A Survival Analysis of Public Guaranteed Loans: Does Financial Intermediary Matter?[1]

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Abstract

This paper investigates the risk of failure of loans guaranteed by public credit guarantee schemes. We analyze the determinants of the time to default of approximately 15,000 loans guaranteed by the Italian Central Guarantee Fund in the period 2007–2009. Using the Cox proportional hazard model, we test the role of the financial intermediary which requests the guarantee on firm's behalf, distinguishing between banks and Mutual Guarantee Institutions (MGIs), controlling for a set of variables that characterize each guaranteed loan. The findings confirm that loans are more likely to default when a bank is involved in the guarantee process than when an MGI is engaged. Considering some elements relevant to SMEs opacity (age, size, and sector) banks seem to perform better than MGIs in the screening and monitoring activity for loans requested by firms operating in the manufacturing sector.

JEL classification: G21, G28

Keywords: Credit risk, Collateral, Mutual Guarantee Institutions, Banks, State-fund guarantee

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Survival Analysis of Public Guaranteed Loans: Does Financial Intermediary Matter?

1. Introduction

The recent economic and financial crises have brought to the forefront public financial risk-bearing. Governments came to the aid of troubled financial markets and institutions, and also provided collateral (public guarantees) to help enable small- and medium-sized enterprises (SMEs) to access credit. More recently, the economic impact of the COVID-19 pandemic has brought the spotlight back onto the strategic role of public support programs (OECD, 2020).

Among public support measures, credit guarantee schemes (CGSs) are the most widespread[6]. CGSs first appeared in the nineteenth century and have become more popular in recent years; many countries have reformed their existing CGSs, enlarging their scope and scale. By 2015, CGSs had been implemented in almost every country in the world (Pombo et al., 2015). CGSs are mechanisms by which a third party (i.e., the public guarantor) pledges to repay some or the entire loan amount to the lender in case of borrower default: "The guarantor bears a part or all the credit risk, reducing the risk faced by financial intermediaries and thus making it possible for firms to obtain credit or improve the terms and conditions under which they can borrow" (Gozzi and Schmukler, 2016, p.105). The guarantor pledges a guarantee directly to the firm's lender or a counter-guarantee to another guarantee organization (i.e., a mutual guarantee institution (MGI))[7] with which the firm is associated. CGSs may allow public agencies to increase the amount of bank financing issued to the private sector whilst using relatively small initial outlays (Action Institute, 2013). During the recent financial crises, the worldwide use of CGSs as counter-cyclical policy tools increased enormously; the total value of outstanding guarantees granted by CGSs globally reached approximately US$ 550 billion, and almost nine million firms benefited from these schemes (REGAR, 2018).

If a large number of guarantees are granted, this provides benefits to SMEs as well as banks, allowing them to share their credit risk and save on regulatory capital. Indeed, banks are allowed to lower the

[6] Other kinds of support programs are direct lending, co-funding, and interest rate subsidies.

[7] As we explain in the next section, MGIs are private guarantee institutions that are created by beneficiary SMEs (i.e., firms that wish to obtain loans). MGIs typically have a cooperative or mutual statute, which means that their capital is provided directly by the participating SMEs in the form of cooperative or mutual shares. The MGI does not grant loans to their participants; its primary activity is to provide members with guarantees to be posted as collateral to back bank loans.

regulatory capital requirements for loans covered by guarantees (EIB, 2017). These features of the scheme are very appealing in situations where the credit risk is high and the capital requirements for banks are increasing (De Blasio et al., 2017). However, the potential intensification of exposure to default risk and an increasing commitment to public finances could threaten the financial sustainability of some programs in the medium and long term. This is crucial also for the stability of the economic and financial systems because the use of CGSs as public policy tools has become so widespread that they are considered a "structural element of financial systems" (OECD, 2013) and, furthermore, they play a strategic role in supporting SMEs' access to credit.

The aim of this paper is to contribute to the assessment of the financial sustainability of the most important public Italian CGS, namely the Fondo Centrale di Garanzia (Central Guarantee Fund, hereafter CGF), analyzing the failure risk of guaranteed loans by seeking to resolve the following research questions: a) Do differences in failure risk depend on the financial intermediaries involved in the guarantee granting process? b) Do these differences depend on the firm's informational opacity?

To monitor the risk of default, many CGSs apply sophisticated scoring models that mainly analyze the borrowers' financial data and, consequently, their repayment capacity. When borrowers are SMEs, the assessment of hard information (related to the analysis of balance sheet data) is not sufficient; these firms are informationally opaque and the management of soft information (related to their relationship with the bank or MGI) is highly relevant (Petersen and Rajan, 1994; Berger and Udell, 1995; Degryse and Cayseele, 2000; Grunert et al., 2005). For this reason, the private actors involved in the guarantee process, i.e., financial intermediaries, must be taken into account in the risk assessment process because they are able to deal with soft information. In the Italian framework, banks and MGIs require the CGF to guarantee loans applied for by firms. The CGF provides direct guarantees to banks or counter-guarantees to MGIs.

In recent decades, literature has analyzed CGSs from three different perspectives. One perspective considers their financial additionality, that is, the increased availability of credit for targeted firms and enhanced financial conditions (Levitsky, 1997; Boocock and Shariff, 2005; Benavente et al., 2006; Riding et al., 2007; Cowling, 2010; Abraham and Schmukler 2017). The second perspective analyses economic additionality, namely the impact of public guarantees in terms of employment growth, tax revenues, increased sales, or profit growth rate (Bradshaw, 2002; Riding et al., 2007; Boockock and Shariff, 2005; Benavente et al., 2006; Lelarge et al., 2010; Schmidt and van Elkan, 2010; Uesugi et al., 2010; Caselli et al., 2019). In this perspective, financial additionality is considered to be an intermediate outcome, while economic additionality is the main policy outcome. The third perspective refers to financial sustainability, namely the ability of the program to cover the costs of its operation and the default that occurs (Green 2003; Beck et al., 2008; Jonsson, 2009; Schich et al., 2017; Saito and Tsuruta, 2018). Maintaining the financial sustainability of the program is a necessary, although not sufficient, condition to ensure that economic and financial additionality are achieved in the medium and long term. The majority of academic studies have focused on economic and financial additionality, while only a few concentrate on the financial sustainability dimension (Schich et al., 2017). Our paper is positioned in this latter strand.

In the literature to date, some contributions (Mensah, 1996; Panyanukul et al., 2014; Cowan et al., 2015) have analyzed the impact of public guarantees on firms' probability of default. However, to the best of our knowledge, this is the first study to investigate the impact of public guarantees on loans' probability of default, considering individual firm-loan observations, and to deepen the understanding of the role played by financial intermediaries.

Our paper fills a gap in this literature regarding the financial sustainability of public credit guarantee schemes, focusing on the role of the financial intermediary involved in the loan process. We use the Cox proportional hazard model (Cox, 1972) and a confidential dataset which covers approximately 15,000 loans granted by public guarantees between 2007 and 2009, observed up to 2012. We control for a set of variables related to loan characteristics (loan size and maturity) and borrower characteristics (size, age, industry, and financial data).

Our findings confirm that loans directly guaranteed by the CGF are more likely to default than loans counter-guaranteed by the CGF. This suggests that MGIs perform better than banks in screening and monitoring the activity of their borrowers. Deepening the analysis of our data, banks seem to perform better in these activities when a public guarantee applies to loans granted to firms operating in the manufacturing sector.

The identification of the determinants of default for guaranteed loans is relevant because loan default means that public funds are used to repay all or part of the loan to the lender. In this sense, the findings of this paper can be useful to improve the design of the public CGSs in order to reduce the number of defaulted loans and improve the financial sustainability of the program in the medium and long term.

This study additionally contributes to the debate on sustainability of CGSs in several ways. First, our paper explores one of the largest and most significant guarantee programs in Europe. The case of Italy is important because guarantee schemes account for 2.03% of the national GDP, which represents one of the higher percentages in Europe (European Investment Fund, 2019). For the period 2007 to 2009, which is the focus of this paper, the CGF issued five billion euros in guarantees, which allowed SMEs to obtain approximately 9.5 billion euros in loans[8].

[8] Calculated based on the dataset used in this study.

Our findings are also of importance to policymakers: when public budgets are curtailed, it is of fundamental importance for public CGSs to carefully manage the guarantee granting process by using robust scoring models and monitoring the activity of the financial intermediaries involved, with the aim of lowering the probability of default on guaranteed loans and consequently reducing public spending. Our findings make important contributions to the development of the set of principles issued by World Bank (The World Bank and FIRST Initiative, 2015) for the design of public guarantees that are efficient and financially sustainable.

The rest of this paper proceeds as follows. Section 2 presents the Italian public CGS and develops our research hypotheses. Sections 3 and 4 describe the dataset and the methodology used in this study. Section 5 presents our main results and discussion, and our supporting robustness checks. Section 6 concludes the paper.

2. The Italian public CGS and the research hypotheses

The CGF is the main Italian public CGS and is designed to improve SMEs' access to credit. The aim of the CGF is to promote funding opportunities for SMEs with limited ability to access the credit market for reasons beyond their level of creditworthiness (i.e., the generalized credit crunch). SMEs are the preferred target of many CGSs for several reasons. First, SMEs tend to be underserved by private financial intermediaries; policy makers and scholars have recognized that SMEs face more difficulties in accessing credit than large firms because of information asymmetry (Berger and Udell, 2006), higher administrative costs for small-scale lending (Cowling and Mitchell, 2003), higher risk perception (Berger and Udell, 2006), and lack of collateral (Jaffee and Russel, 1976; Stiglitz and Weiss, 1981; Beck et al., 2008). Second, it is thought that SMEs' growth has positive externalities, such as improving social cohesion, reducing poverty, and fostering regional and local development (Peterson, 1977; Amini, 2004; Beck et al., 2005). In addition, SMEs tend to contribute to the welfare and stability of society, and such firms provide a large share of total employment (Kang and Heshmati, 2008). For these reasons, improving the feasibility of financing for SMEs may have a positive impact on economic growth.

The CGF was established in 2000, and its role since has been strengthened whenever an extraordinary economic-financial or social-environmental event (i.e., a financial crisis, earthquakes, epidemics) has occurred that could have a strong negative impact on SMEs' survival. The most important reinforcements occurred during the global financial crisis and the Sovereign debt crisis, when the CGF was refinanced with approximately two billion euros between 2008 and 2012, and by an additional 1.2 billion euros between 2013 and 2014. Recently, the economic impact of the coronavirus pandemic has brought the spotlight back onto the strategic role of the CGF in sustaining Italian SMEs, especially those operating in the areas most affected by COVID-19 (CGF, 2020a). The role of the CGF in supporting the financing of SMEs is highly important: in 2019, the CGF issued guarantees for 13.3 billion euros, allowing about 125,000 SMEs to obtain debt of 19.4 billion euros (CGF, 2020b). The CGF operates on the basis of a conventional credit guarantee scheme, whereby the CGF pledges to repay some or all of the loan amount to the lender in case of borrower default. The guarantor therefore bears part of the credit risk, reducing the risk faced by financial intermediaries (banks or MGIs) and thus making it possible for firms to obtain credit or improving the terms and conditions under which they can borrow (Gozzi and Schmukler, 2016, p.105). The public guarantee granting process involves three agents: a financial intermediary, a firm, and the CGF. The request for a public guarantee can be made directly by the borrowing SME, by the lending bank (which may propose that the client firm should apply for the guarantee), or alternatively by the MGI. The latter is a private guarantee institution created by beneficiary SMEs. It typically has a cooperative or mutual statute. MGI members contribute to a guarantee fund, which is then used as collateral to back loans granted to the members themselves. The MGI provides a guarantee to the lending bank that is counter-guaranteed by the CGF, which means that the losses from a credit default are apportioned between the bank, the MGI, and the CGF. The financial intermediary assesses the eligibility of the firm for the scheme by means of a specific scoring model provided by the CGF. This activity is not free of charge. A few years ago, the CGF started to provide scoring model software (recently substituted with a rating model) and the financial intermediary paid a fee for its use. Although this fee is low, there are also labor costs related to performing the credit assessment— namely the cost of bank employees who collect the information and use the software supplied— that are not negligible (De Blasio et al., 2017).

The type of guarantee granted by the CGF is different for banks and MGIs. The CGF provides direct guarantees to banks by acting as the first-level guarantor, and provides co-guarantees and counter-guarantees to MGIs by acting as a co-guarantor alongside them. Unlike some other CGSs, the guarantee issued by the CGF never covers the entire amount of the loan; the coverage rate may be as high as 80% of the loan in the cases of both direct guarantees and counter-guarantees to MGIs, whose guarantee in turn cannot exceed 80% of the loan (the maximum CGF counter-guarantee percentage rises to 90% for counter-guarantees granted on behalf of SMEs operating in areas affected by earthquakes). The maximum amount that can be guaranteed is 2.5 million euros, and, in the case of loans to consolidate short-term liabilities, the maximum amount guaranteed is 1.5 million euros. By applying sophisticated scoring models, the CGF assesses the eligibility of borrowing firms (in addition to the initial assessment performed by the intermediary), measuring several firm dimensions including profitability, financial structure, solvency, and liquidity. The CGF charges a fee to guaranteed companies, generally within the range of 0.25% to 1% of the guaranteed amount, depending on the type of operation (e.g. type of loan, firm’s location etc.) and guarantee. Different types of financing schemes are eligible for the program:

factoring for credit to the public sector, funding loans with a maturity longer than 36 months, consolidation of short-term liabilities, operations on equity capital, and other financial operations. For the period 2007 to 2009, which is the focus of this paper, the CGF issued five billion euros of guarantees, which allowed SMEs to obtain approximately 9.5 billion euros in loans.

Over the years, numerous changes have been made to the operation of the CGF in order to ensure its sustainability in the medium and long term: more sophisticated credit scoring systems have been developed, leading to the implementation of a complete rating model; coverage ratios and fee amounts have been differentiated for different types of SMEs. However, the relationships between the public CGS and private financial intermediaries (banks and MGIs) involved in the guarantee granting process have not been subject to regulatory changes. Indeed, the main interlocutors of the CGF tend to be financial intermediaries. Minelli and Modica (2009) note that this is because the government generally does not have the ability to evaluate and screen for eligible projects and is therefore obliged to make use of specialized intermediaries.

A guarantee scheme can maintain its sustainability by providing the appropriate incentives to financial intermediaries to ensure effective assessment and monitoring of firms' creditworthiness. As the guarantor of last resort, the government bears the risk of loans granted and guaranteed by other financial institutions, which may potentially engage in moral-hazard behaviors. These opportunistic behaviors are common when the assessment of default risk and the associated risk-taking vest with two separate entities as in the case of securitization markets (Boot and Thakor, 1994; Jémenez and Saurina, 2004; Bubb and kaufman, 2009; Hartman-Glaser et al., 2012). Therefore, although the CGF provides a proprietary rating model for the assessment of firms' creditworthiness, the involvement of financial intermediaries can create potential distorting effects in both screening and monitoring activities.

When borrowers are informationally opaque, as is the case for SMEs, the hard information managed by sophisticated scoring and rating models is not sufficient to carry out effective screening and monitoring. In such cases, the analysis of soft information may be highly relevant. Grunert et al. (2005) provide evidence that soft information represents an important factor in assessing the default risk of borrowers in SME finance. They find that the use of a combination of financial (hard information: financial statement and payment information) and non-financial factors (soft information: management skills and the firm's product-market position and strategy) significantly improves the predictive accuracy of banks' internal credit rating systems. This soft information may include an assessment of the future prospects of the SME developed based on past communications with the SME's suppliers, customers, or neighboring businesses (Petersen and Rajan, 1994; Berger and Udell, 1995; Degryse and Cayseele, 2000).

Banks can overcome SMEs' information asymmetries through relationship lending (Rajan, 1992; Petersen and Rajan 1994; Boot, 2000; Berger and Udell, 2002). Through close and continuous interaction, a firm may provide the lender with valuable information that mitigates information asymmetries (e.g., Petersen and Rajan, 1994; Berger and Udell, 1995; Cole, 1998).

Bartoli et al. (2013) point out that when firms have a short relationship with a bank, the MGI can serve as a substitute for relationship lending. MGIs have a very important role because they can prevent some of the moral-hazard problems that limit SME credit availability, owing to their peer-screening and peer-monitoring effects (Zecchini and Ventura, 2009). Because MGIs charge firms' fees when they post collateral, firms pay an extra cost when they obtain credit by means of mutual guarantees. As a consequence, firms requesting mutual guarantees tend to be riskier than the average (indicating adverse selection) (Columba et al., 2009).

Nevertheless, when MGIs implement scoring and rating models that enable firms' eligibility to be assessed and borrowers to be carefully screened, as in the case of loans counter-guaranteed by the CGF, the adverse selection effect may be more than adequately compensated for by the positive effect of MGI members' peer-screening and peer-monitoring activities (Zecchini and Ventura, 2009; Columba et al., 2010). The peer-screening activity allows each member of the MGI to be better informed of the riskiness of other members than a bank. Where an SME has a level of risk that is too high, other members of the MGI may not accept its membership. The presence of MGIs also reduces moral hazard through "peer monitoring"; members have an incentive to monitor each other because the cost in case of default is shared among the members.

Columba et al. (2010) demonstrate, using a sample of overdraft loans, that firms affiliated to MGIs pay lower interest rates for loans than when an MGI is not involved. The authors focus on overdraft loans, for which public guarantees are rare; therefore, it is possible to fully assess the signaling effect associated with being an MGI member. Their result is consistent with a positive role of MGIs in the overall screening and monitoring process of borrowing firms, of which banks seem to benefit. Mistrulli and Vacca (2011) confirm these findings. Moreover, Bartoli et al. (2013) analyze a sample of small firms borrowing loans from one of the main Italian banks and find, first, that borrowers assisted by MGIs are less likely to experience financial difficulties than firms that are not assisted by them and, secondly, that the positive effect of an MGI guarantee is significantly higher for SMEs with a shorter length of firm-bank relationship. This finding confirms that MGIs play a signaling role beyond the pure provision of a guarantee. Columba et al. (2009) suggest that the affiliation of a large number of companies with the MGI strengthens the effects of peer screening and monitoring, although there is a threshold above which this effect weakens. To maintain their solvency, MGIs are sometimes supported by the State using public funds. Busetta and Zazzaro (2012) find that this practice may reduce the efficiency of the MGIs in terms of peer monitoring and increase the level of risk, because in case of default the loss affects public funds rather than members' funds. Gai et al. (2016) analyze the determinants of default risk for 33,229 SME loans guaranteed by an MGI and counter-guaranteed by the Italian CGF. They demonstrate that increases in an MGI's leverage and the size of the counter-guaranteed portfolios increase the default risk. When the counter-guaranteed portfolio increases in size, MGIs take on more risk; however, this risk is still lower than when the MGIs involved operate in a limited geographical area or in specific sectors.

Previous studies indicate that MGIs perform better than banks in screening and monitoring opaque SMEs. Hence, we expect a lower failure risk for public guarantees requested by MGIs than for those requested by banks.

We therefore posit Hypothesis 1: *Loans guaranteed directly through banks have a higher failure risk than loans counter-guaranteed through MGIs.*

As discussed above, the role of financial intermediaries is particularly relevant when the borrower is informationally opaque. Age, size, and presence of tangible assets and collateral are factors that influence SMEs' opacity. When the available financial and economic information is not sufficient to carry out a complete assessment of a borrower's failure risk, the aspects cited above can be helpful in reducing a firm's information opacity. For example, the age of a firm can signal to the market the firm's resilience and ability to cope with difficult conditions (Bougheas et al., 2005; Ngoc et al., 2009). Younger firms are therefore considered more opaque than older ones.

The firm's size is another important element. According to the life cycle paradigm (Carey et al., 1993; Berger and Udell, 1998), SMEs are more informationally opaque than large firms. Finally, Gompers (1995) finds that increases in asset tangibility—which reduce information asymmetry problems because tangible assets' payoffs are easier to observe—reduce the monitoring activity of lenders. Some sectors (e.g., manufacturing) typically have a greater concentration of tangible assets, whereas the asset structures of firms in other sectors are primarily composed of intangible assets (e.g., computer services) (Mac et al., 2010). Firms with lien-free tangible assets may have greater access to debt finance than firms lacking such assets. The importance of inter- and intra-sectoral differences in accessing debt finance is confirmed in a number of studies reporting a statistically significant positive relationship between long-term debt and fixed assets (Van Der Wijst and Thurik, 1993; Chittenden et al., 1996; Jordan et al., 1998; Michaelas et al., 1999).

We expect that when borrowers are informationally opaque, soft information will be highly relevant, and thus MGIs can be considered a substitute for relationship lending. When opacity is lower and monitoring and screening activity is more dependent on the management and evaluation of hard information, we expect that banks are more efficient than MGIs.

Thus, we posit Hypothesis 2: *The default rates of loans featuring guarantees requested by MGIs and banks differ depending on firm age, size, and sector.*

3. Sample and descriptive statistics

This study's data are sourced from a unique confidential database provided by the CGF management committee. The data are related to loan guarantees granted from 2007 to 2009 for a total of 14.917 loan observations, and the loan survivorship is observed up to 2012. We focus on this limited period for two main reasons: i) we only have access to data in this confidential database for this specific time period; and ii) we examine a pre-recession period, because in Italy strong effects of the 2008 global financial crisis started to manifest at the end of 2009 and the beginning of 2010. In the period 2007 to 2009, the banking sector was not affected by persistent low interest rates, which did affect the subsequent period, partly due to European Central Bank (ECB) non-conventional monetary policy, distinguished by quantitative easing. In addition, in the pre-crisis period, the inflation rate was at the European Central Bank (ECB)'s desired level for achieving price stability (as shown in Appendix 1). In light of these considerations, the focus on the specific time period allows us to examine the banks' and MGIs' behavior independently of the consequences of the financial crisis.

Each observation is related to a single transaction, i.e., the issuance of a guarantee for a single loan. For each transaction, the database records the following information:

- The size, geographical area, and economic sector of the firm guaranteed;
- The exact date the guarantee was granted, the amount and expiration date of the guaranteed loan, the type of guarantee (direct or counter-guarantee), and the type of intermediary that applied to the CGF on behalf of the firm (bank or MGI); and
- The exact date of default.

We integrate the dataset with economic and financial information on guaranteed firms, sourced from the database of Italian firms, Bureau Van Dijk Electronic Publishing (AIDA), collecting data starting from 2006 in order to include the period before the issue of the guarantee[9].

[9] The available dataset consists of 24,637 guaranteed loan observations requested by 16,213 firms. We consider firms that received only one guarantee, and for firms that received more than one, we consider only the first one received. Two main reasons motivated this choice: First, a consistent method of analysis should to consider all firms at their first access to the guarantee (Caselli et al. 2019); and second, because the decision to access the credit guarantee could be recurrent, for each firm we consider only the first time it receives the guarantee (see, for instance, the literature about going public, Pagano et al. 1998). We clean our dataset of: observations with missing information about the guarantee granting date; firms in the agricultural sector, because they represent a very small percentage of our data and the sector has unusual characteristics affecting analysis; those with missing data relevant to matching with AIDA firm economic and financial data; and large firms. Our final sample is composed of 14,917 firms. Cleaning the dataset causes us to exclude only three loan defaults.

Table 1. Differences in means

	Total sample			MGI			Banks			T-test MGI vs Banks	DEFAULT			NON DEFAULT			T-test Default vs Non Default
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	P-value	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	P-value
MICRO	58,547	0.472	0.499	40968	0.513	0.5	17,579	0.378	0.485	***	210	0.748	0.435	58,337	0.471	0.499	***
SMALL	58,547	0.396	0.489	40968	0.385	0.487	17,579	0.422	0.494	***	210	0.205	0.404	58,337	0.397	0.489	***
MEDIUM	58,547	0.132	0.338	40968	0.102	0.303	17,579	0.199	0.4	***	210	0.048	0.213	58,337	0.132	0.338	***
LEVERAGE	56,400	10.89	38.49	39277	12.06	40.86	17,123	8.16	32.14	***	188	7.44	28.35	56,212	10.89	38.49	***
REVENUES_TA	58,547	1.088	1.594	40968	1.072	1.644	17,579	1.125	1.471	***	210	0.518	1.266	58,337	1.09	1.595	***
ROA	58,517	-1.832	32.537	40946	-2.87	35.986	17,571	0.585	22.351	***	207	-22.68	61.951	58,310	-1.758	32.362	***
SCORE_CGF	58.547	8.79	2.10	40968	8.63	2.15	17,579	9.14	1.96	***	210	7.02	2.75	58,337	8.78	2.10	***
YOUNG	58,547	0.262	0.44	40968	0.320	0.466	17,579	0.128	0.334	***	210	0.271	0.446	58,337	0.262	0.44	***
MANIFACTURING	58,547	0.405	0.491	40968	0.412	0.492	17,579	0.388	0.487	***	210	0.362	0.482	58,337	0.405	0.491	
CONSTRUCTION	58,547	0.084	0.277	40968	0.089	0.285	17,579	0.072	0.258	***	210	0.057	0.233	58,337	0.084	0.277	
SERVICES	58,547	0.511	0.5	40968	0.499	0.5	17,579	0.540	0.498	***	210	0.581	0.495	58,337	0.511	0.5	**
MATURITY	58,547	52.215	31.84	40968	47.127	31.71	17,579	64.073	28.846	***	210	59.576	25.69	58,337	52.189	31.857	***
LOAN_SIZE	58,547	11.957	1.079	40968	11.813	1.045	17,579	12.292	1.083	***	210	12.162	1.102	58,337	11.956	1.079	***
INVESTMENT	58,547	0.256	0.436	40968	0.241	0.427	17,579	0.291	0.454	***	210	0.314	0.465	58,337	0.256	0.436	*
NORTH	58,547	0.466	0.499	40,968	0.546	0.498	17,579	0.281	0.45	***	210	0.371	0.484	58,337	0.467	0.499	**
CENTER	58,547	0.185	0.388	40,968	0.256	0.436	17,579	0.020	0.139	***	210	0.071	0.258	58,337	0.186	0.389	***
SOUTH AND ISLANDS	58,547	0.348	0.476	40,968	0.198	0.399	17,579	0.699	0.459	***	210	0.557	0.498	58,337	0.348	0.476	***
INTERMEDIARY	58,547	0.300	0.458	-	-	-	-	-	-	-	210	0.666	0.472	58,337	0.289	0.457	***
DEFAULT	58,547	0.003	0.059	40,968	0.001	0.041	17,579	0.007	0.088	***	-	-	-	-	-	-	-

The Table represents guarantee allocation for our sample firms calculated on the period 2007-2012. It shows the results of the differences in means considering i) guarantee requested by MGIs or by banks, and ii) loans in default and loans not in default. "*", "**", "***" indicate 1%, 5%, 10% significance levels
SMALL_FIRM and MICRO_FIRM are two dummy variables that proxy the firm's size, the first is equal to 1 when firm is small and 0 otherwise, the second dummy variable is equal to 1 when firm is micro and 0 otherwise; LEVERAGE is the ratio between firm's total assets and equity as measure of firm's financial leverage; REVENUES_TA is the ratio between total revenues and total assets; ROA is the return on asset that is a measure of firm's profitability; SCORE_CGF is a category variable that spans from 0 to 12. Lower values are associated to lower firm profitability, capitalization and capability to repay interest, while higher values are associated to firms with better profitability, capitalization and capability to repay interests; YOUNG is a dummy variable equals 1 when firm exists less than three years and 0 otherwise; MANUFACTORING and CONSTRUCTION are two dummy variables referring to the sector in which firm operates; INVESTMENT is a dummy variable equals 1 whether the loan is requested for an investment and 0 otherwise; MATURITY (and its square) is the time to maturity expressed in months; LOAN_SIZE (and its square) is the natural logarithm of amount of loans;
NORTH, CENTER and SOUTH AND ISLANDS are three dummy variables that proxy the geographical position of firms; INTERMEDIARY is equal 1 if it is a bank and 0 otherwise; DEFAULT is equal 1 if firm goes in default during the period analyzed, zero otherwise.

Table 1 presents descriptive data regarding guarantees for our sample firms. Furthermore, we categorize guaranteed loans according to two criteria: i) whether the guarantee was requested by an MGI or bank, and ii) whether the loan is in default. We perform t-tests to test the differences in means for subsamples based on these criteria.

For the subsamples split by type of intermediary, Table 1 reports the average value and the t-test results, which show that guarantees requested by MGIs are more oriented to micro firms, younger firms (of age less than 3 years), and those operating in the manufacturing and construction industries, in comparison with firms for which guarantees are requested by banks. In detail, among the counter guarantees requested by MGIs, 51% are for micro firms, 39% for small firms, and 10% for medium firms. Among the sample of guarantees requested by banks, the percentages are as follows: 38% for micro firms, 42% for small firms, and 20% for medium firms. Younger firms are more frequently intermediated by an MGI (32%) than by a bank (13%). Firms intermediated by an MGI belong mainly to the service sector (50%) followed by manufacturing (41%) and construction (9%). The sector distribution is similar for firms intermediated by banks: 54% for the services sector, 39% for manufacturing, and 7% for construction.

Regarding the geographical distribution, MGIs operate more in the north area (54%) followed by the center and south (26% and 20%, respectively). Banks show a different distribution: 70% of firms are located in the south, 28% in the north, and only 2% in the central area.

Counter-guaranteed firms are found to have worse economic and financial conditions (measured by profitability, leverage, and total asset turnover). Considering the originating scoring issued by CGF, the quality of firms intermediated by banks (9.14) seems slightly higher than the quality of those intermediated by MGIs (8.63). Considering the loans' characteristics, when an MGI is used, firms borrow loans of smaller amounts (with a value of 11.81, corresponding to an average amount of 227,100 euro) and with shorter maturities (47.13 months) than for banks (which show a value of 12.29, corresponding to an average loan amount of 357,937 euro, and an average maturity of 64.07 months). In all cases, the differences in mean values are statistically significant. Finally, despite the finding that, on average, firms guaranteed through banks show better financial characteristics, their loans show a higher failure risk. The default rate is higher for directly guaranteed loans than for counter-guaranteed loans.

For the subsamples split by the default or not-default status of the loan, Table 1 reports descriptive statistics and shows that the average maturity of loans on which default did not occur is about 52 months, whereas loans in default have a higher maturity (of 59.7 months). In terms of loan size, loans in default are larger than others and the stated reason for requesting the loan is more frequently for the purpose of investment.

Firms that defaulted on their loan in the period are smaller in size—micro firms show a higher average rate of default—and show lower profitability (as measured by ROA), lower solvency (measured by equity over total asset ratio), and lower revenues over total assets. Therefore, the loans more likely to default are those guaranteed to firms with worse economic and financial conditions. Younger firms (established for less than three years) account for 27% of the firms that subsequently defaulted. In terms of the loans' characteristics, descriptive statistics underline that larger and longer-term loans are more likely to default.

4. Methodology

To test our hypotheses, we run a Cox proportional-hazards model (Cox, 1972), which allows the relationship between loan survival and several explanatory variables to be explored. Survival analysis is a common statistical analysis used in the medical field (Qin and Shen, 2010; Xiao and Moodie, 2013; Halabi et al., 2014); however, in recent decades, it has become a useful technique in the financial and economic fields to estimate the treatment effect on survival after adjustment for other explanatory variables (see, for example, Parker et al., 2002; Glennon and Nigro, 2005a; Kelly and O'Malley, 2016). Lane et al. (1986) pioneered the use of the Cox proportional hazard model to estimate bank failure. This form of analysis also allows estimation of the hazard (risk) of default for a firm based on its specific characteristics.

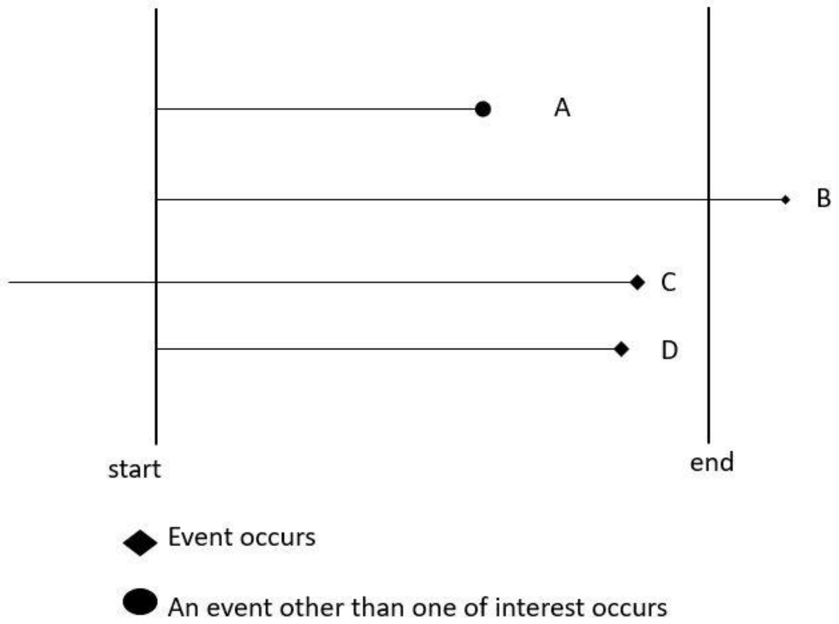
The event of interest in our study is the default on a guaranteed loan. The dependent variable is the period from the day on which the guarantee is granted to the day of default of the loan. If the default does not occur, the loan is observed until the end of the sample period investigated; when the event has not yet occurred, the data are censored[10].

A key characteristic that distinguishes survival analysis from other statistical methods is that survival data are usually censored or incomplete. Censoring occurs when incomplete information is available about the survival time of observations. The observations can be left- or right-censored. As reported in Figure 1, we observe left-censoring (or left truncation) when the missing information refers to the starting point, i.e. the study starts to observe the individual after the beginning of the period of interest (in our study, we would have had left truncation if we had observed a loan after the day on which the guarantee was granted) (subject C). In the case of right-censoring, the two main reasons for censoring data are: a) the study ends before the event occurs: in this case, we can refer to such censoring as *end-of-study censoring* (Subject B); b) an event other than the one of interest occurrs during the period of observation: in this case, the situation can be referred to as *loss-to-follow-up censoring* (Subject A), e.g. in this study, the loss of follow up of the firm or the prepayment. In the case of Subject D, the event of interest (in this

10 We are not able to observe the loans until the maturity date. We observe the firms' loans until 2012, i.e. from a minimum of three years after the loan was issued up to six years.

study, the default of loans and activation of guarantees) is observed during the course of the study; therefore, there are no censored data.
Moreover, it is important to distinguish between non-informative and informative censoring. The former occurs when individuals drop out of the study for reasons unrelated to the study, while the latter occurs when observations are lost to follow-up because of reasons related to the study.
In our study, the only two situations included in the dataset are the cases of subjects B and D. In fact, all loans are observed from the day of loan granting and guarantee pledging up to the end of the study (2012) or the day on which the loan defaults. Generally, in studies on firms' default and loan default, the most important competing risk that is considered is early repayment (Dirik et al., 2016). Therefore, in order to account for this event, we check our sample and observe that no early repayments are present in the dataset: we never have cases A or C.
Under the assumption that the time of entry to the study is independent of the risk period, also the end-of-study censoring is independent of survival time, and hence it poses no problem to the analysis (Leung et al., 1997; Wang et al., 2011).

Figure 1. Censored data



The Cox model is expressed by the hazard function, denoted by h(t). Briefly, the hazard function can be interpreted as the risk of dying (default) at time t, and estimated as follows:

$$h(t)=h0(t)\times\exp(\ \delta_i + \sum_{k=1}^{K} \alpha_k X_{kij-1} + \sum_{k=1}^{K} \alpha_k S_{ki} + Z_{kj} + J_{ik} + W_{kij} + \varepsilon_i) \quad (1)$$

where t represents the survival time; h(t) is the hazard function determined by a set of k covariates (included in vectors $X_{k,}$ $S_{k,}$ J_k, and W_k), and the coefficients (α_k) that measure the impact of covariates on the survival time; i represents each firm; and j is the time variable. The quantity $h_0(t)$ is the baseline or underlying hazard function, and corresponds to the probability of reaching the event (loan default) when all the explanatory variables are zero. Further, in the equation, δ_i represents the type of intermediary that requests the guarantee from the CGF (INTERMEDIARY), which is equal to one for banks and zero for MGIs.

In our analysis, the covariates can be divided into two main groups of variables: a) the vector that includes the firms' financial characteristics (X_k) and b) the vector including the loans characteristics (S_k).

With regard to the first vector (X_k), several authors have underlined that the firms' financial structure can affect the ability of firms to repay their loans (Gelnnon and De Nigro, 2005a and 2005b; Fidrmuc and Hainz, 2010; Modina and Pietrovito, 2014; Duarte et al., 2018). Fidrmuc and Hainz (2010) highlight the importance of profitability in determining the probability of firm's default; therefore, we include the return on assets as measure of firm's profitability (ROA) and expect that firms with higher profitability have a lower hazard of default than others. Further, the firm's indebtedness is a crucial factor of its probability of default, and, consequently, also of the loan's probability of default. We include the leverage (LEVERAGE), measured as the ratio between total assets over equity. Firms with higher financial leverage are more exposed to the probability of default; therefore, we expect a positive relationship between this variable and the hazard ratio (Khieu et al., 2012; Bonaccorsi et al., 2014).). Another determinant of loan default is the asset turnover ratio (REVENUES_TA) which is an indicator of the efficiency with which a firm uses its assets to generate revenues. The higher the asset turnover, the more efficient the firm and, therefore, the lower the hazard of loan default (Pedarzoli and Torricelli, 2010). The CGF assesses the level of firms' creditworthiness before granting the guarantee (using a scoring system); therefore, to consider the score attributed by the CGF to each firm, we create a category variable that ranges from 0 to 12. This variable includes four financial and profitability ratios, which are as follows: (Equity + Long-term debt)/Total fixed assets; equity over total assets; EBITDA over sales; and, finally, EBIT over financial expenses.[11]

Glennon and De Nigro (2005a) assert that new businesses have a higher hazard of default than established firms; therefore, we include in our regression model a dummy that distinguishes firms younger than 3 years old —the so-called startup — from others (YOUNG); firm size proxied by three different dummy variables that distinguish micro- and small firms from medium firms; and, finally, as suggested by

[11] More details about the CGF score methodology are available in Appendix2.

Glennon and De Nigro (2005a) and Duarte et al. (2018), because the industry classification can affect the rate of loan default, we include in our regression model the firm sectors proxied by two different dummy variables that distinguish between construction and manufacturing compared with services (CONSTRUCTION and MANUFACTURING).

As suggested by Duarte et al. (2018), loan characteristics also influence the default. We include in the vector S_k the following variables: loan size, equal to the natural logarithm of the amount issued, and we expect that larger loans are more exposed to default than smaller ones; in fact, larger loans are granted to finance large-scale projects that may be risky (Derban et al., 2005; Duarte et al., 2018); and loan maturity, as measured by the natural logarithm of the number of months taken to repay the loan. In fact, Glannon and De Nigro (2005b) show that the lender's exposure to loss may depend on the average maturity of the loans.

To capture the differences at time- and geographical level that are not captured by other variables, we insert a time-fixed effect vector (Z_t) and a geographical-fixed effect vector that distinguishes between firms located in the north; center; and south and islands (J_k) (Duarte et al., 2018).

Finally, to investigate our second hypothesis linked to the ability of the intermediary to deal with informationally opaque firms, we run the Cox model, including a series of interactive variables where we interact INTERMEDIARY and some firm-specific characteristics that are indicative of the firm's opacity, such as sector, firm size, and firm age (vector W_k), allowing for the sensitivity of the hazard rate (Pappas et al., 2017). Looking at the interaction variables, we can observe the circumstances under which the risk of failure of loans guaranteed by banks is higher or lower than those guaranteed by MGIs. As suggested by Bellotti and Crook (2017), we expect that the inclusion of interactions between some firm-specific variables and the kind of intermediary may lead to better models because one intermediary would be better than another, depending on the characteristics of the borrower. To test the goodness of fit of each model, we run the likelihood ratio test.

The request for a direct guarantee by a bank or for a counter-guarantee by an MGI may lead to a selection bias problem because loans were not randomly allocated to the two groups of intermediaries (banks and MGIs). Sample selection is a problem frequently encountered in applied research. One of the causes may be the self-selection of the individuals being investigated (Kyriazidou, 1997). The presence of a selection bias may lead to bias coefficients (Storey, 2000). Moreover, it is possible that some variables that are statistically significant in the first model may become insignificant in the correct model and vice-versa (Cader and Leatherman, 2011).

In experimental studies, the selection bias problem is dealt using a random assignment of treatment. This ensures that every individual has the same probability of receiving the treatment (Jyotsna and Ravallion, 2003). This is not possible in non-experimental studies, which is the case in our study. To mitigate this problem and eliminate the selection bias, in these non-experimental studies the most common approaches the instrumental variables (IVs) and Heckman selection estimators and propensity-score matching are the most commonly used approaches in non-experimental studies. The two-step Heckman model can help to reduce problems associated with selection bias in the survival analysis to estimate the Inverse Mill's Ratio (IMR) (Heckman, 1981; Cader and Leatherman, 2011). In the first stage, we run a probit model where the dependent variable is the intermediary (MGI or bank), and we calculate the IMR (eq.2). In the second stage, we run the Cox model described before (Eq. 1) and include the IMR obtained from the first stage.

$$INTERMEDIARY_{it} = 1(\mathbf{X}_{ij} + W_i + S_{i,j} + J_i + Z_i + R'_{itj}\gamma + \eta_i + u_{itj} > 0), \quad (2)$$

$\mathbf{X}_{ij}$, W_i, and $S_{i,j}$ (Eq.1) and R_{ij} (Eq.2) are vectors of strictly exogenous explanatory variables with possibly common elements, including both time-variant and time-invariant variables and a constant term. Although $\mathbf{X}_{ij}$, W_i, and $S_{i,j}$ (Eq.1) and R_{ij} (Eq.2) may contain common variables, identification by the exclusion restriction scheme requires Eq. (2) to contain at least one variable that is not included in the main equation and displays a significant time variability (Matyas and Sevestre, 2008; Semykina and Wooldridge, 2013). For this reason, we include the squared variables of each firm-specific and loan-specific characteristic and a dummy variable equals 1 if the purpose of the requested loan is for investment, and 0 otherwise (INVESTMENT). The inclusion of quadratic approximation can greatly decrease selection bias (Stanley and Doucouliagos, 2014; Havranek, 2010), whereas investment represents our exclusion restriction included in the first step of our model; we choose this variable because it is not statistically significant when included in the second step (the determinants of probability of loans default).[12] η_i represents unobserved time-invariant individual specific effects that are possibly correlated with each other.

In this step, we estimate a probit model in which the dependent variable is a dummy variable that equals 1 if the guarantee is requested by a bank, and 0 otherwise (i.e., if it is requested by an MGI). This first-stage equation is relevant in itself because it allows us to observe the determinants of the intermediary used. Using the first-stage results, we construct the dynamic Mills ratios for every j:

[12] As a robustness check, we substitute INVESTMENT with the firm's liquidity at time t-1, which is not statistically significant in the second step; therefore, it is not a determinant of the probability of the loan's default but a determinant of the probability of obtaining the loan directly from the bank or though the counter-guarantee offered by the MGI. However, we prefer the probit model with INVESTMENT because it fits better than that with the firm's liquidity.

$$\lambda_{ij}^{d} = \frac{\phi(Z'_{ij}\hat{Y})}{1 - \Phi(Z'_{ij}\hat{Y})} \tag{3}$$

where $\phi()$ and $\Phi()$ denote, respectively, the probability density function and cumulative distribution function of a standard normal distribution. We incorporate the IMR into our main Cox model to control for the selection bias. The level of significance of the IMR reveals the presence or absence of the selection bias problem. Moreover, the size and level of significance of the ratio offers additional information about the severity of the selection bias problem (Cader and Leatherman, 2011). To test the adjustment of selection bias, we check the level and significance of the correlation between the residuals of equation (2) and equation (1) with IMR as covariate. In fact, it is useful to note that the IMR is the generalized residual for the probit model (see Gourieroux et al. 1987, Vella 1993). This term possesses two important characteristics of a residual. First, it has mean zero over the whole sample. Second, it is uncorrelated with the variables that appear as explanatory variables in the first-step probit.

5. Empirical results

As the first step, we plot the survival function for the group of guaranteed loans requested by banks (Intermediary=1) and the group intermediated by MGIs (Intermediary=0). The survival functions show that, at any point in time, having a bank as the intermediary in the relationship with the CGF is associated with lower survival rate (Fig. 2). This means that if the CGF grants a guarantee through a bank (directly), the firm's loan is more likely to go into default. In other words, when the CGF intervenes as guarantor on a loan already guaranteed by MGIs, the probability that the CGF will be called to repay the debt is lower. Therefore, through screening and monitoring activities, MGIs are usually better able to mitigate the loan's failure risk than banks.

Figure 2 Kaplan-Meier survival estimates

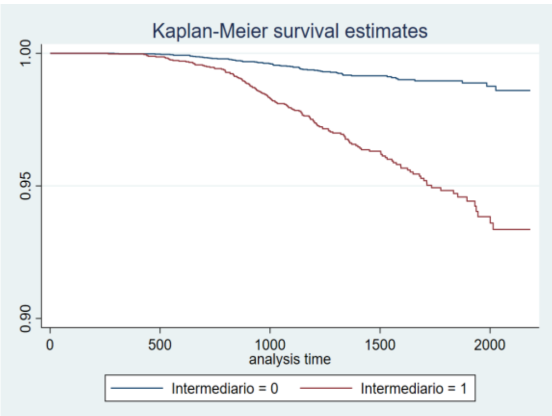


Figure shows the Kaplan–Meier survival curves in loans with a direct guarantee and loans with an indirect guarantee. The testing of the proportional hazard assumption is most straightforward when we compare two groups with no covariates. The simplest check is to plot the Kaplan–Meier survival curves together.

Table 2 The description of time to default

Category	**Total**	**mean**	**min**	**median**	**max**
no. of subjects	14,917	-	-	-	-
no. of records	58,116	3.896	1	4	6
(first) entry time		0	0	0	0
(final) exit time		1281.452	9	1,283	2,183
subjects with gap	0	-	-	-	-
time on gap if gap	0	.	.	.	.
time at risk	19,115,419	1281.452	9	1,283	2,183
Failures	210	0.0141	0	0	1

Table 2 shows the time to default and the distribution of loans between defaulted and non-defaulted loans. In the sample, we have 14,917 guaranteed loans and 58,116 year-observations. Loans are observed, on average, for 3.89 years, with a minimum of one year and a maximum of six years. On average, the loan remains in the sample — before the default — for 2,281 days. Within the total sample, there are 210 failures.

Table 3 reports results of our main analysis in which we do not consider the problem related to selection bias. The dependent variable is the hazard of default, and we run three different models: in the first one, we include only the bank-specific characteristics; in the second we add the loan's characteristics; and finally, in the last model, we include the interactive variables between the type of intermediary and some firm-specific characteristics such as size, sector, and age. Our results underline that the type of intermediary that requests the CGF guarantee is important in determining the hazard time to default and, in particular, when the guarantee is requested directly by the bank, the hazard of default is higher. Looking at the firm's characteristics, micro firms and those with a worse financial situation — in terms of leverage, profitability, and revenue/turnover — are more exposed to loan default than other firms. With regard to the loan characteristics, it seems that only loan size is relevant — showing a positive relationship with failure risk — while loan maturity does not show any statistically significant relationship with the hazard of default.

Finally, our findings show that the failure risk of counter-guaranteed loans in favor of younger firms is 2.13% lower than that of directly guaranteed loans. The result confirms that when the firm is young and has not yet developed a long-term relationship with the bank, the MGI is a substitute for relationship lending (Bartoli, 2013). Banks seem to be more efficient when manufacturing firms are involved. In this case, directly guaranteed loans show a failure risk 0.50% lower than that of counter-guaranteed loans.

Table 3. Cox hazard model for time to default

	Mod. 1		Mod. 2		Mod. 3	
VARIABLES	Coeff	Hazard Ratio	Coeff	Hazard Ratio	Coeff	Hazard Ratio
INTERMEDIARY	1.902***	6.699	1.867***	6.468	1.425*	4.157
	(0.162)		(0.177)		(0.734)	
MICRO	1.300***	3.669	1.899***	6.679	1.589**	4.898
	(0.357)		(0.394)		(0.641)	
SMALL	0.446	1.562	0.730**	2.075	-0.076	0.926
	(0.354)		(0.364)		(0.700)	
LEVERAGE(t-1)	0.004***	1.004	0.004***	1.004	0.004***	1.004
	(0.001)		(0.001)		(0.001)	
REVENUES_TA(t-1)	-0.470***	0.625	-0.377**	0.685	-0.382**	0.682
	(0.171)		(0.164)		(0.165)	
ROA(t-1)	-0.005***	0.995	-0.005***	0.995	-0.005***	0.995
	(0.001)		(0.001)		(0.001)	
SCORE_CGF	-0.246***	0.781	-0.244***	0.783	-0.244***	0.783
	(0.031)		(0.030)		(0.030)	
YOUNG	0.128	1.136	0.322*	1.379	-0.079	0.924
	(0.173)		(0.176)		(0.264)	
MATURITY	-	-	-0.002	0.998	-0.002	0.998
			(0.002)		(0.002)	
LOAN_SIZE	-	-	0.416***	1.515	0.459***	1.582
			(0.087)		(0.090)	
MANIFACTURING	-	-	-	-	0.351	1.420
					(0.260)	
CONSTRUCTION	-	-	-	-	-0.167	0.846
					(0.498)	
INTERMEDIARY*MICRO	-	-	-	-	0.433	1.541
					(0.720)	
INTERMEDIARY*SMALL	-	-	-	-	1.078	2.938
					(0.799)	
INTERMEDIARY*YOUNG	-	-	-	-	0.757**	2.131
					(0.346)	
INTERMEDIARY*MANUFACTURE	-	-	-	-	-0.691**	0.501
					(0.316)	
INTERMEDIARY*CONSTRUCTION	-	-	-	-	-0.354	0.701
					(0.634)	
SECTOR_FE	YES		YES		-	
GEOGRAPHICAL_FE	YES		YES		YES	
TIME_FE	YES		YES		YES	
Observations	55,975		55,975		55,975	
Pseudo R2	0.104		0.111		0.115	

This table shows the results of the Cox Regression Model. “*”, “**”, “***” indicate 1%, 5%, 10% significance levels respectively. The dependent variable is a dummy variable equals 1 whether the firm’s loan defaults and 0 otherwise. The independent variable are: INTERMEDIARY is a dummy variable equals 1 if the guarantee to the MGF is requested by a bank and 0 otherwise; SCORE_CGF is a category variable that spans from 0 to 12. Lower values are associated to lower firms’ profitability, capitalization and capability to repay interest, while higher values are associated to firms with better profitability, capitalization and capability to repay interests. SMALL_FIRM and MICRO_FIRM are two dummy variables that proxy the firm's size, the first is equal to 1 when firm is small and 0 otherwise, the second dummy variable is equal to 1 when firm is micro and 0 otherwise; LEVERAGE is the ratio between firm's total assets and equity as measure of firm's financial leverage; REVENUES_TA is the ratio between total revenues and total assets; ROA is the return on asset that is a measure of firm's profitability; YOUNG is a dummy variable equals 1 when firm exists less than three years and 0 otherwise; MANUFACTORING and CONSTRUCTION are two dummy variables referring to the sector in which firm operates; INVESTMENT is a dummy variable equals 1 whether the loan is requested for an investment and 0 otherwise; MATURITY (and its square) is the natural logarithm of the loans time to maturity expressed in days; LOAN_SIZE (and its square) is the natural logarithm of amount of loans; SECTOR_FE, GEOGRAPHICAL_FE and YEAR_FE are three vectors that capture differences at sector, time and geographical levels. Columns "Coeff" report the coefficient of the Cox regression; Columns "Hazard ratio" report the hazard ratio of the cox regression (the exponential of the coefficient).

However, as reported in the methodology section and observed in the descriptive analysis, our analysis may be affected by the problem of selection bias. In particular, the selection bias problem refers to the decision of firms to make the loan request with or without a counter guarantee (i.e. whether between the firm and bank there will be an MGI that offers an additional guarantee to the bank). The presence of selection bias may lead to biased results, both in terms of the magnitude of coefficients and in terms of statistical significance. To control for the presence of selection bias and adjust for this error, we run a Heckman two-step model, first running the probit model to define the IMR and, second, adding the IMR to the Cox proportional hazard model.

In Table 4, the results of the regression analysis are reported, where the dependent variable is a dummy variable that equals 1 when the intermediary is a bank and zero otherwise (i.e., when it is an MGI). We observe the determinants of the choice of intermediary and derive the IMR, which we insert into the Cox regression. Our results highlight that firms with higher capitalization, higher revenues/turnover, and higher CGF score are more likely to ask for a direct guarantee through the bank than a counter guarantee through the MGI. In regard to firm size, small and micro firms are more frequently intermediated by an MGI than medium-sized ones. Moreover, younger firms are more likely to ask the State for counter-guarantees through an MGI than older firms. Furthermore, the motivation behind the loan request is a determinant of the probability of requesting the guarantee directly through bank or through an MGI: our results show that when investment (and not access to a liquidity line) is the motivation for the loan, firms access direct guarantees more frequently than counter guarantees. With regard to the sector, firms that operate in the manufacturing sector are more likely to resort to direct guarantees through banks than firms that operate in the service sector, while firms that operate in the construction sector are more likely to resort to MGI counter-guarantees than firms that operate in the service sector.

Finally, with regard to loan characteristics, loan maturity and loan size are two determinants of the probability to ask for a direct guarantee by banks or a counter guarantee trough MGI. In particular, firms asking longer and smaller loans are more likely to obtain direct guarantee without the interposition of a MGI.

Table 4 Probit regression to define the IMR

VARIABLES	Mod. 0
Constant	2.019***
	(0.695)
LEVERAGE(t-1)	-0.001***
	(0.000)
LEVERAGE^2(t-1)	-0.001***
	(0.000)
REVENUES_TA(t-1)	0.142***
	(0.011)
REVENUES_TA^2(t-1)	-0.006***
	(0.001)
SCORE_CGF	0.039***
	(0.003)
SMALL	-0.207***
	(0.022)
MICRO	-0.312***
	(0.026)
YOUNG	-0.482***
	(0.017)
INVESTMENT	0.008
	(0.015)
MATURITY	-0.193***
	(0.025)
MATURITY^2	0.163***
	(0.017)
LOAN_SIZE	0.033***
	(0.000)
LOAN_SIZE^2	-0.000***
	(0.000)
MANIFACTURING	-0.753***
	(0.118)
CONSTRUCTION	0.041***
	(0.004)
GEOGRAPHICAL_FE	YES
YEAR_FE	YES
Observations	56,399
Pseudo R2	0.364

This table shows the results of the Probit Regression. “*”, “**”, “***” indicate 1%, 5%, 10% significance levels respectively. The dependent variable is a dummy variable equals 1 whether the intermediary is a bank and 0 otherwise. The independent variable are: LEVERAGE is the ratio between firm’s total assets and equity as measure of firm’s financial leverage; REVENUES_TA (and its square) is the ratio between total revenues and total assets; SCORE_CGF is a category variable that spans from 0 to 12. Lower values are associated to lower firm profitability, capitalization and capability to repay interest, while higher values are associated to firms with better profitability, capitalization and capability to repay interests. SMALL_FIRM and MICRO_FIRM are two dummy variables that proxy the firm’s size, the first is equal to 1 when firm is small and 0 otherwise, the second dummy variable is equal to 1 when firm is micro and 0 otherwise; YOUNG is a dummy variable equals 1 when firm exists less than three years and 0 otherwise; MANUFACTORING and CONSTRUCTION are two dummy variables referring to the sector in which firm operates; INVESTMENT is a dummy variable equals 1 whether the loan is requested for an investment and 0 otherwise; MATURITY (and its square) is the natural logarithm of the loans time to maturity expressed in days; LOAN_SIZE (and its square) is the natural logarithm of amount of loans; GEOGRAPHICAL_FE and YEAR_FE are two vectors that capture differences at time and geographical levels.

Table 5 shows the results of the Cox proportional hazard model. We run three regression models; in each, we add one vector of regression (1). In all models, sector-, the time- and geographical-fixed effect are included. In order to test which is the best model, we run the likelihood ratio (LR) test. This test is used to evaluate the difference between nested models. One model is considered nested in another when the first model can be generated by imposing restrictions on the parameters of the second. In a regression model, restricting the parameters to zero means removing the covariate from the non-restricted regression model. Therefore, in our analysis, we can observe that Model 4 is nested with Model 5, and Model 5 is nested with Model 6. Our LR test shows that adding the loan characteristics to the baseline model results in a statistically significant improvement in the model fit, because the p-value of chi^2 of the LR test is statistically significant. Moreover, adding the interactive variables in Model 6 allows the model fit to be improved relative to Model 5.

We run the same test to check whether Model 6 is superior to Model 3 (the model with interactive variables but without the IMR, and therefore without the selection bias adjustment). In this case also, the LR test shows that the model with IMR is better than the Cox proportional hazards model without IMR, thus providing preliminary information that the IMR improves the model fit.

Table 5. Cox model – coefficients and hazard ratio controlling for selection bias

	Mod. 4		Mod. 5		Mod. 6	
VARIABLES	Coeff	Hazard Ratio	Coeff	Hazard Ratio	Coeff	Hazard Ratio
INTERMEDIARY	1.623***	5.068	1.690***	5.419	1.501**	4.486
	(0.167)		(0.170)		(0.748)	
MILLS	-0.850***	0.427	-1.064***	0.345	-0.978***	0.376
	(0.213)		(0.345)		(0.343)	
MICRO	1.680***	5.366	2.168***	8.741	1.957***	7.078
	(0.378)		(0.405)		(0.676)	
SMALL	0.665*	1.944	0.910**	2.484	0.178	1.195
	(0.362)		(0.368)		(0.719)	
LEVERAGE(t-1)	0.006***	1.006	0.006***	1.006	0.006***	1.006
	(0.001)		(0.001)		(0.001)	
REVENUES_TA(t-1)	-0.487***	0.614	-0.447***	0.640	-0.446***	0.640
	(0.167)		(0.165)		(0.166)	
ROA(t-1)	-0.005***	0.995	-0.005***	0.995	-0.005***	0.995
	(0.001)		(0.001)		(0.001)	
SCORE_CGF	-0.271***	0.763	-0.271***	0.763	-0.270***	0.763
	(0.031)		(0.031)		(0.032)	
YOUNG	0.406**	1.501	0.618***	1.855	0.322	1.380
	(0.181)		(0.206)		(0.297)	
MATURITY	-	-	-0.010**	0.990	-0.010**	0.990
			(0.004)		(0.004)	
LOAN_SIZE	-	-	0.276***	1.318	0.319***	1.376
			(0.098)		(0.101)	
MANIFACTURING	-	-	-	-	0.391	1.478

					(0.261)	
CONSTRUCTION	-	-	-	-	0.048	1.049
					(0.494)	
INTERMEDIARY*MICRO	-	-	-	-	0.270	1.310
					(0.736)	
INTERMEDIARY*SMALL	-	-	-	-	0.965	2.625
					(0.809)	
INTERMEDIARY*YOUNG	-	-	-	-	0.529	1.697
					(0.352)	
INTERMEDIARY*MANIFACTURE	-	-	-	-	-0.739**	0.478
					(0.318)	
INTERMEDIARY*CONSTRUCTION	-	-	-	-	-0.461	0.631
					(0.633)	
SECTOR_FE	YES		YES		-	
GEOGRAPHICAL_FE	YES		YES		YES	
TIME_FE	YES		YES		YES	
Observations	55,975		55,975		55,975	
Pseudo R2	0.109		0.114		0.117	
LR Test Mod4-Mod5	-		0.0000		-	
LR test Mod5-Mod6	-		-		0.0654	
LR test Mod3-Mod6	-		-		0.0042	
Corr. Residuals					0.9891***	

This table shows the results of the Cox Regression Model. "*", "**", "***" indicate 1%, 5%, 10% significance levels respectively. The dependent variable is a dummy variable equals 1 whether the firm's loan defaults and 0 otherwise. The independent variable are: INTERMEDIARY is a dummy variable equals 1 if the guarantee to the MGF is requested by a bank and 0 otherwise; MILLS is the inverse mills ratio obtained from the probit regression to control for the selection bias problem; SCORE_CGF is a category variable that spans from 0 to 12. Lower values are associated to lower firms profitability, capitalization and capability to repay interest, while higher values are associated to firms with better profitability, capitalization and capability to repay interests. SMALL_FIRM and MICRO_FIRM are two dummy variables that proxy the firm's size, the first is equal to 1 when firm is small and 0 otherwise, the second dummy variable is equal to 1 when firm is micro and 0 otherwise; LEVERAGE is the ratio between firm's total assets and equity as measure of firm's financial leverage; REVENUES_TA is the ratio between total revenues and total assets; ROA is the return on asset that is a measure of firm's profitability; YOUNG is a dummy variable equals 1 when firm exists less than three years and 0 otherwise; MANUFACTORING and CONSTRUCTION are two dummy variables referring to the sector in which firm operates; INVESTMENT is a dummy variable equals 1 whether the loan is requested for an investment and 0 otherwise; MATURITY (and its square) is the natural logarithm of the loans time to maturity expressed in days; LOAN_SIZE (and its square) is the natural logarithm of amount of loans; SECTOR_FE, GEOGRAPHICAL_FE and YEAR_FE are three vectors that capture differences at sector, time and geographical levels. Columns "Coeff" report the coefficient of the Cox regression; Columns "Hazard ratio" report the hazard ratio of the cox regression (the exponential of the coefficient).

To test whether there is a selection bias problem and if the introduction of the IMR variable in the second stage of our model mitigates this problem, we perform correlation between the residuals of the first and second stages of the Heckman two-step model (correlation between ε and u). Our result highlights that the correlation is 0.9891 with statistical significance at 99%, suggesting that the selection bias problem exists and that the IMR is able to reduce this problem (Certo et al., 2016). This evidence is confirmed by the significance of the IMR coefficient which, in all models shown in Table 5, displays statistical significance at 99%.

Table 5 reports the coefficient and the hazard ratio of our results (in the first and second column of each model, respectively). In particular, our findings suggest that loans guaranteed through banks experienced higher risk of default than those guaranteed through MGIs (positive and significant coefficient for all the models presented). When the CGF grants a direct guarantee, the failure risk is higher than 4.49% compared with that for counter-guarantees (see Model 6, column showing hazard ratios). The results confirm the higher effectiveness of MGIs than banks in carrying out monitoring activities, especially in this specific segment of firms that are characterized by higher opacity. Peer screening and peer monitoring seem to reduce the default rate by a larger extent than the screening and monitoring activities carried out by banks (Mistrulli and Vacca, 2001; Columba et al., 2010, Bartoli et al., 2013; Zecchini and Ventura, 2009). The results confirm our first hypothesis, in that loans guaranteed directly through banks have a higher failure risk than counter-guaranteed loans through MGIs.

With regard to firm's characteristics (Model 6, Table 5), loans issued to micro firms are more likely to default and show lower loan survival duration than loans issued to medium-sized firms. Guaranteed loans granted to micro firms register a 7.08% higher failure risk than medium firms. Guaranteed loans granted to small firms have a 2.48 % higher failure risk than medium+ firms (see Model 5, Table 5; although this is not confirmed in the Model 6). These results confirm the life-cycle paradigm (Carey et al., 1993; Berger and Udell, 1998). Larger firms are more diversified, and hence less likely to face bankruptcy; additionally, they are more profitable and less informationally opaque. The results confirm the relevance of firm's age: younger firms have a higher hazard rate than older firms (even if not confirmed in the last model). Guaranteed loans granted to young firms have an 1.85% higher failure risk than older firms (Model 2 Table 5), according to Bougheas et al. (2005), Ngoc et al. (2009), and Huyghebeart and Van de Gucht (2007), although this result is not confirmed in the Model 6. This result is not surprising, considering the survival rate of startup firms in Italy: on average, only one of every two startups survives (AIAF, 2017); consequently, loans issued to these younger firms are riskier and more likely to default than loans issued to older firms.

In regard to firm-specific characteristics, results confirm that more profitable firms and firm with higher ratios of revenues to total assets are less likely to default on the reimbursement of their guaranteed loans: increases of one percentage point in profitability and total asset turnover decrease the failure risk by 0.99% and 0.64%, respectively, while an increase of one percentage point in leverage increases failure risk by 1%. Moreover, our results demonstrate that the rating score has a statistically significant and negative relationship with the dependent variable, and therefore firms with a better score have a lower hazard default rate.

In regard to loan characteristics, statistically significant coefficients are found for both loan maturity and size. In particular, the longer the maturity and the larger the loan size, the longer the loan survival duration. An increase of one month in loan maturity decreases the loan's failure risk by 0.99%. Moreover, larger loans are more likely to experience default than smaller ones: an increase in the loan amount by 10 euros increases the failure risk by 1.37% (Model 6, Table 5).

Our results do not indicate statistically significant differences between the sectors in which firms operate. Some authors (McCann et al., 2013; Lawless et al., 2013) highlight the higher riskiness of the manufacturing sectors relative to others; Gompers (1995) finds that, in this sector, lenders may reduce monitoring activities because of the lower level of information asymmetry.

Previous findings show that MGI-counter-guaranteed loans have a lower failure risk than directly guaranteed loans and that some firm's characteristics, which can be considered signals of firm informational opacity, influence the failure risk of guaranteed loans. In accordance with the literature on the role of soft information in the case of informationally opaque borrowers, we analyze the failure risk of guaranteed loans as a function of the firm's size, age, and sector (used as a proxy of availability of tangible assets).

Our results show that the failure risk of guaranteed loans requested by MGIs and banks does not differ based on firm size. Firm size affects the loan's failure risk, in accordance with the existing literature, but with the same magnitude, regardless of the type of financial intermediary that asks for the guarantee. These results show that banks and MGIs perform management of soft information with the same efficacy when monitoring informationally opaque firms. However, we observe that banks are able to reduce the loan failure risk only in the case of manufacturing firms. In fact, loans issued to manufacturing firms and directly guaranteed by the CGF have a 0.48% lower failure risk than counter-guaranteed loans. In comparison with construction and trade and services sectors, the manufacturing sector has a higher amount of tangible assets (Mac et al., 2010). This is an important factor because the informational opacity and asymmetry that, in this case, also characterize borrowers, owing to the fact that they are all SMEs, can be partially reduced by the presence of tangible assets (Gompers, 1995). In this case, efficient management of hard information can provide more benefits than in other sectors, enabling better performance of banks in terms of failure risk mitigation.

Our second hypothesis is partially confirmed in that the failure risks of guaranteed loans requested by MGIs and banks do not differ based on firm size and age, but do differ based on sector.

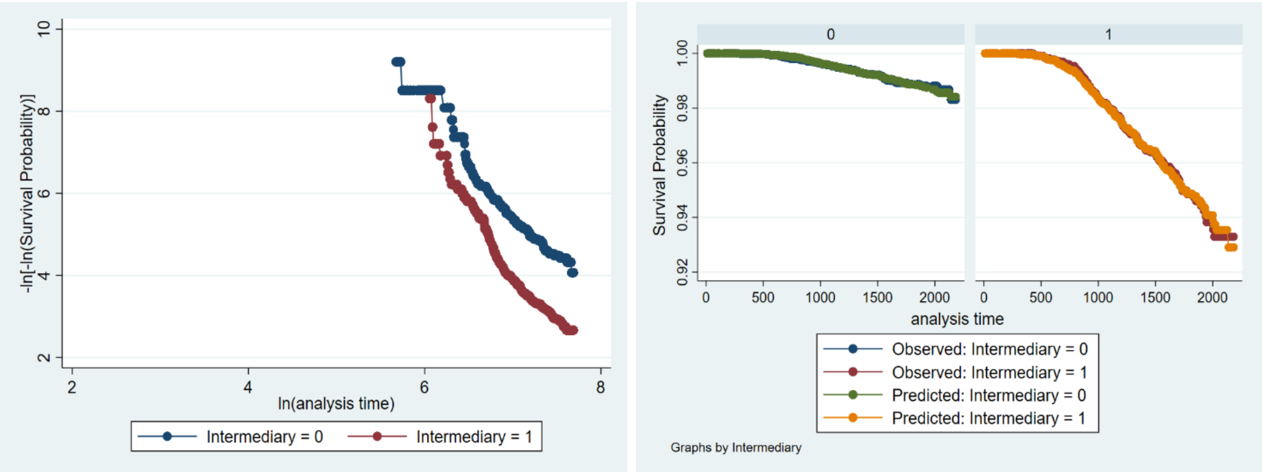
Finally, comparing Table 3 and Table 5, we can observe that, considering the selection bias and adjusting for it by including in the regression model the IMR, some variables that were not statistically significant in the previous model become significant; furthermore, the magnitude of coefficients and hazard ratios change, suggesting that the results in Table 3 were subject to selection bias

5.1 Robustness checks

Cox proportional hazards models assume that the hazard ratio remains constant over time. Because the Cox model, by definition, is constrained to follow this assumption, it is important to evaluate its validity. We test the proportional hazard assumption and report our results in Figure 3A and Figure 3B. Figure B shows lines that are parallel, implying that the proportional-hazards assumption for intermediary has not been violated. This is confirmed in Figure A, where the observed and predicted values are close together. This assumption is important and indicates that the ratio of the hazards of two individuals is constant over time, and, therefore, they are proportional.

Figure 3 Proportional Hazard Assumption

A) *B)*



This figure shows the proportional hazard assumption (PHA) and shows the relationship between time and survival probability. When Intermediary is 1, it is a bank, when it is 0 it is an MGI.

The result of the proportional hazards assumption is also confirmed by the test runs on the basis of Schoenfeld residuals after fitting the Cox model. We run the test for individual covariates and globally. The null hypothesis of zero slope is equivalent to testing that the log hazard-ratio function is constant over time. Thus, rejection of the null hypothesis of a zero slope indicates deviation from the proportional-hazards assumption. Table 6 shows the results of the proportional hazards test and that the prob>chi^2 of the global test is not statistically significant; therefore, there is no evidence that the proportional hazards assumption has been violated.

Table 6. The proportional hazard assumption test

Variables	rho	chi2	df	Prob>chi2
INTERMEDIARY	-0.02500	0.19	1	0.6625
MILLS	0.00464	0	1	0.9437
MICRO	-0.03577	0.56	1	0.4528
SMALL	-0.02330	0.22	1	0.6402
LEVERAGE(t-1)	-0.03499	0.37	1	0.5427
REVENUES_TA(t-1)	-0.10814	12.04	1	0.0005
ROA(t-1)	-0.08839	1.07	1	0.3015

SCORE_CGF	0.00606	0.02	1	0.8954
YOUNG	0.06441	1.1	1	0.2944
MATURITY	-0.04494	0.57	1	0.4485
LOAN_SIZE	-0.06529	1.38	1	0.24
MANIFACTURING	0.08150	1.93	1	0.165
CONSTRUCTION	-0.05409	1.27	1	0.259
INTERMEDIARY*MICRO	0.02283	0.16	1	0.685
INTERMEDIARY*SMALL	0.05671	1.12	1	0.2894
INTERMEDIARY*YOUNG	-0.07583	1.38	1	0.2393
INTERMEDIARY*MANIFACTURE	-0.01105	0.03	1	0.8587
INTERMEDIARY*CONSTRUCTION	-0.00638	0.01	1	0.9152
GLOBAL TEST		30.8	24	0.1597

Table reports the proportional hazard assumption test for individual covariates and globally.

As an additional robustness test to control for selection bias, we run the propensity score matching procedure. Because loans were not randomly allocated to the two groups of intermediaries (banks and MGIs), the propensity score was applied to reduce the potential bias and make the two groups more comparable.

A probit regression of type of intermediary was fit. We run the same regression used to determine the IMR (2); from this regression, the propensity score is defined as the probability to be treated (the loan is guaranteed only by the CGF and issued by banks) given the covariates. Individuals with similar estimated propensity scores will have, on average, similar chances of receiving that treatment and, overall, a similar covariate distribution. We check the distribution of the propensity score before and after the matching procedure (Figure 4).

Figure 4. Distribution of Propensity score before and after the matching procedure

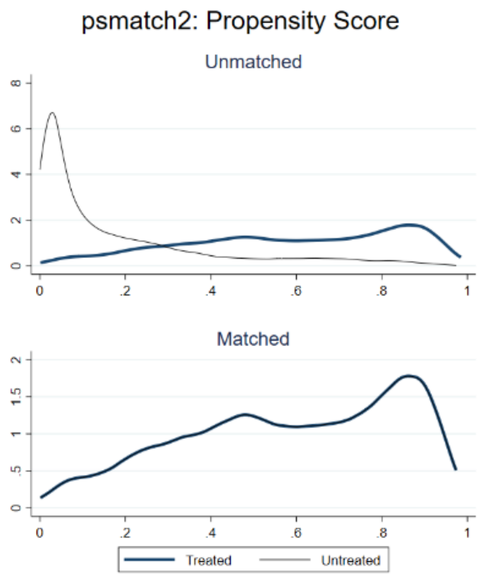


Figure shows the distribution of the propensity score before and after the matching procedure. Treated refers to the loans granted by banks without the counter-guarantee of MGI; Untreated to loans granted by banks with the counter-guarantee of MGI.

The propensity score can be used to reduce confounding via different strategies, which include, among others, regression adjustment (Patorno et al., 2013). In our analysis, the treatment effect is estimated using the propensity score (pscore) as covariate adjustment to control for confounding by indication bias due to the non-random selection process in the Cox proportional hazard model (Wuethrich et al., 2010; Ali et al., 2013; Chalermrum et al., 2020).

Table 7 The Cox proportional hazard model with pscore adjustment

	Mod. 7		Mod. 8	
VARIABLES	Coeff	HR	Coeff	HR
INTERMEDIARY	1.744***	5.720	1.514*	4.545
	(0.170)		(0.840)	
PSCORE	1.045***	0.352	2.029***	7.606
	(0.320)		(0.669)	
MICRO	-	-	2.098***	8.150
			(0.759)	
SMALL	-	-	0.415	1.514
			(0.805)	
LEVERAGE(t-1)	-	-	-0.000	1.000
			(0.001)	
REVENUES_TA(t-1)	-	-	-0.447***	0.640
			(0.171)	
ROA(t-1)	-	-	-0.005***	0.995
			(0.001)	
SCORE_CGF	-	-	-0.283***	0.754
			(0.032)	

YOUNG	-	-	-0.063	0.939
			(0.279)	
MATURITY	-	-	-0.007**	0.993
			(0.003)	
LOAN_SIZE	-	-	0.311***	1.365
			(0.105)	
MANIFACTURING	-	-	0.288	1.334
			(0.269)	
CONSTRUCTION	-	-	-0.025	0.975
			(0.504)	
INTERMEDIARY*MICRO	-	-	0.178	1.195
			(0.825)	
INTERMEDIARY*SMALL	-	-	0.727	2.069
			(0.889)	
INTERMEDIARY*YOUNG	-	-	1.010***	2.746
			(0.365)	
INTERMEDIARY*MANIFACTURE	-	-	-0.628*	0.534
			(0.324)	
INTERMEDIARY*CONSTRUCTION	-	-	-0.505	0.604
			(0.648)	
GEOGRAPHICAL FE	YES		YES	
YEAR FE	YES		YES	
SECTOR FE	YES		-	
Observations	56,197		56,190	
Pseudo R2	0.0460		0.115	

This table shows the results of the Cox Regression Model. "*", "**", "***" indicate 1%, 5%, 10% significance levels respectively. The dependent variable is a dummy variable equals 1 whether the firm's loan defaults and 0 otherwise. The independent variable are: INTERMEDIARY is a dummy variable equals 1 if the guarantee to the MGF is requested by a bank and 0 otherwise; PSCORE is the propensity score obtained from the probit regression to control for the selection bias problem; SCORE_CGF is a category variable that spans from 0 to 12. Lower values are associated to lower firms profitability, capitalization and capability to repay interest, while higher values are associated to firms with better profitability, capitalization and capability to repay interests. SMALL_FIRM and MICRO_FIRM are two dummy variables that proxy the firm's size, the first is equal to 1 when firm is small and 0 otherwise, the second dummy variable is equal to 1 when firm is micro and 0 otherwise; LEVERAGE is the ratio between firm's total assets and equity as measure of firm's financial leverage; REVENUES_TA is the ratio between total revenues and total assets; ROA is the return on asset that is a measure of firm's profitability; YOUNG is a dummy variable equals 1 when firm exists less than three years and 0 otherwise; MANUFACTORING and CONSTRUCTION are two dummy variables referring to the sector in which firm operates; INVESTMENT is a dummy variable equals 1 whether the loan is requested for an investment and 0 otherwise; MATURITY (and its square) is the natural logarithm of the loans time to maturity expressed in days; LOAN_SIZE (and its square) is the natural logarithm of amount of loans; SECTOR_FE, GEOGRAPHICAL_FE and YEAR_FE are three vectors that capture differences at sector, time and geographical levels. Columns "Coeff" report the coefficient of the Cox regression; Columns "Hazard ratio" report the hazard ratio of the cox regression (the exponential of the coefficient).

Our main results are also confirmed in this robustness analysis. The treatment effect remains statistically significant and shows that loans issued by banks and guaranteed by the CGF but not counter-guaranteed by MGIs are more likely to default. In particular, the hazard ratio of loans issued by banks is 4.54% higher than that of loans counter-guaranteed by MGIs. Looking at the interactive variables, banks are better than MGIs when loans are issued to manufacturing firms, but not when loans are issued to younger firms. The presence of a direct guarantee for loans granted to firms operating in the manufacturing sector reduces the failure risk by 0.53%, whereas the presence of a counter-guarantee for loans granted to younger firms reduces the failure risk by 2.75%.

6. Discussion and conclusions

This paper makes a useful contribution to the literature on the financial sustainability of the public CGS. We analyze the failure risk of public guaranteed loans, with a specific focus on the role of the financial intermediaries involved in the guarantee-granting process. The public CGS works on behalf of private actors in sustaining SMEs' access to credit and growth opportunities. Because of the informational opacity of these borrowers, financial intermediaries involved in the granting process are called in to manage soft information in reducing loans' failure risk. Indeed, although the public CGS has introduced, year upon year, more sophisticated credit scoring or rating models for the assessment of firm eligibility, the presence of information asymmetries and opacity makes the role of banks and MGIs extremely important.

We contribute to the limited number of studies on the financial sustainability dimension of public CGSs (Schich et al., 2017). Beck et al., (2008) and Green (2003) argue that the degree of overall efficiency and effectiveness of a program is largely dependent on the criteria according to which it is designed and implemented. Green (2003) identify an optimal level of leverage (the ratio between the public guarantees and credit availability), while Jonsson (2009) analyzes the level of default rate that would avoid a complete exhaustion of funds in the medium-long term. Riding and Haines (2001) emphasize the effect of the percentage of guarantee coverage on default risk.

Our study provides new insights into the influence of the financial intermediary on the failure risk of guaranteed loans. Public guarantees are addressed to smaller firms that, according to the main literature, can be considered informationally opaque; the literature argues that, in this context, banks that apply relationship lending and MGIs are the actors best able to manage soft information and deal with information asymmetry.

The paper demonstrates that, overall, the failure risk of counter-guaranteed loans through MGIs is lower than that of guaranteed loans through banks. MGIs, through peer monitoring and peer screening, are better able to mitigate the risk of default than banks. This is especially true in the relationship with informationally opaque firms: in our sample, which comprises SMEs, MGIs seem to be able to manage soft information better than banks, representing a substitute for relationship lending (Bartoli, 2013). Considering the various indicators of firm's opacity, we do not find specific differences in terms of firm size; however, the sector appears to be relevant in this context.

The analysis shows that when screening and monitoring can rely on the management of hard information, as in the case of manufacturing firms, banks' expertise can better mitigate the loan failure risk than MGIs. The results of this paper can be analyzed in the light of another recent study on the Italian CGF. Caselli et al. (2019) demonstrate the effectiveness, in terms of firm profitability, of the Italian public guarantee schemes, only for micro and small firms operating in the manufacturing sector. Given their results, we suggest that although, in general terms, MGIs are associated with a lower risk, banks should remain a key actor in public guarantee schemes because they are able to reduce the risk of default of one of the most profitable sectors. Considering the magnitude of our estimated hazard rates, the type of the financial intermediary is one of the most relevant factors affecting the loan's time to default (preceded only by the firm's micro size). In the context of micro and small firms, the territorial proximity of the MGIs and their more in-depth knowledge of the borrowing firms are important factors for loan monitoring that could be helpful in the reduction of failure risk. Our findings may be of support to international studies seeking to analyze credit guarantee schemes in countries where the role of the MGI is not as strong as in Italy. In fact, the characteristics cited above could also applicable to certain type of banks, i.e. cooperative banks, which, owing to the proximity with their clients, can take on the role of the MGI. The positive effect of MGIs on SMEs' cost of financing diminishes when smaller banks (i.e. cooperative banks) are involved (Columba et al. 2010). Future research should aim to analyze in more detail which types of banks are able to manage informationally opaque firms more efficiently: our results suggest that smaller banks characterized by territorial proximity—such as cooperative banks—could be more efficient in the management of soft information.

The findings of our paper also have important policy implications. In accordance with the European SME-Action Programme, we emphasize the importance of the strength of guarantee institutions in facilitating SMEs' access to finance.

Given that they have proven to be able to help address financial market imperfections, guarantee institutions should be reinforced through EU programs such as COSME and InnovFin (i.e., EU Finance for Innovators program). The national public CGSs should receive a counter-guarantee from these programs, with several advantages such as higher leverage effect, more efficient support to SMEs, and the involvement of a large number of experts with specific local knowledge and expertise.

The paper provides an important contribution to the set of principles issued by the World Bank (The World Bank and FIRST Initiative, 2015) for the design of CGSs that are efficient and financially sustainable. In particular, we contribute to principle number 8: "*The CGS should have an effective and comprehensive enterprise risk management framework that identifies, assesses, and manages the risks related to CGS operations*" and principle number 12: "*The CGS should adopt a transparent and consistent risk-based pricing policy to ensure that the guarantee program is financially sustainable and attractive for both SMEs and lenders*".

Our findings additionally contribute to CGS risk management. As suggested by The World Bank and FIRST Initiative, 2015 "an effective credit risk management should establish and enforce a set of relevant exposure limits (for example, by subsector, geographical area, and so forth) as well as use any appropriate technique or instrument available, such as counter-guarantees or co-guarantees, to mitigate concentration risk”.

Our findings show that counter-guarantee instruments seem to be more effective in containing failure risk. Although distinctions should be made by sector, direct guarantees seem to be more effective in sectors characterized by high levels of tangible assets, such as manufacturing.

Our findings also contribute to principle 12. The CGS should adopt a transparent and consistent risk-based pricing policy to ensure that the guarantee program is financially sustainable and attractive for both SMEs and lenders. Fees should always be levied on the basis of risk exposure. The CGS should be able to adjust its pricing policy on the basis of the CGS’s credit loss history and market developments. To date, the fees are differentiated based on firm’s size, type of operations, and geographical area (north or south Italy). Our results demonstrate that, in addition to these aspects, fees should be taken into account as well as the financial intermediary involved in the guarantee-granting process.

Appropriate design of the public credit guarantee scheme is crucial for limiting moral hazard in financial institutions and borrowers, mitigating failure risk, and ensuring the financial sustainability of public interventions. Given the relevance of the public CGSs worldwide and their strategic role in supporting SMEs, this is also a crucial factor for the stability of the economic and financial system.

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Appendix 1. Macroeconomic conditions 2007-2019

Appendix 2 The CGF scoring model

The CGF assesses the creditworthiness of SMEs through a scoring system based on the ratios shown below, related to the last two balance sheets and income statements (CGF 2015).
CGF pre-reform financial ratios are included in the scoring system.
Financial ratio and Reference value
A) (Equity + Long-term Debt)/Total fixed assets ≥ 100%
B) Equity/Total liabilities ≥ 10%
C) EBITDA/Financial expenses ≥ 2
D) EBITDA/Sales ≥ 8%

On the basis of the reference values of the ratio, the CGF assigns a score from 0 to 3 in accordance with the figure presented below. The total score for each company varies from a minimum of 0 points to a maximum of 12 points.

Value	Score
"A" ≥ 100%	3
50% < "A" < 100%	2
0 < "A" ≤ 50%	1
"A" ≤ 0	0
"B" ≥ 10%	3
6% < "B" < 10%	2
0 < "B" ≤ 6%	1
"B" ≤ 0	0
"C" ≥ 2	3
2 >"C" ≥ 1.5	2
1.5 > "C" ≥ 1	1
"C" < 1	0
"D" ≥ 8%	3
8% > "D" ≥ 5%	2
5% > "D" ≥ 3%	1
"D" < 3%	0