE A1 Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Size	119,138	8.99	23.83	0.0	997.44
HI_4	119,138	68.50	164.11	3.9	3364.2
Short-term_bank_debt (1000 €)	119,138	99.75	1110.75	0.0	114,878.7
Long-term _bank_debt (1000 €)	119,138	78.91	2811.18	0.0	324,752.6

TABLE A2 Sectoral Innovation intensity.

Manufacturing industries	Ateco 2007 code	Innovation level	Services industries	Ateco 2007 code	Innovation level
Food, drink and tobacco industries	10–12	LOW	Wholesale and retail trade and repair of motor vehicles and motorbikes	45	LOW
Textile industries	13	HIGH	Wholesale trade (excluding motor vehicles and motorbikes)	46	HIGH
Manufacture of wearing apparel, manufacture of leather and fur articles	14	LOW	Retail trade (excluding motor vehicles and motorbikes)	47	LOW
Manufacture of leather and similar articles	15	LOW	Transport and storage	48	LOW
Wood and wood and cork products industry (excluding furniture), manufacture of articles of straw and plaiting materials	16	LOW	Land, pipeline, sea and water transport, air transport	49–51	LOW

TABLE A2 (Continued)

Manufacturing industries	Ateco 2007 code	Innovation level	Services industries	Ateco 2007 code	Innovation level
Manufacture of paper and paper products	17	LOW	Warehousing and support activities for transportation, postal and courier activities	52–53	LOW
Printing and reproduction of recorded media	18	LOW	Publishing activities	58	HIGH
Manufacture of coke and refined petroleum products	19	LOW	Telecommunications	61	HIGH
Manufacture of chemical products	20	HIGH	Software production, computer consultancy and related activities	62	HIGH
Manufacture of basic pharmaceutical products and pharmaceutical preparations	21	HIGH	Information service activities and other computer service activities	63	LOW
Manufacture of rubber and plastic products	22	HIGH	financial service activities (except insurance and pension funding)	64	HIGH
Manufacture of other non-metallic mineral products	23	LOW	Insurance, reinsurance and pension funding (except compulsory social security)	65	HIGH
Metallurgy	24	LOW	Activities auxiliary to financial services and insurance activities	66	HIGH
Manufacture of metal products (excluding machinery and equipment)	25	LOW	Business management and management consulting activities	70	LOW
Manufacture of computers and electronic and optical products, electromedical equipment, measuring equipment and watches	26	HIGH	Architectural and engineering activities, technical testing and analysis	71	HIGH
Manufacture of electrical and non-electrical household equipment	27	HIGH	Scientific research and development	72	HIGH
Manufacture of machinery and equipment n.e.c.	28	HIGH	Advertising and market research	73	HIGH
Manufacture of motor vehicles, trailers and semi-trailers	29	HIGH	Other professional, scientific and technical activities	74	HIGH
Manufacture of other transport equipment	30	HIGH			
Manufacture of furniture	31	HIGH			
Other manufacturing	32	HIGH			

(Continues)

TABLE A2 (Continued)

Manufacturing industries	Ateco 2007 code	Innovation level	Services industries	Ateco 2007 code	Innovation level
Repair, maintenance and installation of machinery and equipment	33	LOW			
Supply of electricity, gas, steam and air conditioning	35	HIGH			
Water supply sewerage, waste management and remediation activities	36	LOW			
Water collection, treatment and supply	37	HIGH			
Sewerage, waste collection, treatment and disposal activities material recovery, remediation and other waste management services	38–39	LOW			

TABLE A3 Estimation results: discrete Cox proportional hazard regression model. Small versus medium-large-sized firms.

Variables	(1) MAN_short small size	(2) SERV_short small size	(3) MAN_long small size	(4) SERV_long small size	(5) MAN_short medium-large size	(6) SERV_short medium-large size	(7) MAN_long medium-large size	(8) SERV term medium-large size
Debt_ST	0.774***	0.794***			0.793***	0.751***		
	(0.00771)	(0.00337)			(0.0384)	(0.0272)		
Debt_LT			0.848***	0.880***			0.914**	0.917***
			(0.00949)	(0.00418)			(0.0356)	(0.0255)
LSIZE	0.311***	0.233***	0.0820***	0.0759***	1.873	67.99	2.585	28.57
	(0.0912)	(0.0402)	(0.0214)	(0.0120)	(6.836)	(444.4)	(10.38)	(125.7)
LSIZE_sq	1.048	1.159**	1.252**	1.330***	1.013	0.598	0.926	0.660
	(0.109)	(0.0751)	(0.123)	(0.0839)	(0.430)	(0.502)	(0.434)	(0.366)
LHI_4	0.891**	1.070*	0.883**	1.108***	0.988	0.945	0.949	0.600
	(0.0487)	(0.0424)	(0.0485)	(0.0421)	(0.299)	(0.476)	(0.406)	(0.397)
D1	0.0269***	0.00874***	0.0140***	0.00560***	0.0330**	0.0206***	0.0185**	0.0138***
	(0.00846)	(0.00156)	(0.00416)	(0.000939)	(0.0500)	(0.0234)	(0.0294)	(0.0159)
D2	0.00944***	0.00554***	0.00818***	0.00457***		0.0218***		0.0237***
	(0.00386)	(0.00110)	(0.00307)	(0.000852)		(0.0203)		(0.0238)
D3	0.00271***	0.00197***	0.00346***	0.00271***				
	(0.00143)	(0.000474)	(0.00175)	(0.000611)				
D4	0.00135***	0.000733***	0.00225***	0.00121***	0.0258***	0.00825***	0.0285***	0.0126***
	(0.000727)	(0.000215)	(0.00118)	(0.000350)	(0.0339)	(0.00857)	(0.0334)	(0.0138)
D5	0.0538***	0.0319***	0.0907***	0.0572***	0.194	0.0535***	0.285	0.0723***
	(0.0100)	(0.00297)	(0.0147)	(0.00474)	(0.195)	(0.0358)	(0.268)	(0.0463)
D6	0.176***	0.116***	0.217***	0.166***	0.185*	0.166***	0.206	0.194***
	(0.0284)	(0.00933)	(0.0332)	(0.0125)	(0.182)	(0.0982)	(0.217)	(0.115)

(Continues)

TABLE A3 (Continued)

Variables	(1) MAN_short small size	(2) SERV_short small size	(3) MAN_long small size	(4) SERV_long small size	(5) MAN_short medium-large size	(6) SERV_short medium-large size	(7) MAN_long medium-large size	(8) SERV term medium-large size
D7	0.592***	0.480***	0.672***	0.578***	1.654	0.449	2.014	0.428
	(0.0859)	(0.0345)	(0.0989)	(0.0408)	(1.524)	(0.287)	(1.844)	(0.266)
Constant	4.262***	2.298***	5.669***	1.442	0.0155	0.000139	0.00144	0.000273
	(1.597)	(0.560)	(2.046)	(0.339)	(0.122)	(0.00181)	(0.0127)	(0.00248)
Legal status dummies	YES	YES	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES	YES	YES
Cohorts dummies	YES	YES	YES	YES	YES	YES	YES	YES
Regions dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	27,360	81,078	27,344	81,025	2302	3615	2301	3615
Log pseudolikelihood	−1445.61	−5959.78	−1822.40	−7638.88	−77.66	−134.53	−88.88	−162.22
Wald	2275	6237	1801	5564	247	300	186	273

Note: Robust seeform in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.